# AN INTEGRATIVE APPROACH TO HUMAN EMOTIONS: TOPOLOGY, NETWORKS, INTEROCEPTION

Kamilya Salibayeva

Submitted to the faculty of the University Graduate School
in partial fulfillment of the requirements
for the degree
Doctor of Philosophy
in the Department of Psychological and Brain Sciences,
Indiana University

May 2024

Accepted by the Graduate Faculty, Indiana University, in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

Aina Puce, Ph.D., Co-Chair

Olaf Sporns, Ph.D., Co-Chair

Doctoral Committee

Ann-Sophie Barwich, Ph.D.

April 9, 2024

Nathalie George, Ph.D.

James T. Townsend, Ph.D.

*To my family: my sister Zoe and my mother Sabira*

## ACKNOWLEDGMENTS

I would like to express sincere gratitude to my advisor Dr. Aina Puce for her guidance of my endeavors and acceptance of my varied interests in the area of emotion studies. Without her help and encouragement, I would not be able to conduct the studies described, nor would I be strong enough to come to the finishing line of this five year-long journey. Her welcoming approach to our work made the years of the COVID-19 pandemic and associated lockdowns more bearable — the forced closing of our lab to in-person work notwithstanding. Our relationship truly means a lot to me on both professional and personal levels.

I would also like to thank the members of my Committee: Dr. Olaf Sporns, Dr. Ann-Sophie Barwich, Dr. Nathalie George, and Dr. James T. Townsend. Their presence and supervision made my wanderings in the eclectic areas of computational and networks neuroscience, philosophy of mind, neurophysiology, and mathematical psychology possible. Their willingness to help me in developing arguments, writing code, finding relevant literature, and mastering a plethora of professional skills is a priceless contribution to the process of writing this dissertation.

The next two people who brightened my years as a doctoral student are my laboratory mate Matt Winter and Dr. Fatma Parlak, my closest friends and confidants. I thank them both from the bottom of my heart for their round-the-clock availability, be it for a quick chat about the definition of heteroscedasticity, a lengthy discussion of neural mechanisms of cognition, or nightly musings about the nature of Life, Universe, and Everything.

My warmest appreciation also extends to Jake Isenman and Annie Abioye, who were irreplaceable during the time of data collection for the study of emotion dynamics (Chapter 4). Their tenure at Puce Lab was marked by a cheerful atmosphere, and I sincerely wish them both the best with future plans.

A separate expression of gratitude should be noted with regards to the study of cardiac cycle phases and brain functional connectivity (Chapter 5). Among the authors of the paper which will hopefully follow the defense of my dissertation are Drs. Aina Puce, Olaf Sporns and Nathalie George, as well as those not listed yet, Christophe Gitton and Dr. Laurent Hugueville. It truly takes a village, and I cannot stress enough how valuable everyone's contributions have been to the fleshing out of this study.

Finally, I would not be able to finish this without the support of my family: my mother, Dr. Sabira Kulsariyeva, whose lifelong academic guidance shaped me as the researcher I am today, and my sister Zoe Kulsariyeva, whose wisdom, humor, and intellectual prowess I have been trying to emulate since childhood. Many a sleepless night and stressful video call later, I cannot begin to put into words how indebted I am to both of them for the endless stream of love and support.

The research in this dissertation was supported in part by Lilly Endowment, Inc., through its support for the Indiana University Pervasive Technology Institute.

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# AN INTEGRATIVE APPROACH TO HUMAN EMOTIONS: TOPOLOGY, NETWORKS, INTEROCEPTION

This dissertation presents an interdisciplinary exploration of human emotions, bridging psychology, neuroscience, and mathematics to address the limitations of traditional emotion theories. It highlights the dynamic and evolving nature of emotions, influenced by physiological changes and environmental contexts, as well as sociocultural backgrounds.

Borrowing mathematical concepts from topology and differential geometry, combined with machine learning techniques, one of the experimental studies analyzes emotional experiences as dynamic phenomena. It maps individual emotional experiences on complex three-dimensional structures and thus shows how multifaceted emotions are.

Additionally, the dissertation explores the brain-body relationships by examining the influence of heart rhythms on brain activity, illuminating the value of embodiment and laying ground for future investigations of physiology of emotional states. By analyzing data from resting-state neurophysiological recordings, the other experimental study underscores the interconnectedness of bodily functions and brain networks.

This work advocates for a comprehensive understanding of emotions as complex phenomena influenced by both biology and personal experiences. With this approach, it aims to offer a richer interpretation of complex behaviors and emotional states,

challenging conventional methodologies and suggesting new avenues for emotional research.

Aina Puce, Ph.D., Co-Chair

Olaf Sporns, Ph.D., Co-Chair

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

# Chapter 1

## Introduction

This dissertation is a narrative about emotions — a complex phenomenon which has been dissected, observed, and described by many philosophers, artists, and scientists. Emotions have long been recognized as complex entities reliant on context in the physiological, cognitive, and social senses (Berrios, 2019). Yet, despite the many attempts at describing them in a scientifically rigorous way, the fields of psychology and neuroscience do not currently have a consensus about what emotions are. As the authors of the Human Affectome (Schiller et al., 2023) point out, the discrepancies in various subfields of affective science arise largely due to the differences in teleological understanding — that is to say, the multitude of approaches developed to day attribute very different properties to emotions when studying them.

In my dissertation, I propose to revise our approach to emotions and experimental designs surrounding a variety of research questions. This revision is motivated by an extensive literature review. Chapter 2 is thus dedicated to a synthesis of existing approaches to modeling emotions. As I bring together the advantageous aspects of frameworks and methods used in the fields of psychology and neuroscience, I will also demonstrate the knowledge gaps. Finally, I will develop an operational definition of emotion which will be used throughout the rest of the dissertation. Mainly, I aim to redefine emotions as points on a differentiable manifold, so that the practical and computational approaches to the analysis of emotion data can focus on the dynamics occurring between emotions as opposed to within them. This aligns with the Developmental Systems Theory (DST) (Ford and Lerner, 1992) and 4EA (*Embodied, Embedded, Enacted, extended, and Affective* mind) approaches (Protevi, 2009) which I argue to be the most modality- and method-agnostic in developing new experimental paradigms and underlying assumptions when it comes to the questions of cultural diversity and physiological universality.

This will segue into the description of my proposed model based on topological and differential geometric methods as they apply to continuous data. Chapter 3 is an overview of some foundational criteria necessary for an empirical realization of the model, such as the parameters of a topological space defined by the emotion repertoire of an individual — or all emotions that they can have. I show that my assumptions about such a space align well with the method of choice for analysis of experimental data, the Uniform Manifold Approximation and Mapping (UMAP) algorithm (McInnes et al., 2018).

I then proceed to demonstrate the direct application of said method in Chapter 4. I describe in details the methods and findings of a behavioral study conducted via remote online logs filled out by a sample of 68 adult participants, each of whom described their sensations of intensity as they transitioned from one moment to another. The three factors they described were interoceptive (or body-related) feelings, the degree of self-reflection and cognitive engagement, and the level to which their social environment contributed in their shift between the two emotions. Those three aspects align with the biopsychosocial model (BPSM), which I propose to use in conjunction with responses to demographic and psychological trait questionnaires. Note that I also propose to eschew the notion of valence in my analysis of emotion data (following Solomon and Stone 2002), as the question of cultural diversity and considerations about the universality of valence values are quite pertinent in the field (Shuman et al., 2013). I demonstrate in my findings that there might indeed be a relationship between the cultural identity of my participants and the feasibility of embedding their data onto one of two types of non-Euclidean surfaces (spheres or tori).

In order to test future applicability of my approach to electrophysiological, neuroimaging, or other biosensing data, it was thus necessary to evaluate the possibility of elucidating brain-body relationships in multimodal datasets. Performing an analysis of embodied processes would aid in the validation of my framework in two ways: first, it would establish a neurovisceral relationship and thus demonstrate the importance of 4EA within my framework; second, it would aid in developing a solid methodological foundation to future combination of data in various modalities when analyzing emotion dynamics as proposed by the topological model.

I therefore emphasize the methodological approach to analysis of multimodal data in resting participants in Chapter 5. There, I analyzed a multimodal MEG-EEG-ECG (magneto- and electroencephalographic and electrocardiographic) dataset collected from four adult participants for a prolonged period of time. My primary goal was to determine the relationship between an estimation of the dynamic patterns of functional connectivity and network structure in the neurophysiological data as a function of the two main parts of the cardiac ventricular cycle, systole and diastole (see Al et al. 2020 for a similar method applied to somatosensory evoked potentials). Through application of a variety of methods (from ECG analysis to source localization of neurophysiological signals within canonical frequency bands), I found significant differences in resting-state functional connectivity and network structure between systole and diastole. My analysis in *resting-state data* aligned with the results of prior studies which explored *task-related paradigms* and their relationships with the cardiac rhythm. Moreover, the methods of analysis of these data also underlined the importance of multimodal investigations in psychology and neuroscience. Thus, methods such as the ones developed in Chapter 5 will be essential for future realizations of more complex analyses of emotion-related data, an example of which can already be seen in Chapter 4.

I then conclude my dissertation with a brief discussion of the findings, as well as an overview of future directions and implications of the research.

# Chapter 2

## Modeling emotions: a historiographic review

### Introduction

Emotion is a key concept in Western psychology, yet defining it succinctly has proven to be a challenge over the last century and a half: this term, along with "percept", "affect", and "feeling", has been used extensively by researchers since the 19th century. Despite this long history, there is surprisingly little agreement on what exactly an emotion is, even within specific fields such as the history of emotions, or disciplines such as the humanities, social sciences, and life sciences. This chapter of my dissertation will explore these varied understandings and the lack of consensus and argue why a proposed topological model of approaching emotion dynamics as functions in an n-dimensional space could open new avenues of research in the future. Moreover, I will address the questions of the operationalizations that might aid or hinder more integrative approaches to empirical research in each of the existing models. This critical overview of the history of affective sciences as it pertains to psychological and neuroscientific research will highlight the epistemological gaps in the current understanding of emotion and lay the necessary ground for a proposed mathematical framework of emotion.

The need for such a framework has been recently emphasized in a special issue of Neuroscience and Biobehavioral Reviews in February 2024 focused on the Human Affectome Project. The most notable work in that issue is the monumental capstone review by a collective of authors (Schiller et al., 2023), where the philosophical underpinnings of many extant operationalizations and theories of emotion across various fields and subdomains were synthesized into a singular paradigm of the human affectome. The authors emphasize the need for an integrative approach that would encompass all of the aspects of affective phenomena, including but not limited to the psychological and physiological processes (which the domains of psychology and neuroscience typically concentrate upon), the linguistic and cultural variability, as well as mechanistic and computational implications included in the general paradigm of the human affectome.

It therefore appears imperative for me to outline in the present chapter the most pertinent historical advancements in the area of affective research as they pertain to all of the aforementioned subdomains. This context will serve as a basis of the model proposed in Chapter 2, as well as underline the importance of studies conducted in Chapters 3 and 4.

## 2.1 Psychological and neuroscientific research into emotions: a brief history

The following section of this chapter focuses primarily on the theoretical aspects of investigations into the nature of emotions. Most of the research outlined here is thus focused on the behavioral approaches characteristic of the psychological sciences, and not the relation between the brain and the body — that will be addressed in the section that follows. However, it appears prudent to separate these areas of research, if only due to the dominance of the “top-down” view of cognition prevailing over affect, which was particularly distinctive in the psychological treatises of the late 19th and early 20th centuries. While the brain-body unity has been addressed in some recent frameworks, categorizing emotions (affect, passions, etc.) as phenomena separate from cognition has been a hallmark of many fundamental paradigms. Thus, the historical overview below is designed to familiarize the reader with the evolution of thought schools in psychology and neuroscience which have undergone refinement yet remain functionally important in current psychoanalytical, therapeutic, and theoretical research. A brief guideline is provided in Figure 2.1 to illustrate the chronological progression in its rough outline.

### 2.1.1 Early paradigms of emotion

The discussion of formalized models cannot begin without a brief excursus to the 19th century. The origins of investigations into emotions as human universals began with Sir Charles Bell's *Essays on the Anatomy of Expression in Painting* (1806), Alexander Bain's *The Emotions and The Will* (1859), Guillaume-Benjamin Duchenne's *Mécanisme de la physionomie humaine ou analyse électro-physiologique de l'expression des passions* (1862) and Charles Darwin's *The Expression of The Emotions in Man and Animals*(1872). These early attempts at defining emotions were largely driven by the works of prominent neuroanatomists and neurophysiologists of the era. Among them was Sir Charles Bell, whose *Essays* (1806) could probably be named the most influential in establishing the movements of body and face as the external marker of an internal emotional experience. Bell expressed in his writing a belief in that the process of translating the inner emotional state to the face was an innate mechanism, universal for humans as a result of intelligent design. He appealed, for instance, to the expressions of emotion in human infants, referring to perceived "kindness" as

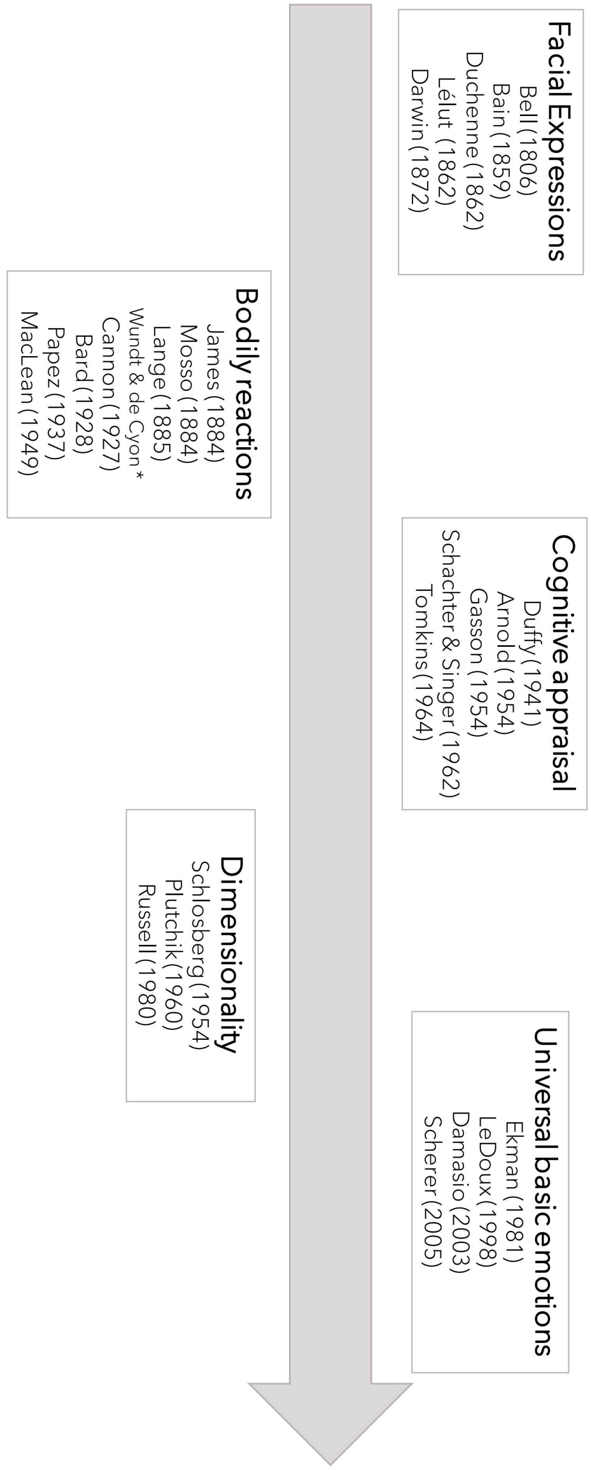


*Figure 2.1.* **Timeline of major researchers in the area of emotion sciences.** Some names omitted for brevity, especially in the area concerning more contemporary constructionist investigations.

the driving force behind a smile, and a frown being caused by an anticipation of "blows" (*Essay V*). This appeal to developmentally early signs of emotional expression inspired the further course of conceptualizing faces as conduits of communicated emotion.

One of the pioneers of such views, for instance, was Alexander Bain, who espoused this position in several of his works (such as *The Senses and the Intellect,* 1855; or *Mind and Body: The Theories of Their Relation*, 1873). Of most relevance to my work, however, is the 1859 philosophical treatise *The Emotions and the Will* , in which Bain referred to the physiological mechanisms accompanying an emotional experience, such as the functions of the cardiovascular system (see *Chapter XIII, Of Ideal Emotion*). Yet, Bain supported a widely prevalent notion of duality of mental and physical phenomena in human experience, which he underlined by insisting upon the brain and the endocrine system simply maintaining emotional "tremors". One can easily draw parallels between the beliefs in human superiority and idealization of the yet unknown mental processes in both Bell and Bain. Nevertheless, it is important to note that Bain did highlight a quasi-mechanism of an emotion (or a feeling) being "a wave of nervous influence emanating from the brain" which, by Bain's supposition, only supported the emotion as a mental concept, but did not exist at the point of origin of the feeling in the "peripheral" systems of the body. This definition (albeit bearing more explanatory power in terms of physiology) is thus inarguably important for my later consideration of the *temporal continuity* of emotions.

Returning to Charles Bell's work and those inspired by him, it is important to mention Guillaume-Benjamin Duchenne de Boulogne, whose 1862 monograph of *Mécanisme de la Physionomie Humaine ou Analyse Électro-Physiologique de L'Expression* *des Passions* was a comprehensive endeavor into the electrical stimulation of the musculature of the face to reproduce natural facial expressions. Like Bell, Duchenne attempted to demonstrate the inadequacy in the artistic depiction of emotion at the time. By creating a truly unmatched nomenclature of facial movements, he provided insight into a mechanistic and detailed account of musculoskeletal interactions from both an expressive perspective and from the point of view of the neuromuscular junctions connecting the brain and the face. Yet, unlike Bell, Duchenne wrote in *Mécanisme*: "[p]erhaps it isn't given to man to express all his emotions on his face", acknowledging the manifold of emotional experiences in humans and pointing to a (rather extensive) list of emotional states composed by Louis-Françisque Lélut (Lélut, 1862) as the source of his conviction (Duchenne, 2006). This incompleteness of the accounts of emotional experiences was thus a sign of progress in the understanding of the relationship between facial expressions and internal emotional experiences.

Such sentiment is, of course, quite concordant with the three Principles of expression outlined by Charles Darwin in his 1872 book *The Expression of the Emotions in Man and Animals*. In fact, Darwin cited Duchenne's works as highly influential, in that Darwin's views on expression were that facial movements are largely generated by force of habit (in a Lamarckian sense, peculiarly, Darwin asserted that habits were a heritable trait — which today we might at best attribute to a mechanism of epigenetic markers being transmissible vertically). Moreover, in *The Descent of Man* (1871) Darwin seemed to be referring to emotions as those which can be evoked by various stimuli, yet he also agreed with Bell, Bain, and Duchenne on the notion of universality of emotions as experiences.

An important note about emotions as internal lived experiences has to be made about Claude Bernard's seminal contribution to understanding emotions through his concept of homeostasis (milieu intérieur) introduced in 1878. Bernard's work influenced neurophysiology and the study of emotions, laying foundational insights that my research builds upon. Further details on Bernard's influence and the concept of homeostasis will be explored later in this work. Yet, it is important to mention that In his writings, Bernard emphasized a systemic view of human physiology and introduced the idea of stable intervals within which certain physiological parameters should have resided for optimal function of some organ systems (for instance, the vasomotor interactions between the blood vessels and the peripheral nervous system). Of note here is the need to consider the aspects of bodily processes related to the shifts in environmental adaptation, which play a crucial role in my proposed model.

### 2.1.2 Formalized approaches: from James to Russell

Undoubtedly related to the notion of embodied physiological functions are the views of William James, who in his 1884 essay *What is an Emotion?* outlined what would further become the basis for the James-Lange framework. Of particular interest to my model are the following characteristics of emotions as proposed by James: first, he postulated that emotions are events *discrete in time,* always elicited by the perception of a (presumably external) stimulus. Second, according to James, emotions were both the *embodied processes* encompassing a multitude of organ systems *and* conscious awareness about them. Notably, the former view of emotions being separable from any other state — even when viewed as embodied, — has been largely accepted in the field of neuroscience for more than a century (see, for example, Roseman, 1996, or Adolphs & Anderson, 2018), while the latter combination of the physiological function and its "mental" counterpart has been debated heavily in constructionist theories of emotion (see below in discussions of Schachter and Singer, Arnold, or Russell). Overall, Jamesian views of emotion have successfully reigned supreme for a few decades in the field of psychological and physiological science — until a change of direction in the perception of modeling frameworks was instigated by a critical review and a proposal of an alternative theory by Cannon in 1927 (see below).

The renowned Italian physiologist Angelo Mosso, was publishing his works contemporaneously with James. Mosso's works concerned the vasomotor functions correlated with different states of the body and the brain (for example, his 1884 book *La Paura* — translated into English as *Fear* in 1896). Mosso developed novel apparatuses for his investigations into the dynamics of blood circulation in the brain (see, for instance, a translated version of one of his essays in Field & Inman, 2014) and presented the results of his studies into the emotion-induced changes in the pulsatile motion of his "human circulation balance". It is remarkable to note that such research into embodied processes tied with the emotional experiences was performed at such an early stage of the field's development — and to see us now circling back to the same motifs of understanding the brain.

Meanwhile in Denmark Carl Lange arrived at the same conclusions as James vis-a-vis the two characteristics of emotion (discreteness and embodiment), when he published his original essay *The Emotions: A Psychophysiological Study* in 1885 (see in Lange & James, 1922). Undoubtedly, both James and Lange were familiar with the works of Mosso and other physiologists of that era — including but not limited to Wilhelm Wundt and Elie de Cyon — and they acknowledged the complexity of investigations into emotions.

Returning to the pertinent question of dominant theoretical frameworks of emotion in the fields of psychology and early neuroscience, it is prudent to mention the popularity of the so-called Cannon-Bard theory of emotions. Walter Cannon's (1927) critical review of the preceding James-Lange theory — methodical and evidence-based — was dismissive of the link between emotional states and physiological processes. For instance, he pointed to the evidence obtained by Woodworth and Sherrington (1904) in their spinal cord-severing experiments as that which dismantled the Jamesian assumption of emotion embodiment — for if there were no afferent connections between the central nervous system and the periphery, no interoception could occur. Thus, posited Cannon, subcortical centers — specifically the thalamic region (which encompasses the hypothalamus and our modern understanding of the thalamus as a collection of subcortical nuclei) — were the ones responsible for the production of emotion. Moreover, later explanatory publications of his thalamic theory (such as Cannon, 1931) outright rejected the importance of visceral signaling in the formation of emotion altogether.

The 1928 publication of Philip Bard's diencephalic mechanistic hypothesis for the expression of emotion resonated with the thalamic theory of Cannon — the field thus refers to the Cannon-Bard in juxtaposition to James-Lange (interestingly enough, the recently augmented interest in interoceptive contributions to emotional processes is referred to as neo-Jamesian, and not neo-James-Langian).

Building off the thalamic theory was James Papez (1937), whose proposal introduced a complete anatomical account of how hypothesized emotional processing occurred in the brain. According to Papez, the emotional circuit was indeed passing through the "switchboard" of the thalamus and encompassed the cingulum, the hippocampus, the fornix, and the mamillary bodies — while its opponent "cognitive" route propagated the signals towards the cortex. Notably, Papez differentiated in his anatomical pathways the two supposedly distinct phenomena which both bear the name of "emotion" — the outward expression and the emotional "feeling". However, Papez did not argue with the previous proposals of Bard and even discarded the possibility of an embodied emotion by denying participation in the process to even the olfactory system. Papez's view of the emotion as a hierarchically "lower" process thus became an established view which influenced the field of neuroscience for quite some time.

Yet another concordant piece of evidence to Papez's mechanism came from the work of Paul D. MacLean (1949), whose classification of the "psychosomatic disease" further divided emotion into the three hierarchical levels: "primitive", social, and cognitive control of emotion (which he also assigned to the "reptile", "old mammalian", and "new mammalian" brains). This has cemented the view of emotions being in need of cognitive control and being ontologically separate from the cortical function, which has persisted in the field for decades to come, up until the beginning of the 20th century (see, for instance, Jaan Panksepp's foreword to Geary, 2002, or Cory, 2003).

Meanwhile, Magda B. Arnold and John A. Gasson (1954) (while supporting the basic assumption of emotion being separate from other, *aware* processes) proposed a mechanism which largely depended on the appraisal of a stimulus or a percept before an emotional experience took place. According to their proposal, emotions were merely reinforced by bodily processes during stimulus appraisal. Thus, any embodiment of emotion is not a part of Arnold and Gasson's framework — which unites them somewhat with the views of Elizabeth Duffy (1941), who discussed the interpretation of a stimulus which leads to a conscious appraisal of an emotional state. Notably, Duffy also argued for a departure from the nomenclature of emotions as such (see below in the discussion of linguistic and cultural context in 2.3).

However, here I would be remiss to not mention Schlosberg (1954), who espoused the dimensionality of emotion as that based on arousal (meaning the "intensitive dimension" of an emotional experience, which in his framework ranges from sleep to tension), valence (termed as "pleasantness-unpleasantness") and attention-rejection (which he uses to point out conscious attraction or repulsion of the stimulus). His article, while heavily reliant on Duffy's ideas of a continuum of activation, importantly pointed to the understanding of emotional experiences as those which are hard to disentangle from states of being which are *not* an emotion. While Schlosberg did point to skin conductance responses and measurements of facial expression, both of which may be viewed as continuous measures of embodiment, the framework presented in his article was still reliant on the differentiation of these responses to the environment. His approach was inextricable from the notion of the existence of "pure" or "basic" emotions, and thus failed to agree with my proposed definition.

Also in concordance with Duffy's view was the model of emotions proposed by Stanley Schachter and Jerome E. Singer (1962). Another early attempt at the formalization of emotional processing, their model was one of the first instances of presenting a *constructionist* view of emotion as a phenomenon encompassing several discrete stages in the progression of signaling, cognitive, or other biological processes. Emotion, according to Schachter and Singer, was comprised of a perception (or interpretation) of the presented stimulus in context, where the stimulus itself might have elicited a generalized arousal of the autonomic nervous system, while the circumstances of the encounter with the stimulus determined the particular emotion experienced at that moment. Notably, they did not shy away from acknowledging cognitive processing of the percept being crucial for the formation of the emotion as a complex experience. Thus, the overall paradigm was indeed inclusive of the idea of *context*, which I highlighted in the definition; yet, the Schachter-Singer model does lack explanatory power with regards to the *continuity* of an emotional process — presenting a stark contrast with Schlosberg's model.

At around the same time as Schachter and Singer comes also the multifactorial understanding of emotions of Robert Plutchik (1960). His approach to emotions was formalized through a series of postulates, the most important of which underlined the existence of primary emotions, the prevalence of mixed emotions in everyday life, and the relative pairwise opposition of all emotional states akin to the one we may see in color theory. It is important to note here that the multidimensionality Plutchik referred to in the title of his paper was largely stemming from Schlosberg's assumptions of *activation* being one of the primary dimensions along which emotions may be measured and formally assessed. Of course, the arbitrary nature of such an assessment was acknowledged in the description of the model. Yet, the primary emotions in his model were placed on a circumplex plane similar to a color wheel — in a manner determined by Plutchik's own intuition. As Plutchik puts it, more "complex" emotions would be formed from the mixtures of primary ones — which explained to the reader that the main postulate bore an assumption of the *discreteness* of emotions.

Thus, a view that is pertinent in the field to this day is that emotions need to be defined in terms of their folk psychological verbal counterparts, and any level of nuance in either the temporality or conscious awareness of the experience must be solely reliant on existing terminology and not on observations of body signals and/or registration of such.

This brings us to the model that remains an important contributor to the theoretical foundations of emotion research in the neurosciences to this day — namely, James A. Russell's circumplex model of affect (1980) — see the original model construct from self-report data in Figure 2.2. It is also crucial to point out that Russell's model included a principal components analysis of the similarity scores between self-reports of English-speaking human participants (for a more recent review of circumplex models, including those which have been transposed into Mandarin Chinese, see Stanisławski et al., 2021). Interestingly, Russell did also point out that the assumption of bipolarity of the proposed dimensions (see, for example, Russell et al., 1999) — as well as the much smaller percentage of explained variance in others — was strongly speculative and based on evidence from semantic analyses. Thus, Russell's framework — although ubiquitous in the field to this day — lacked formal neuroscientific translation to physiological terms, and thus appears to be less empirically feasible from the point of view of experimental design than other, more quantitative models.

Not dissimilar to the views of Plutchik and Russell were the writings of Silvan S. Tomkins, whose affect theory has greatly influenced the field of psychology. Notably, one of the later iterations of his theory (Tomkins, 1991) also pointed out the semantic and verbal bases for the categorizations of "affects" and not emotions. Tomkins defined an "emotion" as a feeling which was coupled with the memory of similar feelings.

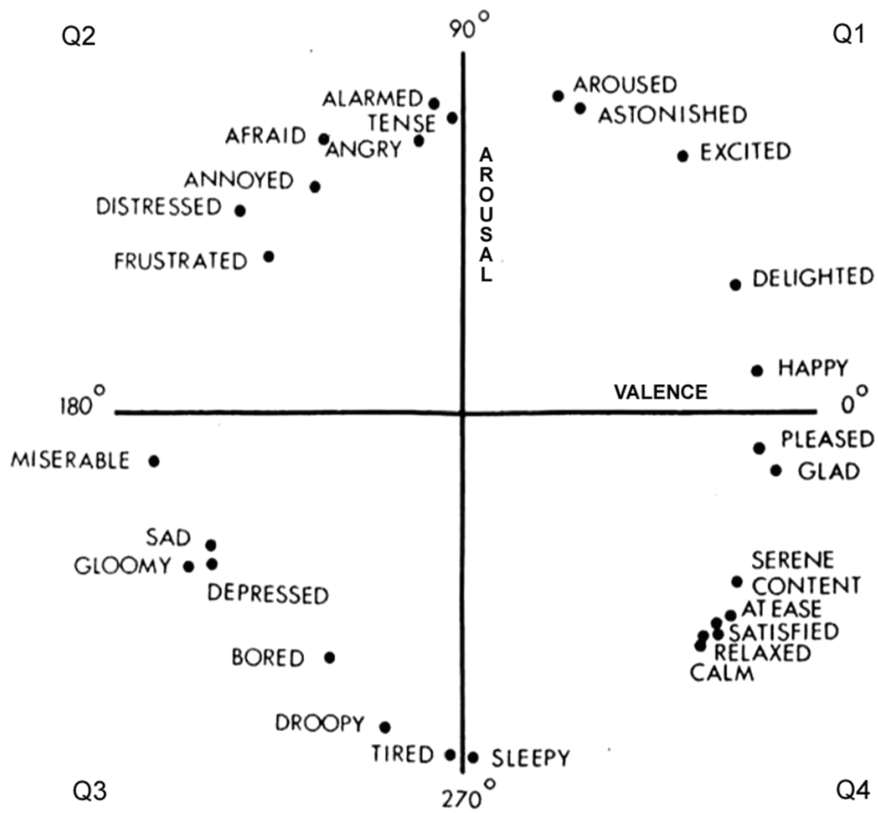


***Figure 2.2.*** **Russell circumplex model of affect.** *28 verbal labels of emotions were gathered in self-report data, and all of them are located on a unit circle circumscribing the origin point of the two dimensions of valence (x-axis) and arousal.(y-axis). Reproduced from Russell 1980.*

Operationalizing emotion in this manner did introduce continuity and historicity of the term with Russell's prevalent usage, yet fell outside the scope of our modern approach to emotions. In contrast, Tomkins's "affect", underlined by the characteristics of urgency (or immediacy), abstractness, and generality (cf. repeatability), was compared in his theoretical framework to other mechanisms of cognitive functions and thus distanced from "proper" cognition. It is easy to see that such views are not aligned with my proposed understanding of emotional states (as I view them as not independent or orthogonal to the putative network of cognitive mechanisms), but rather they perpetuate the juxtaposition of emotion and cognition. Thus, even if the intuitive understanding of affect's relationship to motivation or other named functions of the mind might fall under the umbrella of folk psychological cognitive ontology, I conclude here that behaviorally tested approaches such as that outlined by Tomkins are functionally divergent from the purposes I would like to posit for the proposed mathematical and analytical approaches to both extant and newly acquired empirical datasets.

### 2.1.3 Note on mathematical models of emotion space

It is also worth noting here that the last several decades leading up to 2024 have seen a resurgence of theoretical frameworks of emotion which incorporate interoceptive information as well as the "psychological" side of the phenomenon. A detailed overview of mathematical models of emotions briefly listed in the following paragraph can be seen in Chapter 3. The Jamesian movement incorporated physiological multiplicity of emotional characteristics, but this was reduced to "arousal" in the latter half of the 20th century. A marked resurgence, however, was seen in the works of

Klaus Scherer, Joseph LeDoux, and Antonio and Hannah Damasio. A brief listing of mathematical and multidimensional models (at least those seen before the rise of use of machine learning techniques in affective computing) is as follows: (1) Robert Plutchik's "affective cone" (1960); (2) Russell circumplex model (1980); (3) O'Rorke and Ortony ontological model and computational analysis thereof (1994); (4) Sokolov and Boucsein's three-dimensional comparison of emotion space with the color hue, lightness, and saturation (2000); (5) Klaus Scherer's proposal for the Geneva Emotion Wheel (2005); (6) Reisenzein's belief-desire theory of emotion (2009); (7) Trnka and colleagues' multidimensional approach which departed from the notion of valence and arousal as seminal components of emotion (2011). Contrasting those approaches are more modern techniques of computational nature such as MVPA-based clustering of fMRI BOLD signals (e.g., Saarimäki et al., 2018) or manifold learning techniques applied to data from facial expressions or verbal labels of emotions (such as those used by Liu et al., 2018; Yang et al., 2022; Zou, 2022). Notably, Townsend's approach to face spaces (2005) as a geometric model of parametrization of a human face is of particular relevance to the model described in Chapter 3. Thus, while the history of research into the question of emotion ontology, as well as the manifold of approaches to exploring this seemingly universal aspect of human psychology has been vast, none of the reviewed frameworks or models successfully address the multimodal nature of the phenomenon of emotions itself.

### 2.2 Brain-body unity: history of embodied emotion research

In this section, the historical overview continues with the presentation of the extant body of literature focused on emotions from the perspective of the relationship between the brain and the body — or, as the authors of the Human Affectome might posit, more "mechanistic" paradigms and tests thereof. This bibliographic inquiry will highlight the most important findings and knowledge gaps from the areas of neuroscience and various medical subfields which pertain to the subjective experience of emotion and its relationship to the emotional expression. It will also integrate some of the literature already mentioned in Section 1 with the paradigms more closely aligned with the cognitive science conceptual frameworks crucial for the development of more rigorous and teleologically founded definitions and operationalizations within my model.

### 2.2.1 Developmental Systems Theory (DST) as it pertains to emotion theory

The phenomenon of emotion has long been studied in neurosciences from the perspective of their juxtaposition to rationality — in which the latter has been assumed to represent all cognitive processes related to "thought". While the historical reasons for such a dichotomy have been challenged for several decades now, the ontological framework for the study of affective processes — as opposed to neural substrates of cognition — remains predominantly constructionist. That is, the majority of empirical investigations target the behaviors which follow emotional experiences in a participant or the reactions to such experiences in others. While it is true that some contemporary publications aim at exploring the neurophysiology of both emotions as experiences and the perception of emotion in others (for reviews, see Barrett & Satpute, 2019; Spunt & Adolphs, 2019), the common experimental approaches in EEG and fMRI remain uncritical of the status quo. For instance, many publications nowadays use solely the operationalizations concordant with the circumplex theory of emotions pioneered by Russell in 1980 (for just a few examples of such, see Liu et al., 2018; Bhole & Ingle, 2019; Joshi & Ghongade, 2021). Meanwhile, other operational definitions of emotion (such as those proposed by Lisa Feldman Barrett, 2012, or Desmidt and colleagues, 2014) do acknowledge the multifactorial nature of phenomena yet delimit the temporality of an emotional experience to factors preceding the experience, the emotion itself, and its aftermath, while the dimensionality of the experience itself remains at the discretion of the investigator. This reliance on a simplistic model proposed more than forty years ago overlooks the advances in other areas of research (such as clinical and translational psychology, history of emotions, sociology, and cognitive semantics, to name a few). Moreover, I would argue that this creates an epistemological lacuna in the field of cognitive and affective neuroscience. As elegantly posited by Overton (2013), the discourse in a scientific discipline progresses from observational to a metatheoretical level (see Figure 2.3). Current understanding of emotions as discrete, temporally isolated incidents with varying degrees of precision in the operational definitions used across laboratories and investigators appears to be most closely related to the observational discourse rooted in the folk psychological reading of the term "emotion". This lack of consensus creates an obstacle for accuracy in the application of the scientific method *eo ipso*, as the procedural norms of natural sciences dictate at the very least some degree of repeatability — or consistency — in the phenomenon of inquiry. By introducing a more systematized view of emotions as complex processes, an approach such as that described below would ease the transition from observational to theoretical and metatheoretical levels of discourse, and

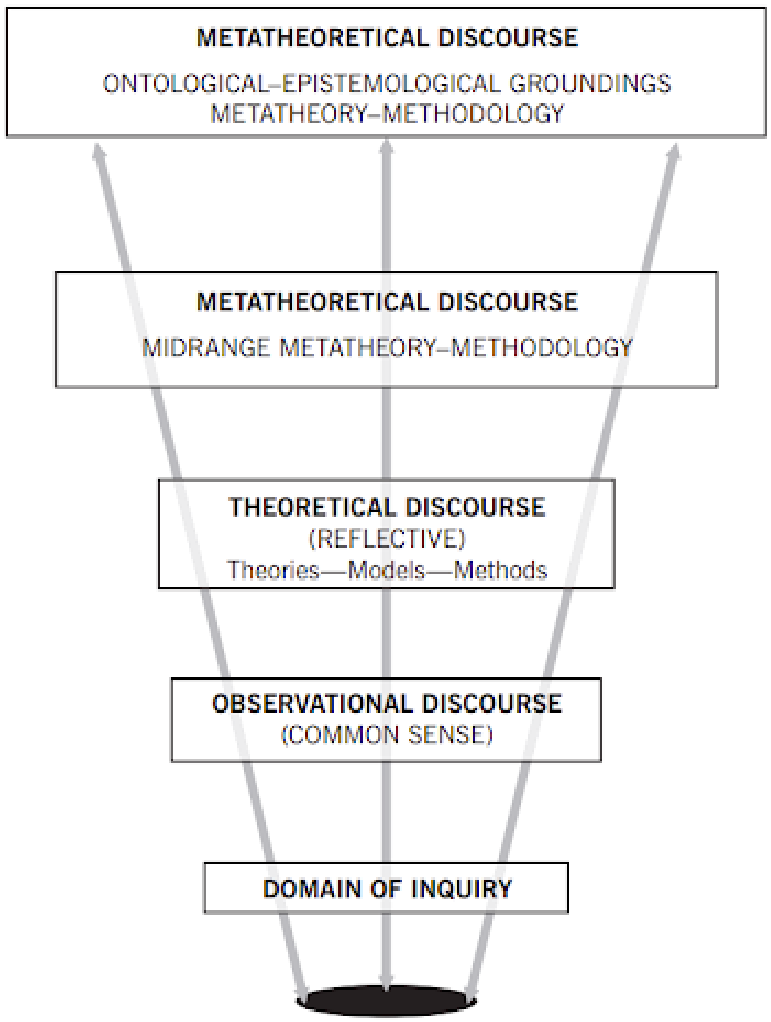


***Figure 2.3.*** **Levels of discourse in a scientific research program**. Cited from Overton (2013).

thus advance the translation of findings from cognitive laboratory settings to a more ecologically valid environment or the clinic.

Thus, I think it is necessary to address here the status quo of the ontology of emotions. The most fruitful approach in that regard is currently advocated by critical neuroscientists (Choudhury & Slaby, 2016). This framework, dubbed 4EA signifying the *Embodied, Embedded, Enacted, Extended, and Affective* mind, was initiated by John Protevi (2009) and proposes a departure from the dichotomized view of cognition and emotion that prevailed in the field for the later half of the 20th century. Thereby, 4EA considers affective experiences an integral part of mind and cognition. In opposition to the traditional binary of "rational" and "emotional", 4EA is in agreement with another overarching framework borrowed from theoretical and critical biology: the developmental systems theory (DST) (Ford and Lerner, 1992).

DST approaches biological organisms as "relational, spontaneously active, complex adaptive systems, that are self-creating,... self-organizing (i.e., a process according to which higher-level-system organization arises solely from the co-action of lower level components of the system), and self-regulating" (Overton, 2013). Thus, DST is a complex methodological paradigm within which both the contextual environment and the parameters of the organism itself are considered crucial and inseparable elements, which operate on various interconnected and self-organized levels of activity. Because 4EA and DST agree on several stances with regards to the embodiment and the embedding of the human body as a biological system, the following paragraphs address them as tenets of the DST, and aspects particular only to 4EA will be highlighted as such.

The anti-reductionist ontological perspective of DST is based on the assumption of the parity of an individual's biology and their environment or culture. According to DST, both determine any and all processes associated with living beings. Moreover, the relational nature of contemporary views of DST supposes holistic positions with regards to the definitions of causality and interrelationship of dynamic processes at different levels of resolution from cellular dynamics to cognitive processes — thus eliminating the antithetical opposition of biology and culture. From this perspective, any biological system as a collection of attributes associated with physiology may at the same time be viewed within its cultural environment, thus introducing convenience in the methods of investigation: by black-boxing a given component (say, the physiological substrate of an emotion), the investigator may focus on the cultural aspects of it, and vice versa (see Griffiths & Hochman, 2015, or Lindquist & Satpute, 2012 for a similar argument from the point of view of the intersection of linguistics and affective neuroscience).

Of utmost interest to the hypothesis of embodiment and embedding of emotions is the central tenet of causal interconnectedness. DST posits that any biological structure in the process of ontogeny assembles new structures, and the two thus comprise two differing levels of operation. What is more intriguing is that DST proposes irreducibility of each level onto "lower" or "higher" structures — thus introducing some degree of emergence of qualities characteristic for each structure. This, of course, imposes some difficulty into the investigations of complex phenomena such as emotions, yet DST (and, by consequence, 4EA) withstands the criticism by appealing to the issue of cryptic representations (Oyama, 2000), or precisely the issue of emotion nomenclature and ontology (for a more detailed discussion of this argument, refer to Section 3 of the present chapter).

That brings me to the point of convergence between DST and 4EA, namely, the understanding of embodiment and the cultural embedding of the elusive phenomenon of emotion. In the works of Protevi (2009), who brings together the two approaches, as well as Michelle Maiese (2017), emotions were viewed as holistic first-person experiential processes that occurred in complex environments. But, as Protevi pointed out, these processes occurred not only synchronously with other events in the environment, but were also surrounded by the diachronic influencing agents — such as preceding causal factors. From a perspective of interconnectedness, this applies not only to the traditional ontological entity of the "environment" as "not the body in question", but also to the multitude of linked properties within the body. Thus, the argument of embodied-embedded emotion is well supported by both DST and 4EA.

It is imperative to recognize that the level at which neuroscience may attempt to answer the questions related to the affective processes is therefore restricted to that directly observable in both the temporal scale (how fast we can recognize the dynamics of the brain-body activity) and the spatial resolution (how closely we can observe such changes) of human cognition. Note that I do not propose to eliminate the achievements of cellular or tissue-level investigations into the biology of emotional states in the body; rather, in agreement with the tenets of DST, I consider such information contributing to emotions but not defining them. Cellular processes occur at a subsecond time scale — much more rapid than available to human awareness (Buzsáki et al., 2012); even the relatively "slow" processes captured by the low temporal resolution methods such as functional magnetic resonance imaging (fMRI) operate still on the scale of seconds. Meanwhile, human interactions capture the entirety of an emotional state which in folk psychological terms would correlate to a single word (e.g. "angry", "sad", etc.), but do so typically at a lower temporal resolution of seconds to minutes. Speaking broadly, emotions as they have been viewed traditionally — and within the framework that I propose — simply occur "in real time" (see Lewis & Liu, 2011, for an extended argument of time scales).

Thus, according to DST, there is inevitably an addition of gestalt-type emergent properties in the phenomenon of emotion as opposed to the biological mechanistic interactions underlying that emotional state in the body. This makes emotions irreducible to simply the physiological, embodied point of view, and necessitates the consideration of emotional cultural embedding.

It must also be noted that the semantics of this argument are by no means novel: turning to renowned researchers in the area of visceral and affective neuroscience, one can easily find examples of the same sentiment. For instance, Erickson and Schulkin (2003) suggested that "no specific emotion center exists over and above cognitive systems in the brain, and that emotion should not be divorced from cognition". Along the same lines lies the conclusion of Ruth Leys (2011), who, while making a plea for a novel paradigm related to emotions, said that such frameworks "will be based on assumptions that make the question of *affective meaning* to the organism or subject of the objects in its world a central issue and concern" (emph. added). Lisa Feldman Barrett (2016) appealed: "the science of emotion <...> should explicitly theorize about how to integrate physical, mental, and social levels of construction". Similarly, Ralph Adolphs (albeit opposing the views of Feldman Barrett and discounting her holistic approaches to emotions) (2016) acknowledged as well: "while I believe that emotions are brain states, I also believe that we need to begin by understanding them as psychological states".

The abundance of arguments for the inclusion of cultural factors at a "macro" scale of investigations also lends support to my proposition of turning to electrophysiological measurements of brain and body signals. This methodology spans a wide spectrum of possible frequencies at high sampling rates: for instance, a typical EEG signal is recorded at the frequency 500 Hz or higher (Hari & Puce, 2023), while a surface EMG (Li et al., 2010) or an electrocardiogram (ECG) (Hejjel & Roth, 2004) would be routinely acquired at a sampling rate of 1000 Hz. This high temporal resolution of the electrophysiological signals harkens back to the notions of interconnectedness and diachronicity.

The data relevant to the analysis of emotion can thus be recorded from a multitude of embodied signals: EEG as a modality of brain imaging, ECG for the heart-brain axis, electrogastrogram (EGG) or electroenterogram (EEnG) as markers of the gut activity, surface facial electromyography (EMG) for the analysis of facial expressions related to the synchronously experienced emotional states, etc. The use of these modalities therefore allows an accurate estimate of the global levels of embodied signals at the scale of human conscious awareness — for instance, it would be possible to correlate low-frequency components across different parts of the body and contrast them to the behavioral measures such as self-report of emotional states.

In addition to that, it also provides an important window into the higher frequency scale of resolution which would lend the explanatory power for a mechanistic approach to the embodied aspect of an emotional state. The cultural components of an embedded emotion can be similarly deconstructed and examined in ways appropriate for the area of research — such as linguistic and semantic analysis of the words associated with the folk psychological terms of emotional states reported by the subject, or an analysis of the historicity of the used term, as well as the relationship between the reported term and cultural or social background of the subject.

### 2.2.2 Facial expressions as conduits of emotion

When speaking of the issues of embodiment of emotions, it is natural to begin with the relationship between facial expressions and vernacular related to emotions. Indeed, the earliest example of a formalized anatomical exploration of emotions was published by Charles Bell (1806), whose treatise on the anatomy of facial expression — although focused primarily on the artistic aspect of capturing human faces — served as an inspiration for further scientific inquiries in the later decades of the $19^{th}$ century. The primary focus of his work was the social aspect of facial expression, or rather the *percept* of the emotion experienced by the subject of an artistic work by a third party — be they the artist creating the image or the beholder of the final art. Meanwhile, the work of Guillaume-Benjamin Duchenne (1862) alongside his contemporaries such as Louis-Françisque Lélut (1862) introduced more grounded approaches to the relationship between the countenance and emotion as a *mental* phenomenon. This led the path of development of this thought to the theories of emotion well received in the history of psychology, such as the James-Lange theory of emotion as the very feeling of bodily changes following an external stimulus (James, 1884; Lange & James, 1922). Notably, this also stimulated further unraveling of ideas related to body signals as temporal components of emotions (Cannon, 1927; Bard, 1928). Yet, the popularity of this constructionist approach (discussed in more detail in Section 2.2) fluctuated throughout the 20th century. Thus, there existed parallel lines of investigation into emotions, as they were historically viewed as either communicative devices that utilize facial musculature or complex constructs that relied on external stimuli, involved integration of bodily signals and cognitive processes, and produced an output.

The first line of thought pertaining to the (pro-)social meaning of emotions has been widely spread in the scientific community, in no small part due to the influence of such researchers as Silvan Tomkins (1991 — originally published in 1964) and Paul Ekman (Ekman & Friesen, 1971). The research of Tomkins in particular emphasized the importance of facial expressions in the communicative aspect of emotions (Tomkins & McCarter, 1964). By writing about particular changes in facial movements as related to the "primary affects" (interest, enjoyment, surprise, distress, fear, shame, contempt, and anger), Tomkins introduced the foundational understanding of the interpersonal invariance — later dubbed "universality" — of several commonly used folk psychological terms for emotion. Notably, Tomkins also acknowledged the existence of "referential" facial expressions which were not synchronous with the subjective emotional experience, thereby subscribing partially to the notion of not perfect one-to-one relationships between emotions and embodied functions.

Inspired partially by the existence of both "referential" and truly "affective" facial responses, Paul Ekman developed the idea of invariance further. Perhaps too reductive at times, his paradigm of universal basic emotions (Ekman & Friesen, 1971) incorporated only six (later seven) concepts: joy, sadness, anger, fear, surprise, and disgust (contempt being the seventh). While Ekman himself acknowledged several weak points of the argument of such scarcity in the assumption of basic emotions (see, for example, Ekman, 1999), his stance remains strong on the very premise of the definition of emotions. In the second edition of a thorough review, *The Nature of Emotion: Fundamental Questions* (Fox et al., 2018), Ekman explicitly stated that "we are not in the grip of emotion all the time. Emotions come and go" (Ekman, 2018). This — combined with Ekman's continuation of Tomkins's understanding of facial expressions as elements connected but not strictly dependent on emotions — fortifies the possibility of dismissal of his elementary assumptions in the applications of my proposed paradigm.

However, Ekman's contribution must also be noted in the development of the Facial Action Coding System (FACS) (original publication by Ekman & Friesen, 1978; current edition by Freitas-Magalhães, 2021). FACS uses numbers corresponding to individual action units denoting individual muscles and head-level anatomical features of a face, with combinations of those numbers denoting stereotypical changes in the muscular activity synchronous with an emotional experience. Notably, FACS is not universal in terms of the nomenclature related to the relationship between emotions and facial expressions: more advanced techniques may include facial image analysis, such as those described in Coan & Allen (2007) or thermal facial imagery used by Nguyen and colleagues (2014).

One of the more practical approaches to the study of emotions within the proposed paradigm, however, is the employment of facial EMG for the assessment of intrapersonal experiences. A comprehensive (at the time of publication) review of facial EMG as a tool of research into the physiology of emotions can be seen in Fridlund (1986), although he primarily referred to emotions as evolutionary processes within the larger social and ethological framework. In that sense, he followed the facial feedback hypothesis (Adelmann & Zajonc, 1989), wherein he referred the reader to the ethological accounts of the dichotomy between "innate" and "learned" nature of facial expressions. The facial feedback hypothesis proposed a more holistic approach to the assessment of facial expressions as communicative devices, reliant on the context of interactions between conspecifics in situations necessitating immediate appraisal of common stimuli (for a more detailed review see Matsumoto et al., 2009).

Of course, within the paradigm of emotional states as a continuous attribute of all bodily processes the communicative aspect becomes but a part of the "global" state. However, multiple examples of interesting investigations suggest empirical utility of EMG in the composite description of an emotion. Examples of such studies include an overview of surface EMG by Schumann and colleagues (2010), who studied the electrophysiological characteristics of facial musculature signal acquisition in healthy adult males and thus provided quantitative statistics useful for future comparative analyses of EMG data. On the other hand, there are also studies into the emotional expression and perception of emotions in others: e.g., Dimberg & Thunberg (1990), Varcin and colleagues (2019), or Kuang and colleagues (2021), all of which employed EMG as a graded measure comparable across participants and demonstrated agreement of muscular responses to the imagery of faces with varied emotional expressions. The question of interpersonal variability, of course, remains pertinent in the utilization of EMG (see Hess et al., 2016), yet the criticism of the modality lies primarily in the lack of specificity in the definition of stimulus dimensionality, not in the reliability of the technique itself.

To conclude, I would like to reiterate that facial expressions, albeit being a singular component of emotions, have been traditionally viewed as a direct correlate of the experience *in toto*. While not arguing with the importance of expression as a factor playing an immense role in the social and communicative aspect of emotional experiences, I also emphasize that very few studies focused on the *embodied* aspect of facial expressions and their relationship to emotional states not directly related to nonverbal communication. Moreover, in the traditional discrete temporal view of emotions, facial expressions are temporally disconnected from the primary appraisal of an environment, while in a holistic view such a position of post-stimulus activity of the facial musculature would contradict the very definition of continuous emotional states (evidence for which can be seen in Coutinho et al., 2018).

### 2.2.3 Brain and body signals as markers of emotional states

In previous sections I demonstrated that consciously sensed emotional states are partially composed of some levels of activity recordable with electrophysiological techniques. In this section, I will delineate the history of brain and somatic electrophysiology as well as modern examples of studies which correlate embodied signals and emotions. A review of the early endeavors into this research can be seen in Dror (1999), while more modern summaries are found in Siegel and colleagues' (2018), Azzalini and colleagues' (2019) and Šimić and colleagues' (2021) reviews, as well as Zhou and colleagues' (2021) recent model proposal.

The earliest example of research into the physiological functions associated with emotional states is conventionally accepted to be Angelo Mosso's research into the cerebral thermometry concomitant with the experience of dynamic emotions (see, e.g., Mosso, 1896). His experimental results showed small ($<0.1$°C) perturbations in the temperature of different areas of the brain and skull in animals and humans, as well as minute changes in intracranial volume (see also Mosso, 1880; Mosso, 1890). This research appeared as a stark contrast to the previously assumed peripheralist doctrine which dictated emotions to be functionally distal from the cranial physiology. It is perhaps the influence of Mosso and other continental European researchers (e.g., Elie de Cyon, 1873) at the end of the 19th century that then developed into the studies of the first half of the 20th century.

The cranial physiology of mammalian emotions thus commenced to flourish with the rise of publications by such researchers as Sherrington (1903), Bechterew (1905), Head and Holmes (1911), Wells and Forbes (1911), and Bazett and Penfield (1922). An important characteristic of these studies is, of course, the emphasis on the use of decorticated animals (primarily dogs and cats), which followed from Sherrington and Bechterew's convictions in the subcortical locus of the "seat" of emotion. It would be remiss to not notice the pattern which was then picked up by Walter Cannon (1926) and Philip Bard (1928): the widespread understanding of the anatomical localization of emotional experiences was firmly established to concern solely the thalamus and other subcortical structures. Further developments in research reflected this localizationist approach — and they do, in fact, seem to relocate emotions as experiences from the periphery into the subcortical structure, yet do not contradict the overall principles of the peripheralist doctrine. For instance, the historical acceptance of the Papez circuit (Papez, 1937) as the sole substrate of affective processes cannot be exaggerated. Even in the form of the "limbic system" (as modified by Paul D. MacLean, 1949) which includes the amygdala and thus reflects a modest amount of functional correspondence to later advances in research, the circuit prevails as a reference to the locus of affect in the brain. See, for instance, MacNamara and Phan (2016), who discuss the circuitry in terms of emotion *regulation* well into the second decade of the 21st century.

It is thus not surprising that the majority of publications in the area of embodied emotions has been focused on an ontology which stems from these localizationist studies. As Dror (2001) puts it elegantly, "the absence of accumulated experience in decerebrated animals <...> standardized emotions and was emblematic of their industrialization as products of a factory-like production process". Further references in this section will likely reflect this popular ontological understanding of emotions as disengaged, discrete processes which may be replicated due to the lack of dynamic context or experiential attributes.

Along these lines of reasoning lie the developments stemming from the works published in the 1980s and 1990s. Among them are the arguments of Jaak Panksepp, Joseph LeDoux, and Antonio and Hanna Damasio. Of these, perhaps most aligned with the decorticated localization of emotions in the limbic area is the research of Jaak Panksepp. What Keith Oatley (2008) called "the MacLean-Panksepp conjecture" posited that experience of emotions stemmed not from any cortical area, but from the limbic system. The basis of this conjecture, however, is questionable in relation to human research, as Panksepp (1996) built his assertions off animal studies which involved pointed stimulation of the limbic system and the neocortex. In his experience, the latter lacked the responses characteristic for the former. Because these observations showed conservation of "motivational" and "affective" responses in decorticated animals, the conclusion was made that the neocortex was indeed not relevant to emotions as functions of the nervous system. Of course, this also entailed an assumption of homology between other mammalian species and humans. But even if the evidence collected by Panksepp were to be taken as contributing to the overall scientific inquiry into the nature of emotions, it contradicts my proposed paradigm at the root of argumentation. Panksepp's original hypothesis, outlined in Chapter 2 of *Affective Neuroscience* (1996), pointed directly to the doctrines espoused by the proponents of behaviorism in psychology. Behaviorism thus concerned the researcher solely with the aftermath of any internal experience, black-boxing the bodily environment and not allowing for integrative positions. As one can see from the argument in Section 1, however, this contradicts the *embodied-embedded* emotion.

Roughly contemporary to the findings published by Panksepp came Joseph LeDoux's *The Emotional Brain* (1998) (an updated compendium of LeDoux's views can be seen in Heller et al., (2014)). While overall understanding of emotional experiences in *The Emotional Brain* did not directly oppose the 4EA framework, it is at times evident that LeDoux continued his research along the lines of localizationist doctrine. See, for instance, the concluding chapter to the book: "a subjective emotional experience <...> results when we become consciously aware that an emotion system of the brain, like the defense system, is active". Not only does this underline the assumption of functional demarcation of "defense system" and a sum of other substrates in the brain, but also implicitly points to a possibility that such a system can be inactive at a certain time, presumably of a (non-emotional) experience. Notably, *Revisiting the Emotional Brain* (Heller et al., (2014)) does not update LeDoux's views in terms of either of the two assumptions: firstly, the introductory section of the book included a direct copy of LeDoux (1998) and expanded upon the ethological and evolutionary bases of the circuitry underlying the very same functional demarcations discussed in *The Emotional Brain*; secondly, the premise of stimulus-based transitory and discrete emotions underlay the entirety of the essay. Thus, while LeDoux's considerations of larger phylogenetic relationships between brain anatomy, physiological activity, and evolutionary strategies of survival remain important as contributions to the overarching framework of emotionology, the conclusions drawn are hardly applicable to the proposed empirical approach.

Perhaps more related to the embodiment position are the works of Antonio R. Damasio, vivid examples of which are summarized in *Looking for Spinoza* (2003). Damasio's contribution to the science of emotion needs to be acknowledged because of his introduction of the somatic marker hypothesis. According to this hypothesis, bodily signals — such as changes in heart rate, feelings of nausea, or profuse sweating — constitute the emotional response and thus guide the behavior that follows. At the first glance, this appears to be perfectly in line with the embodied view of emotion, and Damasio's intense interest in the brain anatomical networks encompassing the ventromedial prefrontal cortex (vmPFC) and the amygdalae seems to be inclusive of the ideas of multifactorial nature of emotions. However, a closer reading of his arguments — especially those given in *Descartes' Error* (1994) — reveals that he once again subscribes to the localizationist views: "The changes caused by [peripheral activations of autonomic, motor, or endocrine systems] cause an "emotional body state," and are subsequently signaled back to the limbic and somatosensory systems". A pointed critique of Damasio's position can be seen in Daniel Gross's *The Secret History of Emotion* (2008). For instance, as Gross pointed out, Damasio was prone to overlook the social and cultural components of emotions, even if emotions themselves were allowed to be constructed of multiple contributors from within — only — the body. The importance of neural or visceral substrates thus trumped any relevant information about the cultural background of the emotional state, and dominated "cognition", which, according to Damasio, was sharply separated from emotion. In addition to that, as Gross noted, "what matters to Damasio is only where the subject of the experiment falls in a normal pattern" (2008). In other words, Damasio followed the pattern of standardization of emotional experiences. However, even if he applied reductionist perspectives to the data obtained via neuroimaging in the process, the introduction of somatic markers was undoubtedly an important addition to the overall understanding of the ontology of emotions. Yet, Damasio's theoretical rationale remained firmly rooted in the framework of undefined (or even undefinable) emotion which was separate from cognition, removed from the environment, and temporally discrete.

A researcher less intent on maintaining the position of emotion as a transient experience is Luiz Pessoa, whose views were perhaps best summarized in his book *The Cognitive-Emotional Brain* (2013). In summary, he proposed a rather radical departure from the traditional dichotomy of cognition and emotion, and a large portion of the book followed the logic of interactions between "cognitive" and "emotional" processes. Importance was also given to the amygdalae, the hypothalamus, and medial prefrontal cortex as hubs within the larger neural network that integrated the functions of the nervous system *in toto*. Pessoa also emphasized the fallacy of oversimplification in the positions of dualists of any kind (for instance, criticizing the approach of "system 1" vs. "system 2"), and thus he argued for more integrative approaches to the study of cognitive-emotional processes.

It is also necessary to mention that since publication of *The Cognitive-Emotional Brain*, the majority of his views have developed significantly, yet the core of his style of scientific inquiry remains. It has become increasingly vivid in recent years: the latest preprint from Open Science Framework (Pessoa et al., 2021) highlighted the shift of his terminological preferences. While the book critically approached the traditional ontology of "motivation", "emotion", "cognition", and similar terms, Pessoa and colleagues now categorically proposed them to be epistemically sterile. From the point of view of the scientific method, it thus became apparent that approaches which demarcated such functions would yield little semantic value or explanatory power. Notably, this proposal was based on the overview of evolutionary processes in vertebrate neuroarchitecture.

However, the implications of their proposal did have certain limitations. For one, the narrow focus on environmental interactions and the assumption of "coping" with externally posed threats remained in line with the behaviorist and ethological paradigms already mentioned in the discussion of MacLean-Panksepp conjecture. This pointed view did not allow for the exploration of the internal environment of the body or, indeed, the implicit *continuity* of emotional states (as complex interactions with the ever-changing environment would still be broken down into constituent parts according to the "behavioral systems"). Hence, while Pessoa's theoretical understanding of emotion ontology was relevant to the development of my proposal in the sense of social and environmental *embeddedness*, it failed to incorporate the *embodied* aspect of emotions.

Embodiment is, however, central to several arguments proposed by Lisa Feldman Barrett (see, e.g., Oosterwijk and Barrett 2014; Barrett and Simmons 2015). The most prominent hypothesis of Barrett is her constructionist view of emotions (Barrett 2016), which can be summarized as a view of unique instantialization of brain and bodily states as they are contextualized within the environmental variables. Emotion, according to Barrett, was a construct which is composed of biological activity in the brain and the body, as well as the cultural and social context surrounding the time point at which an emotion occurs. In a proposal outlined by Oosterwijk and Barrett (2014), they argued for such situated conceptualization of emotions as both the interoceptive and exteroceptive signaling that converged in brain states and was realized through the activity of several established brain networks. At a first glance, this hypothesis aligns perfectly with my proposal, as it develops the argument of embodiment and embedding. However, there are several noticeable differences between Barrett's understanding of emotions as situated conceptualizations and the DST-4EA postulates. For one, Barrett categorically disputed the one-to-one correspondence between bodily states and emotions. Her views are not necessarily opposed to my proposal in this case: what Barrett argued was that any relationship between physiological states and cultural notions of different emotion terms existed purely by association that human culture imposed through the process of development of communicative language. But it is important to note here that, while this was phrased somewhat ambiguously in Oosterwijk and Barrett's proposal (2014), what they likely meant was that there were no fixed embodied states which would correspond to every instance of a particular emotion — that there was no guaranteed physical substrate to a given emotion term (no freezing at all occurrences of fear, for example). This therefore does align with the paradigm of contextual embodied-embedded emotions.

Where my proposal diverges from Barrett's is in the usage of the conventional ontological classification of psychological terms. In Oosterwijk and Barrett (2014), the authors wrote: "even though each instance of emotion is most likely reflected by a unique brain state, incremental evidence indicates that these brain states are best understood as different interactions between the same basic psychological processes". The processes in question are the same ones discussed in Barrett & Satpute's (2013) overview of major functional networks described in neuroscientific literature (e.g., mentalizing, salience, attention), as well as the review of interoception in the brain by Barrett and Simmons (2015). In fact, while Barrett's latest publications (e.g., Berent et al. 2019) emphasized a degree of semantic baselessness and the learned nature of categories commonly used in the psychological sciences, she maintained beliefs in the empirical application of such nomenclature. Moreover, see Feldman and colleagues (2022), among which is Barrett, argue for the importance of considering interoceptive signaling as that separate from affect induction in social judgment tasks — thus highlighting the separation of the biological and social contexts in the shaping of affective responses. Thus, while Barrett's views on the phenomenology of emotions do incorporate the importance of embodied processes and cultural contextuality, she maintains the hierarchical belief that cognition is restricted solely to the nervous system and the function of the brain networks.

One last researcher whose framework of approaching an embodied emotion perhaps stands out is Ralph Adolphs. His firm disagreement with Barrett (Adolphs, 2016) highlighted some of the important beliefs underlying most of his research, such as the definition of emotions as functional states which regulate behavior in response to the environment. It thus pointed to the discrepancies between his basic assumptions and my proposed paradigm. For instance, if we turn to The Neuroscience of Emotion Adolphs and Anderson 2018, several other theses of the book were notably irreconcilable with the DST-4EA tenets. For brevity's sake, it suffices to point out the primary characteristics of emotion that Adolphs himself put as the first attribute in his response to Barrett (Adolphs, 2016): namely, that emotions were claimed to be scalable, or variable in intensity, which harkened back to the widespread assumption of the existence of several "basic" emotions (for an expanded criticism, see Ortony 2022). This has been discussed above with regards to Ekman and shown to be not applicable to the present proposal.

It must be noted, however, that the last few decades have shown a rise of interest in affective neuroscience which would incorporate more holistic understandings of emotion. Visceral dynamic interactions with the central nervous system have been repeatedly shown to play an important role in cognitive-emotional states in both healthy and clinical populations. The previously mentioned overview of visceral dynamics, performed by Azzalini, Rebollo, and Taillon-Baudry (2019), highlighted some of the most important findings relevant to the research of the heart-brain and gut-brain axes. Importantly, the review touched upon the lack of information about the viscerotopic organization in the human cortex: the only available study pointed to evidence from rat studies (Cechetto and Saper, 1987). Examples from recent literature mostly pointed to the involvement of the insular cortex in viscerosensory and visceromotor functional pathways (Critchley et al. 2004; Avery et al. 2017; Mazzola et al. 2019); however, most of these findings came from clinical literature (Larson and Csikszentmihalyi 2014; Icenhour et al. 2017; Contreras-Rodríguez et al. 2019; Kano et al. 2019) which may be biased towards the investigations of visceral dynamics because of the somatic focus in treatment of patients. Moreover, these examples may also be prone to the issue of reverse inference: because prior literature pointed to the insular cortex as a potential restricted locus of afferent viscerotopic connections, the cited neuroimaging studies followed seed-based analytic methods, thus limiting the scope of the results.

Synthesizing the hypothesis of embodied continuous emotions and thus linking the viscerosensory signaling to neuroanatomical substrates at any temporal point, one might turn to a relevant review of the brain basis of emotions by Lindquist and colleagues (2012) or a review of neural networks underlying affect by Barrett and Satpute (2013). In both of these works, the authors conducted a meta-analysis of network neuroscientific literature pertaining to the affective focus of the study — and they concluded that the brain has "broadly distributed functional networks that interact to produce a range of emotional states" Barrett and Satpute 2013. It is thus important to consider a broader distribution of connective circuitry underlying emotional states, while, of course, not disregarding the findings from the studies which define a preliminary ROI.

One must also be aware of the severe lack of examples in current literature that would refer explicitly to the relationships between visceral dynamics (especially those registered with electrophysiological techniques) and perception or experience of emotions. However, the modulation of tactile sensation and proprioception by the cardiac pulsatile function (Macefield 2003; Birznieks et al. 2012; Al et al. 2020; Al et al. 2021), the modulation of visual perception (Salomon et al. 2016; Salomon et al. 2018; Kunzendorf et al. 2019), and the relationship between functional connectivity analyzed via fMRI neuroimaging and the cardiac rhythm (e.g., Chang et al. 2013; Nikolaou et al. 2016) have all been demonstrated extensively. Meanwhile, few studies addressed the dynamics of emotion recognition tied to the arterial pulse or cardiac rhythm. In this regard, I consider especially relevant to this issue the works of Sarah Garfinkel (summaries of which may be found in Quadt et al. 2018; Zhou et al. 2021). While most of the studies of Garfinkel were related to issues of clinical relevance — such as alexithymia, — the most recent proposal of an integrative model of embodied emotion based on interoceptive processes is of interest precisely because of her prior work on the heart-brain axis (e.g., Mulcahy et al. 2019). This interest in the relationship of the phases of the cardiac cycle to the emotional states is, of course, aligned with my proposal — even though Garfinkel's model of emotion followed a more traditional hierarchical view of the temporally discrete emotion which "unfurls" along the concrete-abstract axis and follows conventional hierarchy of "lower" to "higher" neuroanatomical substrates. Especially relevant is the utilization of heart rate variability (HRV) as a proxy of the modulation of cardiac function by the central nervous system (this is not unique to Garfinkel's study; see, for example, Kastaun et al. 2016).

Even more useful for the development of an aggregate function from various electrophysiological modalities are measurements of the cardiac cycle phases and comparisons of the phasic modulations between, e.g., canonical frequency bands of EEG (Berger, 1935) and the systolic/diastolic contractile stages of the ventricular cycle (for examples of implementation, see Al et al. 2020, Schulz et al. 2020). Cardiac cycle entrainment of brain oscillatory functions may illuminate further the relationship between the pacemaker functions of the cardiovascular system, slower respiratory function, and neural system activity. Notably, a recent study by Varon et al. (2020) also suggested that approaches based on the analysis of the QRS waveform — such as those incorporated into works of the Villringer laboratory (Al et al. 2020; Al et al. 2021) and emulated in our pilot projects — may also be utilized to obtain ECG-derived respiration (EDR) and subsequently processed to yield more information about the embodied processes. This tremendously aids the practicalities of experimental design, and allows for a more comprehensive understanding of the interactions between visceral organ systems and the neural substrates of affective processes co-occurring with the environmental stimuli.

Other exciting novel findings in the area of affective viscerosensory and visceromotor pathways come from the area of EGG, which, in spite of its name, encompasses the entirety of electrophysiological recording techniques from the skin surface of the abdomen, not limiting the recorded function solely to the gastric contractions (other names for the technique might include electroenterography and electrointestinography, such as in Garcia-Casado et al. 2003; Prats-Boluda et al. 2007, or Hashimoto et al. 2015). Perhaps a most remarkable example of these findings come from the research of the laboratory of Catherine Tallon-Baudry. Tallon-Baudry and colleagues revealed a novel network of resting-state activity linked to the low-frequency contractions of the smooth muscle of the stomach (Rebollo et al. 2018; Rebollo et al. 2021), which indeed points to the distributed neural processes underlying the synchronous dynamics between the digestive system and the brain. An intriguing link to the proposed temporal diachronicity of emotional states might be drawn from the fact that gastrointestinal rhythms typically fall in the range of 0.05-0.06 Hz (or 2-4 contractions per minute), thus occurring at a time scale not only comprehensible at the level of conscious awareness (cf. heart rate at 1-1.5 Hz or respiration at 0.5 Hz), but also linked to the time scale of emotion identification (Lewis and Liu, 2011). EGG thus appears to provide yet another component to the praxis of descriptive evaluation of continuous emotional states, albeit being a nascent research method.

### 2.2.4 Addressing allostasis

Previous sections have addressed exclusively macro-scale observations of human physiology in both resting state and emotion-related tasks. Because the proposed emotional ontology supposes a DST-like subsequent construction of levels with emergent characteristics in both spatial and temporal dimension, electrophysiological measurements of embodied dynamics at the scale of organ systems and organism as a whole do indeed appear to be the most relevant to the discussion. However, it is also prudent to remember that the acknowledgement of unique emergent properties of emotion as phenomena must not preclude one from considering the dynamics of physiological processes at meso- and micro-scale. Thus, it appears important to discuss the issues related to neuroendocrinology and the allostasis of the body.

Addressing allostatic properties of biological substrates stems from the preceding doctrine of homeostasis. Rooted in the historical studies of Claude Bernard which concerned le milieu intérieur (the internal environment) of the body, the paradigm was developed over the course of several decades (finalized in Bernard 1878). The existence of a stable optimum for multiple bodily systems, such as thermoregulation, pancreatic aid in digestion, or glucose level management in the liver — all of which regulated tightly by the nervous system — was established by Bernard through a series of studies (see Bernard 1878, or Cooper 2008 for an extended description). Although his research predated the discovery of the endocrine regulation and hormonal equilibria in the body, the notion of this internal environmental control inspired the introduction of the term homeostasis by Walter Cannon (1926). Notably, Cannon's definition of homeostatic mechanisms, although more lax than that of Bernard — Cannon proposed that the regulation of measurable body variables was kept “within narrow limits”, — still prescribed the existence of set optimal points for each biological characteristic of the human body, such as cellular osmotic pressure, temperature, etc.

Enter the notions of allostasis (first described in Sterling and Eyer 1988; see also Schulkin 2003; McEwen and Wingfield 2003; Sterling 2012; Karatsoreos and McEwen 2011) and adaptive homeostasis (Davies 2016). Primarily of interest to researchers in the areas of neuroendocrinology and molecular physiology, the two concepts are closely related to homeostatic principles first elucidated by Cannon. The concept of allostasis is inextricable from the notions of allostatic states and allostatic loads. An allostatic state supposes a change to a sustained yet different from “normal”, homeostatic level of activity or concentration of, e.g., glucocorticoids or catecholamines, as dictated by an unusual environmental circumstance. Meanwhile, allostatic load refers to the result of existing in an allostatic state (such as accumulation of adipose tissue because of an unexpected drop in temperature). These conceptualized considerations of the homeostatic range and exceptions from it thus necessitate the expansion of computational estimations of equilibria to also include in the “equation” the energy expenditure imposed by conditions outside such “normal” range. Adaptive homeostasis, in turn, can be described as the changes in the definition of the “normal” homeostatic range as a response to unusual environmental conditions.

The notions of (adaptive) homeostatic and allostatic regulation in the body rely on the fundamental claim of executive control by the nervous system. As Barrett and Satpute (2019) hypothesized, for instance, “whatever else a brain is doing – thinking, feeling, perceiving, preparing for action - it is also implementing allostasis in the service of behavior - regulating your autonomic nervous system, your immune system, and your endocrine system – as well as representing interoception" (note that the terminology in this quote separates "you", "your brain", and "your systems", which does not align well with the understanding of emotion as an integrative state). This facet of emotion modeling approach of Barrett and colleagues comes to a culmination in a formalism summarized by Sennesh and colleagues (2022). This elegant mechanistic understanding of diachronicity of the environmental variables which are in a state of constant interaction with the bodily signals lends itself to the empirical realization of my proposed paradigm: if we are to understand emotions as temporally continuous contextualized states of the body, considering the allostatic shifts and adaptations of the homeostatic equilibria will provide a higher degree of explanatory power to the dynamics between emotional states, as well as factors concomitant to the changes — if not causing them.

### 2.2.5 Emotion observed in others versus experienced emotion

Another important aspect in defining and categorizing emotion as a physical state involves contrasting the induction of emotion with its experience. The induction pertains to triggering emotional states in the subject, whereas experience concerns assessing the subject's recognition of those emotions after presenting a version of the emotional state through various means (such as visual representation, social interaction, or a mix of multimodal sensory stimuli common in cognitive neuroscience settings). This is closely related to the limitations of a laboratory setting with regards to ecological validity. A summary of these considerations may be seen in Shamay-Tsoory & Mendelsohn (2019), where the authors delineated the pertinent issues of approaches to social cognition and affect, arguing for semi-controlled experimental designs which would better approximate real-life behavior (see also the call to action with regard to ecological validity in Hoemann et al. 2023).

Indeed, the induction of an emotional state would be hard to control in a laboratory setting. The first problem with a design involving guided generation of emotional states in the participants would, of course, be the issue of potential discomfort and possibility of harmful consequences (for a brief address of ethics, see Canli and Amin 2002; potential impact shown in Limonero et al. 2015), which in turn could result in unreliable data and possible disturbances in the accuracy of self-reports. Moreover, these methods also appear to be quite subjective in their implementations and not suitable for a controlled environment when using electrophysiological techniques of data collection, which rely mostly on temporally precise paradigms (Gerrards-Hesse et al., 1994). Ethical and technical considerations notwithstanding , obtaining consent for the induction of set emotional states would also prime a participant and drive the attentional focus towards the experience of emotions in an uncontrollable fashion (Zemack-Rugar et al., 2007). In contrast, the perception of emotional expressions in others has been studied extensively (for an overview, see Barrett et al. 2019); yet, this approach yielded moderately varied results even from the point of view of simple inferential categorization tasks, where participants were asked to identify the expression demonstrated in the stimulus (see Gross and Canteras 2012; Oosterwijk and Barrett 2014).

Nonetheless, there is some evidence to the incorporation of traditional stimulus-based recognition approaches inducing an embodied response somewhat similar to the spontaneous emotional experience in the individual. For instance, EMG recordings coupled with the presentation of emotional stimuli yielded some degree of "contagion", where the observer experienced the emotion they observed (Dimberg 1990; Hess et al. 1992; Lundqvist 1995; Hess and Blairy 2001; Achaibou et al. 2008; Dimberg and Thunberg 2012). Moreover, neuroimaging studies showed the involvement of previously established mentalizing and "mirroring" networks in the process of emotion recognition (Bastiaansen et al., 2009), which indicates at least some degree of embodiment of a recognized emotion in an individual observing a conspecific's facial expression. Of course, the arguments against mimicry and/or contagion of emotional stimuli may indicate an involvement of socially relevant neural circuitry and thus an influence of a "top-down" process (Wróbel and Imbir, 2019); yet, this does not negate the pragmatic implication of using emotional stimuli as inducers of some mimicked embodied processes in an observer.

More evidence of embodiment in emotion meta-cognition comes from publications such as the investigation of bodily maps of emotions by Nummenmaa and colleagues (2014) and Volynets and colleagues (2020). This research relied primarily on the verbal comprehension of emotion concepts and identification of embodied sensations associated with those concepts (NB: the methodology only included concepts in English for ease of interpretation), and the results of the studies showed concordance across cultures in the meta-cognitive embodiment of emotions. While these studies have not involved a specific visual stimulus-based paradigm, the results point towards the possibility of meta-cognitive conceptualization of emotion concepts when presented with their verbal counterpart. Thus, it would be reasonable to assume that the presentation of a conspecific expressing an emotion concept and a task in which the participant would actively engage with said concept would likely result in registrable changes in the embodied dynamics and/or correlates of brain activity.

Of course, there are criticisms, such as those espoused in Barrett and colleagues' (2019) review. For instance, they pointed out that the research of facial expressions necessarily relies on stereotypes and non-universal notions of facial expressions correlated to specific emotional vocabulary. They also recommended paying attention to the fact that emotional experiences may vary in meaning across cultures and times. All of these objections are indeed valid and would require consideration in the construction of an experimental paradigm. I believe that the arguments given in the following section will address the issues of ecological validity and diversity of cultural backgrounds.

## 2.3 Linguistic and cultural context of emotion: need for integration

Let us now turn to the question of linguistic variance, translatability of emotion terms, and the ever elusive concept of cultural diversity in the experience, description, and definition of emotion. This discussion cannot be held without considering the breadth of affective science subdomains, which range from the history of emotions to systems and physiological neurosciences. Now, while this explains an undoubtedly varied teleological nature of the definitions developed in those fields, it also presents numerous challenges when faced with the quest of converging on a rigorous definition of "emotion". For instance, the history of emotions as a subfield of the humanities presents us with the methodology of exploring primary sources and the considerations about historicity — is what we denote as "emotions" in 2024 the same natural phenomenon as that which William James labeled "emotions"? Would it be the same still as "passions" in the writings of Guillaume-Benjamin Duchenne? If a specialist in

Classics were to discuss what Thucydides meant by “happiness”, would it be the same “happiness” that we use colloquially to refer to an emotional state in folk psychology?

In other words, there is a high probability of introducing anachronisms into the research of the nebulous and omnipresent emotion. Yet, turning to historical sources and the development of paradigms is important to avoid fruitless approaches of the past. As Rob Boddice demonstrates in his 2017 book The History of Emotions (in which he mirrors the approach of Jan Plamper’s 2015 book under the same name, as well as a general stance taken by Rosenwein and Cristiani in What is the History of Emotions, 2017), the overwhelming majority of historians of emotions and other humanitarian explorers of the phenomenon prefer to use the term “emotion” as an overarching category — thereby uniting “affects”, “moods”, “passions”, and “feelings” under one umbrella of “emotions”. Of course, such lax demarcation of the phenomenon in question greatly complicates our opportunity to formalize empirical approaches to emotions as human states. Thus, it is pertinent to begin with a definition of emotion that will satisfy both past examples of theoretical frameworks and possible new developments in the area.

While it is hard to arrive at a definition of emotion that is sufficiently detailed while not being overly complex and riddled with jargon, several recent attempts do indeed appear empirically useful. An invaluable source of historical information can be found in Kleinginna and Kleinginna’s 1981a review of definitions which encompassed more than 100 publications in the psychological sciences (although it is also not hard to imagine that in the last 40 years, the number of definitions has most likely grown on a non-linear scale). The definitions analyzed in their review highlight the necessity of synthetic and critical rethinking of the approach to emotions. For example, not all operationalizations considered the physiological aspects of emotional experiences, and those which did might not have included affective or adaptive characteristics of emotion (for more on need of synthesis, see also Plutchik and Kellerman 1980). The 1981 review also ended with a more broad proposed definition by the authors. According to Kleinginna and Kleinginna, emotion was defined as

> a complex set of interactions among subjective and objective factors, mediated by neural-hormonal systems, which can (a) give rise to affective experiences such as feelings of arousal, pleasure / displeasure; (b) generate cognitive processes such as emotionally relevant perceptual effects, appraisals, labeling processes; (c) activate widespread physiological adjustments to the arousing conditions; and (d) lead to behavior that is often, but not always, expressive, goal directed, and adaptive.

This example illustrates a number of important criteria highlighted by the authors as necessary and sufficient for an emotion to be considered as such — yet it is evident for a modern reader that the definition is also not inclusive of the context in which an emotional experience occurs.

Meanwhile, more recent publications on theories of emotion and their measurement (such as Meiselman 2021) include definitions coined in the last few decades. Take, for instance, one given by Matsumoto and Ekman: "[emotions are] transient, bio-psychological reactions designated to aid individuals in adapting to and coping with events that have implications for survival and well-being" (2009). This succinct wording did make a nod to the necessary inclusion of "well-being" — which highlighted the importance of the concept of embodiment of emotion in the current discourse. This definition also insisted on the transiency of emotion — a view particularly attributable to Ekman (see also Ekman's introductory essay to Fox et al. 2018).

Importantly, this underlines that emotions are viewed in the fields of psychology and neuroscience as a phenomenon transient and discrete in time, yet continuous with other biological attributes of an individual; emotions are dependent on stimuli, whether external or internal; and, finally, emotion is necessarily causally linked with further survival and adaptation of a human to their environment.

However, we can also refer to an early attempt at calling for a more careful consideration of the term, published by Elizabeth Duffy (1941). She attracted the attention of her reader to the inherent inconsistency of the word "emotion" by remarking that any impulses motivated by "stimulating conditions" lead to an adjustment to the environment and that using an ill-defined term for a collection of varied adjustments without discrimination may be "worse than useless". However, what she proposed instead related more to the behavioral aspects of emotional states. Within her framework, behavior was described as a confluence of energy level, direction, and response to the relationships — which, of course, still did not allow for a formalized empirical approach to operationalization. Yet, an idea of a departure from the term "emotion" is definitely interesting — especially when taking into consideration the fact that most of the research in the area of emotions psychology and neuroscience has been published in English, where the word has particular connotations and relationships to the folk psychological understanding of "feelings", "affects", and "moods".

The linguistic dominance of English as the primary language of science communication is hardly arguable in 2024. Multiple studies have pointed to staggering figures of more than 90% of all publications in databases such as Web of Science and Scopus being in English (NSF, 2018, or Vera-Baceta et al. 2019). At the same time, neuroscience as a field aims at proving the universality of mind-related phenomena by appealing to the shared nature of biologically grounded mechanisms — at least within the paradigm of reductive materialism, which appears to be a common ground of debates in the modern discourse (see Choudhury and Slaby 2016). Thus, it would not be an overstatement to assert that it is important for modern neuroscience to bridge the gap of linguistic and cultural limitations imposed by this prevalence of anglophone cognitive ontologies.

But is an assumption of universality of emotion perhaps well-grounded in empirical evidence? Proponents of such views, such as Ekman, would perhaps argue that since emotions are universal human experiences, it should not matter whether we talk about "anger" in English, "colère" in French, or "злость" in Russian — whichever language we happen to use, the state we refer to is physiologically indistinguishable from that of our fellow human who uses a word in a different language (a more detailed preview of Ekman's central postulates will be given in Section 2). However, culturally diverse research in the humanities points to an alternative perspective.

An example of research drawn from different cultures can be seen in the works of Zoltán Kövecses, a prominent investigator who operationalizes emotion language in the framework of conceptual metaphor theory (CMT). A recent chapter of his authorship (Kövecses, 2018) is an excellent primer for a variety of linguistic metaphors that reflect not only the universality of embodied factors in the human experience, but also the contributions of cultural experiences. Take, for instance, the Zulu metaphor for the heart as "the seat of anger" (ibid.) and contrast it with the Kazakh heart-related embodied idioms such as "jürek awzğa tığılw" – lit. "heart pressing into the mouth", meaning "be worried, be anxious", which may reflect states of worry, hunger, or nausea. Meanwhile, the metaphor of "angry person as a pressurized container" appeared in his research to be nearly universal across varied cultures and languages (English, Zulu, Chinese). From the examples provided, one can see that cultural contributions shape the perception of many concepts which in the Western tradition would be attributed to emotional states. Consider here also the explicit demonstration through colexification of emotion semantics across cultures (Jackson et al., 2019).

Taking this evidence into account, it is then possible to transform the original question of universality of emotions to experiences grounded in shared species-wide biological features. I can now ask: if these metaphors reflect the differences in the language of embodied emotions that are driven by cultural factors alone, then should I perhaps reconsider the view of true equality between the English "anger" with the Kazakh "aşw"?

Of course, it might well be that exploring emotions via anglophone subjects and research paradigms might provide satisfactory answers and reflect the ground truth of the problem at hand. But it might also be that human primates specialize on more levels than just those which we happen to have defined and operationalized at the moment. Of course, trying to account for the cultural contributions to evolutionary processes might be perceived as appeals to hard constructionism. Yet, an inferential method of inducing universals from one exemplar subculture does defy the purpose of the scientific method.

It is important to note that this approach from the point of view of CMT, while certainly not novel in the land of cognitive linguistics (stemming from Reddy 1979, and Lakoff and Johnson 1980), does highlight an important gap in our studies of affective neurosciences. Namely, the contextualist interpretation of CMT points to the exaggeration of universality in neuroscience, and the latter may thus be missing contextuality of experiences within its empirical framework of operationalization and laboratory controls.

The praxis of (cognitive/affective) neuroscience so far has largely been formulated on the basis of several critical assumptions. Of interest to my work is one crucial tenet of viewing emotions: namely, that emotional experiences — whatever they may be defined as — are temporally non-unique or repeatable. Meaning: an instance of "anger" at time point x will be physiologically and/or psychologically indistinguishable from another experience of "anger" at time point y. This core definition of an emotion appears to be trivial and natural to humans — which an overwhelming majority of researchers in the field happen to be.

Therefore, emotions as they are determined must agree with the shared biological characteristics of human physiology — such as hormonal fluctuations, neurochemical and electrophysiological markers of brain activity, cardiovascular and respiratory function, levels of blood glucose, blood gases, etc.

The history and development of thought about the embodiment of emotion is a subject of enormous breadth. Yet, here it would suffice to point towards the undoubtedly integrated nature of an emotional state. Such physiologists as François Lélut (1862), Claude Bernard (1878), or Angelo Mosso (1890) argued at the dawn of formal neurophysiology for an embodied approach to the investigation of how discrete emotional states differ from one another. In turn, I argue that emotions, while (possibly) non-unique temporally, are assumed to be separable in as much as our intuitive understanding of "sadness", for example, is different from "happiness" — and that they correspond to two complexes of physiological characteristics which differ in at least one aspect (be it a level of a specific hormone, relative power contribution of a specific canonical band frequency in a subset of EEG electrodes, or a measured response of facial musculature).

## Conclusion

Synthesizing the assumptions and counter arguments thus allows me then to disregard certain theories of emotion which are founded solely in vague definitions operationalized in terms of behavioral ontology, such as the appraisal theories (which imply that cognitive processes are involved in the evaluation of an external stimulus before an emotion itself may occur as a response) pioneered by Magda B. Arnold or Robert Lazarus, or clinical theories that approach phenomenology from the point of view of defects produced by hypothesized dysregulation of emotion-related mechanisms (see Kellerman's chapter in Plutchik & Kellerman, (1980)). It is, of course, an unfortunate limitation imposed by the scope of the present chapter, yet the more rigorous terminology within the upcoming comparative analysis of existing frameworks necessitates my narrowing of the focus. Thus, I propose the operational definition of emotions:

**Definition 1.** *Emotions, or emotional states, are embodied states of an individual which satisfy the following criteria:*

*— They are <u>continuous</u> in time and may be registered as the aggregate of a subset of physiological characteristics of the body at any time point, no matter the temporal resolution;*

*— They are dependent on the context which may include, but is not limited to, the sociocultural environment at the time point of the registration of the emotional state; the history of the individual's cultural, social, and clinical characteristics; and*

*the internal bodily environment directly preceding the point of the registration of an emotional state;*

*— They are non-unique in the verbal description of a said state based on an individual's self-report: the same term may be applied to states separate in time and context; similarly, speakers of different languages may ascribe the same physiological state to verbal expressions not conventionally accepted as translations of each other.*

Note that the definition as given does not require prior determination of any physiological modality of registration of an emotion (such as fMRI, EEG, MEG, or functional near-infrared spectroscopy — fNIRS), nor does it necessitate linguistic specialization of a physiological aggregate which results from such registration — moreover, I would propose that emotions reliant solely on self-report of an individual in question may also be used to determine certain characteristics of a modeled space in which all such emotional states may lie (which is the n-dimensional manifold in the original question). It should also be remarked that emotional states which correspond to known, folk psychologically intuitive terms such as "angry", "happy", "sad", etc. do not possess specific characteristics which would distinguish them from any other non-verbalized state, which thus refutes the notion of "basic" emotions which has been used extensively in research since at least the first half of the 20th century (see Arnold, (1954), for an abundance of examples; see also Ogarkova, (2021), for a critical overview of the issue of interlingual translatability, and Ortony, (2021), for a review of "basic" emotions).

The use of my definition frees one from the need to observe any environmentally "directed" behavior either as a result or as a correlate of the emotional state: by acknowledging temporal continuity of emotional states as momentary aggregates of physiological characteristics, I can successfully avoid the question of utilitarian functions assigned to emotions rather arbitrarily (see functionalist accounts of emotions and their refutation reviewed in Barrett, (2016)). Moreover, emotional states are then no longer constrained by the component of "resulting" behaviors or goal-oriented actions and are solely defined by the momentary descriptors used in a particular experimental paradigm. Thus, this definition is specific enough to be sufficient for its comparison with existing frameworks of approaching formal investigations of emotions, yet it is flexible for the purposes of a mathematical model that would generalize to empirical approaches in future studies. In addition to that, as shown in Section 2, this definition also agrees with the frameworks such as 4EA and the developmental systems theory (DST) approach to biopsychosocial processes of interest to the neuro- and psychological sciences.

# Chapter 3

## Towards a rigorous definition in modeling emotions

### Introduction

Emotion, a central concept in Western psychology, eludes concise definition, oscillating between being too brief or overly detailed. Historical usage of "emotion," alongside "percept," "affect," and "feeling," has lacked consensus, particularly in mathematical modeling contexts. Despite challenges in crafting a precise yet uncomplicated definition, efforts like Kleinginna and Kleinginna's (1981a) meta-analysis have been empirically valuable, advocating for a synthesized reevaluation of emotion definitions. Their review, critical of definitions ignoring physiological and adaptive aspects, proposed defining emotion as a complex interplay of subjective, objective, neural-hormonal factors leading to affective experiences, cognitive processes, physiological adjustments, and behavior, pointing out the necessity for inclusive definitions. An attempt at such a definition was made in the previous chapter, where I posit that:

> **Definition 1.** *Emotions, or emotional states, are embodied states of an individual which satisfy the following criteria:*
> *— They are* <u>continuous</u> *in time and may be registered as the aggregate of a subset of physiological characteristics of the body at any time point, no matter the temporal resolution;*
> *— They are dependent on the context which may include, but is not limited to, the sociocultural environment at the time point of the registration of the emotional state; the history of the individual's cultural, social, and clinical characteristics; and the internal bodily environment directly preceding the point of the registration of an emotional state;*
> *— They are non-unique in the verbal description of a said state based on an individual's self-report: the same term may be applied to states separate in time and context; similarly, speakers of different languages may ascribe the same physio-*

*logical state to verbal expressions not conventionally accepted as translations of each other.*

This definition sidesteps behaviorally "directed" actions, focusing on momentary physiological aggregates, offering a flexible yet specific framework for future empirical research.

Contrast that with several other recent definitions (mentioned above), like that of Matsumoto and Ekman (2009) which stipulates that emotions are transient and separate from, albeit related to well-being, which reflects modern views on embodiment. However, it is hard to disagree with Elizabeth Duffy's critique (1941) of the term's vagueness, suggesting a shift towards behavioral descriptions. The predominance of English in scientific literature and its implications for emotion research, noted by Vera-Baceta & Kousha (2019), underscores the challenge of transcending linguistic biases to affirm emotion universality, a stance contested by culturally diverse humanities research.

As described in the previous chapter, CMT had influenced behavioral sciences with diversity of linguistic instruments when approaching emotions. Zoltán Kövecses (2018) exemplifies cultural influences on emotion language, indicating both universality and cultural specificity in emotional metaphors. This evidence suggests reevaluating the universality of emotions, given the cultural variations in emotional language. Cognitive linguistics, drawing from Reddy (1979) and Lakoff & Johnson (1980), critiques neuroscience's exaggerated claims of universality, urging a consideration of emotions' contextuality.

Disregarding certain theories like appraisal or clinical approaches due to their vague definitions, I propose defining emotions as continuous, context-dependent, and non-uniquely described physiological states, challenging the concept of "basic" emotions and allowing for a more nuanced, manifold-based model of emotional space, which can be analyzed with an approach akin to that of Busch and colleagues (2023), described in detail in Section 3.2.

## 3.1 Historiography of Mathematical Models of Emotions

To see if a mathematical model of emotions is plausible, it is important to determine how I operationalize the concept of emotions as embodied and environmentally embedded processes. Namely, how would I approach measuring the physiological, environmental, and "psychological" aspects of emotions? In this section, I will outline prevalent theories of emotions developed in the field of experimental psychology and cognitive neuroscience since the 19th century. For each proposed model, I will provide an explanation with regards to which assumptions of existing modeling approaches can be transferred to the proposed framework, and which are discordant with it. To start, let me turn to the appraisalist approach characteristic of such researchers as Magda B. Arnold and John A. Gasson (1954). While supporting the basic assumption of emotion being separate from other, aware processes, they proposed a mechanism which largely depended on the appraisal of a stimulus or a percept before an emotional experience took place. According to their proposal, emotions were merely reinforced by bodily processes during stimulus appraisal. Thus, any embodiment of emotion is not a part of Arnold and Gasson's framework — which unites them somewhat with the views of Elizabeth Duffy (1941), who discussed the interpretation of a stimulus which leads to a conscious appraisal of an emotional state. Let me note here that Duffy also argued for a departure from the nomenclature of emotions as such. However, here I would be remiss to not mention Schlosberg (1954), who espoused the dimensionality of emotion as that based on arousal (meaning the "intensitive dimension" of an emotional experience, which in his framework ranges from sleep to tension), valence (termed as "pleasantness-unpleasantness") and attention-rejection (which he uses to point out conscious attraction or repulsion of the stimulus). His article, while heavily reliant on Duffy's ideas of a continuum of activation, importantly pointed to the understanding of emotional experiences as those which are hard to disentangle from states of being which are not an emotion. While Schlosberg did point to skin conductance responses and measurements of facial expression dimensionality, both of which may be viewed as continuous measures of embodiment, the framework presented in his article was still reliant on the differentiation of these responses to the environment. His approach was inextricable from the notion of the existence of "pure" or "basic" emotions, and thus failed to agree with my proposed definition. Also in concordance with Duffy's view was the model of emotions proposed by Stanley Schachter and Jerome E. Singer (1962). Another early attempt at the formalization of emotional processing, their model was one of the first instances of presenting a constructionist view of emotion as a phenomenon encompassing several discrete stages in the progression of signaling, cognitive, or other biological processes. Emotion, according to Schachter and Singer, was comprised of a perception (or interpretation) of the presented stimulus in context, where the stimulus itself might have elicited a generalized arousal of the autonomic nervous system, while the circumstances of the encounter with the stimulus determined the particular emotion experienced at that moment. Notably, they did not shy away from acknowledging cognitive processing of the percept being crucial for the formation of the emotion as a complex experience. Thus, the overall paradigm was indeed inclusive of the idea of context, which I highlighted in the definition; yet, the Schachter-Singer model does lack explanatory power with regards to the continuity of an emotional process — presenting a stark contrast with Schlosberg's model. At around the same time as Schachter and Singer comes also the multifactorial understanding of emotions of Robert Plutchik (1960). His approach to emotions was formalized through a series of postulates, the most important of which underlined the existence of primary emotions, the prevalence of mixed emotions in everyday life, and the relative pairwise opposition of all emotional states akin to the one I may see in color theory. It is important to note here that the multidimensionality Plutchik referred to in the title of his paper was largely stemming from Schlosberg's assumptions of activation being one of the primary dimensions along which emotions may be measured and formally assessed. Of course, the arbitrary nature of such an assessment was acknowledged in the description of the model. Yet, the primary emotions in his model were placed on a circumplex plane similar to a color wheel — in a manner determined by Plutchik's own intuition. As Plutchik puts it, more "complex" emotions would be formed from the mixtures of primary ones — which explained to the reader that the main postulate bore an assumption of the discreteness of emotions. Thus, a view that is pertinent in the field to this day is that emotions need to be defined in terms of their folk psychological verbal counterparts, and any level of nuance in either the temporality or conscious awareness of the experience must be solely reliant on existing terminology and not on observations of body signals and/or registration of such. This brings me to the model that remains an important contributor to the theoretical foundations of emotion research in the neurosciences to this day — namely, James A. Russell's circumplex model of affect (1980). While it would be redundant to reiterate the minutiae of the model, the bird's eye view of the framework merit highlighting the following important points: Russell emphasized the presence of eight main affective concepts (or emotions), all of which might be located on a unit circle circumscribing the origin point of the two dimensions of valence and arousal. It is also crucial to point out that Russell's model included a principal components analysis of the similarity scores between self-reports of English-speaking participants (for a more recent review of circumplex models, including those which have been transposed into Mandarin Chinese, see Stanisławski et al. 2021). Interestingly, Russell also pointed out that the assumption of bipolarity of the proposed dimensions (see, for example, Russell and Carroll 1999) — as well as the much smaller percentage of explained variance in others — was strongly speculative and based on evidence from semantic analyses. Thus, Russell's framework — although ubiquitous in the field to this day — lacked formal neuroscientific translation to physiological terms, and thus appears to be less empirically feasible from the point of view of experimental design than other, more quantitative models. Not dissimilar to the views of Plutchik and Russell were the writings of Silvan S. Tomkins, whose affect theory has greatly influenced the field of psychology. Notably, one of the later iterations of his theory (Tomkins, 1991) also pointed out the semantic and verbal bases for the categorizations of "affects" and not emotions. Tomkins defined an "emotion" as a feeling which was coupled with the memory of similar feelings. Operationalizing emotion in this manner did introduce continuity and historicity of the term with Russell's prevalent usage, yet fell outside the scope of my modern approach to emotions. In contrast, Tomkins's "affect", underlined by the characteristics of urgency (or immediacy), abstractness, and generality (cf. repeatability), was compared in his theoretical framework to other mechanisms of cognitive functions and thus distanced from "proper" cognition. It is easy to see that such views are not aligned with my proposed understanding of emotional states (as I view them as not independent or orthogonal to the putative network of cognitive mechanisms), but rather they perpetuate the juxtaposition of emotion and cognition. Thus, even if the intuitive understanding of affect's relationship to motivation or other named functions of the mind might fall under the umbrella of folk psychological cognitive ontology, I conclude here that behaviorally tested approaches such as that outlined by Tomkins do not fit in the process of empirical testing of my definition. It is also worth noting here that the last several decades leading up to 2024 have seen a resurgence of theoretical frameworks of emotion which incorporate interoceptive information as well as the "psychological" side of the phenomenon. This movement has been proclaimed as neo-Jamesian, in accordance with the original proposal by William James which incorporated physiological multiplicity of emotional characteristics — and which I have seen gradually be reduced to a singular measurement of "arousal" in the latter half of the 20th century. However, because of the so-called "psychological imperialism" (an expression coined by Tomkins in 1991), the conceptualization of emotions as embodied and experienced states has been largely dismissed up until the resurgence of the interest in this approach by such researchers as Klaus Scherer, Jaan Panksepp, Antonio and Hanna Damasios, and Joseph LeDoux. While a detailed overview of their interpretations of affect and emotion are also covered in my second essay, it perhaps suffices to refer to The Emotional Brain (Ledoux, 1998) and Looking for Spinoza (Damasio, 2003) as the most vivid and complete outlines of the corresponding ontological frameworks, while one of Scherer's reviews provided a rather rigorous semantic analysis of the views on emotion (Scherer, 2005). Of note here is Scherer's summary of the Russell circumplex which diverged from free-response and other self-report based methods of assessing emotional states in individuals: he justifiably questioned the communicability of emotions between individuals. However, his paper also highlighted a proposal for the Geneva Emotion Wheel, which, while lacking the strict dimensionality of a circumplex model, also introduced a potential bias in the process of metrization of an arbitrary emotional space, since the proposed wheel was oriented towards the verbal expressions related to emotions in English. Therefore, it ran into precisely the same issue of language specificity as the circumplex model (see Ogarkova 2021). A brief overview of more mathematically rigorous models of emotion revealed that attempts at developing a comprehensive description of a sui generis emotional space were published throughout the 1990s, 2000s, and 2010s (e.g. O'Rorke and Ortony 1994; Sokolov and Boucsein 2000; Reisenzein 2009; and Trnka et al. 2016). However, one can also observe certain trends of each one of exemplar approaches neglecting at least one of the following contributors to emotion (as viewed in accordance with Definition 1): continuity, contextuality, dependence on physiological allostasis, and interlingual variance. The earliest example of a model parallel to that of the traditionally accepted circumplex model is the framework developed by O'Rorke and Ortony (1994). The model closely followed the ontological understanding of emotions outlined in Ortony et al. (1990), in which a formalized view of emotion as a valenced appraisal was formed by the perception of aspects of objects, actions of various agents, and the consequences of said actions. While the computerized approach to the digitization of such a contextualized model presented in O'Rorke and Ortony's work appears to have multiple advantages for an empirical application, neither did the model concern itself with other, non-valenced (and thus non-bipolar) views of emotion, nor did it appreciate the physiological aspects of embodiment. Moreover, because of the early time of publication, this approach (even when followed by more recent works in, e.g., Ortony and Clore 2015) was perhaps more suitable for a cognitive scientific investigation of self-reported emotional states and not a more holistic neuroscientific experimentation. In a similar manner, Sokolov and Boucsein's model (2000) also limited the dimensionality of emotions to the behavioral perception of the phenomenon rooted in the "commonsense" cognitive ontology. Their model equated the hue-lightness-saturation dimensionality of the perception of color to the tone, intensity, and saturation of emotion. While approaching the multidimensionality of emotions from the point of view of this familiar three-dimensional Euclidean projection of the color space, the authors, however, continued the conventional labeling of emotionality as that dependent solely on a relationship that appears to be universal and invariant to time, context, or stimulus modality. They also proposed a simplistic model of the "neuronal basis" for the perception of emotions. They appealed to a hierarchical organization of circuits encompassing the levels from the hypothalamus to the cortex and assigned some of the commonly accepted cognitive schemata to cartographic loci within the brain. Yet, little to no attention was paid in their argument to the autonomic signaling which must accompany a subjective experience of emotion, thus leading the reader to conclude that a perception of an emotional stimulus in the environment is the experience itself, and emotions are thus only precursors to other, already formalized behaviors which become associated with stimuli by the process of learning. Thus, their model, while increasing the dimensionality of the Russell model, still appears to accept as axiomatic the discreteness, temporal invariance, and verbal constancy of emotions as experiences. Hence, a contradiction with the proposed definition. Other recent researchers have also approached the behavioral dimensionality of emotions solely as states of mind. For instance, Rainer Reisenzein's (2009) belief-desire theory of emotion was a computational model which addressed the issues of contextuality and interlingual translatability of emotions as experiences. Emotions in his framework were viewed as a summarized output of the detectors of belief- and desire-congruence. Therefore, Reisenzein pointed out, emotions were appraisals reliant on learning and/or conditioning to external stimuli, but they were also composed of feelings — notably, the latter were poorly defined. In this, the belief-desire theory was congruent with Radek Trnka and colleagues' proposed multidimensional model of emotions (Trnka et al. 2011; Trnka et al. 2016), which highlighted a necessary object of an emotional experience and underlined the importance of the semantic relationships between different emotions (cf. with Arnold's relatedness as attitude towards the stimulus from an evolutionary perspective). Both of these frameworks illuminated the importance of an interdisciplinary approach to emotions in the neurosciences by introducing the much called for critical evaluation of the implied reverse inference between the verbal descriptions of affect, emotions, or feelings, and measurements of changes in the physiology of the human body (see Boddice 2020; Delplanque and Sander 2021). However, both Reisenzein and Trnka focused solely on this semantic aspect of emotionality as a human experience, utilizing self-report and psychophysical measures in their methods. Thus, their approaches lacked physiological correlates which would have tied their models to the more prevalent views of embodiment of emotion. In contrast with them, researchers who approach the physiology of emotions by utilizing more quantitative techniques such as multi-voxel pattern analysis (MVPA)-based clustering of fMRI blood-oxygen-level-dependent (BOLD) signal recordings (e.g., Saarimäki et al. 2018) demonstrated an approach which appears to be more suitable for empirical reasoning, yet did not allow for a firm ontological grasp of the phenomenology of emotions. Neither did such approaches incorporate the ontology of the terms used in both folk psychological understanding of emotions and formal academic investigations of emotions as human states of existence. It is also prudent to note that mathematically rigorous approaches to modeling psychologically relevant phenomena are not new: for instance, James T. Townsend's approach to face spaces (Townsend et al., 2005) was a geometric model of parametrization of a human face which allowed for a more stringent perspective on faces as stimuli of perception. This differential geometric and topological framework is of particular relevance to the mathematical framework outlined in Section 1, even if the semantic meaning of facial configurations as percepts might not be directly related to the view of emotional states as embodied phenomena defined above. Thus, while the history of research into the question of emotion ontology, as well as the manifold of approaches to exploring this seemingly universal aspect of human psychology has been vast, none of the reviewed frameworks or models successfully address the multimodal nature of the phenomenon of emotions itself. While the definition provided a few pages ago may not be all-encompassing, it does highlight the limitations of every model and serves as a good basis for the novel approach outlined below.

### 3.2 Proposed Mathematical Model

As seen from the previous section, none of the past and current models of emotion-related processes were in complete agreement with the operational definition proposed in Section 1. For instance, while some of the frameworks (such as a neo-Jamesian account of Barrett) might account for the interoceptive aspects of emotion, they lack formal nomenclature and descriptors which would provide not just explanatory but predictive power to the model. Thus, the question of whether emotions can be modeled as an $n$-dimensional manifold will be answered in the following pages in the form of several assumptions and a proposition (all of which can be also found in the Appendix).

It is pertinent to remember that in my proposed definition, *emotional states of the individual in question are continuous in time.* Therefore, mathematically, I can declare:

**Definition 2.** *Physiological correlates of an individual's body can be represented symbolically as an n-dimensional differentiable manifold B, where dimension 0 represents time, and any dimension i of $\mathbb{Z}_+$ such that $i < n$ corresponds to a singular channel of any correlate's recording (such as an electrode in EEG, a voxel in fMRI, or a coded correlate of a contextual factor such as personal history, language, etc.).*

The implications that this definition poses are such that the dimensionality of the entire manifold B may well correspond to a countable infinity: a refinement of spatial resolution for a given method would result in the increase of available data and thus possible increase in dimensionality (compare the resolution of a 16-channel EEG recording to a 256-channel one). Thus, the recordings of bodily signals acquired for an extended period of time by any one modality accessible to a researcher would correspond only to a subset $\mathrm{B_j}$ of the manifold B (where $j \in \mathbb{Z}_+$) — for instance, such signals detected via continuous (or quasi-continuous) methods of data collection, such as EEG, MEG, fMRI, or others, would constitute but a part of the entirety of the body's activity *in toto*. The differentiability of the manifold B relies, of course, on the continuity of the data collection method chosen by the modality of recording; however, typically, the continuous nature of the bodily signals acquired is implied by the method itself. Similarly, the methodology of data analysis in any given neuroimaging technique — be it a dimensionality reduction done via principal components analysis or independent components analysis, or a coherence analysis of waveforms — conveniently lends itself to a pragmatic confirmation of the differentiability of such data. It is also worth noting that the *local* topological characteristics of the manifold B may indeed be viewed as Euclidean, as is commonly done in the field of neuroscience.

The addition of the contextual dimensions corresponding to an individual's linguistic, cultural, historical, or social background might seem controversial — yet as they might not be disentangled from the very definition of emotional states, an introduction of categorical codification for ease of analysis is necessary. Seeing as research based on self-report has dominated the fields of clinical, social, and (to an extent) cognitive psychology for many decades (Wagner et al., 2014), while the statistical analysis of such "qualitative data" has been implemented with the likenesses of Likert scales and other quasi-numerical methods, this addition to the manifold B appears to be the most practical at the current moment of development of psychological sciences.

It is also necessary to note that the global characteristics of manifold B will perhaps not be as important, if I consider the following:

**Definition 3.** *Verbal and non-verbal expressions related to emotional states in human consciousness can be viewed as a topological space E, that is a set of points $\{e\}$ such that each $e_k$ (where $k \in \mathbb{Z}_+$) corresponds to a singular emotional state.*

Because the definition of a topological space in general is non-specific, it allows to combine into a set any and all verbal and non-verbal expressions related to emotional states with no limitations on the language, medium of expression, or imposed temporal constraints. Thus, the topological space E would contain “angry”, “triste” (“sad”, French), “kama muta” (feeling of “moved by love”, Sanskrit) as points on it. Moreover, the possibility of intuitively grasping each of the verbalized states as a point allows me also to define space E via a set of axioms related to its topology:

**Definition 3.1.** *The topological space represented by an ordered pair (E, $\varepsilon$) consists of E, a set of all points representing expressions of emotional states, and $\varepsilon$, a collection of subsets of points $e_k$, such that:*

– *An empty set and E itself belong to $\varepsilon$;*

– *Any union of members of $\varepsilon$ belongs to $\varepsilon$;*

– *Any finite intersection of members of $\varepsilon$ belongs to $\varepsilon$.*

Thus, any $\varepsilon$ satisfying these conditions would represent a topology of the space E containing any verbal or nonverbal expressions used to communicate emotional states between individuals. One could think of such a topology easily if imagined that the subsets of E were to be demarcated by differences in languages: because I defined in **Definition 1** emotional states as those independent of the medium of their communicative expression, any arbitrary union of subsets belonging to two different languages would also belong in the emotional space. For instance, if I were to imagine a collection of subsets of emotion-related words separated by linguistic conventions (such as English, Tamil, Japanese, etc.), a union of any arbitrary number of these expressions would still be in $\varepsilon$, as would be an intersection nomenclatured by a common attribute such as the relationship to "joy" in English. Thus, E can easily be viewed as a topological space.

However, a relationship between E and B cannot yet be established, as the following series of assumptions need to be tested first.

**Assumption 4.** *Topological space E is connected.*

The attribute of connectedness of E bears importance for further exploration of the relationships between the empirically assessed embodied characteristics of emotions and their expression in the language or other means of communication across individuals.

Note that in topology, a connected space is a topological space X (let's use X as an example designation) if there does not exist a pair U, V of disjoint nonempty open subsets of X whose union is X (Munkres, 2015) — meaning that there are no two points u, v such that their *neighborhoods* (open sets "centered around" each point) only have an empty set as their intersection, and the union of these two neighborhoods comprises the entirety of X. However, because of **Definition 1**, I view emotional states as those independent of interlingual translatability and solely dependent on their physiological attributes. I thus assume by definition the possibility of *closeness* of words used in different languages (intuitively, I can refer to that as the proximity of English "anger" to Russian "злость" or French "colère"). Now, assume for contradiction, that I can indeed separate E into two disjoint subsets A and C, such that both of them belong to $\varepsilon$ (are open) and the union of the two is E — for instance, I could assume A to contain the point "anger" and its immediate neighborhood, and C to contain the rest of E. Now "anger" lies in A, but "sadness" lies in C. If A and C are disjoint, then no emotional state which would encompass the semantic properties of both "sad" and "anger" could exist, as then it would have to lie in the neighborhood of either "anger" or "sadness". However, according to either the discrete emotional theory (such as those proposed by Plutchik 1960 or Matsumoto and Ekman 2009) or the dimensional framework (Russell, 1980), the existence of *complex* emotions is indisputable. Moreover, even an intuitive reading of words like "sullen", "resentful", "bitter", "disappointed" communicates a degree of both "sadness" and "anger". In addition to that, **Definition 1** also posits that emotional states are continuous in time — therefore, even if for a given state $\mathrm{e_i}$ there is no corresponding verbal expression, there must exist a nonverbal communicative method of relaying the information about such state to another individual (in my case, the researcher). It is not hard then to assume that for any given $\mathrm{e_i}$ and $\mathrm{e_j}$ there exists at least one point $\mathrm{e_k}$ such that the intersection of the neighborhoods I and J of $\mathrm{e_i}$ and $\mathrm{e_j}$, correspondingly, contains $\mathrm{e_k}$. But that would contradict the original claim that neighborhoods I and J are disjoint.

It is also prudent to mention that connectedness of E does not preclude it being a Hausdorff space (meaning a space in which for each pair of distinct points of E there are two disjoint neighborhoods of such points). Indeed, it is possible to incorporate the assumptions of the discrete emotions approach in this framework still: the existence of a *path* between $e_i$ and $e_j$ does not contradict the existence of an arbitrary threshold of either neighborhood I or J, or, semantically speaking, there might still be an intuitively understandable difference between "anger" and "sadness" which posits these as two different emotions in the folk psychological understanding of the term.

Note also that a more rigorous proof which would utilize the quantitative nature of physiological measurements of momentary states would have to rely on the claim of embodiment outlined in **Definition 1**, but is otherwise trivial, which will be shown next.

We can demonstrate the relationship between manifold B (or rather, its accessible subset $B_i$) and space E by means of a map M such that:

**Definition 5.** *A map M relates manifold B to the connected space E by a certain rule of assignment (function m(x)) such that for any point $b_i$ in B there exists an image $m(b_i) = e_i$ where $e_i$ is in a member of at least one nonempty subset of E.*

The exact attributes of any such function $m$ would rely on the choice of the submanifold $B_i$ of B (e.g. the specification of the modality of neurophysiological measurements or behavioral approaches) and the topologies of both B and E suitable for the needs of a particular experiment. Possible methods and their limitations are outlined in the Experimental Implications. The following several assumptions and propositions concern any general function $m$, however, and thus must be included within this section.

**Assumption 6.** *A function $m : B \to E$ is continuous, because for each open subset I of E, the set$n^{-1}$(I) is an open subset of B. In other words, both subsets I and $m^{-1}$(I) lie in the topology of their corresponding topological spaces E and B.*

The existence of open sets on E has been shown in the previous paragraph. Thus, openness of any set I is assumed by the first part of the proposition. In order to assess the openness (whether or not the inverse of I lies in the topology of B), establish a convention that for any point $e_i$ in E its immediate neighborhood I consists of points $e_{i+1}, e_{i+2}, \ldots, e_j$, which comprise the entirety of a finite set I. According to **Definition 1**, points $e_i$, $e_{i+1}$, $e_{i+2}$, $\ldots$, $e_j$ must each correspond to at least one $b_k$ in B. Without making assumptions about possible identity among the indices $i$, $i+1$, $i+2$, ..., $j$, for practicality, make those indices correspond to arbitrary indices $k$, $k+1$, $k+2$, ..., $l$ of points {b} in B. Then, the neighborhood of $b_k$ that is the set of points $m^{-1}$(I) (call it K) is a set of points containing each of points corresponding to their images in I.

Remember that a set of points centered around a singular physiological state in B must be continuous along at least one dimension (be it dimension 0 of time or any physiological registration of a signal, or even nomenclature corresponding to environmental and contextual factors — in the last case, continuity is synonymous with constancy) in order for the neighborhood to be such. But continuity along dimension 0 of any dynamic change in the physiological state is always guaranteed by the property of evenness of temporal resolution in the registration of physiological states.

Now, is it possible that neighborhood K is *not* in the topology of B or its sub-manifold $B_i$? Suppose that for a given emotional word there is a point $p$ such that a neighborhood P is not in the topology of B. That would imply that there is at least one member Q of a certain topology $\mathcal{B}$ of B such that either P ∪ Q is not in $\mathcal{B}$ or that P ∩ Q is not in $\mathcal{B}$ by definition of the topology $\mathcal{B}$. However, for any topological space (such as B, by definition), a point lies in all of its neighborhoods — and P ∩ Q where $p \in$ Q necessarily is a neighborhood of $p$. $P \cup Q$ is also a neighborhood of $p$ as it contains all points of P. But a neighborhood of a point in B is an open set by it being differentiable! Thus, K must be an open set in B, and therefore, $m$(K) is a continuous map of B to E.

Notably, this also confirms the following:

**Assumption 7.** *Both manifold B and emotional space E are Hausdorff spaces.*

Topologically speaking, a topological space is declared to be a Hausdorff space, when for each pair of distinct points $p_i$, $p_j$ on P there exist neighborhoods of those points $P_i$, $P_j$ that are disjoint.

A logical question which follows, of course, concerns the exact nature of the map $m$. Because the proof of **Assumption 6** contained an assumption of an existence of the inverse $m^{-1}(e)$, it is evident that an explanation is needed for this assumption of $m$ being bijective.

**Proposition 8.** *The function $m$:B $\rightarrow$ E is bijective. In other words, there is a one-to-one correspondence of each of the points of B to their images under m in E.*

To demonstrate my point, I need to answer the following: are there such points $b$ in B that there exist more than one solution to $m(b) = e$? Conversely, is there a point $e$ in E that is mapped to from more than one $b$? Is $m$ thus injective, surjective, or bijective?

It is rather easy to see that, following a rather lax description of E provided in **Definition 3**, one could construct E such that it would satisfy either of the three scenarios. If I are to say that emotional states are *repeatable* (meaning one single verbal expression, e.g. "angry", corresponds to multiple instances of projections from B to E, which would solely vary on the dimension of time), then the function $m$ is surjective but not injective. However, if it is allowed for different points in E to bear the same "name" (i.e. the correspondence of them to an identical lexeme in a given language) while having different "coordinates" in the space E, based on the time of occurrence of the state (if nothing else), then it naturally follows that there exists a possibility for me to construct a function $m$ such that the image of any given submanifold $B_i$ (restricted by the technological capabilities of the researcher as well as the emotional states of interest in the context of any given experimental investigation) is contained in E, and a function $m$ that projects $B_i$ onto E is bijective. It is thus possible for a verbal dictionary of point descriptors of E to be non-exhaustive and smaller in length than the size of $m(B_i)$. I would then argue the case for the latter approach simply for the purposes of simplicity in further exploration of the properties of the two spaces. However, pragmatic considerations might then force one to use "$\text{angry}_1$", "$\text{angry}_2$", ..., "$\text{angry}_i$" to differentiate between the cognitively common understanding of the word and physiologically distinct states corresponding to the instances of it.

Now that I have addressed the basic properties of both B and E, I can start to address specific cases of submanifolds of B and subspaces of E which would be confined to the conditions of any given psychological and/or neuroscientific experiment. For instance, let me address the question of compactness of a submanifold $B_i$ of B.

**Assumption 9.** *A submanifold $B_i$ of B is compact under the assumptions of a finite empirical study that is finite in time and restricted to the existing finite physiological and psychological measures.*

To prove Assumption 9, I focus on how these conditions satisfy the criteria for compactness in the context of differentiable manifolds. According to the Heine-Borel theorem, a subset is compact if and only if it is closed and bounded. While manifold B is not strictly $\mathbb{R}^n$ for all cases, if I can analogously apply this principle, showing closedness and boundedness of $B_i$ in its context would imply compactness. Given that the physiological correlates are measured within a finite amplitude range and the data are recorded for a finite period of time, I can argue for both boundedness and closedness.

The boundedness of $B_i$ can be established by definition, if I record data for a finite period of time. I thus ensure that the temporal dimension of the $B_i$ is bounded by having minimum and maximum time points beyond which no data are recorded. Moreover, the application of selective criteria to physiological measurements, such as limiting the study to EEG channels with finite amplitudes, ensures that each physiological dimension is bounded. This means for each correlate dimension $i$, there exists a maximum and minimum measurable value, further contributing to the boundedness of that $B_i$.

To argue for closedness, I must ensure that B contains all its limit points. In the context of an applied study with selective criteria, that would necessitate the inclusion of limit points. The selection criteria for physiological measurements inherently include the limit points of the data set. For instance, the maximum and minimum values for EEG amplitudes are part of the data, ensuring no sequence of points in $B_i$ converges to a point outside of it. In addition to that, the finite precision of measurement instruments ensures that the space of possible measurements is discretized to a degree, although modeled continuously. This discretization, in practice, means that the space of recorded data, including its boundaries, is effectively closed because measurements can only approach a limit within the resolution of the measurement tool (such as the sampling rate of EEG or fMRI, or Likert scale spacing).

If, however, these arguments are unsatisfactory to the reader, one can simply assume closedness and boundedness of B as necessary requirements for a chosen modeling approach prior to the realization of empirical testing and select an appropriate computational tool with that caveat in mind.

We can thus apply the Heine-Borel theorem for $\mathbb{R}^n$ analogously, given that $\mathrm{B_i}$ is a differentiable manifold modeled in a study with finite time and physiological measurement bounds: a space is compact if and only if it is closed and bounded. Here, the submanifold is both closed and bounded due to the selective criteria of the study, implying compactness.

This compactness facilitates the application of various mathematical and analytical techniques, such as the existence of solutions to differential equations modeling physiological dynamics or the applicability of certain statistical methods to the data represented by a given study. Moreover, if the study in question uses the model as a framework and satisfies the requirements for compactness in a topological sense, the analysis of data acquired in such experimental settings gains power in the areas of topology and differential geometry.

Let me now approach the question of the compactness of the topological space E that contains all the points of emotion verbalization (and non-verbal points that lie *between* emotion terms). Can we, for instance, prove that a given subspace of E, that would be constrained by the conditions of an empirical study on a single individual (with a finite vocabulary), is compact?

**Assumption 10.** *A subspace $E_i$ of the topological space E that is constrained by a given empirical study on a singular individual (analogous to that in **Assumption 9**), is compact.*

We can apply the concept of compactness in a manner analogous to how I approached manifold B. This time, however, the focus shifts to the space of emotional expressions rather than physiological correlates.

Given E represents verbal and non-verbal expressions of emotional states, and considering the constraints of an empirical study on a single individual with a finite vocabulary, I have a natural boundary on the "size" of E, particularly its subspace $E_i$ relevant to the study. Here, $E_i$ could be thought of as the subspace of E that includes all emotional expressions (verbal and closely associated non-verbal) utilized by that individual in the contexts provided by the experimental design. The individual's finite vocabulary limits the number of discrete points in $E_i$ representing distinct verbalized emotional states. This inherently suggests a bounded nature of $E_i$ because there's a maximum number of distinct emotional expressions the individual can produce. The non-verbal expressions that lie between verbalized emotion terms can be considered to form a continuum that connects discrete verbal expressions. However, the range of non-verbal expressions is also bounded by the finite nature of human expressive capacity and the study's focus on a single individual within a limited temporal and situational context.

For $E_i$ to be compact, it must also be closed, meaning it contains all its limit points. The study design and the nature of emotional expression ensure that all limit points within the emotional expression space $E_i$ are included. For instance, the smallest nuances in emotional expression that can be verbalized or non-verbally expressed by the individual are encompassed within $E_i$ by definition. As for the discreteness, both the verbal expressions and the continuum of non-verbal expressions form a closed set when considering the individual's limited expressive range within the assumed context. Every sequence of emotional expressions within Ei, whether approaching a verbal term or a nuanced non-verbal expression, converges to a point within Ei.

By demonstrating both boundedness and closedness of the subspace $\mathrm{E_i}$ under the study's conditions, I can argue for its compactness. This compactness is particularly relevant when considering the empirical constraints and the analytical convenience that this proof lends itself to in the area of further investigations into the topological nature of the manifold model.

**Corollary 11.** *Given that $B_i$ and $E_i$ are compact subspaces within the confines of a given empirical study, and assuming they satisfy the Hausdorff condition, it follows directly that $B_i$ and $E_i$ are metrizable.*

Following the properties outlined for the model, it would not be hard to imagine an empirical application for the mathematical foundations. For instance, more empirical research is necessary to establish certain vital assumptions about the proposed framework: for example, am I supposing that the manifold B describes the multitude of physiological states for a single given individual, or does it encompass the entirety of the possible states of being for any representative of the human species? If the latter is true, then what is the relationship between a given submanifold $\mathrm{B_i}$ and its corresponding subspace $\mathrm{E_i}$ for a given inter-subject investigation in a psychological or a neuroimaging laboratory? Does every $m$ used for a specific experimental approach generalize to the group of participants, or does every individual merit the development of their own unique $m$? Would it be possible to identify a homeomorphism of a subset $\mathrm{B_i}$ to a subset $\mathrm{E_i}$ for a particular investigation?

Those (and other questions) would necessitate both a rigorous definition of initial conditions for any given experimental design, as well as careful consideration of some of the implications listed below.

### 3.3 Experimental Implications

The metrizability of a set $B_i$ of B (see Corollary 11) is quite trivially provable due to the conventional assumptions of the local Euclidean nature of any bodily measurement and the existence of established metrics for every dimension of B in a given modality (e.g. the temporal resolution and topographic relationships of channels in EEG or voxels in fMRI, or Likert scale assumptions of evenness of intervals in behavioral or environmental measures). That allows to test not only the continuity of transformations of a given subset $B_i$ to its corresponding subset $E_i$ of E, but even assume their homeomorphism. But if a given set $B_i$ is homeomorphic to $E_i$, it is therefore possible to incorporate the temporal dimension of B into the investigations of E. Thus, I would propose the following paradigm of testing the metrizability of E.

A metric on a set $E_i$ (a subset of E) would be defined as a function $d$ such that the distance between any two points $e_i$ and $e_j$ would be positive, and a triangle inequality $d(e_i,e_j) + d(e_j,e_k) \geq d(e_i,e_k)$ would hold for any three points $e_i$, $e_j$, $e_k$. Because it is possible to assume that the temporal dimension of B carries through the homeomorphism to $E_i$, I propose that the distance between any two points of $E_i$ may be viewed as a time interval — which is justified by **Definition 1** and the assumption of *continuity* of emotional states.

Thus, a metric of points in E might be investigated via a behavioral assessment of *closeness* of emotional states as the time which it might take for a given individual to transition between two known and established emotional states. An exploratory investigation of self-reported measures of such transitions may be carried out in a safe and controlled environment either in a laboratory setting or via online means. Simple $z$-score analysis of reported time intervals may then illuminate the plausibility of such an approach and provide a basis for future experiments — such as those which focus on the physiological recordings of functions time-locked to a delivery of emotional stimuli.

The physiological approach would necessarily employ the notion of *embodiment* in order to construct the submanifold $\mathrm{B_i}$ in a manner which would describe the body as fully as possible. Thus, it would necessitate the acquisition of not only traditional neuroimaging modalities such as EEG, MEG, or fMRI, but also ensure the simultaneous recording of electrocardiography (ECG), facial electromyography (EMG), electrooculography (EOG) and other possible routes of monitoring the functions of the entire body along with the self-reported emotional states, behavioral variables such as response times, and contextual information about the experimental conditions surrounding the time of the recording. The resulting dataset comprised of multidimensional quantitative registrations of bodily signals would then have to be assessed and analyzed in order to develop an aggregate function for the placement of every time point of the recording in the symbolic manifold space $\mathrm{B_i}$ — and thus would provide an opportunity to not only assess the comprehensive nature of such multimodal experimentation, but also introduce a way of mathematically defining a function $m$ that would map the points of the embodied submanifold $\mathrm{B_i}$ onto the points of the emotional subspace $\mathrm{E_i}$.

Continuing from the framework established for assessing the metrizability of $E_i$ and the construction of the submanifold $B_i$, the application of UMAP (Uniform Manifold Approximation and Projection, see McInnes et al. 2018) for the analysis of such data is both justified and promising. Given that $B_i$ is homeomorphic to $E_i$ (indicating a one-to-one, continuous, and invertible mapping between these spaces), I have a strong foundation for applying advanced dimensionality reduction techniques to explore the intricate relationship between physiological states and emotional expressions. UMAP, in particular, stands out due to its effectiveness in preserving both the local and global structure of high-dimensional data in a lower-dimensional representation.

The reasoning behind my decision to suggest exploration of datasets collected with the proposed framework in mind is two-fold and based upon several characteristics of the algorithm.

First, UMAP preserves the local structure of the data while reducing the dimensionality for ease of interpretation. This is crucial for my dataset, as the physiological and emotional states that $B_i$ and $E_i$ represent are expected to have nuanced, locally consistent patterns that are important for understanding the dynamics of emotional states and their physiological underpinnings.

Second, UMAP is particularly well-suited for handling the temporal dimension. The proposed metric for $E_i$, based on the time interval between emotional state transitions, aligns well with UMAP's ability to work with the notion of distance. UMAP can thus effectively model transitions between emotional states as observed in the empirical data, providing insights into the temporal dynamics of emotional experiences.

Thus, the application of UMAP to such a multidimensional dataset allows for an exploratory investigation into the structure of emotional and physiological state spaces. By visualizing the data in a lower-dimensional space, I can identify clusters, patterns, and trajectories that may not be apparent in the high-dimensional space, thereby generating new hypotheses about the nature of emotional states and their physiological correlates.

However, several caveats must be considered before applying UMAP to a dataset of the nature described above. One of the pertinent criteria for the proper interpretation of the data is the selection of relevant features at the stage of experimental design. As such, careful selection of physiological features and modalities that are most relevant to the emotional states of interest should be prioritized in the theoretical construction of the submanifold $B_i$. This will ensure that the dimensionality reduction focuses on the most informative aspects of the data.

It is also imperative to be aware of the need to validate the embeddings visualized with the help of UMAP. The low-dimensional embeddings produced by UMAP should be ensured to meaningfully represent the original high-dimensional data. This can involve correlating distances in the UMAP space with known physiological or emotional differences, or assessing how well the embeddings reflect the temporal dynamics captured by the proposed metric for $E_i$.

In summary, applying UMAP to the described dataset offers a powerful method for uncovering the complex relationships between embodied physiological states and emotional expressions. This approach not only facilitates a deeper understanding of the multidimensional nature of these states but also opens up new avenues for empirical research into emotional and physiological dynamics.

## Conclusion

In this chapter, I have embarked on a pioneering journey through the complex and nuanced terrain of emotional states and their physiological underpinnings, employing a rigorous topological and mathematical framework. My exploration has led me to define and analyze the manifold B and the topological space E, delving into their properties, compactness, and metrizability, and establishing a foundational basis for understanding the continuous, yet distinct, nature of emotional states as influenced by physiological and contextual factors.

I have also suggested that the application of UMAP for dimensionality reduction could enrich further analytical approaches to suitable datasets, allowing me to visualize and hypothesize about the intricate relationships between physiological states ($B_i$) and emotional expressions ($E_i$). This approach will therefore allow for the empirical validation of the proposed model through carefully designed experimental studies.

As I conclude, it is clear that my journey through the topological modeling of emotions is only beginning. The framework presented here opens numerous avenues for future research, encouraging a deeper empirical investigation into the manifold of human emotions, the exploration of individual and collective emotional landscapes, and the development of more nuanced, holistic models that can inform both theoretical and practical applications in psychology, neuroscience, and beyond. My work underscores the potential for a symbiotic relationship between mathematical modeling and empirical research in advancing my understanding of the human emotional experience.

# Chapter 4

## Modeling emotions as a topological space: an empirical test

### Introduction

Empirical approaches to emotion are manifold. One can dissect the dynamics of a single emotional event or study the differences between those isolated occurrences. Yet, few examples of modeling approaches can be found with relation to the inter-emotion dynamics, or the individual variability of the "emotion space". In this study, I propose a novel empirical approach built on the foundation of a rigorous model which posits emotional phenomena as continuous multidimensional variables and provides insight into potential applications of novel computational techniques in assessing and monitoring emotion dynamics.

For this study, the main inspirations behind the theoretical framework underlying the empirical application is the ontological basis of developmental systems theory (DST) (see Chapter 2 for an overview of DST; refer also to Oyama 2000; Overton 2013). The tenets of DST correspond to my approach in terms of methodology and experimental design, and this foundation also aids in the explanation of my choice for the biopsychosocial model as the main methodological framework. While applications of DST in the life sciences and psychology are broad, the most crucial assumption for my research is that of causal interdependence of factors. Drawing from DST, my approach illustrates the interplay of interoceptive, environmental, and cultural strands in shaping emotion dynamics. DST's principle of 'causal democracy' (Oyama, 2000) refuses to weigh some of the factors (such as mechanistic explanations) more heavily than others (e.g. cultural context), advocating instead for a vision where factors combine on multiple levels to mold emotional phenomena. This holistic lens mirrors the biopsychosocial model in that it seeks to supplement conventional emotion studies by acknowledging the complex development of emotional space. Herein, DST not only informs but enriches my approach, allowing for a richer understanding of emotions.

In the following overview of the existing modeling approaches to emotions I aim to demonstrate that, while comprehensive and well-founded in their niche operational spaces, current developments in the affective sciences remain limited in one aspect or another with respect to this multilayered view of causal interdependence in DST. Namely, I wish to display the areas of knowledge and methodological gaps where a more comprehensive approach would be: (a) more ecologically valid; (b) incorporate multimodal data; and (c) be suitable for complex computational analysis in cases where the multidimensional nature of the acquired data is difficult to interpret with traditional methods.

Historically, emotion studies in psychology and neuroscience in the Western tradition span more than two centuries and encompass a wide array of theoretical approaches to such affective phenomena as emotions, moods, dispositions, feelings, and affect (see Chapter 2). A brief survey of the literature reveals several characteristic assumptions made about the teleological basis of affective phenomena. One such assumption concerns the universality of facial expressions accompanying the experience of emotion — indeed, early authors such as Duchenne or Darwin have focused primarily on the outward presentation of an affective phenomenon and not the subjective lived experience as it pertained to the biological context of an embodied process. The focus on faces as the primary conduit of emotion as an ontological entity later saw its reflection in the works of Silvan Tomkins (1964) and Paul Ekman's theory of universal basic emotions (1973, 1988). This universality was postulated to reflect the ground truth with regards to the biological basis of emotion as lived experiences — yet the theory presented multiple limitations for multimodal analyses and frameworks which posited emotions as situated within social and cultural contexts. The categorical classification of emotions within these paradigms thus presents a simplified representation of emotions and does not allow for analysis of shifts between different classes of affective entities. Yet, the notion of universality remains a crucial contributor to the biological and psychological understanding of emotions as phenomena shared between people — which would therefore allow for comparative analyses of the data collected from a sample.

Contrast that with the approaches of James-Lange or Cannon-Bard, or more neuroanatomically leaning theories of Maclean and Papez, as well as more modern undertakings of neo-Jamesian researchers such as Antonio Damasio (1994), Joseph LeDoux (1996), James Gross (1998), Richard Davidson (2000) or Lisa Feldman Barrett (2007; 2013; 2023) (see Chapter 2). The cornerstone of their approaches (which may seem disparate at first glance) is the notion that emotions result from perceptions of bodily changes and are integral to experiencing and reacting to the world. Their approaches notably do not align with a purely reductionist view in terms of physiological mechanisms, and this holistic perspective served as a source of inspiration for the development of the current model. At the same time, the empirical approaches realized by these researchers and many others (see Adolphs and Anderson 2018) are often designed with hypotheses which necessarily require (neurobiological) mechanistic explanans as the basis for testing. Nowadays, these endeavors are, of course, never purely reductionistic (see Hoemann et al. 2023), and this paradigmatic shift provides impetus for a study like the present one to expand upon the past models and introduce more nuanced findings to the field.

Compare the views of neo-Jamesians with the branch of affective sciences pertaining more to classical cognitive science theorization, one of the largest examples of which is the appraisal theory of the latter half of the 20th century. Appraisal theory suggests that emotions result from one's assessment of a situation, influencing emotional responses through the evaluation of events as beneficial or harmful. It integrates cognitive processes, where an individual's perception and judgment about an experience shape their emotional reaction, emphasizing the subjective interpretation of emotions rather than their universal, physiological expressions (for a concise review of appraisal theory and other cognitivist paradigms see Calvo and D'Mello 2010). This family of approaches is thus firmly rooted in the understanding of internal and subjective factors contributing to emotional experiences (e.g. consistency motives or harm evaluation, agency, motivational state, etc.). At the same time, the appraisalist approaches such as the cognitive theory of emotions (Ortony et al., 1990) is rather sparse in terms of details pertaining to the biological level of explanation. The appraisalist school of thought is seminal in the research of dynamics within emotions, yet the implicit lack of acknowledgement of the physiological and social context of a situated phenomenon leaves the modeling approach too restrictive and difficult to reconcile when assessing its findings in contrast with those of others.

To summarize this brief overview of the major branches of affective sciences from the perspective of bridging the gap between the theoretical framework and practical applications, it would help to turn to the work of Schiller et al. (2023). In "The Human Affectome", a recent titanic undertaking, expands upon a multitude of frameworks and paradigms in affective research and differentiates them by teleological (purpose-based rather than cause-based) principles guiding the design. They point out that the methodological differences between various branches of affective sciences diverged not only due to pragmatic concerns about the empirical design and data collection, but also because of variance in the metaphysical understandings of emotion. As such, they highlight practical considerations of testability, falsifiability, and controlled empirical settings of emotions within the lax scope of early operationalizations of the first half of the 20th century. These considerations precipitated the gain in popularity of major emotion theories focused on the operationalization based on proximity to the stimulus or valence of the affective response such as the theory of basic emotions (Ekman 1973; Ekman and Heider 1988) or the circumplex theory of emotion (Russell, 1980). Meanwhile, other subfields of emotion science focused on the evaluative and predictive aspects of emotion operationalization, thus carving out theoretical space for such areas as affective computing, Bayesian models, or reinforcement learning in the development of computational algorithms (Younis et al., 2024). In addition to that, multiple endeavors of recent years list manifold learning analyses to emotion data (see, e.g., Chang et al. 2013; Liu et al. 2014a; Peng et al. 2014; Delis et al. 2016; Xing et al. 2018; Cowen and Keltner 2021; Hua et al. 2021; Gao et al. 2022; Zou 2022; Wu et al. 2022; She et al. 2023; Wu et al. 2024), those studies repeatedly focus on emotional expressions and not subjective experiences of emotion. The aforementioned techniques have created a rich basis for understanding some aspects of affective phenomena, yet the diversity of evidence cannot compensate for the lack of convergence within and between the subfields of studying emotions.

Importantly, existing reviews of affective computing techniques also highlight the bias towards discrete or categorical models of emotion employed to construct the computational strategy. This brings me to the point of temporal continuity which is often highlighted by proponents of more complex mathematical approaches in cognitive scientific, psychological and neuroscientific investigations. For instance, arguments towards recruitment of techniques from dynamical systems theory (the unfortunate clash of abbreviations of dynamical systems theory with DST causes me to use DynST from now on). The quantitative part of DynST concerns a mathematical description of a dynamic system in terms of differential equations which adequately reflect the complexity of the system's behavior — a classic example of which is, for instance, the illustration of the hysteresis effect. Meanwhile the qualitative part of DynST aims at graphical representation of the trajectories between the states of a dynamical system in a global state space (see overviews of DynST and its implied importance in behavioral sciences in Leeuwen 2005; Favela 2020). This proposition to employ more temporally continuous models in the study of cognitive phenomena provides an impetus for the current project.

Namely, I would like to posit emotions as points on a differentiable manifold, with trajectories or transitions between any two such points being described in terms of continuous functions in time. Several theoretical reviews and studies have attempted to describe these fluctuations in the past (e.g., Davidson et al. 2000; Scherer 2009; Grühn et al. 2013; Hamaker et al. 2015; Dejonckheere et al. 2019; Hoemann et al. 2021a), yet none of them have attempted to describe emotion dynamics at the level of granularity that the present project aims at. Moreover, the discussion of dynamics of emotion states is typically based on one of the notions incongruent with my approach, not the least of which is the tacit understanding of valence. Calls to "abandon valence" or at the very least reconsider the universality of valence as it pertains to cultural, social, and generational context have been made elsewhere (see Solomon and Stone 2002; Shuman et al. 2013). For the purposes of this project, a multi-level understanding of one-dimensional valence proposed by Shuman and colleagues (2013) appears to be much more suited to studying emotions in a more objective, diversified context which would strive to truly explore universality of affective states. Yet, as mentioned above, modern computational approaches tend to opt for Russell circumplex-based data. This represents a theoretical gap in the studies of emotion, as the lack of unity in empirical and computational experimentation makes it impossible to directly compare the results of studies. This lack of convergence has also been observed by prominent researchers in the area of constructionist approaches to emotion, e.g., Lisa Feldman Barrett. A recent commentary in Affective Science speaks to the degree of the ecological validity of past studies (Hoemann et al., 2023). As such, the authors issue a call to action for idiographic, experience-sampling based investigations which would enrich the existing frameworks by offering more diverse datasets corresponding to emotions situated within the context of real life, as opposed to the more traditional approach of studying subjective experiences in a laboratory setting with a presupposed set of affective labels. This speaks to the choice of the biopsychosocial model (BPSM) (Engel, 1977) as the basis of experimental design which aligns with the tenets of DST and would allow for interpretation of causal democracy (see Oyama 2000) in further analyses of the data collected. In short, BPSM argues for an integrative approach and inclusion of psychological and social factors in analysis of both clinical and healthy human data — which is why the three axes of the current project were selected to closely mirror the basic components of BPSM in contrast to the traditional notions of valence and arousal in emotion studies. This multifactorial paradigm is thus paramount to further interpretation of the dataset in future studies.

Within this study, I addressed the knowledge gap in current research by using an operationalization that was developed using the modeling approach described in Chapter 3. The main objective of this exploratory investigation was to test an empirical realization of this mathematical paradigm, namely, the topological analysis of a differentiable manifold which I hypothesized to underlie the data corresponding to the three dimensions of the biopsychosocial paradigm. Note that another aspect of my proposed practical solution involves a degree of blindness with regards to the previously established notion of valence in the description of emotion. I posit that, in the vein of computational research mentioned above, algorithms which aim at dimensionality reduction via construction of a graph with geometrically (as opposed with semantically) defined dimensions of interest may be more valence-agnostic.

My hypothesis is that subjective data about experienced (lived) emotions as dynamic phenomena can be embedded into a non-Euclidean (Riemannian) space such as the surface of a sphere or a torus. To test this hypothesis, I collected a set of longitudinal samples of emotion transitions in a remote setting which allowed participants full autonomy in their choice of timing, wording, and descriptions of levels of intensity of the three main factors influencing their emotional state — their interoceptive (bodily) sensations, their thought process, and their social surroundings.

The daily log was designed in this project based on the principles of Experience Sampling Method (ESM) devised by Larson & Csikszentmihalyi (originally published in 1983, reprinted in 2014) and further expanded upon in Hektner and colleagues' book (2007), as well as the recommendations for development of diary and other intensive longitudinal methods by Bolger & Laurenceau (2013). The daily log (adapted for online computer- or smart device-based responses) gave participants flexibility to enter freeform phrases associated with the emotions they experienced at the two endpoints of the described transition. In addition to that, the developed log and the method of online delivery ensured complete participant anonymity and privacy, and encouraged compliance via an initial protocol briefing session. During debriefing, many participants shared additional thoughts regarding the way the log allowed them to "check in" with their emotional state, which speaks to the high level of comfort with the procedure.

This study is an exploration of an approach novel to affective sciences in many aspects. I manage to show the feasibility of a computationally founded mathematical model when testing idiographic, modality-agnostic data from individual participants while maintaining privacy and taking cultural background and social context of their emotional state into careful consideration. This study also aims to expand our understanding of emotion dynamics through the integration of DST and BPSM. By exploring complex interactions between different emotions, it seeks to fill significant gaps in current research.

## Methods

### Participants

Adult individuals were recruited via online advertising on social media (Facebook, X) and an institutionally affiliated classifieds page. The protocol and recruitment strategies of the present study were approved by the Indiana University IRB (protocol #17026). The participants self-selected according to the posted eligibility criteria (22 years old or older, residents of the United States, able to read and write English, have an electronic device with Internet access, and not have history of uncorrected psychiatric disorders). Participants responded to the advertisement by emailing the investigator expressing desire to learn further details about the study. They were provided with an information sheet and an anonymous link to a Qualtrics form (Qualtrics, Provo, UT).

Individuals not compliant with the logging procedure (left too few records, or left repeated entries) were subsequently excluded from the study at the analysis stage.

### Informed consent and the initial questionnaires

Informed consent was provided by participants upon proceeding to the Qualtrics form through the link in the email response. The participants were thus introduced to the procedure and the flow of the experimental stages, namely, the initial questionnaires, the scheduling of a virtual briefing session, independent logging, and the subsequent debriefing and compensation ($50 USD Amazon.com gift card).

The participants then provided their email (to be securely stored on Qualtrics at an anonymized database) and were assigned a random five-digit PIN to be associated with their responses.

The initial questionnaires were selected to measure baseline levels of the participants' cognitive awareness along the three axes of the biopsychosocial framework, namely, their interoception (the biological/physiological functions of the body), their metacognition and insight (the psychological or mind-related activities), and their perceptiveness of social surroundings (the social environment).

The selected questionnaires were: multidimensional assessment of interoceptive awareness, version 2 (MAIA-2, see Mehling et al. 2018), self-reflection and insight scale (SRIS, see Grant et al. 2002), and interpersonal reactivity index (IRI, see Davis 1980).

MAIA-2 includes 6-point Likert scale measures along eight axes of an individual's ability to perceive bodily signals: noticing, not-distracting, not-worrying, attention regulation, emotional awareness, self-regulation, body listening, and trusting. SRIS includes 6-point Likert scale measures of self-reflection (across two domains of engagement in self-reflection and need for it) and insight. IRI contains four 5-point Likert subscales of social setting awareness: perspective taking, fantasy, empathic concern, and personal distress.

All questionnaires were reproduced verbatim from their proper publications in form of matrix questionnaires on Qualtrics (non-randomized).

In addition to these initial questionnaire responses, participants could voluntarily provide their demographic information, including their age, gender (male, female, or non-binary/other), and free-form expression of their ethnic or cultural identity.

## Briefing

Upon filling out the questionnaires, all participants received an automated confirmation email via Qualtrics, which contained a secure link to a scheduling page (Calendly, n.d.) with available time slots for a remote Zoom-based briefing with the research group representative. An automated Zoom link was generated upon selection of suitable date and time, and the research group was informed of the appointment anonymously (participants were requested on the web page to provide only their assigned PIN and not their name). The briefing procedure was not recorded, and participants were free to opt out of turning on their camera to maintain anonymity.

During the briefing, the participants were familiarized with the study protocol, the logging procedure, and the logistical details of reimbursement. After a short introduction into the main hypothesis of the study, a brief demonstration was run with the use of screen sharing to familiarize them with the mock up of the web page. The participants were given specific instructions about filling out the journal (see below) related to their perception of their bodily sensations, state of mind, and social surroundings in the aspects related to the emotion. The participants were instructed to select emotion label words at their own discretion. At the end of the briefing, free time was left for questions about the logistics of the study. Follow-up emails were generated and sent out to the participants after the end of the briefing, containing an anonymized link to the logging page on Qualtrics.

## Logging

The participants were requested to log transitions between their emotions for ten separate days, preferably consecutive barring exigent circumstances. Upon logging

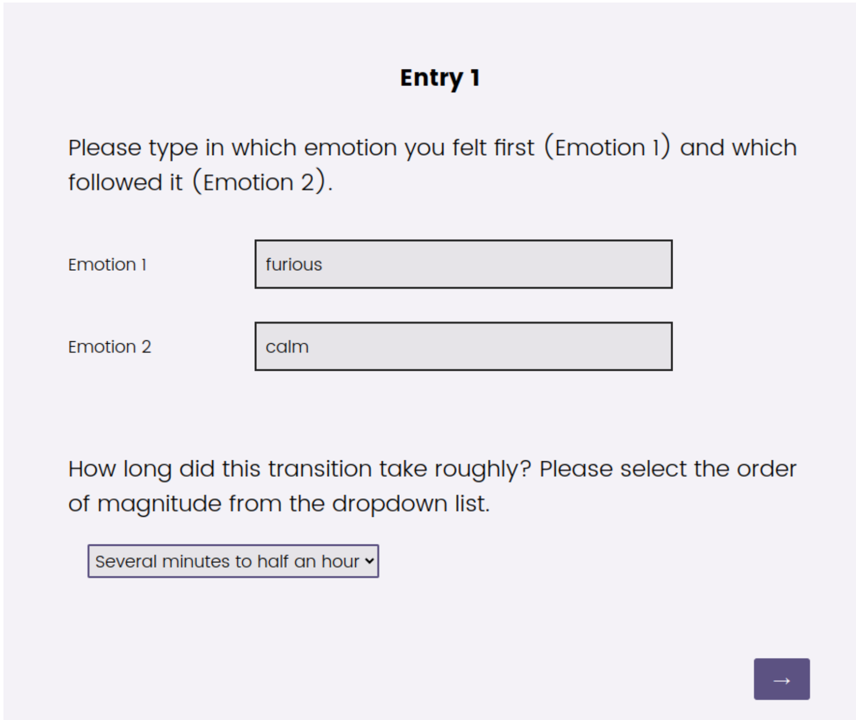


***Figure 4.1.*** **Example page 1 for a log entry** *A screenshot taken from the preview of the log form on Qualtrics with sample emotion labels entered for reproduction purposes.*

their PIN number, the fields for emotion 1 (E1) and emotion 2 (E2) were filled out at liberty, and timing of the transition was selected from a drop-down menu ("A few seconds", "Several minutes to half an hour", "Half an hour to a few hours", "Half a day or more") (Fig. 4.1).

Participants then proceeded to the three pages corresponding to the biopsychosocial axes. On each of those pages, they had up to 20 "slider" selectors (from 0 to 10) of sequential intensity values to which they ascribed the corresponding sensation. For example, if they were to mentally describe their biological (body) sensations as "I felt as if my head was spinning with anger" at the beginning of a transition from "furious" to "calm", they would select intensity 8 on slider 1, then "I felt as my heart started slowing down" would correspond to 5 on slider 2, perhaps a 3 on slider 3, and

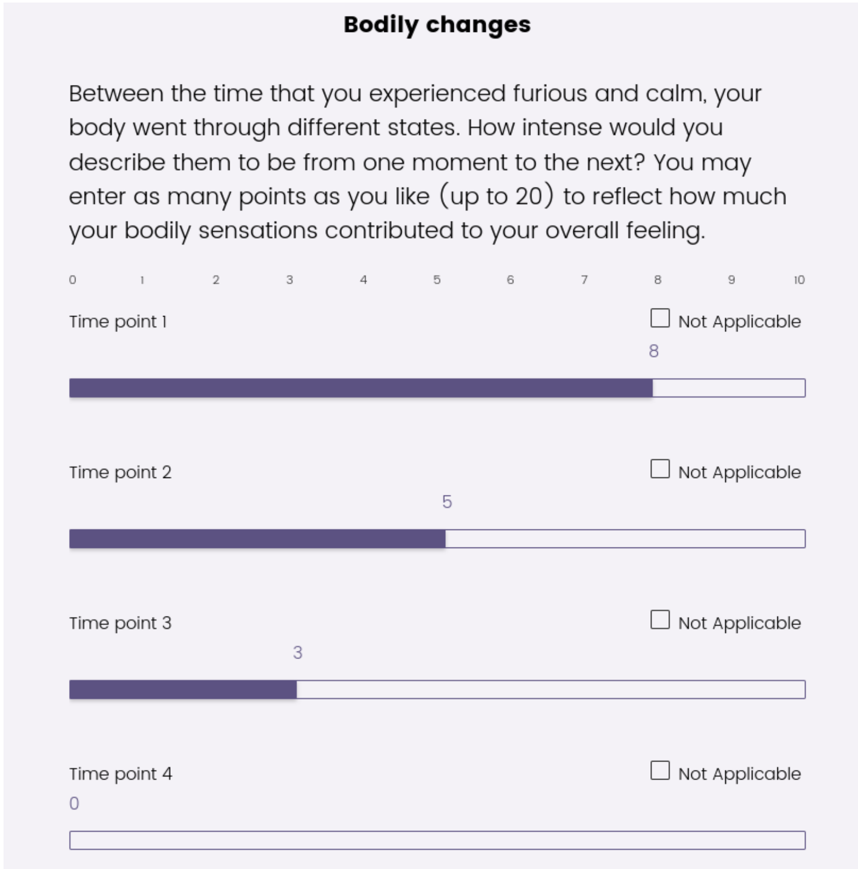


***Figure 4.2.*** **Example page 2 for a log entry.** *A screenshot taken from the preview of the log form on Qualtrics with sample values entered for reproduction purposes.*

"I felt completely calm and no longer paid attention to my body" would correspond to a 0 on slider 4 (Fig. 4.2). Additionally for the bodily changes part of the log, participants were free to fill out a body map as per the emBODY paradigm developed by the Nummenmaa laboratory (Nummenmaa et al., 2014). The body map blank page was accessed at https://version.aalto.fi/gitlab/eglerean/embody, and a rough seven body part segregation schema was designed out of consideration for participants' speed of logging on a daily basis. An example of a page in the log, as well as the body part designation illustration is in Figure 4.3. Similar subjective scales were filled out for the psychological (state of mind, thoughts and reflections) and the social (people around, interactions with them) axes of the biopsychosocial framework. The

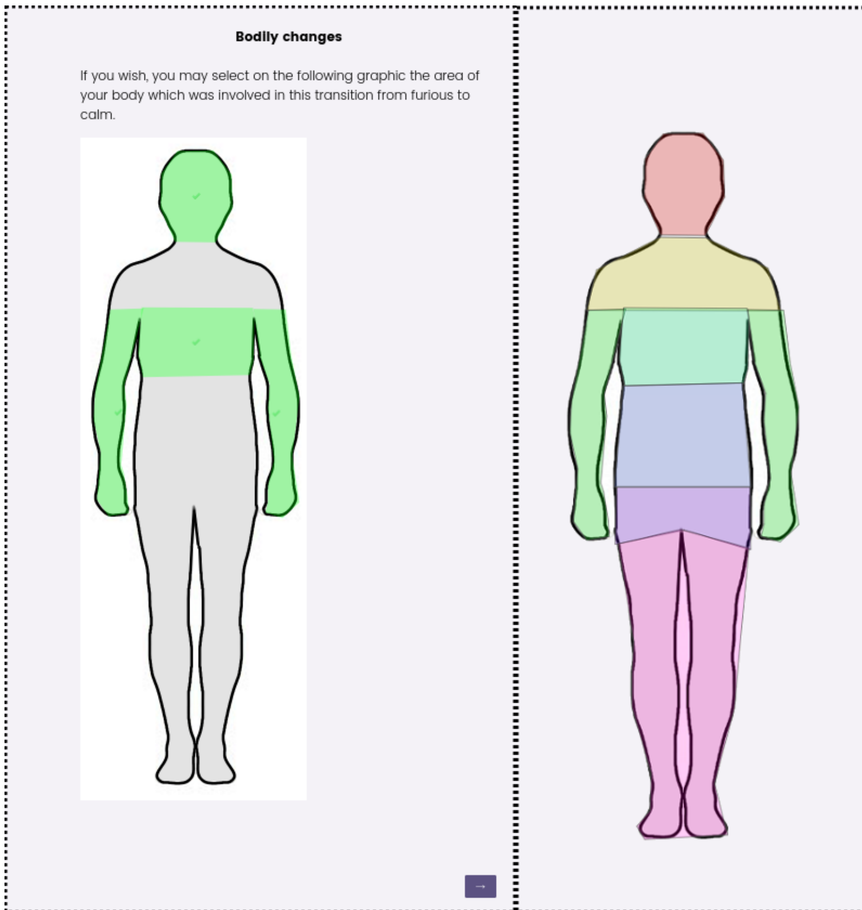


***Figure 4.3.*** **Body map page in the log (left) and designation of body parts in the original Nummenmaa schema (right)** *A screenshot taken from the preview of the log form on Qualtrics with sample values entered for reproduction purposes to illustrate the body map page on the left. Note that the original emBODY instrument assumed freeform "coloring in", yet here discretized body-part approach was chosen to shorten the amount of time spent by participants logging.*

participants then had an option of continuing the logging on the same day with up to 4 more (5 total) transition descriptions, so as to not exceed 10 minutes limit (pilot tests revealed that usual time of filling out one transition information never exceeded 2 minutes). Automated follow-up emails were sent to participants via Qualtrics as reminders 24 hours after the last entry.

### Debriefing & Compensation

Participants scheduled an anonymous Zoom meeting with the research team representative in the same manner as the briefing procedure. The debriefing allowed for any remaining questions to be answered, and for reimbursement to be processed (at this point, participants could provide an alternate email address to receive a $50 Amazon.com gift card). After the end of the debriefing session and processing of reimbursement, email addresses were deleted from the data and PINs were used to identify participants at the analysis stage.

### Analysis

The data were analyzed using *Python 3.10* (specific packages listed below). The data were cleaned with respect to incomplete logs, the criteria for which were: fewer than 10 entries; 10 or more entries of the same transition; incomplete entries with only one or two biopsychosocial factors reported; fewer than 3 points given for time scales larger than "A few seconds". This cleaning was performed with *NumPy* (v. 1.22.4), *Pandas* (v.1.4.2). Visualizations of plots were plotted with *matplotlib.pyplot* subpackage (*matplotlib* v. 3.5.2).

After this initial preprocessing, the relevant dimensions of the data (the responses to initial questionnaires, emotion labels, and biopsychosocial evaluation ratings along with the timing scale chosen by the participants) were pre-analyzed to eliminate incomplete datasets.

Scores from initial questionnaires were aggregated and distributions were tested with Shapiro-Wilk test for normality, as well as visualized as Q-Q plots to investigate the validity of the assumption of normality. This was performed to probe the potential for exploratory linear model research with the use of initial questionnaire data in further analysis of the manifold projection.

The data from BPSM logs were then interpolated in accordance with the time scale. The corresponding values for quadratic interpolation were: "A few seconds" — 1, "Several minutes to half an hour" — 60, "Half an hour to a few hours" — 180, "Half a day or more" — 540 (the values were chosen to maintain the temporal resolution at 1 minute or lower and average the subjective time scales to uniform values).

The interpolated data were then concatenated, and endpoints from one day of transitions to another were interpolated with the highest value of interpolation (presuming larger separation than between individual transitions). From there, appropriate emotion labels were analyzed.

The analysis of words and phrases used by the participants was performed using *word2Vec* (Mikolov et al., 2013) implementation in Python via *spaCy* (Honnibal and Montani, 2017) with the pretrained '*en_core_web_md*' model, which includes medium-sized word vectors trained on web content. The resulting 200-dimensional vectors of the emotion labels were then reduced with PCA to 2 dimensions to increase

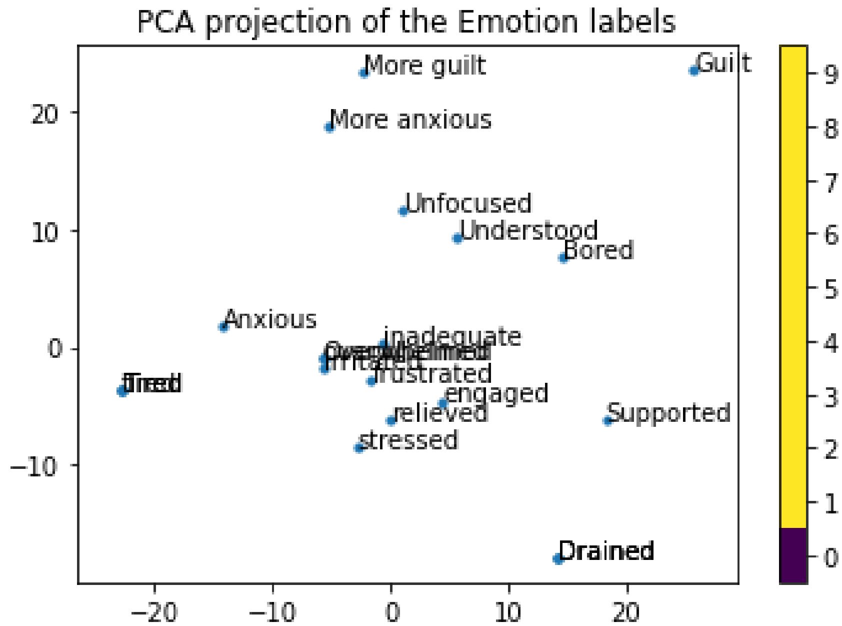


***Figure 4.4.*** **Results of 2-component PCA on verbal labels of emotion.** The results of SpaCy word2Vec algorithm output were reduced in dimensionality to 2 dimensions for ease of interpretation and intermediate check of feasibility of the analysis pipeline. Data taken from participant

speed of computation (see Figure 4.4 for an example illustration of 2-dimensional PCA result from participant 77367).

Those emotion word-vectors were then appended to the interpolated data of subjective ratings of sensation intensity, and the entirety of the dataset was analyzed for each individual participant. The main topological tool used for analysis of underlying manifold structure was *UMAP* (McInnes et al., 2018).

The topological analysis was two-fold: first, a “naive” UMAP embedding was computed from the original dataset with the size of the local neighborhood set to 5 (as my sparse data of no more than 50 possible entries did not provide enough diverse information about the global structure of the overarching topological space) in order to visualize an embedding of the data into an arbitrary three-dimensional manifold. The data were subsequently embedded onto spherical and toroidal surfaces in order to test the hypothesis of non-Euclidean nature of the underlying manifold. The code for such embeddings was modified from the code provided in UMAP documentation (accessed at https://umap-learn.readthedocs.io/).

## Results

### Demographics

After removal of participants non-compliant with the procedure, the final sample size was 68. The gender distribution in the final sample was: 34 male; 30 female; 4 non-binary. The age range was 22 to 35 years old (M = 25.6, SD = 2.9 years).

The cultural identities of participants were binned as follows: 8 White; 41 Black; 2 Hispanic or Latino; 6 Asian; 4 Native American; 1 Middle Eastern; 5 Other. APA style guidelines were used when categorizing the original volunteered identities (see American Psychological Association, 2020), however, in cases of questionable attribution participants were binned in "Other" category rather than interpolated meaning (e.g. three instances of "Alaska" as typed in was not attributed to the Native Peoples group, but "Other" along with one instance of "Florida", due to possibility of confusion in participants pre-briefing). Full breakdown of participant cultural or ethnic identities is given in Figure 4.5, and a Table of correspondences in categorization can be seen in Appendix A (Table 1).

### MAIA-2

The results for 8 MAIA-2 subscales (all measured on a Likert scale from 0 to 5) across our participants are as follows: Noticing (M = 3.59; SD = 0.97); Not Distracted (M

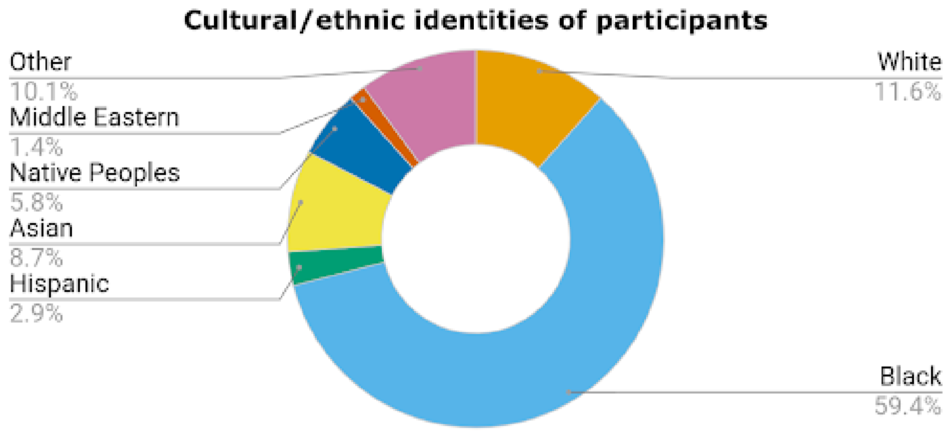


***Figure 4.5.*** **Cultural/ethnic identities of participants.** *Freeform identity markers were categorized according to the APA style guidelines and percentages of representation were computed.*

= 1.73; SD = 1.08); Not Worrying (M = 2.5; SD = 0.66); Attention Regulation (M = 3.54; SD = 0.9); Emotional Awareness (M = 3.52; SD = 1.07); Self-Regulation (M = 3.42; SD = 1.0); Body Listening (M = 3.32; SD = 1.0); Trusting (M = 3.54; SD = 1.01). Note the relatively small SD on the Not Worrying subscale and skewness of Emotional Awareness and Not Distracted subscales.

Full breakdowns of the eight subscales of the MAIA-2 questionnaire can be seen in Figure 4.6. A peculiar variance in the distributions of scores can be seen between the subscales. A Shapiro-Wilk test for normality was computed, and p-values were corrected for the number of multiple comparisons. The p-values for each MAIA-2 subscale are as follows: Noticing (p=0.008); Not Distracted (p=0.081); Not Worrying (p=0.0005); Attention Regulation (p=0.037); Emotional Awareness (p=0.005); Self-Regulation (p=0.023); Body Listening (p=0.029); Trusting (p=0.015). Q-Q plots for each subscale can be seen in Figure 4.7.

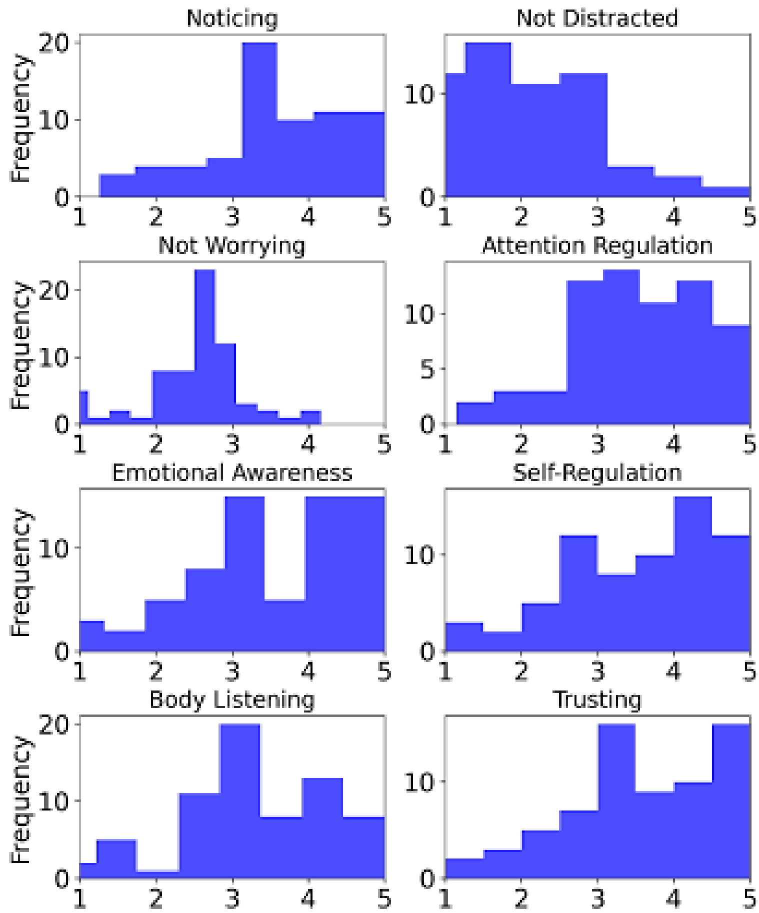


*Figure 4.6.* **Scores on MAIA-2 questionnaire subscales as aggregate distributions of all 68 participants.** Eight subscale scores demonstrate large variance in terms of interoceptive awareness and attention to bodily sensations in the sample (e.g. Not Worrying subscales demonstrating quasi-Gaussian distributions, while Emotional Awareness is clearly left-skewed).

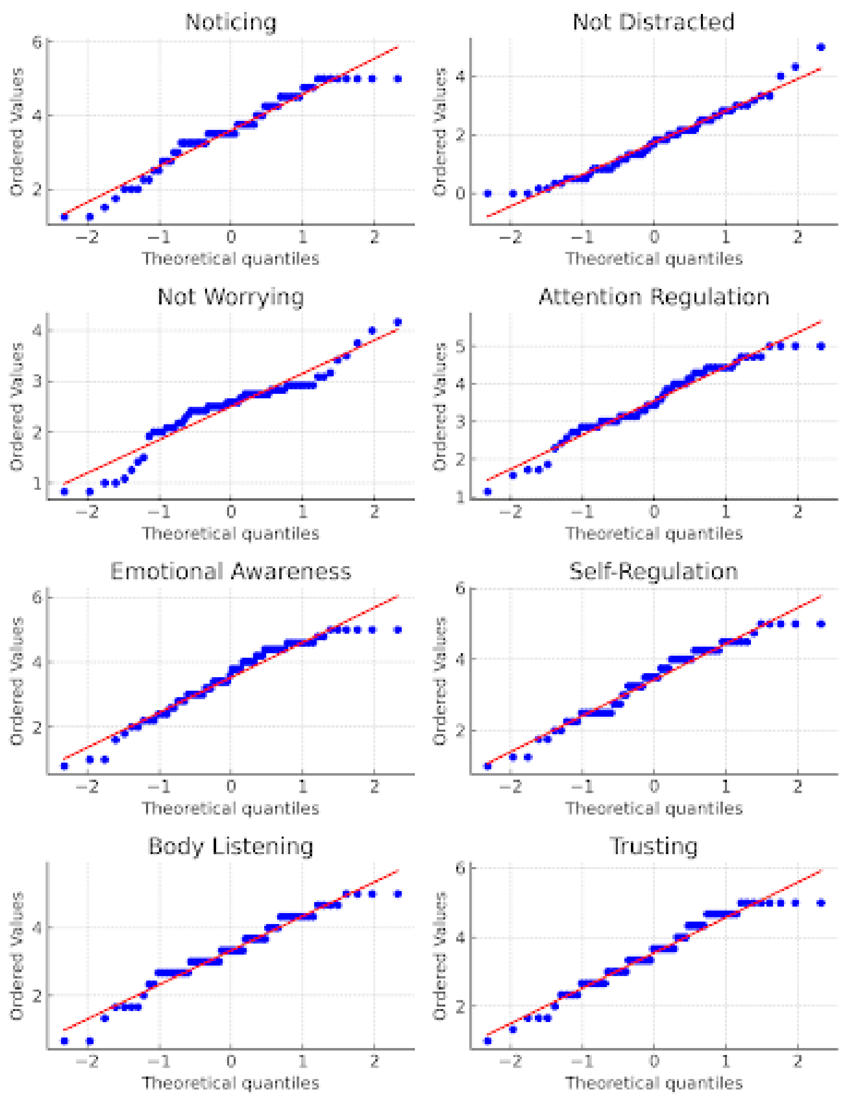


*Figure 4.7.* **Q-Q plots of MAIA-2 questionnaire subscales as aggregate distributions of all 68 participants.**Eight subscale scores as pictured on Q-Q plots demonstrate deviations from normality of varying degree (note, for instance, Not Worrying subscale and its abnormal behavior, and contrast it with Not Distracted which does not violate the assumption of normality).

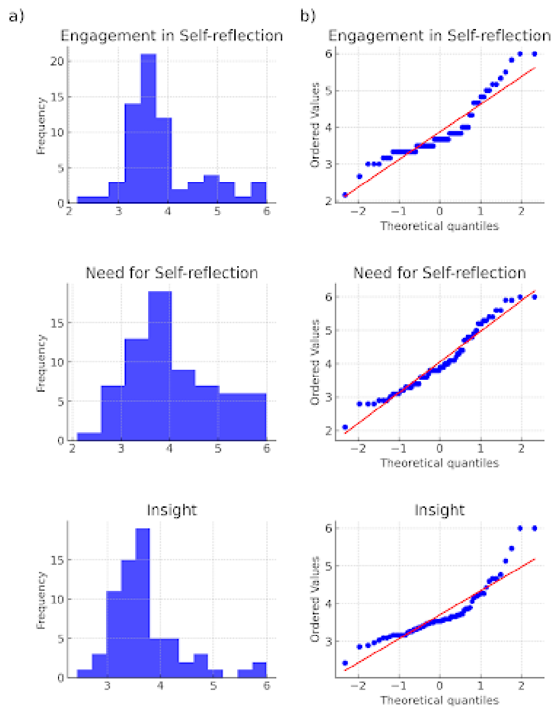


***Figure 4.8.*** **Scores on SRIS questionnaire subscales as aggregate distributions of all 68 participants (a) and Q-Q plots of those distributions (b)**. (a) Three subscale scores reflect the participants' responses along the three axes evaluated by SRIS. Note the slight left-skewness in all three subscales, with the mean slightly shifted above 3, and no values have been entered for level 1 by any participant. (b) While all three Q-Q plots suggest deviations from normality for the three subscales, Engagement in Self-Reflection and Insight clearly show skewness.

**SRIS**

The SRIS subscale scores (on Likert scale from 1 to 6) are as follows: Engagement in Self-reflection (M = 3.87; SD = 0.78); Need for Self-reflection (M = 4.05; SD = 0.91); Insight (M = 3.7; SD = 0.67). Individual distributions are shown in Figure 4.8, panel (a). The Shapiro-Wilk test for normality yielded the following p-values for each subscale: Engagement in Self-reflection ($p=1.33\times10^{-5}$); Need for Self-reflection ($p=0.017$); Insight ($p=1.76\times10^{-6}$). The Q-Q plots generated for each subscale can be seen in Figure 4.8, panel (b).

### IRI

The four subscales of the IRI, measured on a Likert scale from 1 to 5 demonstrated the following distributions: Perspective Taking (M = 2.72; SD = 0.53); Fantasy (M = 2.63; SD = 0.63); Empathic Concern (M = 2.85; SD = 0.69); Personal Distress (M = 2.4; SD = 0.47). The histograms of the distributions can be seen in Figure 4.9. Note the discontinuities and overall skewness of the scores, especially pronounced in the cases of Perspective Taking and Personal Distress. The Shapiro-Wilk test for normality yielded the following p-values for each subscale of the IRI: Perspective Taking (p=$3.37\times10^{-7}$); Fantasy (p=$4.07\times10^{-5}$); Empathic Concern (p=$9.20\times10^{-8}$); and Personal Distress (p=$1.00\times10^{-5}$). The Q-Q plots can be seen in Figure 4.10.

### Manifold projections

The data from all participants were preprocessed and cleaned with respect to possible typographical errors, insufficient information about emotion transitions, or repeated values — those which had significant typographical errors were amended ("Sacred" to "Scared" due to semantic differences; capitalization was preserved in all cases); insufficient information (fewer than 3 points per transition) or repeated values ("Sad" to "Angry" repeated more than 5 times across 10 log entries) were excluded from the dataset.

The data were then analyzed with UMAP with naive mapping (see Fig. 4.11 for an example of a blind application of UMAP with $n\_neighbors = 5$). The results of these blind "intermediary" mappings were sufficiently difficult to interpret, and thus the data were tested with embeddings onto non-Euclidean manifolds with known metrics, such as toroidal or spheric surfaces. Examples of embeddings onto

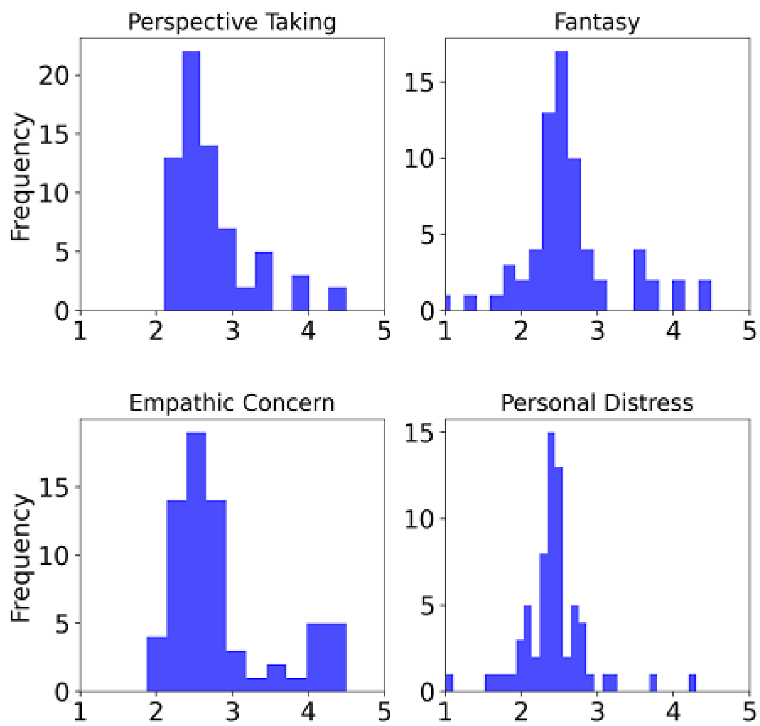


*Figure 4.9.* **Scores on IRI questionnaire subscales as aggregate distributions of all 68 participants.** Four subscale score distributions have been plotted with consideration of the 1-5 Likert scale. All four of the subscales demonstrate values close to normality.

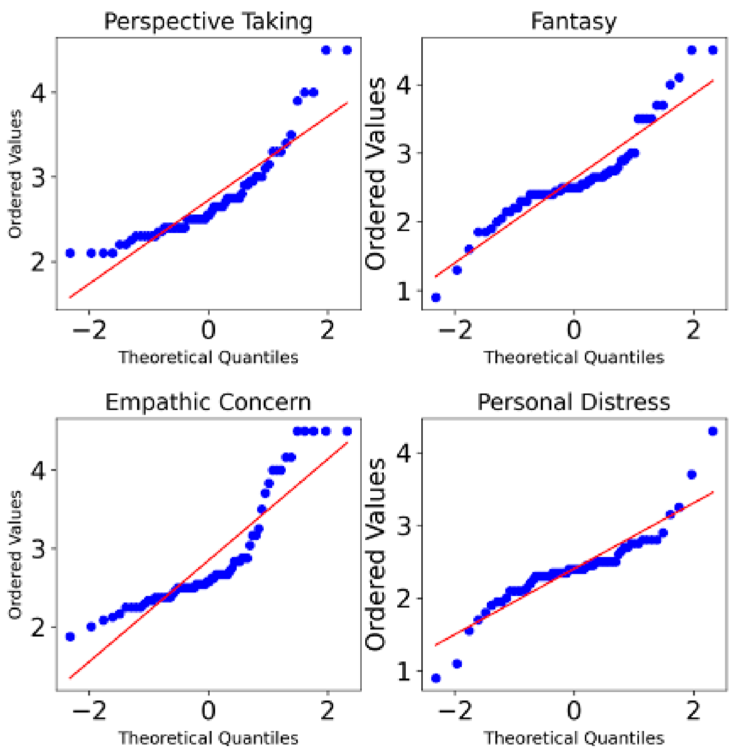


*Figure 4.10.* **Q-Q plots of IRI questionnaire subscales as aggregate distributions of all 68 participants.** Four subscale scores as pictured on Q-Q plots demonstrate deviations from normality of varying degree (note, for instance, how Empathic Concern appears to be strongly violating the assumption of normality, as do the tails of distributions of Personal Distress and Perspective Taking).

such surfaces can be seen in Figures 10-18, where side-to-side comparisons make the mappings more intuitive. Compare Figures 10-12 which depict the mappings of the same dataset of participant 77367 onto a “blind” UMAP classifier space, a spherical, and a toroidal surface embedding, respectively. The full analysis pipeline may be seen in the GitHub repository linked in Appendix C (file *pipeline_participant_UMAP.py* in "Chapter4_Data").

While emotion word labels were clustered too tightly in the case depicted in Fig. 10 and were thus omitted from the visualization, Figs. 4.12 and 4.13 demonstrate well-spaced positioning of those labels and thus represent intuitively readable plots. Moreover, this allows for direct comparison of suitability of one surface over another in each individual case. The contextualized reading of some labels (cf. “Understood” and “Supported” mapped onto the two surfaces) thus offers an informed and individualized representation of the emotional space of the participant situated in their cultural and social surroundings (as in some cases the distance between “Drained” and “tired” (orthography preserved) may be viewed as minuscule, but in others it would be quite significant in the subjective view of either the subject or the researcher).

Compare also the case of participant 87753 (Figs. 4.14 and 4.15), whose emotion labels align more closely with the traditional understanding of basic emotions such as “Happiness” or “Sadness”. Note that in this participant’s case the embedding onto a spherical surface appears to be less expected in terms of traditional semantics of emotion labels (“Happiness” presumed to be the opposite of “Sadness” in terms of valence) than that of the toroidal surface, as “Happiness” instances are grouped more closely together in the latter case. However, in that case “Sadness” is located quite close to one of the “Happiness” points, which also represents the point about

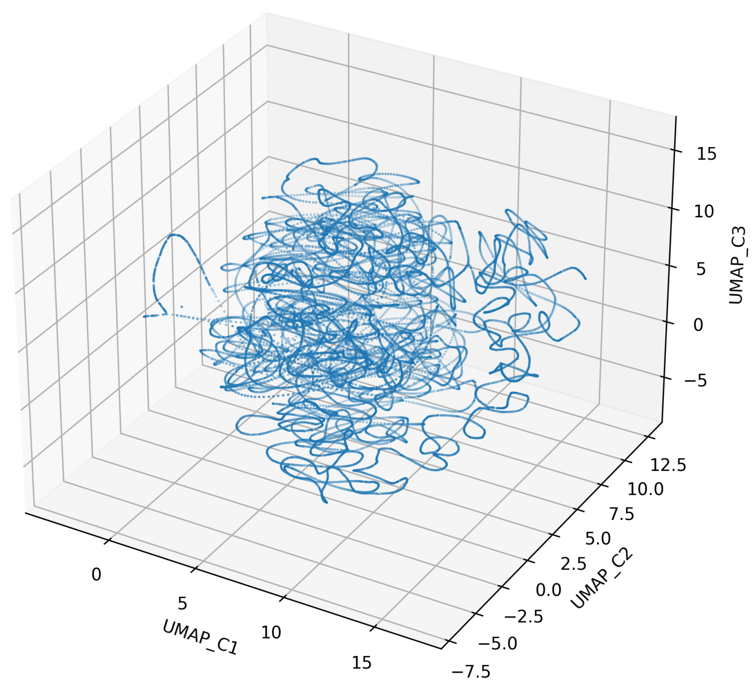


***Figure 4.11.*** **Participant 77367 "blind" UMAP embedding (n_neighbors = 5).** Three axes on this plot and all following figures represent three UMAP components (C1-C3), which represent independent dimensions as determined by the algorithm. Note that the "end points" of each transition got clustered in the center of this embedding and verbal labels of emotions are thus omitted from this visualization to avoid an unfortunate black spot in the middle of the embedded space. NB: 77367's identity was "white/caucasian" (binned as "White").

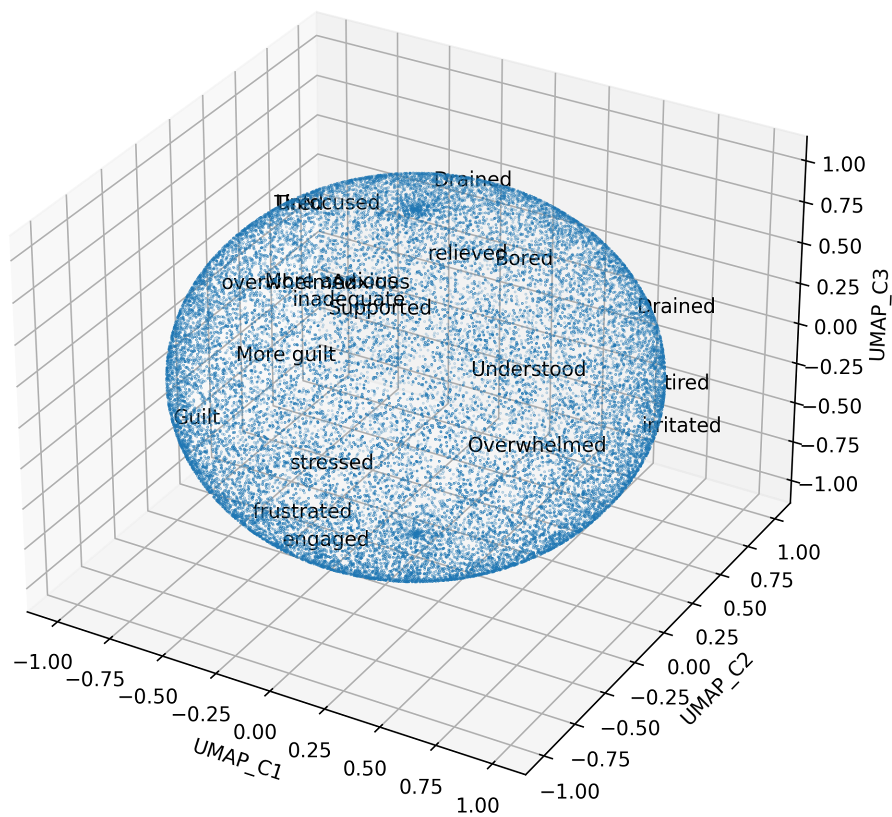


*Figure 4.12.* **Participant 77367 (sphere projection).**The data from participant 77367 embedded onto the surface of a sphere, with emotion labels plotted against the UMAP embedding at timepoints corresponding to those in the original interpolated dataset. 77367's identity was "white/caucasian" (binned as "White").

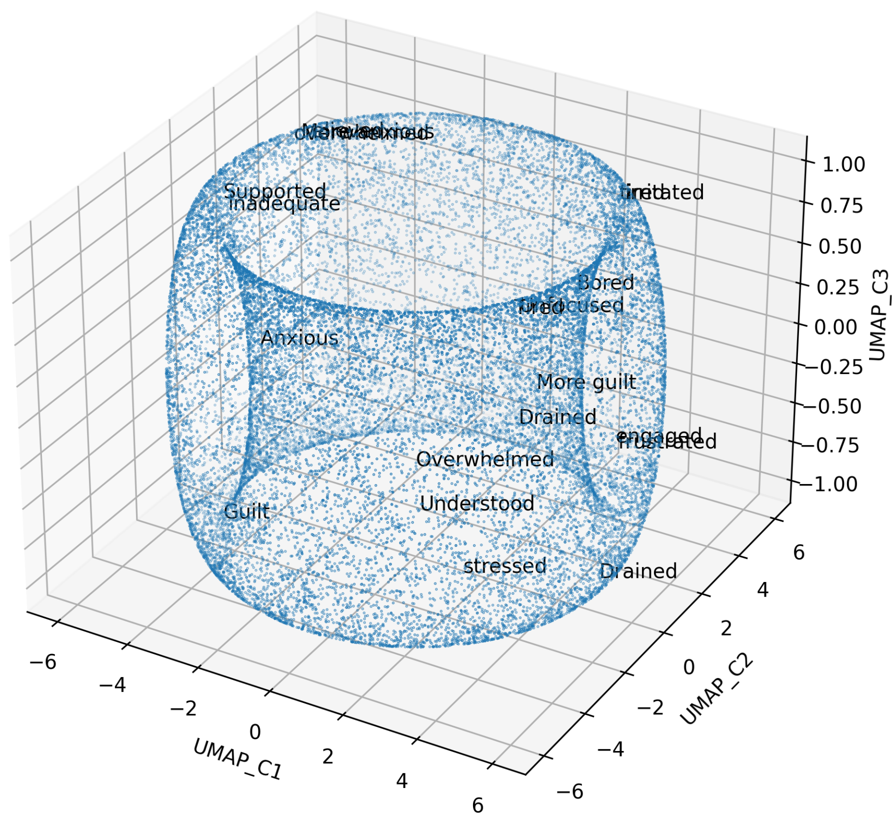


***Figure 4.13.*** **Participant 77367 (torus projection).** 77367's identity was "white/caucasian" (binned as "White").

valence made earlier with regard to the argument against bipolar understanding of valence. This speaks also to the current experimental paradigm which implicitly targeted arousal (or, as put in the protocol, "intensity of sensation") as the dimension of choice for evaluating emotions.

The cases of participants 00502 (Figs. 4.16 and 4.17) and 52913 (Figs. 4.18 and 4.19) also demonstrate interesting differences regarding the embedding of emotion data onto a sphere versus a torus. While in both cases the clustering prowess of UMAP appears to be less adequate than that of previous cases (as more labels get clustered tightly, not covering the entire surface), in the case of 00502 the mapping onto a sphere represents a less dense pattern of grouping, while the opposite is true for 52913. If one were to look more closely at the respective spread, the UMAP classification of 00502 is peculiar in the case of the sphere, where "Happy" and "Fear" are located at neighboring points, as are "Relaxed" and "Surprise" with respect to each other. However, the spherical surface remains a preferred choice in that case, as the imperfect clustering architecture of the toroidal surface is practically illegible to human eye. Contrast that with 52913, where the toroidal mapping appears to be semantically plausible at least with respect to "Happy", three instances of which are located close to each other in the lower left corner of the projection depicted in Figure 4.19. The overall results of the UMAP mappings are provided in the Appendix, with all 68 participants' mappings onto spheres and tori listed in order. Overall, Figures 4.11-4.19 demonstrate the feasibility of an empirical implementation of the proposed framework when modeling emotions as dynamic entities with the BPSM.

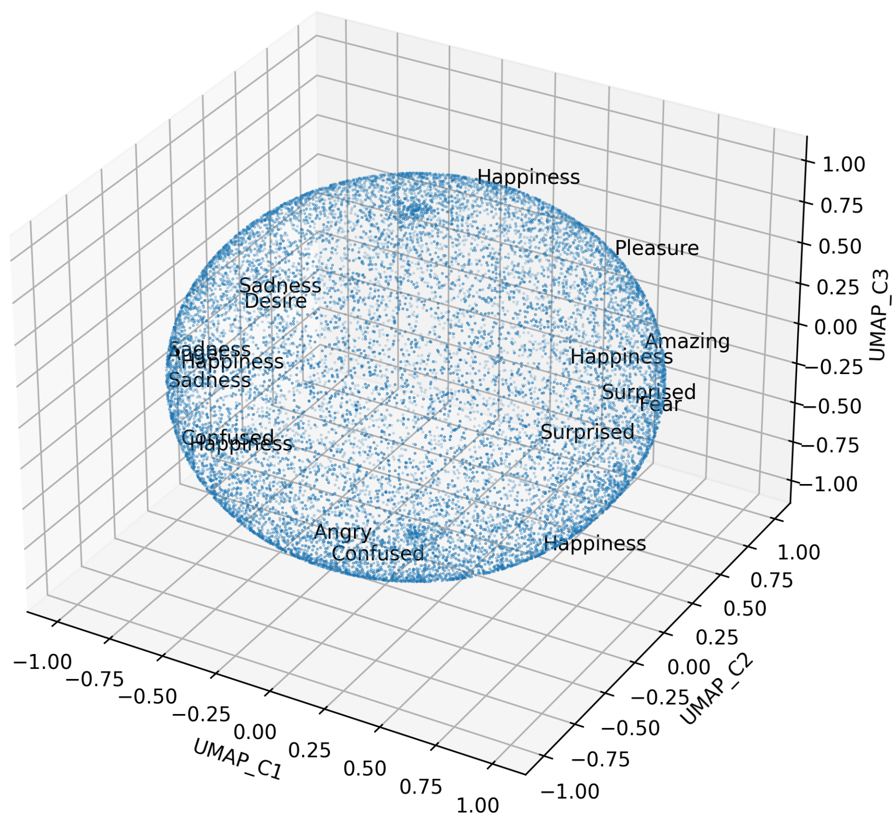


***Figure 4.14.*** **Participant 87753 (sphere projection).** 87753's identity was "African American" (binned as "Black").

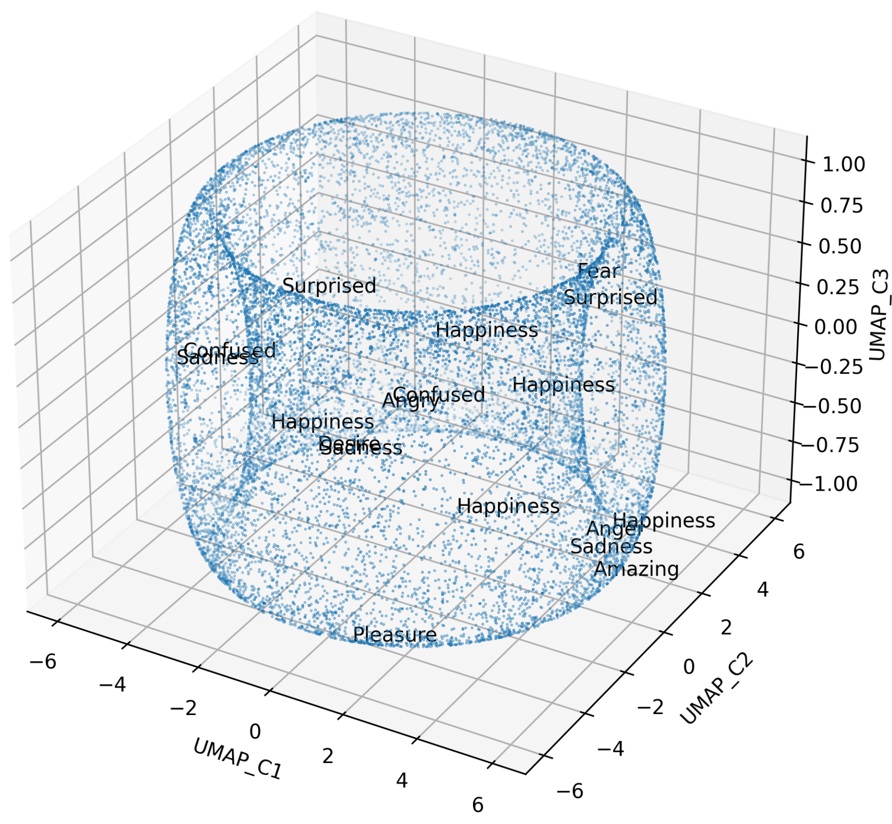


***Figure 4.15.*** **Participant 87753 (torus projection).** 87753's identity was "African American" (binned as "Black".)

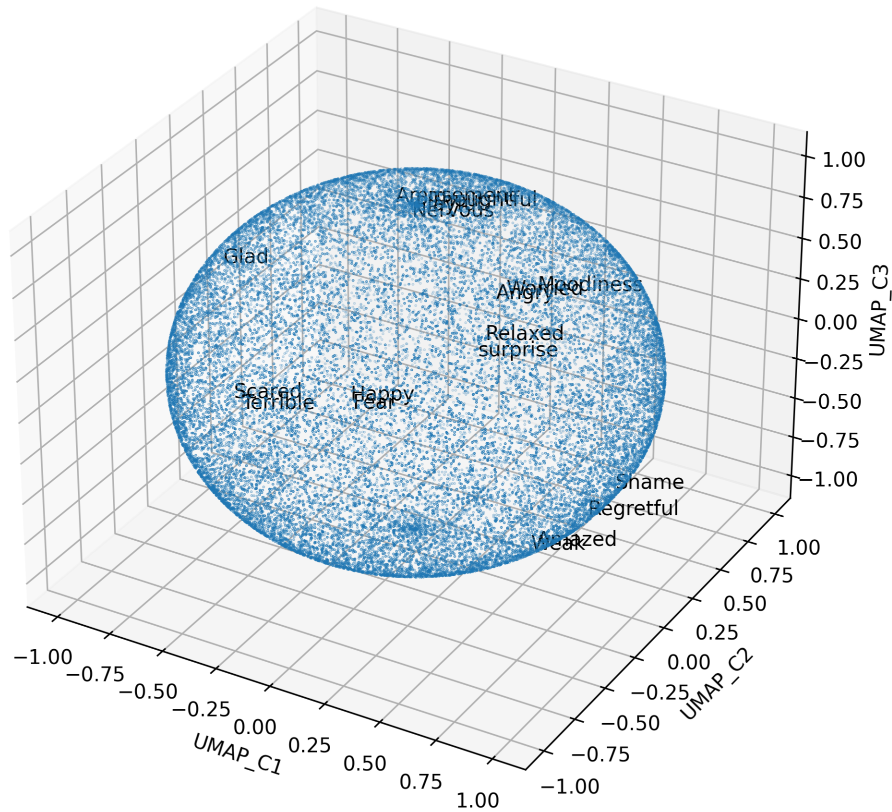


*Figure 4.16.* **Participant 00502 (sphere projection).** 00502's identity was "Black" (binned as "Black").

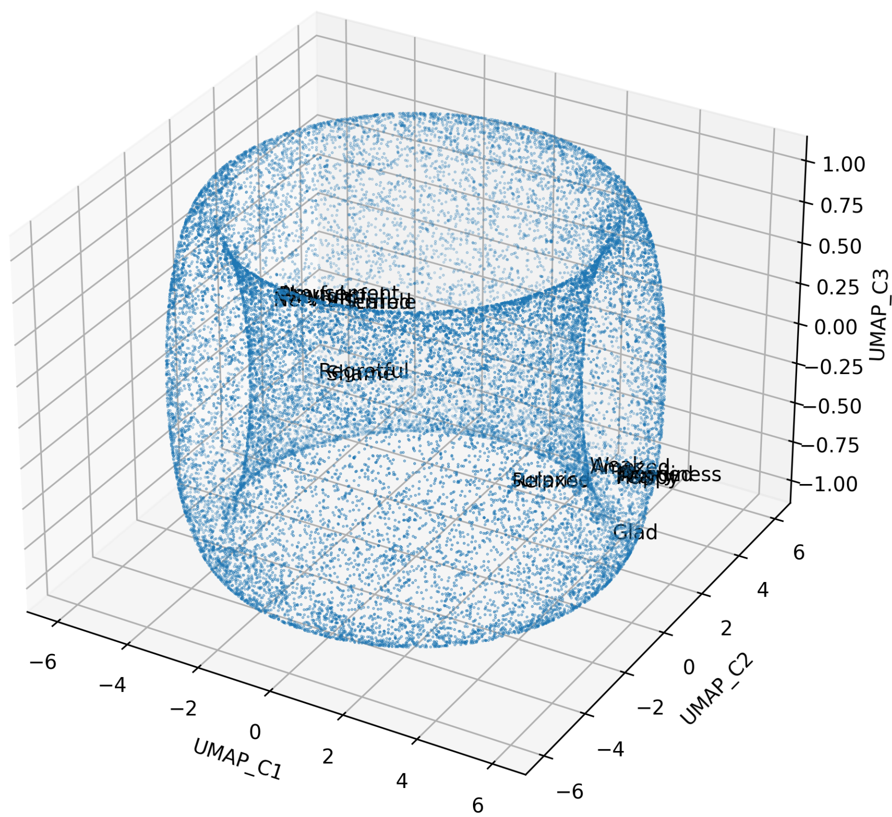


***Figure 4.17.*** **Participant 00502 (torus projection).** 00502's identity was "Black" (binned as "Black").

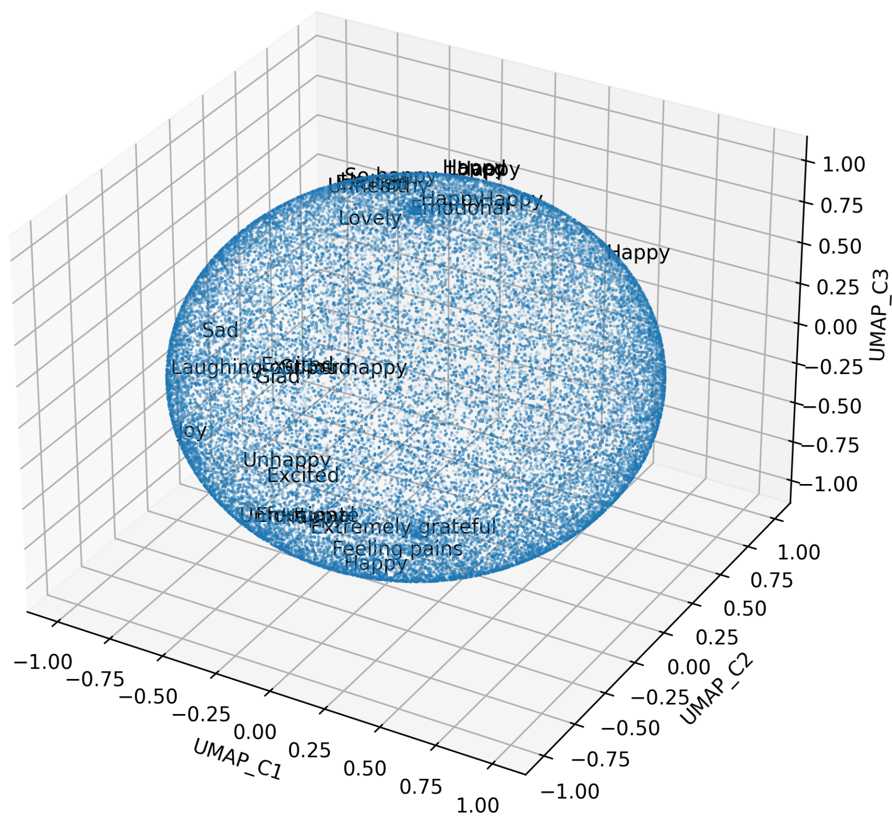


*Figure 4.18.* **Participant 52913 (sphere projection).** 52913's identity was "Alaska" (binned as "Other").

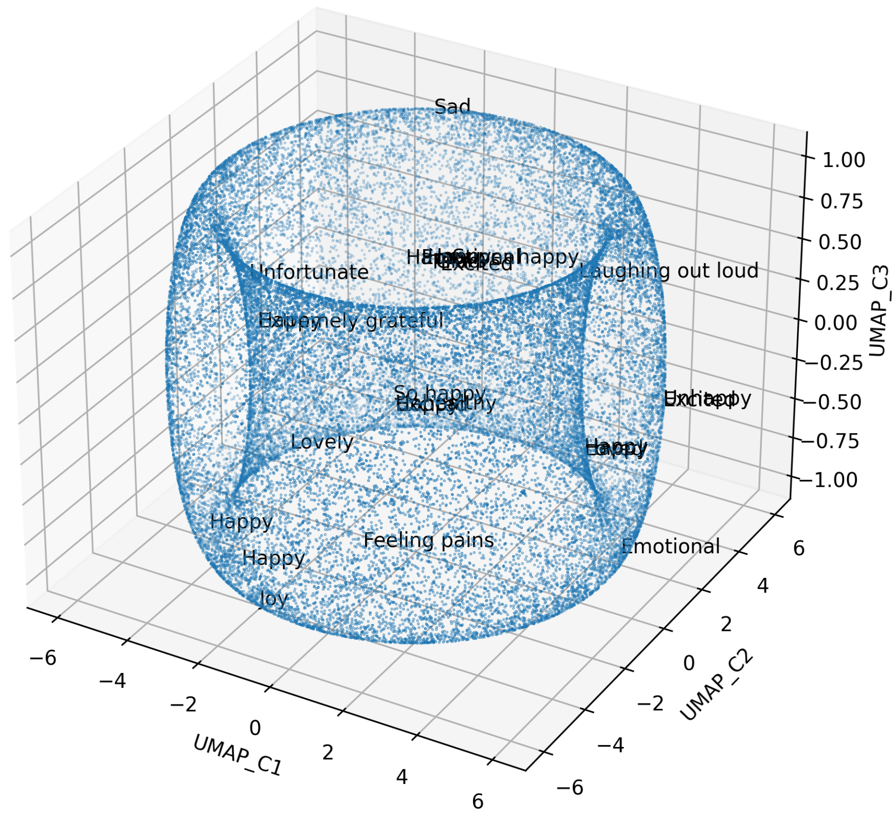


***Figure 4.19.*** **Participant 52913 (torus projection).** 52913's identity was "Alaska" (binned as "Other").

## Discussion

This study is a novel exploration of emotions as dynamic entities, based on a framework guided by the principles of DST and BPSM. Main findings of this research are presented as visualizations of embedding of self-reported data about transitions between various emotions by 68 healthy adults in an online log. These illustrations demonstrate the feasibility of applying state-of-the-art dimensionality reduction techniques informed with topological and differential geometric assumptions and the potential of applying such analyses to multimodal data which would combine both subjective and objective measures of dynamic changes in the participant's emotional states. Moreover, the innovative nature of the project provides fruitful areas for further investigations and testing of the proposed framework as it pertains to the notion of causal interdependence and interactions between the factors underlying BPSM.

One of the more surprising aspects of the sample presented here is the demographic information about the cultural background of the participants. The strategy of online recruitment through social media has recently been discussed to provide advantages in reaching underrepresented groups in psychological research (King et al. 2014; Benedict et al. 2019). In this protocol, the research group members were blinded to the ethnic or cultural identity of the participants at the time of data collection, thus the analysis pertaining to differences was not designed. Nonetheless, updating current models of emotions with culturally diverse data is crucial for either computational approaches as one described here or with any other paradigms dealing with some teleological level of operation (appraisal theory, affective computing, basic emotion theory, etc.). This way of collecting psychometric data about our participants also aligns with the formal approach proposed by Lange and colleagues (2020), where integrative network analyses are posited to be applicable to data such as one provided by the logs. Moreover, in our results chosen for illustration of the UMAP applicability, one can see differences in the cultural identity of the participant as it relates to the interpretability of their spherical and toroidal surface mappings. As mentioned in the Results, our participants demonstrated individual differences when their data were mapped onto the respective surfaces, where one could find a sphere more suitable than a torus or vice versa depending on the richness of the dataset or cultural background of the participant (see, for instance, Jackson et al. 2019, for a colexification analysis across 2474 languages which demonstrates that emotion semantics differ between cultures). While an overarching conclusion is far from reach with regards to the true relationship between the complexity of cultural identity and a preferable surface for an emotion space projection, these examples illustrate the possibility of further investigations into this area of multivariate analyses and possibility of applying DynST methods in the computation related to topological embeddings of emotion dynamics data.

Indeed, this relates to the empirical utility of the proposed framework, as this exploratory analysis offers little in terms of explanatory power. The question of applicability of computational methods in the predictive sense motivated several steps presented in this study. For example, the choice of the Shapiro-Wilk test (and subsequent Q-Q plotting) was determined by the wish to combine the dynamic data about emotion transitions with the constant trait-like characteristics evaluated by the initial questionnaires. Thus, several linear models, such as multiple factor analysis (Escofier and Pagès, 1994) or ridge regression (McDonald, 2009), were considered as potential techniques for establishing a concrete quantitative description for the relationship between the "static" scores in questionnaires and the dynamic descriptors of transitions. Yet, as the results of the Shapiro-Wilk tests of our sample's data demonstrate, our sample shows a violation of the normality assumption in most cases. Moreover, as one can see on the Q-Q plots, in many cases the tails of those distributions tend to influence the otherwise homogeneous data — which could lead to heteroscedasticity if modeled with a linear approach (see Rosopa et al. 2013). Thus, the choice of a predictive model was forgone in favor of descriptive approaches. Yet, this highlights the characteristics of the sample studied, as this speaks to the traits evaluated in the questionnaires. Because MAIA-2, SRIS, and IRI were selected specifically for the measurement of baseline "sensitivity" of the participant to the dynamics of BPSM-associated factors in everyday life, the violation of the assumption of normality by the score distributions suggests that a nonparametric approach would be more appropriate in further analyses. While there are certain arguments against testing for normality for the sake of evaluating linear approach appropriateness (Knief and Forstmeier, 2021), those arguments typically pertain to cases in which the analysis techniques are applied to experimental data with a priori defined design parameters, which is not the case in the present study. I posit that one of the future directions for my proposed model would be to evaluate various nonparametric methods in combining predictors such as these scores and the dynamic data about emotion transitions. Alternatively, a larger sample size evaluation of score distributions in questionnaires like MAIA-2, SRIS, and IRI may indeed demonstrate normality in scores, in which case a linear model would be appropriate for analysis.

This strategy of comparison of various methods could also be useful in future research with regards to the utility of modern dimensionality reduction techniques and their pitfalls. Many reviews to date have addressed the potential issues in using dimensionality reduction in multivariate data and cases of high dimensionality in experimental settings (see, for example, Xu et al. 2019). The most discussed areas of concern are those of changes in the granularity of data when reducing rank and lack of interpretability of the embedding visualization. However, neither of these major criticisms are applicable in the present case. The change in granularity in the data, indeed, may occur in cases of multilevel analysis; however, within the present model, the choice of UMAP as a distance-preserving algorithm which studies the local structure of the data through a neighborhood graph (see Dalmia and Sia 2021 for a review of appropriateness).

Moreover, the argument of lack of interpretability also fails to apply to the present study, as the design of the exploratory analysis aligns with the arguments against predetermined dimensions of emotion valence, eschewing the traditional two-dimensional model in favor of BPSM. This motivation was also expressed in the openness to view UMAP embedding results not only as examples of practical feasibility but also as potential indicators of which techniques may be applied to these types of data in the future. The question of interpretability of individual UMAP components is therefore outside of the purview of this study, as no inherent semantic value can be ascribed to the dataset which combines the information about the BPSM components and quantitative representations of emotion label vectors. However, the results of these embeddings may point towards a more informed, supervised machine learning technique to be used in the future, as commonalities in the distribution of components over large samples may indeed become apparent. Furthermore, novel techniques of interpretable manifold projections may become developed which would serve as better algorithms (for examples, see Yang et al. 2022; Trofimov et al. 2022).

This also speaks to the importance of individualized approaches within the proposed framework. As one can see from the results, the cultural identity of the participants may have inadvertent effects on the results of embedding with UMAP simply due to differences in expressing their levels of sensation intensity (for an overview of interoceptive accuracy as it pertains to cultural identity, see an excellent summary in Ma-Kellams 2014; see also a chapter on cultural influences on the brain by Gendron et al. 2020 or an article by Zhou et al. 2021) or perception of time which would influence the reflection of time scale on which an emotion transition occurred (for reviews of inter-individual differences and psychophysics of time perception see Eisler et al. 2008; for a study of time perception differences across cultural identities, see, e.g. Ji et al. 2009). The interplay of these cultural factors, which in this study were not explicitly included in the analysis, could elucidate some important relationships between the complex identity components and accuracy of subjective self-reports. Moreover, a study of cultural differences in the log protocol may help develop a more precise fitting algorithm for topological embedding of emotion spaces tailored to each individual (see Boiger et al. 2018 for an example of a study of context-situated emotions and subjective measures). In addition to that, one can refer to the multitude of emotion understanding models to augment the baseline measurements of the participants' level of awareness about emotion methods (see Castro et al. 2016).

Another argument about the interpretation of the data presented here is that about the analysis of time series data within the framework of dynamic emotions. Caveats to be taken into account when approaching subjective data include both the possibility of high levels of autocorrelation within the provided time series about emotion states (see Wood and Brown 1994) and the degree of temporal discontinuity introduced by the sparse collection paradigm as that of logs used in this study — and, more importantly, the interruption or intervention of the self report data by the self reports themselves, as participants were learning to "check in" with their emotion states and gain emotional expertise (for a study of emotional expertise, see Hoemann et al. 2021a). However, both of those arguments pertain to analyses of time series between discrete events presumed to be independent in linear models commonly applied to time series, as shown by Jebb and colleagues (2015). The issue of autocorrelation may indeed be an obstacle to an effective linear model — however, the stationarity of the time series in question may not be necessary for an application such as manifold learning with UMAP. As to the interrupted nature of the time series data, the expertise gained throughout the recording of the study may indeed influence one or more of the axes of BPSM — however, as UMAP clustering of separate components is based on the graph of nearest neighbors within the data itself, the inherent topology of this dynamic development will be reflected in the final embedding. Thus, careful consideration must be given to the interpretation of embeddings when analyzing UMAP output of the proposed model.

Finally, I would like to address the sparseness of the dataset with respect to the generalizability of individual embeddings to the "global" emotion space which would represent the full emotion repertoire of said individual. As has been discussed by Grühn and colleagues (2013) and emphasized by Hoemann and colleagues (2023), emotional complexity (and, by extension, the repertoire of all possible emotion states) need repeated longitudinal measures across a prolonged period of time, which this study could not achieve due to obvious empirical limitations such as the method of delivery of the log. It is thus important to highlight the limited interpretability of the results obtained from UMAP embeddings: the sparseness of the datasets for some participants constrained the possibility of clustering analysis and imposed imperfect methods of interpolation onto the self-reported estimates of transition duration.

A possible extension of the proposed method could be realized with the use of smartphone sensing methods (see Harari et al. 2017) and a dedicated application designed to collect data in a manner similar to Grühn and colleagues (2013). Such ambulatory data collection would allow for more precise information about the timing of emotion transitions, as well as enrich the dataset by inclusion of biological sensor signals (possibly further enhanced by peripheral devices such as smart watches or rings). Such development would also undoubtedly aid in reaching underrepresented groups and allowing for multilingual input of emotion labels.

Other, less remote possibilities which this method opens pertain to the gap in subjective data collection simultaneously with more objective measures, as well as tests of various computational approaches including predictive models. For instance, experiments targeting longitudinal collection of data with prolonged protocols on the order of months or even years would provide much richer datasets and more accurately reflect the "global" emotion repertoire of an individual. Another vital component to the evolution of the proposed framework is the validation of the method with manifold shape learning algorithms that could provide a computational solution to the interpretability of the embedding data. Finally, one could develop simulated datasets on the basis of data presented here with the aid of modern large language models to investigate the relationship between various UMAP embeddings and other manifold approximation techniques.

### Conclusion

This study is a pioneering approach which combines multiple advancements in the areas of affective computing and emotion psychology. With a dataset collected from a diverse sample of participants, I demonstrate the feasibility of a protocol of longitudinal logs based on BPSM, and further validate the mathematical model described in Chapter 3 with the aid of UMAP. This exploratory investigation into the practical applicability of modern computational techniques of manifold approximation demonstrates that the emotions evaluated subjectively across the dimensions of BPSM can be examined as complex dynamic entities. Furthermore, I argue that while these findings might not be immediately interpretable at present, this approach represents a multitude of possibilities for further research.

# Chapter 5

## Cardiac cycle-related changes in MEG-EEG resting-state functional connectivity

### Introduction

The brain continually monitors and regulates the internal states of the body, including the viscera and cardiovascular system, and some of this information may, or may not, be amenable to conscious awareness (Berntson and Khalsa, 2021). From time-to-time I may feel the contractile activity in our gut, or be aware of the beating of my heart — however, many of these ongoing bodily processes usually escape attention. Over the last decade in particular, there has been a growing literature devoted to these interoceptive processes (Quadt et al. 2018; Azzalini et al. 2019; Berntson and Khalsa 2021), including task-related studies of cardiac entrainment of brain rhythms (Coll et al., 2021). A number of studies have highlighted the influence of cardiac phase on somatosensory, auditory, and heart evoked potentials in electroencephalographic (EEG) studies (Walker and Sandman 1982; Sandman 1984; Park et al. 2014; Critchley and Garfinkel 2017; Schulz et al. 2020; Al et al. 2020).

Here, I focused on the relationship between the cardiac cycle and whole-brain canonical frequency band functional connectivity (FC), as measured with simultaneous magneto- and electro-encephalography (MEG-EEG) and electrocardiography (ECG). I specifically examined participants resting quietly, because then the natural interoceptive rhythms could be more easily unmasked in the resting-state neurophysiological activity. Therefore, it was necessary to acquire a multimodal dataset at high temporal and spatial resolution. I investigated this complex relationship from the perspectives of: (1) the temporal behavior of canonical frequency band activity; (2) their power envelope correlations in source space; and (3) the types of spatial interactions of community structures in associated brain networks.

I note that my approach focused on individual participant FC dynamics as they related to behavior of the heart-brain axis and network architecture of the FC patterns within each participant. I therefore studied four participants at rest, collecting data for a long period of time (40 minutes total). The richness of the dataset with respect to intra-individual variations allowed me to identify brain networks that either remain stable and do not change their FC during the cardiac cycle versus those whose behavior is modulated by the cardiac ventricular cycle.

Specifically, I explored the temporal dynamics of cardiac phases coupled with FC in three canonical frequency bands of interest ($\alpha$, $\beta$, and $\gamma$). The choice of canonical frequency bands as opposed to the evaluation of the entirety of the power spectrum was partially dictated by the duration of an average systolic phase in each participant ($\sim$350 ms, for exact numbers see below). I was motivated by studies of FC in MEG and EEG data, which have shown differential behaviors across frequency bands, changes in cross-frequency coupling and specificity in functional associations already established in the literature (Buzsáki and Draguhn 2004; Jensen and Colgin 2007; Brookes et al. 2012; Cabral et al. 2014). Importantly, using canonical frequency bands as opposed to evaluating the entire power spectrum was also partially dictated by the duration of average cardiac phases in each participant. Cardiac cycle phases were defined from ventricular activity as systole — the contraction of the ventricles — and their subsequent relaxation in diastole.

Following several studies that investigated the relationship between cardiac activity and MEG and/or EEG signals (Al et al. 2020); Candia-Rivera et al. 2021; Mishra et al. 2022; Zhang et al. 2023) and contrasting my approach to the established literature in the area of task-related activity, I propose an application of cardiac cycle-informed techniques of analysis to task-free (resting state) data. Broadly, I hypothesized that I would find differences in the dynamics of source localized neurophysiological data between the systolic and diastolic phases of the cardiac cycle, as well as FC measures and network structure. Specifically, I expected the higher frequency rhythms (particularly $\gamma$) to exhibit FC linkages over shorter distances (e.g. within a lobe), consistent with previous models (e.g., Hipp et al. 2012), relative to the slower rhythms, such as $\alpha$, whose FC linkages would span longer distances (e.g., Jensen and Mazaheri 2010). For the $\beta$ range, given previously predicted functional significance related to sensorimotor or cognitive states (Engel and Fries, 2010), the FC linkages might be more heterogeneous. With respect to networks that would exhibit differential behavior across the cardiac cycle, I expected to observe at least the involvement of insular cortex (previously shown to participate in viscerosensory regulation by Babo-Rebelo et al. 2016; Park and Blanke 2019; Chouchou et al. 2023).

## Methods

### Participants

The participants of this study were four adults with no prior medical history of neuropsychiatric disorders or uncorrected cardiovascular or visual function. All participants provided written consent in a study approved by the ethical review boards of both the Paris Brain Institute (ICM), Paris, France, and Indiana University, Bloomington, IN USA. The participants were: S1: 59 years old, female (F); S2: 49F; S3: 52M; S4: 30F. Note that in the original labeling schema, S3 was reserved for a different participant, for whom the multimodal MEG-EEG-ECG-EOG data were also recorded; however, due to lack of a structural MRI scan for that participant, their data were omitted in the present dissertation, and the labels S3 and S4 were re-designated to the remaining participants. All the participants were right-handed.

### MEG-EEG and ECG data acquisition

Combined MEG-EEG-ECG recordings were performed with a 306-channel MEG / 74-channel EEG system (Neuromag VectorView, respectively; Elekta Neuromag) in a magnetically shielded room at the MEG-EEG core facility of the Center for NeuroImaging Research (CENIR) of the Paris Brain Institute (ICM, Paris, France). After measuring head circumference and selecting the appropriate EEG Ag/AgCl electrode cap, the cloth cap was sited on the participant's head. Care was taken to ensure that electrodes Fz, Cz and Oz were in the correct positions. Conducting gel was inserted into a hole in each cup electrode using a syringe with a blunted needle. ECG electrodes were placed on the right clavicle and the left lower part of the belly. EOG electrodes (Ag/AgCl) were sited above and below the right eye (for vertical EOG), and on the left and right outer canthi (for horizontal EOG). All electrodes impedances were measured, and adjusted if needed, to ensure that impedances were below 20 KΩ.

Four head position indicator (HPI) coils were sited on the anterior aspects of the head for monitoring head position while under the MEG helmet. Prior to the participant being placed under the MEG helmet, HPI coil and EEG electrode positions were digitized along with the head surface, fiducial points (left and right preauricular points and nasion) with the FASTRAK system (Polhemus, Colchester, VT, USA).

Prior to the participant being placed in the MEG room, an empty room MEG recording was made (for subsequent use in artifact rejection procedures). After being placed under the MEG helmet and made comfortable, each participant rested quietly with eyes open, gazing at a fixation cross on the wall of the shielded room while resting state physiological activity was recorded. Participants attempted to keep their head and body movements, as well as blinking, at a minimum. For all participants, one bipolar ECG channel, two (vertical and horizontal) electro-oculographic (EOG) channels and 74 EEG electrodes (referenced to the vertex) were recorded concurrently with Ag/AgCl electrodes.

The MEG-EEG data were acquired at a 1000 Hz sampling rate for at least 40 minutes, typically being divided into four continuous runs of 10 minutes each. The MEG-EEG data of each subsequent run were aligned with respect to the first run's head position based on changes in HPI coil locations. Electrode, HPI coil and fiducial position digitization information was preserved for alignment with structural MRI scans.

### Structural MRI data acquisition

Structural MRI scans were obtained at either CENIR in the ICM, or the Imaging Research Facility (IRF) at Indiana University (IU), Bloomington. At both locations, scans were performed on identical 3T Siemens PRISMA systems with 64-channel head coils. Identical high-resolution isovoxel (0.8 $mm^3$) anatomical T1 scans of the whole head were performed at both locations using an MP-RAGE sequence (FOV = 256 mm, TR = 2400 ms, TE = 2.68 ms, slice thickness = 0.8 mm, flip angle = 8°).

### ECG data preprocessing

While most previous studies (such as Al et al. 2020) have operationalized diastole as the part of the diastolic phase directly preceding the next systole (and equal in length to the systolic interval), I chose the beginning of the diastolic phase due to possible physiological influences of the relaxation period prior to, and including, the mitral valve opening between the left atrium and ventricle. Thus, operationalization of the cardiac phases within the current paradigm corresponded to the interval between the measured ECG R-wave peak and the end of the following T-wave (for systole), and subsequent equal time interval of activity from the end of the T-wave (diastole) (see the left panel of Fig. 5.1 for locations of R-wave peak and the T-wave).

I expected this choice to introduce more pronounced effects within a task-free paradigm, as opposed to the full relaxation of the ventricles during atrial systole after the atrial kick (or increased force late in atrial contraction) (Widmaier et al., 2022). My decision was motivated by critical cellular findings indicating possible mechanisms of arteriolar dilation being reliant and coupled to neuronal electrochemical signaling (see Uhlirova et al. 2016), thus indicating possible dilation and contraction of vas-

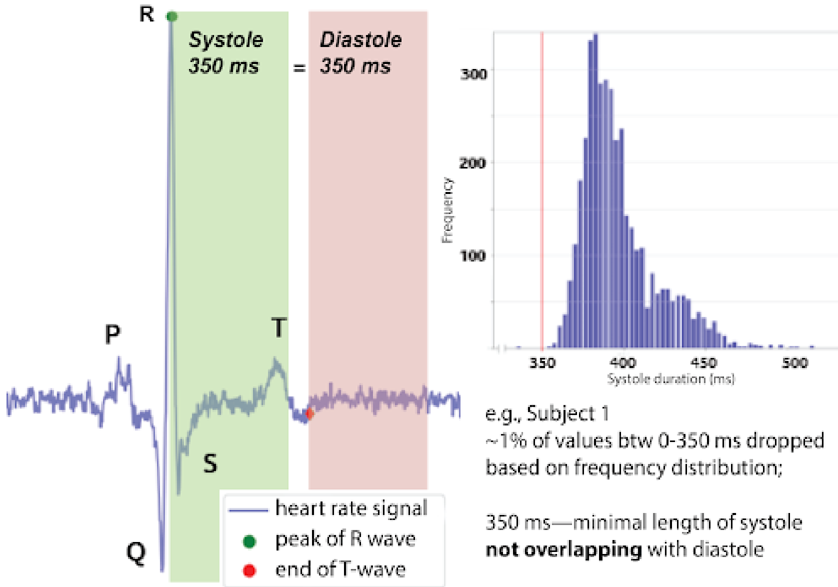


***Figure 5.1.*** **Schematic representation of systole-diastole definition and determination of minimal appropriate length of the systolic phase.(Left panel)** Example of a single cycle of an ECG waveform. Length of systole was determined first by identifying the R-wave peak and the end of the subsequent T-wave. Diastole was calculated as an equal interval starting at the end of T-wave. **(Right panel)** Minimal systolic interval length. The length of the systolic interval as a determinant of the epoch of MEG-EEG data was chosen as that of the 1st percentile of the entire distribution to retain the maximal number of non-overlapping systolic and diastolic epochs. Data from Participant 1 (59F).

culature (which directly follows cardiac ejection) being closely related to activity of neural circuitry. While my approach warrants caution when comparing previous literature (based more on the atrial systolic phase juxtaposed to the late diastolic phase of the ventricles), I believe neurophysiological functional connectivity may be reliant on either choice of the cyclic dynamics of the heart. The ECG preprocessing was performed with *HeartPy v1.2* open-source Python package (van Gent et al., 2019). The ECG data were extracted from the raw MEG-EEG recording, after which baseline drift wander was eliminated using *hp.remove_ baseline_ wander()*. ECG activity was rescaled using *hp.scale_ data()*, and R-wave peaks were detected with *hp.process()*

(details on the specifics of algorithm functioning are provided in the HeartPy documentation).

The T-wave end was identified identically to Al et al. (2020). To that end, sample code of the trapezoidal area algorithm (Vázquez-Seisdedos et al., 2011) graciously provided by the authors in response to my request. The code was adapted from R to Python, reshaped to fit the data available from HeartPy output, and implemented on the ECG data (which remained at the original sampling rate of 1000 Hz).

The output of the trapezoidal area algorithm was overlaid on the original ECG channel waveform and used to compute the lengths of the systolic phases throughout the entire recording. The diastolic intervals were considered to have directly followed systole. The diastolic periods were truncated to maintain an equal length to systole. Note that I did not compensate for the interval between the cardiac cycle and heart-evoked potentials or the cardiac artifact, as there are studies suggesting that the interval between the "true" ECG R-wave peak and that derived from ICA in neurophysiological data can be variable, however, the phase shift is insignificant upon averaging across a long recording (Raimondo et al., 2017).

In addition, the intervals between the end of the corresponding diastolic phase and the following systole were also computed. Data were plotted as a frequency distribution (see Fig. 5.1, right panel) and used to determine the final systolic and diastolic epoch duration using the 1st percentile of systolic phase duration and the 99th percentile of the interval duration to eliminate maximal amount of overlap between systolic and preceding diastolic phases in the final MEG-EEG epoched waveform, because systole for the four participants has thus been shorter than the interval between the R-wave peak and the end of T-wave.

The systolic and diastolic phase data were correspondingly reduced to the length of the average epoch (350 ms for S1, 330 ms for S2; 260 ms for S3; 330 ms for S4), counting from the start of the R-wave peak to the end of the T-wave. These variable durations were also related to the participants' heart rate (S1: 54.96 bpm; S2: 62.42 bpm; S3: 67.18 bpm; S4: 80.72 bpm) and the degree of variance in the individual systolic length distributions. Every cycle of insufficient length, where systole was overlapping with diastole, was discarded at that stage, and the time point data were transferred back to MNE/Python for further epoching of the MEG-EEG signal and continuation of the preprocessing/analysis, as described below.

### MEG-EEG data preprocessing

Preprocessing steps for identification and removal of artifacts in the MEG-EEG dataset were conducted in MNE/Python v0.8-1.1 (Gramfort et al., 2013) on IU's high-performance computing clusters (Carbonate & Quartz; see Acknowledgements).

Preprocessing stages were:

(1) spatiotemporal signal-space separation (tSSS) and Maxwell filtering;

(2) high- and low-pass filtering at 0.1 and 100 Hz, respectively;

(3) signal-space projection (SSP) blink, eye movement. and cardiac artifact repair;

(4) second round of filtering at 1 and 40 Hz;

(5) epoching and visual inspection to eliminate epochs with large isolated artifacts;

(6) independent component analysis (ICA) movement and miscellaneous EEG artifact repair.

Preprocessing began with reducing environmental noise by applying tSSS/Maxwell filter to the raw signal (Taulu and Kajola, 2005). As recommended by Hari et al. in

(2018), the application of tSSS was limited to the suppression of environmental noise (such as generated by external noise sources, e.g., electronic equipment) and head movements. Runs 2, 3, and 4 were aligned to the first in terms of head movement.

Signal filtering performed at stages (2) and (4) followed identical patterns of application: a 4th order Butterworth infinite impulse response (IIR) filter was chosen for high-pass filters and overlap-add finite impulse response (FIR) for low-pass filtering procedures (see Widmann et al. 2015 and Smith 1993). Steps (2) and (4) followed the logic of stepwise narrowing of the "bandpass" window due to the limitations of artifact repair methods in (3) and (6). SSP can be performed on data filtered with a broader band, whereas ICA performs significantly worse on data not high-pass filtered to at least 1 Hz.

In Step (3) I applied signal-space projectors (SSP: a technique common in MEG data preprocessing, as seen in Uusitalo and Ilmoniemi 1997, or Puce and Hämäläinen 2017) for a twofold purpose: suppressing empty-room noise by creating projectors from the empty room recording and repairing artifacts of EOG and ECG by creating projectors based on the signal from corresponding "biological" channels. The procedure was performed three times: first, the ECG projectors were computed based on the provided information from the ECG recording; then, two separate sets of projectors were computed from horizontal and vertical EOG channels data to eliminate blinks and eye movements.

At this stage, the MEG-EEG data recordings were epoched according to the time-points guided by the ECG analysis, as described in the previous section (resulting number of epochs: S1 — systole 2226, diastole 2225; S2 — systole 2231, diastole 2227; S3 — systole 2312, diastole 2323; S3 — systole 1839, diastole 1822).

The next steps in the preprocessing of the MEG-EEG data were the visual inspection and elimination of bad channels/epochs (those in which the amplitude of artifacts was determined to be transiently increased by 50% of ambient signal). Bad channels were then interpolated using head-digitization-based origin fit (based on the digitization encoded in the raw MEG-EEG recording).

The two methods of artifact removal (SSP and ICA) were chosen, perhaps, redundantly, yet both provided fruitful suppression of most instances of common artifacts, such as blinks or cardiac activity, as well as spurious environmental noise and/or artifacts brought on by muscle fatigue towards the end of each 10-minute run. Step (6) of the pipeline employed the functionality of MNE/Python's *mne.preprocessing.ICA* module, which automates the process of decomposition. A threshold of 0.95 cumulative explained variance was set for the pre-whitening PCA in order to gate the number of components to be passed onto the ICA fitting stage (and thus empirically determine the explained variance of the data after its reduction in steps (1) and (3)). The results of the decomposition were visually inspected to reject components mostly consisting of power line noise at 50 Hz and its harmonics, consistent with European data collection, and instances of facial muscle activity. Consideration was taken as to not reject components totaling at 10% of explained variance of the data (reports provided within MNE/Python software), with most of the rejected components constituting temporally and spatially isolated muscle artifact-related incidents. Final numbers of rejected ICs were: S1 — 15 (out of 67); S2 — 12 (out of 61); S3 — 10 (out of 70); S4 — 9 (out of 52).

### Structural MRI data preprocessing for source localization

Structural MRI data were processed in the FreeSurfer image analysis suite v6.0.0 (Fischl et al., 2004) using the automatized procedure recon-all (which includes head motion correction, Talairach transformation, skull stripping, removal of non-brain tissue via watershed/surface deformation, spherical registration, and cortical parcellation according to the Destrieux atlas, which includes 148 anatomical labels across the two hemispheres). The Bayesian parcellation computation (Fischl et al., 2004) takes a surface geometry input and nonlinearly performs a spherical transformation of the data.

### MEG-EEG forward solution and co-registration

The forward solution for the MEG-EEG data was computed in MNE/Python via the watershed algorithm of computing the boundary element model (BEM) surfaces based on the Freesurfer processed anatomical scans in previous steps. The defined BEM surfaces were the inner skull, outer skull, and skin (due to the presence of EEG signal in the data), and were computed as follows (following the convention of using *mri_make_bem_surfaces()* for MP-RAGE sequences as the best practice for FreeSurfer suite). A fourth order icosahedron was fit around the brain volume itself (excluding the cerebellum) and smoothed. The algorithm then used this estimate to search from 3-30 mm outside of this surface in the FLASH volume for the inner skull boundary. This new surface was then smoothed, generating the ”inner skull” surface. Next, skull thickness was estimated from the FLASH volume by searching from 3 mm stepping out to 30 mm for the boundary of the ”outer skull” surface. A check was performed to make sure that the algorithm had not stepped outside the head (in which case it would reset the value to 3 mm, which is useful for places where the skull was particularly thin, e.g., squama temporalis). Another fourth order icosahedral surface was fitted and smoothed to make up the ”outer skull” surface. Finally, a fourth order icosahedral surface was fitted around the entire FLASH volume to generate the ”outer skin” surface.

The co-registration of the head and relative positions of MEG/EEG sensors and reference fiducials was obtained via MNE/Python GUI utility (*mne.gui.coregistration()*) by specifying the MRI fiducial positions (nasion, left, and right preauricular points) and subsequently aligning the MEG/EEG digitization to specified coordinates.

Finally, a volumetric source space was computed using the previously established BEM surfaces and confining all sources of the MEG/EEG signal to the surface of inner skull. The spacing of the source space was set to "oct6" for a recursively subdivided octahedron, as per Jas and colleagues (2017).

### MEG-EEG inverse solution and power envelope correlation

The MEG-EEG sensor space (not source localized) data were filtered into the canonical frequency bands of interest ($\alpha$, $\beta$, and $\gamma$) at this stage and the epochs were separated according to the cardiac phase. Note that my limited epoch intervals, based on parts of the cardiac cycle, did not allow me to evaluate MEG-EEG activity in the $\delta$ and $\theta$ ranges. A regularized noise covariance matrix was computed from the selected epochs (noise levels presumed to be the same across a single recording). The inverse solution was then computed using the forward solution (see previous section) with dynamic statistical parametric mapping (Dale et al., 2000).

Envelope correlations were calculated for each frequency band and averaged within each MEG-EEG frequency band and cardiac cycle phase. The power envelope correlation measure was calculated using MNE connectivity subpackage's envelope_correlation() function 5.2, in accordance with the Hipp and colleagues' (2012) procedure. This procedure ensures elimination of spurious correlations between time courses within a chosen parcellation (which could arise due to a similar localization of the source dipole which got attributed to two different labels). Achieved via enforced pairwise orthogonalization, it is implemented in the current study.

The computed pairwise correlations of power envelopes for each of the labels in the Destrieux atlas parcellation (148x148, excluding the two bilateral "Unknown" parcels) were averaged across the time courses of the epochs in each of the cardiac cycle phases and canonical MEG-EEG frequency bands.

**Quantifying connectivity via community structure: MRCC/mutual information**

The final step in the data analysis was performed in MATLAB R2020a using code for a modified version of MRCC analysis (Jeub et al., 2018) with a computation of community structure (which utilizes a Louvain algorithm). MRCC computes partitions over a range of spatial resolutions, and combines them into a single consensus estimate in order to avoid the issue of scale-dependence inherent in standard (single scale) applications of modularity maximization.

One of the more intuitive quantifiable measures of network similarity within this computation is mutual information (MI) — which in this case would demonstrate the amount of information shared by the communities within the functional connectivity

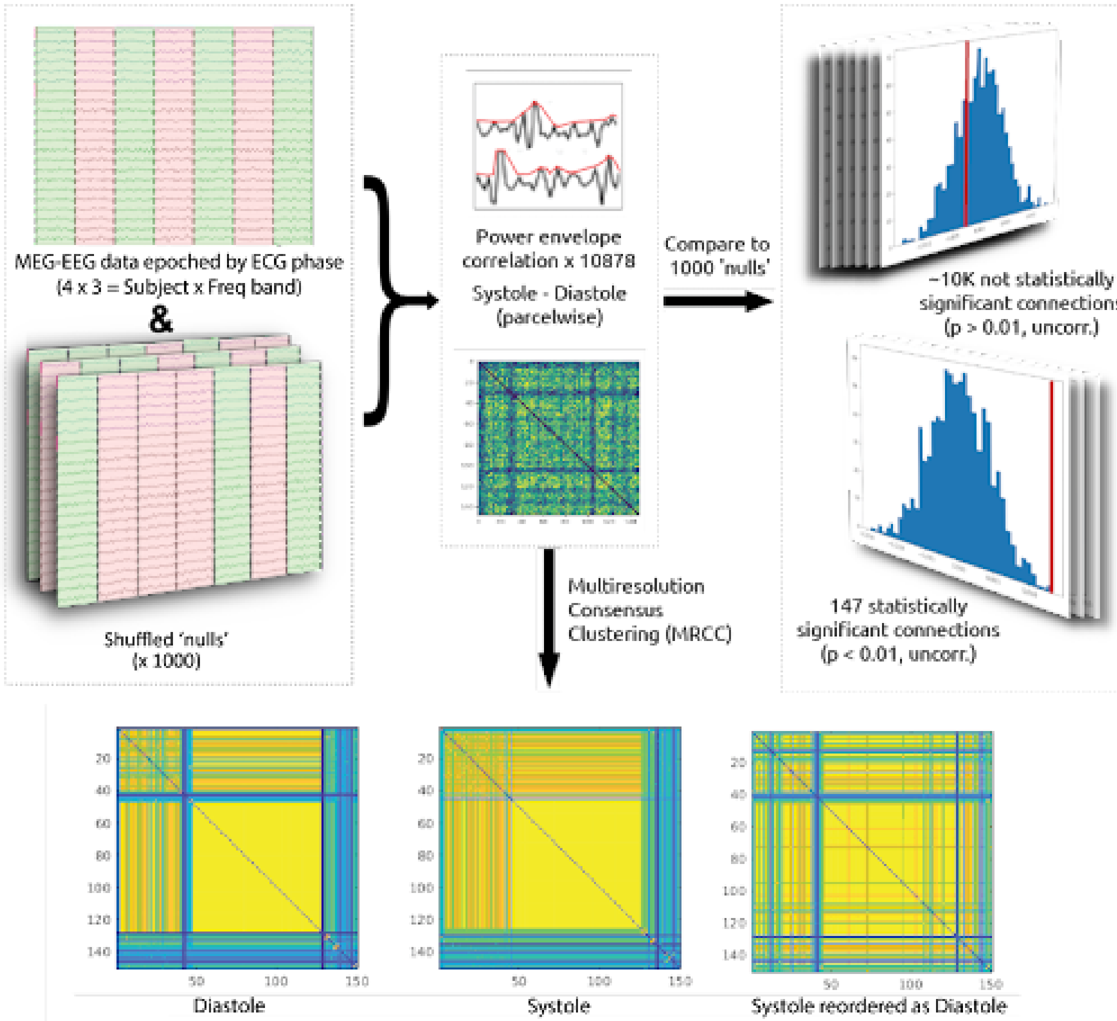


***Figure 5.2.*** **Data analysis schematic for analysis of individual participant data.** Preprocessed MEG-EEG data were filtered to extract frequencies for a given frequency band (e.g., a) and were epoched by cardiac phase. The number of systolic epochs for each individual participants were: S1: 2224; S2: 2226; S3: 2312; S4: 1839. Labels of "systole" & "quasi-diastole" were shuffled 1000 times per participant to create a "null" dataset. Power envelope correlations were applied to the unshuffled source-localized data and the shuffled "nulls', generating adjacency matrices of paired parcel-wise correlations for each dataset. The matrix for the diastole-synchronized epochs matrix was subtracted from that of the systole, and the resulting difference matrix was tested statistically across the distribution of 1000 nulls/parcel pairs (10878 comparisons) and network-wise analysis with MRCC to obtain modularity values and community structures.

matrices observed in systole and diastole, respectively. I specifically choose to use MI as my similarity metric across the two cardiac cycle phase estimates of functional connectivity, as it behaves in a geometrically consistent way on the set of clusterings imagined to exist within a functional MEG-EEG connectome (see Meilă 2007).

Careful consideration was given to the choice of a “null” model, as no raw data recorded from the brain can be fully “rid” of the influence of the heart. In the fetus, the heartbeat as a cyclical entity onsets between days 22-23 of gestation, upon the closure of the early cardiac tube. Heart chamber septation is completed by weeks 7-8 of gestation, coinciding with the end of neurulation. These cardiac developmental phases, therefore, well precede the maturation and structural development of the cerebral hemispheres from progenitor pallium (Sadler, 2020).

I note that any “regular” epoching of data (as would be usual in the resting state literature) might not avoid some “fortuitous” entrainment by either the ventricular or atrial phases of the cardiac cycle. Thus, a "quasi-null" distribution was computed for each pairwise comparison of systole-to-diastole in each canonical MEG-EEG frequency band by a randomized shuffling of the labels corresponding to either of the cardiac phases. The full analysis was repeated for the entirety of the null distribution (1000 shuffles) per MEG-EEG frequency band per cardiac cycle phase per participant ($\alpha$, $\beta$, $\gamma$ bands for S1, S2, S4; $\beta$ and $\gamma$ bands for S3). In these calculations, both systolic and diastolic envelope correlation matrices were constructed from “complement” bins of the shuffled data to avoid redundancy.

Simple z-score values were computed for the participant data as they related to the distribution of the null values in each of the 148x148 correlation pairs. The threshold of significance of the p-value was set at $<0.01$ so as to allow for exploratory analysis of the data which would not impose too conservative of a constraint on interpretable results (see Liégeois et al. 2021 for an expanded discussion of arguments for and against the use of lax constraints on statistical significance in evaluating Gaussian and presumed-to-be Gaussian distributions). I did not employ family-wise error rate corrections for multiple comparisons in this case due to the consideration of Destrieux atlas parcellation "overlaps" mentioned below.

**Parcel proximity and lobe-wise grouping**

The Destrieux atlas assigns voxels into tissue parcels based on group averaged anatomical gyral and sulcal locations. It is known that individual participants can have idiosyncrasies in gyral and sulcal anatomy even when placed into a normalized 3D brain atlas space. Therefore, there will be imprecision in the application of the parcellation atlas. I noticed this when examining the resulting inverse solutions of cardiac phase-correlated dipole maps within the Destrieux atlas: my initial analysis of anatomical overlap across participants suggested that there were minimal commonalities. However, on closer inspection it became clear that there might be the possibility of voxels potentially being placed into a neighboring parcel - if they were close to a border between two or more parcels. I therefore implemented a procedure to allow for this possibility. First, the power envelope correlation pairs of parcels were cross-matched to contain at least one parcel in common. For example, correlation between the right lateral occipito-temporal sulcus and the right calcarine sulcus in S1 was matched to the correlation between the right lateral occipito-temporal sulcus and the right cuneus in S2, S3, and S4. The four correlation pairs were then visually assessed in the Destrieux atlas as to the potential “mismatched” parcels’ proximity to one another. If the second parcels in the pairs were found to share a border, the correlation remained in the list.

Further, the obtained parcel lists were also grouped into six lobes (frontal, temporal, parietal, occipital, insular, and limbic), following Irimia et al. (2012). Simple percentage statistics were assessed in within- and between-lobe correlations. I note however, that the "limbic" lobe designation is somewhat of a misnomer, as it is applied to voxels in parcels generally located on the mesial surface of the hemispheres. The "limbic" lobe designation here includes mesial structures in not only temporal cortex, but also infrontal, parietal and occipital cortex.

**Results**

Power envelope correlation aggregate measures Statistically significant power envelope correlation values were thresholded at $\alpha = 0.01$ in each participant (S1, S2, S3, and S4) per MEG-EEG frequency band. After conducting parcel proximity analyses in pairs of participants, correlations common across 3 (for $\alpha$ and $\beta$ bands) and 4 (for $\gamma$ band) participants were identified. Note that analysis was limited to 3 participants for $\alpha$ and $\beta$ bands for two reasons. First, in the $\alpha$ band, analysis of S3 was not carried out due to the short duration of the systolic phase (260 ms). Second, in the $\beta$ band, no common correlations were detected across 4 participants. All detected correlations with their corresponding Destrieux atlas number codes, followed by the hemisphere notation (L or R), and attributions to lobes as per Irimia et al. (2012) are presented in Tables 5.1 and 5.2.

Overall, common power enveloped correlation aggregate measures across participants were not very abundant, but that said, they did not appear to be randomly

| $\alpha$ **band (S1-S2-S4)** | | | | | |
|---|---|---|---|---|---|
| **1 corr.** | **2 corr.** | **3 corr.** | **Lobes 1** | **Lobes 2** | **Lobes 3** |
| (26)L,(10)L | (34)L,(10)L | (43)L,(10)L | Parietal, Limbic | Temporal, Limbic | Temporal, Limbic |
| (34)L,(9)L | | | Temporal, Limbic | Temporal, Limbic | Temporal, Limbic |
| (43)L,(10)L | | | Temporal, Limbic | Temporal, Limbic | Temporal, Limbic |
| (55)R,(18)R | (25)R,(18)R | (25)R,(18)R | Parietal, Insular | Parietal, Insular | Parietal, Insular |
| (60)L,(34)L | (60)L,(33)L | (60)L,(36)L | Occipital, Temporal | Occipital, Temporal | Occipital, Temporal |
| (60)L,(35)L | | | Occipital, Temporal | Occipital, Temporal | Occipital, Temporal |
| (68)L,(23)L | (29)L,(23)L | (68)L,(61)L | Frontal, Occipital | Frontal, Occipital | Frontal, Occipital |
| (72)R,(36)L | (72)R,(26)L | (37)R,(26)L | Temporal, Temporal | Temporal, Parietal | Temporal, Parietal |
| $\beta$ **band (S1-S2-S4)** | | | | | |
| (20)R,(5)L | (65)R,(5)L | (65)R,(31)L | Occipital, Frontal | Parietal, Frontal | Parietal, Frontal |
| (54)R,(22)L | (54)R,(10)L | (54)R,(44)L | Frontal, Occipital | Frontal, Limbic | Frontal, Occipital |
| (73)R,(14)L | (73)R,(13)L | (34)R,(14)L | Temporal, Frontal | Temporal, Frontal | Temporal, Frontal |
| | | (38)R,(14)L | Temporal, Frontal | Temporal, Frontal | Temporal, Frontal |
| $\beta$ **band (S2-S3-S4)** | | | | | |
| (26)L,(7)L | (25)L,(7)L | (41)L,(7)L | Parietal, Limbic | Parietal, Limbic | Insular, Limbic |
| | | (38)L,(7)L | Parietal, Limbic | Parietal, Limbic | Temporal, Limbic |
| | (56)L,(7)L | (41)L,(7)L | Parietal, Limbic | Parietal, Limbic | Insular, Limbic |
| (49)R,(8)L | (12)R,(8)L | (49)R,(7)L | Insular, Limbic | Frontal, Limbic | Insular, Limbic |
| $\beta$ **band (S1-S2-S3)** | | | | | |
| (33)R,(3)R | (33)R,(8)R | (33)R,(67)R | Temporal, Parietal | Temporal, Limbic | Temporal, Parietal |
| (48)L,(26)R | (41)L,(26)R | (41)L,(73)R | Insular, Parietal | Insular, Parietal | Insular, Temporal |

Table 5.1: **Power envelope correlation aggregate measures by canonical MEEG frequency band.** Pairs of connections that were found to be statistically significant against the 1000-iteration label shuffle within-participant null at $\alpha = 0.01$. These are grouped by proximally located parcels, common to three participants (S1-S2-S4 in the $\alpha$ band, followed by S1-S2-S4, S2-S3-S4 and S1-S2-S3 in the $\beta$ band).

| $\gamma$ band (all participants) | | | | | | | |
|---|---|---|---|---|---|---|---|
| **S1 corr.** | **S2 corr.** | **S3 corr.** | **S4 corr.** | **Lobes S1** | **Lobes S2** | **Lobes S3** | **Lobes S4** |
| (37)R, (41)L | (43)R, (41)L | (43)R, (74)L | (43)R, (74)L | Temporal, Insular | Temporal, Insular | Temporal, Insular | Temporal, Insular |
| (60)L, (44)R | (60)L, (11)R | (60)L, (11)R | (60)L, (11)R (21)L, (11)R | Occipital, Occipital | Occipital, Occipital | Occipital, Occipital | Occipital, Occipital |
| (72)R, (12)R | (43)R, (12)R | (43)R, (29)R | (43)R, (29)R | Temporal, Frontal | Temporal, Frontal | Temporal, Frontal | Temporal, Frontal |

Table 5.2: **Power envelope correlation aggregate measures by canonical MEEG frequency band.** Pairs of connections that were found to be statistically significant against the 1000-iteration label shuffle within-participant null at $\alpha = 0.01$. These are grouped by proximally located parcels, common to all four participants in the $\gamma$ band.

| **Subject** | **# nodes (core)** | **# nodes (periphery)** | **Comms (core)** | **Comms (periphery)** | **# nodes (core)** | **# nodes (periphery)** | **Comms (core)** | **Comms (periphery)** |
|---|---|---|---|---|---|---|---|---|
| $\alpha$ **band (systole)** | | | | | $\alpha$ **band (diastole)** | | | |
| **S1** | 119 | 29 | 2 | 20 | 121 | 27 | 2 | 23 |
| **S2** | 119 | 29 | 2 | 22 | 116 | 32 | 2 | 26 |
| **S4** | 112 | 36 | 2 | 26 | 115 | 33 | 2 | 25 |
| $\beta$ **band (systole)** | | | | | $\beta$ **band (diastole)** | | | |
| **S1** | 115 | 33 | 2 | 24 | 115 | 33 | 2 | 23 |
| **S2** | 110 | 38 | 2 | 24 | 115 | 33 | 2 | 24 |
| **S3** | 124 | 24 | 3 | 18 | 118 | 30 | 2 | 20 |
| **S4** | 112 | 36 | 4 | 10 | 132 | 16 | 3 | 12 |
| $\gamma$ **band (systole)** | | | | | $\gamma$ **band (diastole)** | | | |
| **S1** | 115 | 33 | 2 | 17 | 120 | 28 | 3 | 17 |
| **S2** | 136 | 12 | 4 | 4 | 144 | 4 | 5 | 2 |
| **S3** | 107 | 41 | 3 | 12 | 127 | 21 | 5 | 6 |
| **S4** | 127 | 21 | 4 | 5 | 138 | 10 | 4 | 6 |

Table 5.3: **Counts of nodes in the community structure compared across the core and periphery.** Data from the MRCC analysis are broken down by participant as a function of MEG-EEG frequency band and cardiac cycle phase.

distributed. All in all, in the $\alpha$ band (across S1, S2, and S4; top panel of Table 5.2), 7 of the 8 significant measures were located within-hemisphere, with 6 of the 7 being in the left hemisphere and 1 in the right hemisphere. Only 1 of the 8 measures linked the right temporal cortex to the left hemisphere (temporal and parietal lobes).

In the $\beta$ band I did not observe aggregate measures that were common to all 4 participants. However, I did observe commonalities when data from 3 participants were compared (Table 5.2, 3 lower panels). The first grouping (S1-S2-S4; panel 3 of Table 5.2) has the same participants as reported for the $\alpha$ band. In the $\beta$ band all 4 significant measures were cross-hemispheric, unlike the $\alpha$ band measures which were predominantly within-hemisphere.

I performed 2 other $\beta$ band comparisons across 3 participants with common significant aggregate measures, i.e., S2-S3-S4 (4 measures) and S1-S2-S3 (2 measures). For S2-S3-S4, 3 of the 4 measures were confined to the left hemisphere and one was cross-hemispheric. For S1-S2-S3, 1 measure was cross-hemispheric and the other was confined to the right hemisphere.

Finally, in the $\gamma$ band, 8 common aggregate measures were observed across the 4 participants and all were located within-hemisphere (5 right, 3 left) and within the same lobe. These results from the $\gamma$ band stand in striking contrast to those in from the alpha and beta bands, where common connections not only could cross hemispheres, but also span lobes.

**Analysis of functional connectivity networks: Architecture and community structure**

I noticed that the MRCC analysis of the resting state functional connectivity (FC) demonstrated a "core-periphery" architecture in all participants across all MEG-EEG frequency bands. The core-periphery structure is characterized by the existence of two clear groups within the overarching network: a large cohesive core that contained the majority of well-interconnected nodes, and a smaller group of sparsely connected "lone" nodes (Borgatti and Everett, 2000). In particular, the size of "core" modules were comparable across the four participants and the 3 MEG-EEG frequency bands - as shown by the data in Table 5.3. For example, in S1, the sum of nodes in the $\alpha$-band core (represented by the two largest communities) of the systolic phase was 119 nodes (from 148 possible parcels), while in the diastolic phase the number of nodes in the core was 121 (analogous numbers for S2 and S4 were 119 and 116 for systole, and 112 and 115 for diastole, respectively).

Of note is the similarity in grouping pattern of both core and periphery across MEG-EEG $\alpha$ and $\beta$ bands for both cardiac phases. Specifically, the typical pattern for Participants 1, 2, and 5 in the $\alpha$ band — and for all four participants in the $\beta$ band — is the presence of a strong core (comprising 80% of all nodes) and a periphery of poorly connected "lone" nodes. This is in stark contrast to that of the $\gamma$ band pattern (seen mainly in Participants S2 and S4), where the systolic phase community clustering demonstrates a more densely connected periphery with fewer core groups, while the diastolic phase shows a remarkably well-connected network with virtually no peripheral "lone" nodes ( 95% of nodes in the core) (see Table 5.3).

**Analysis of functional connectivity networks: migration of nodes across cardiac phases**

Another interesting aspect of the network analysis is represented by Figures 5.3 to 5.8, which demonstrate the distribution of nodes in clusters across the two phases of the cardiac cycle and their "migration" — by which I mean the change in the attribution of a singular node from a large cluster in the core to the status of a "lone" or sparsely-connected node, or vice versa.

Figures 5.3-5.5 represent the relative correspondence between participants as to the composition of the clusters where nodes retain their level of connectedness to the large core or status as a "lone" node — where same nodes are shown at the intersection of the sets, and differences lie in the sets individual to the participant. For the $\alpha$ band, comparisons are drawn between Participants 1, 2, 5; for $\beta$ and $\gamma$, all four participants' overlap in the node composition is shown.

In Figures 5.6-5.8, the changes in these attributions are also color-coded according to the lobe in which the node resides for ease of understanding the corresponding brain anatomy and the composition of the large core and small peripheral clusters. Of note are the following changes of attribution.

In the $\alpha$ band: stable composition of well-connected large clusters to the small "lone nodes" ratio across participants in the nodes which preserve their attribution to the core and to the periphery (the "staying" side of Figure 5.6); relative representation of frontal lobe involvement of dynamic change in attribution of nodes from periphery to core, and vice versa, in S2 and S4, as compared to S1.

In the $\beta$ band: a relatively stable representation of the core and peripheral nodes on the "stable" side of Figure 5.7 in S1, S2 and S3, and smaller proportion of lone nodes that remain so across the cardiac cycle in S4; much larger proportion of the occipital lobe involvement in the dynamic changes across the cycle in S1, S3, and S4 as opposed to S2.

In the $\gamma$ band: lack of peripheral node involvement in the "stable" behavior nodes shown on the left of Figure 5.8, as well as a lack of parietal lobe involvement in that behavior in S3, but not in S1, S2, and S4; presence of well-connected relatively large clusters of "migrating" nodes in all participants and their diverse anatomical composition in all participants — notwithstanding the relative dominance of frontal lobe involvement of the dynamic shifts in node attribution in S1.

**Analysis of functional connectivity networks: mutual information (MI)**

Mutual information scores were derived for each participant by applying variation of information techniques, followed by normalization, to compare the adjacency matrices for systolic and diastolic phase power envelope correlations over 148 regions defined by the Destrieux atlas. Values for mutual information can be seen in Table 5.4. Notably, in all participants and all frequency bands, MI between the matrices of the null distribution tends to the value of 1 (indicating little difference), while MI of systolic and diastolic phase MEG-EEG data do not exceed 0.67, and the average values of MI for $\beta$- and $\gamma$-bands are indeed $< 0.5$.

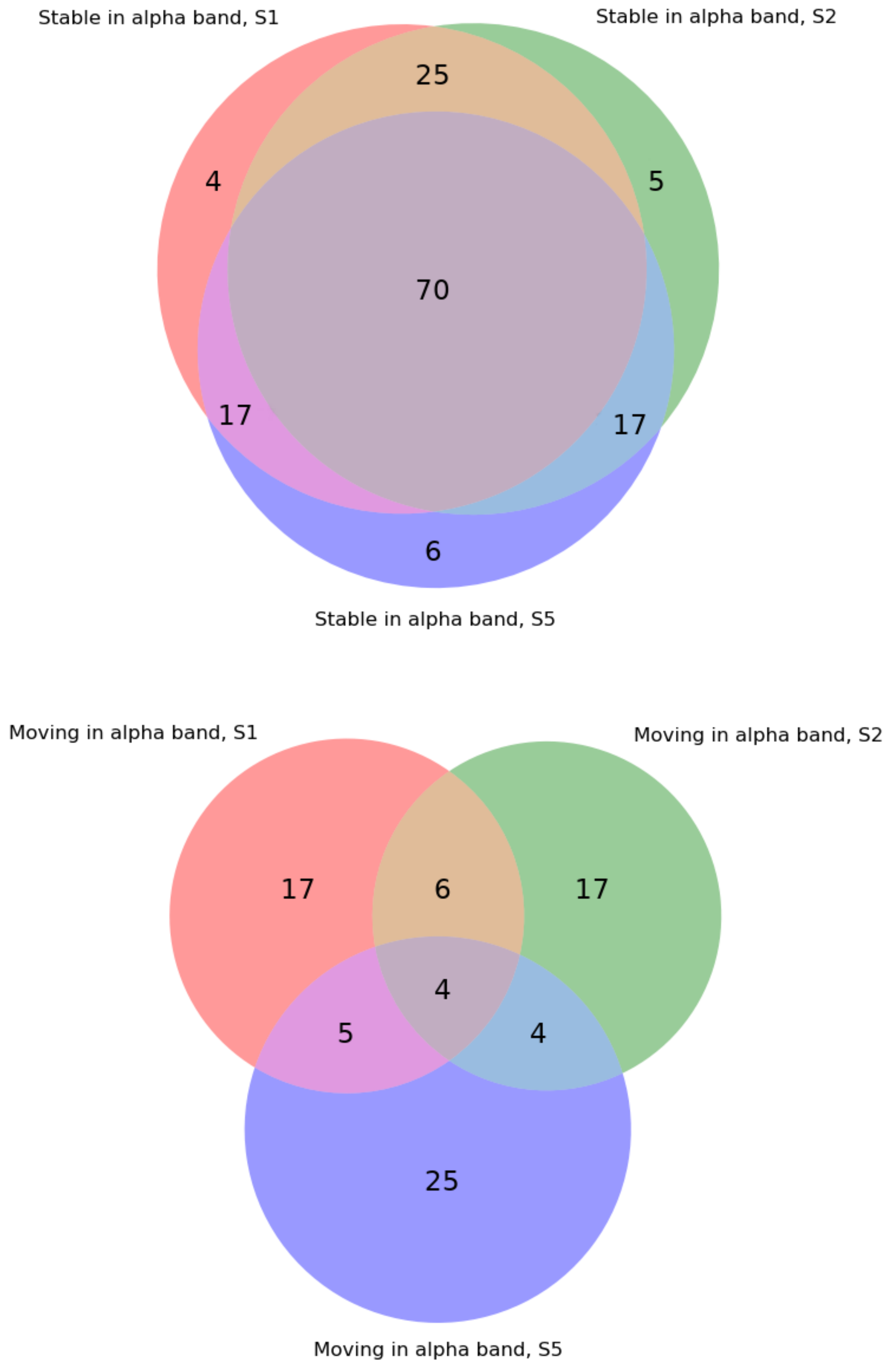


***Figure 5.3.*** **Venn diagram representation of $\alpha$ band inter-participant overlap in the node distribution.** Nodes that retain (top panel) or change (bottom panel) their attribution relative to the large core or periphery (as a lone node) for S1-S2-S4.

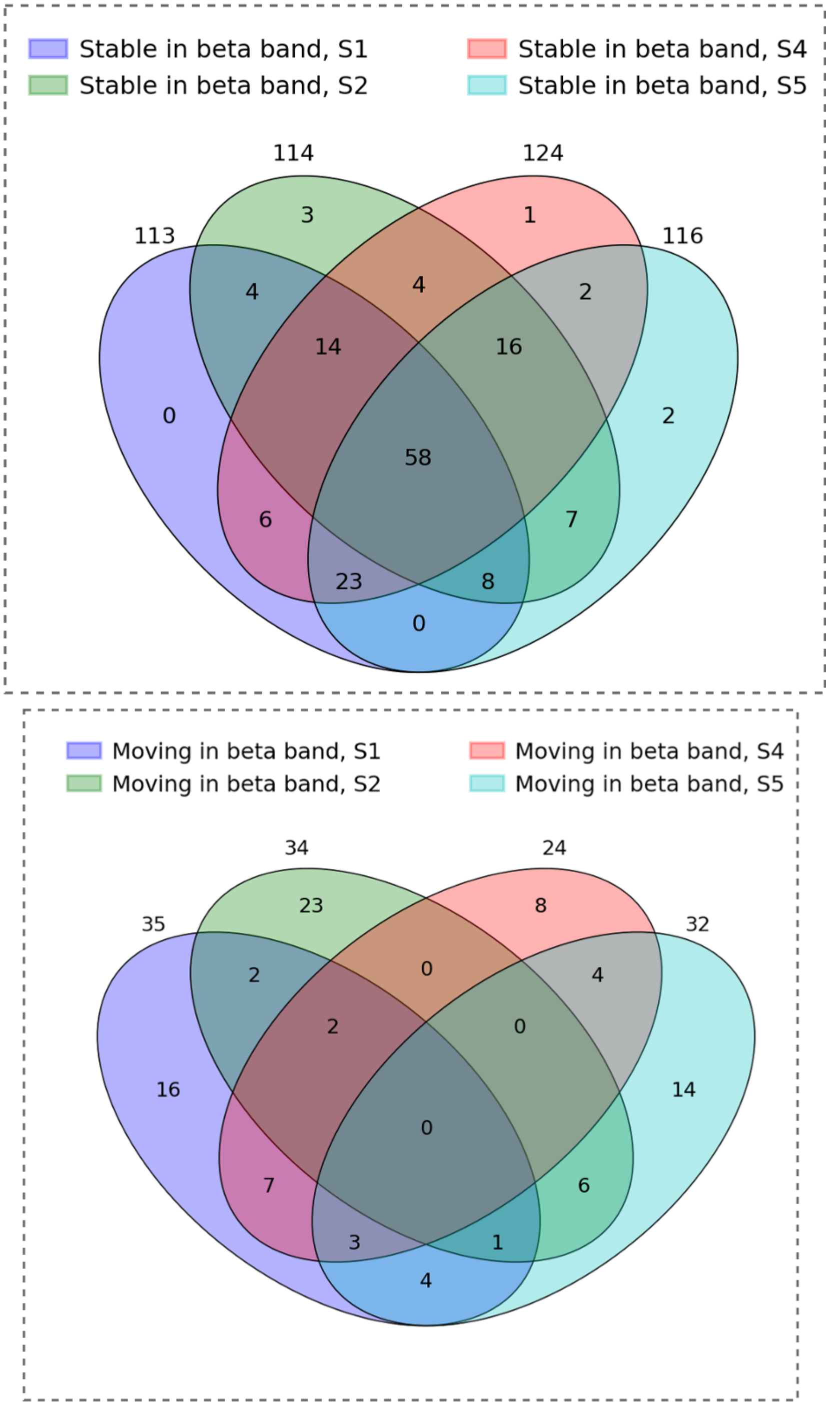


*Figure 5.4.* **Venn diagram representation of $\beta$ band inter-participant overlap in the node distribution.** Nodes that retain (top panel) or change (bottom panel) their attribution relative to the large "core" cluster or periphery (as a "lone" node) for the four participants.

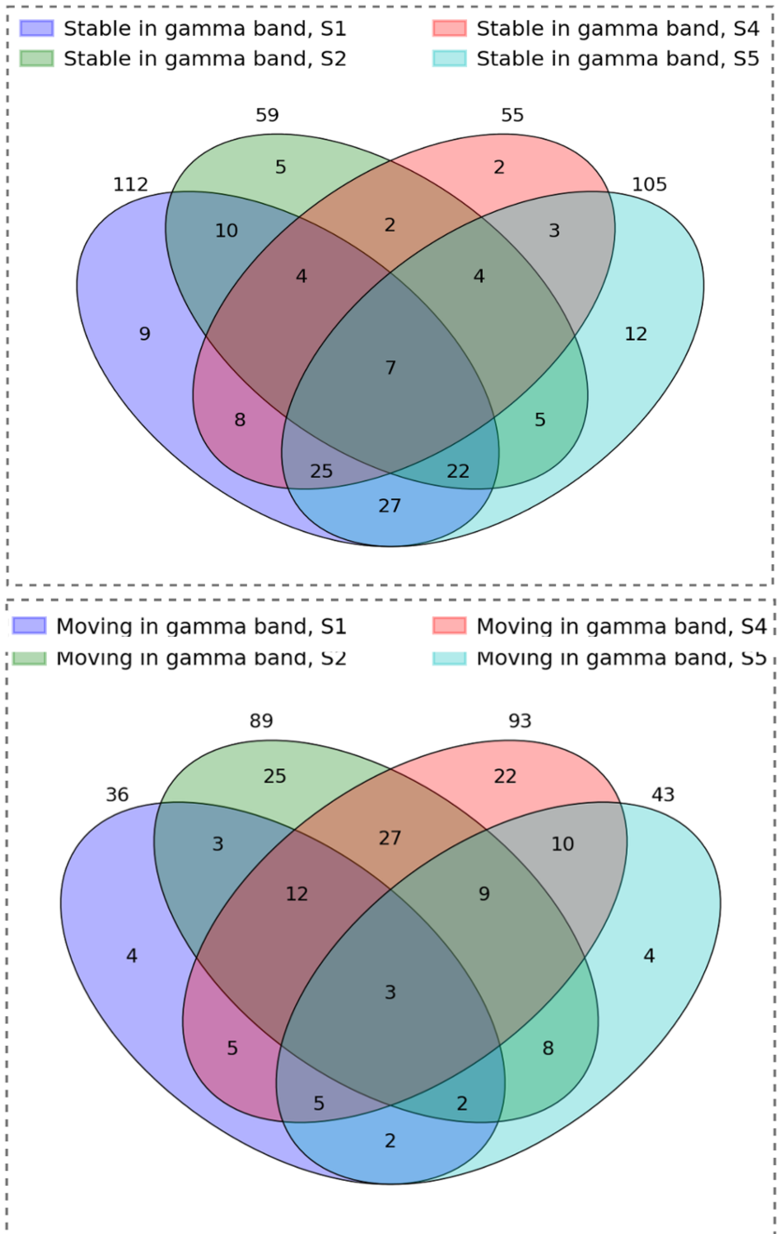


*Figure 5.5.* **Venn diagram representation of $\gamma$ band inter-participant overlap in the node distribution.** Nodes that retain (top panel) or change (bottom panel) their attribution relative to the large "core" cluster or periphery (as a "lone" node) for the four participants.

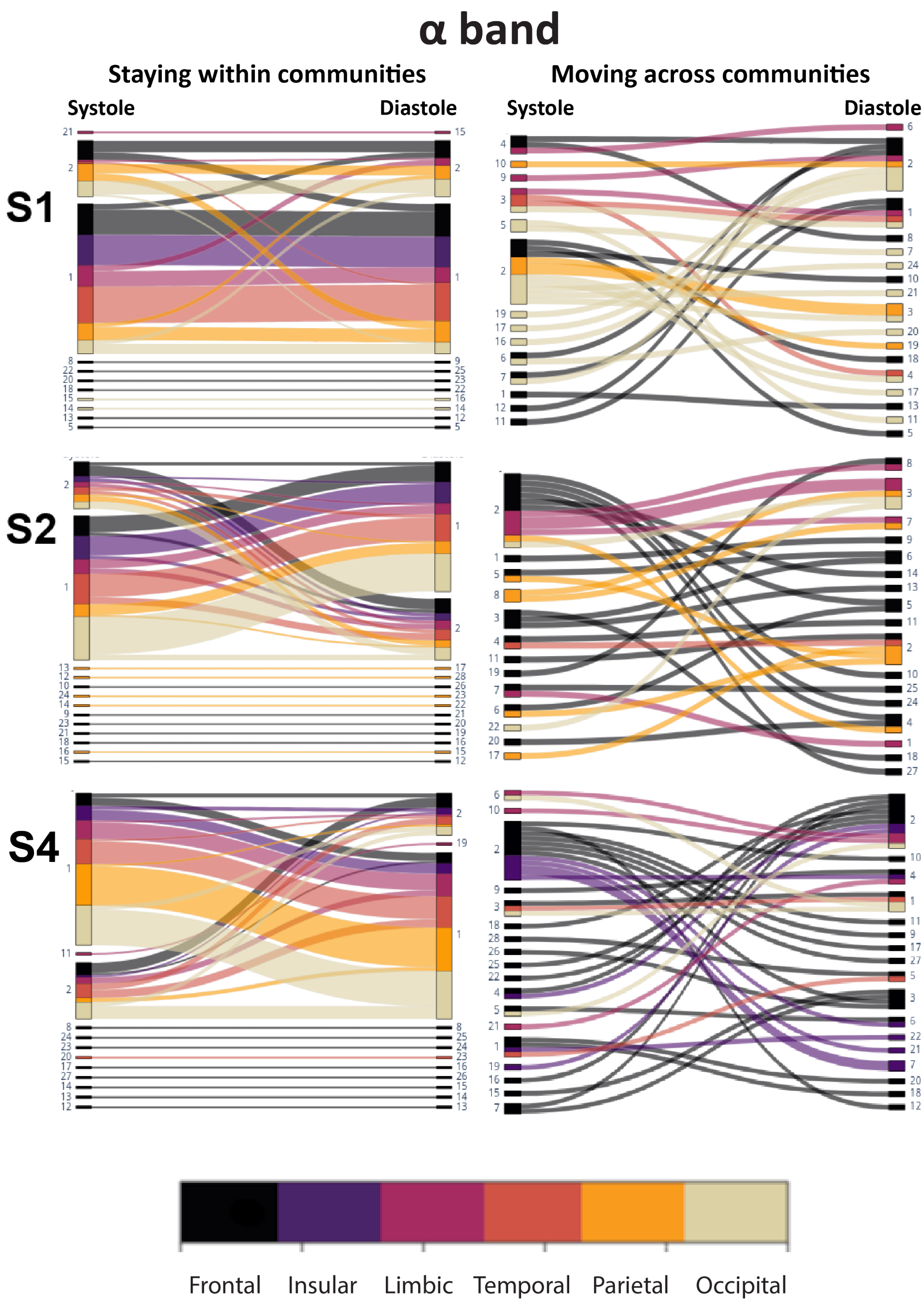


*Figure 5.6.* **Dynamics of node membership in community clusters of large core and "lone node" peripheral groupings in the $\alpha$ band for S1, S2, and S4.** Note the color legend corresponding to each of the lobes specified by Irimia and colleagues. Left panels represent the relative lack of movement by the nodes which maintain their attribution to core or periphery; right panels demonstrate the shifts from core to periphery or vice versa.

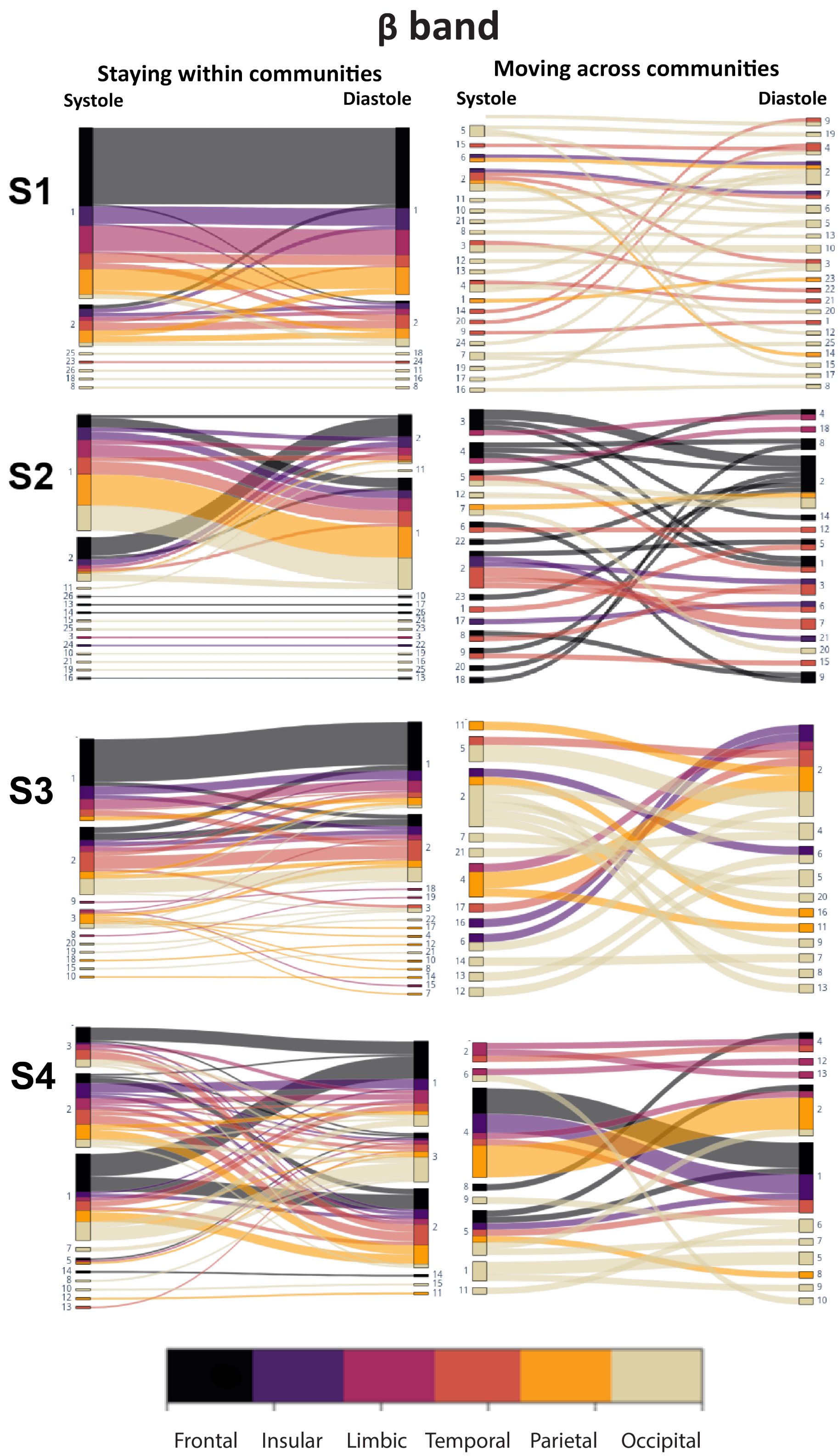


*Figure 5.7.* **Dynamics of node membership in community clusters of large core and "lone node" peripheral groupings in the $\beta$ band.**

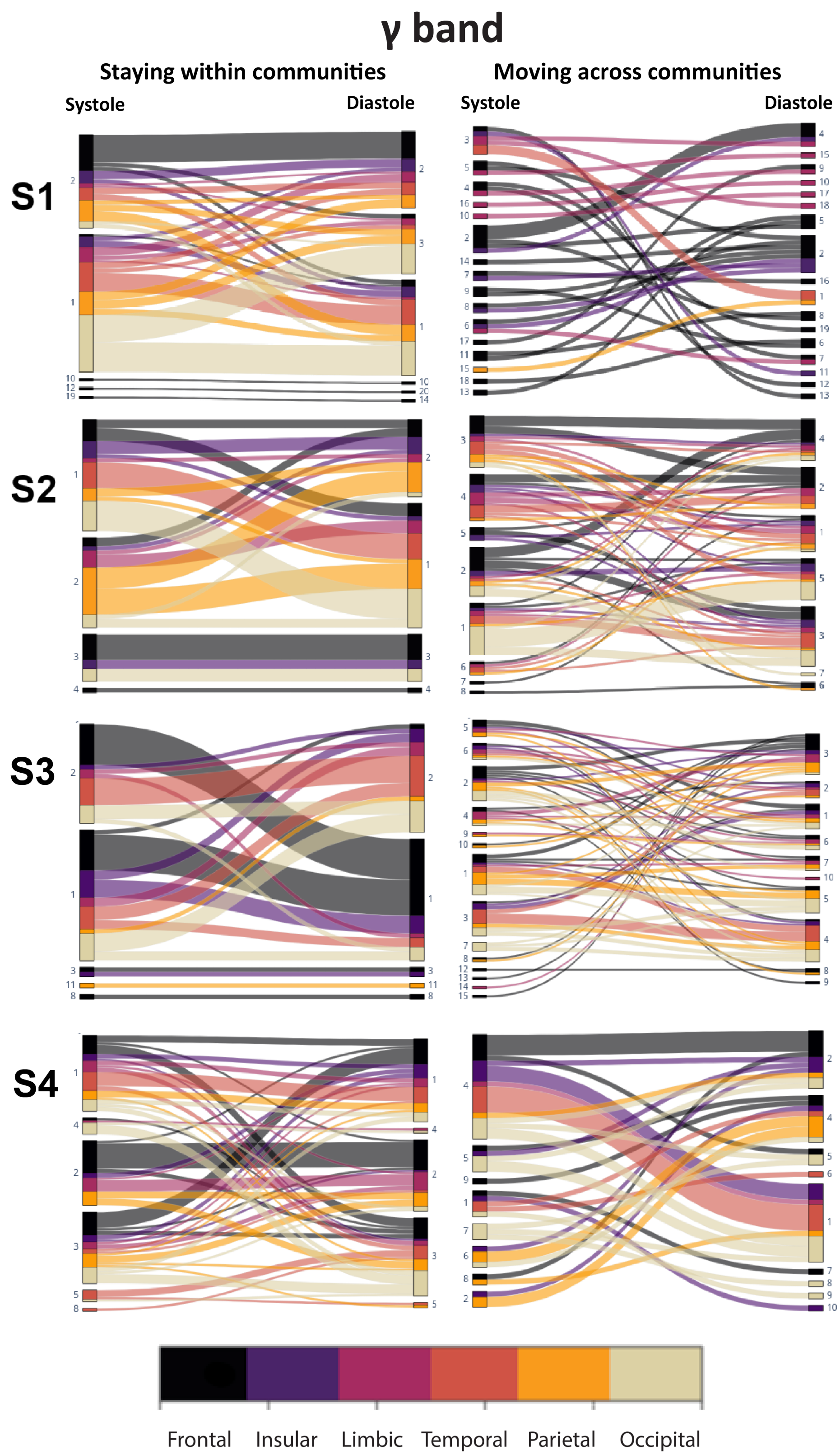


*Figure 5.8.* **Dynamics of node membership in community clusters of large core and "lone node" peripheral groupings in the $\gamma$ band.**

| | $\alpha$ | $\beta$ | $\gamma$ |
|---|---|---|---|
| *S1* | 0.4971 | 0.6647 | 0.4437 |
| *Null (S1 data)* | 0.9164 | 0.9531 | 0.9418 |
| *S2* | 0.5904 | 0.5540 | 0.1154 |
| *Null (S2 data)* | 0.9573 | 0.9387 | 0.8182 |
| *S3* | - | 0.4724 | 0.2306 |
| *Null (S3 data)* | - | 1 | 0.8214 |
| *S4* | 0.4967 | 0.2669 | 0.1757 |
| *Null (S4 data)* | 0.9396 | 0.8891 | 0.8813 |
| ***Average MI (S1-4)*** | **0.5281** | **0.4895** | **0.2413** |
| ***Average MI (null)*** | **0.9378** | **0.9452** | **0.8657** |

Table 5.4: **Mutual information values computed for comparisons across systolic and diastolic phases of the cardiac ventricular cycle from power envelope correlations in MEG-EEG.**

#### Discussion

In this study, I calculated various FC measures in individual participants' MEG-EEG data with respect to systolic and diastolic phases of the cardiac cycle from simultaneously acquired ECG.. I specifically examined how FC measures related to canonical MEG-EEG frequency bands that either *remained stable or changed* across systole and diastole. The main outcomes of this exploratory investigation concurred with my hypotheses of significant differences in patterns across cardiac phases in terms of both behavior across canonical MEG-EEG frequency bands and overarching network architecture. Overall, across participants, gamma rhythms tended to have local functional links (i.e., within-lobe) relative to the longer cross-lobe links, particularly in the$\alpha$ range. Below I discuss the functional significance of the observed cardiac phase differential FC features across MEG-EEG frequency bands.

**The $\alpha$-band**. I observed significant differences in *ipsilateral* fronto-occipital or occipito-temporal correlations across cardiac phases (see Table 5.1). This is in stark contrast with the pattern in the $\beta$ or $\gamma$ bands, where short-range (occipito-occipital in $\gamma$) correlations were more typical particularly for the$\gamma$ band (Table 5.2). The $\alpha$-band behavior supports the idea that lower frequency band oscillations have a greater likelihood of spreading via longer distance connections (see Von Stein and Sarnthein 2000; Thatcher et al. 2007; Ferri et al. 2008; Gruzelier 2009). Interestingly, my findings also include the presence of cross-hemispheric temporo-insular functional linkages that varied across the cardiac cycle. Given that the length of these cross-hemispheric connections would be much longer than their ipsilateral cousins, these data also fit with the idea of slower rhythms being of more utility for spanning longer distances.

It thus appears prudent to discuss the issue of possible cross-frequency coupling (CFC) between brain activity and the cardiac cycle itself which is functioning as an oscillation in its own right. Future analyses of multimodal data might consider the ECG waveform as a slow oscillation and look at the FC over a long resting period. In my current study, the separation of cardiac phases in the ECG waveform could not allow me to examine theta or delta activity because of sampling issues. It would not be unexpected to potentially observe some coupling between ECG-EEG/MEG that is driven by the ECG signal which lies in the neurophysiological delta range. (Because I am constrained — by the nature of my method — to the sparse number of differences between the phases, and not the whole-brain “snapshots” in each one, the anatomical distribution of these findings (common to all of my participants) plays a vital role in the interpretation of my results.)

**The $\gamma$-band**. The presence of simultaneous contralateral correlations in the occipital lobe must be cautiously interpreted as to the true number of coinciding correlations between participants (as one correlation in S1 and S2 corresponds to two in S4). Moreover, contralateral connections between the occipital lobes still represent short range connectivity. The same cannot be said for the contralateral temporo-insular connection found in the same band. As Hipp and colleagues (2012) point out, the application of power envelope correlation estimation to source level data in the $\gamma$ band may indeed be related to the diminution of signal power, as well as the prominence of saccadic (or other visual) and myogenic artifacts. Thus, when taking into account that source-localized data tend to overrepresent the occipital lobe-associated correlations in the $\gamma$-band, I turn the attention of the reader to the possibility of cross-frequency coupling in the contralateral temporo-insular connection. In particular, due to the methodological constraints of the present study, $\theta$-band activity could not be studied due to the short duration of epochs — yet, as documented by numerous studies (e.g. Munn et al. 2017; Zhong et al. 2017; Hammer et al. 2021), this relationship may be explained by the $\theta$ entrainment of $\gamma$-band frequencies. While there are multiple factors which may have influenced this entrainment, it is well documented that the lower frequency entrainment in the insula is related to visceral perception such as nociception or thermosensation (Fardo et al. 2017; Liberati et al. 2018). Meanwhile, it has been shown that lower frequency bands in EEG data (such as $\theta$ and$\alpha$) influence the $\gamma$-band through a cross-frequency coupling mechanism in the wake of cardiac function alteration via anesthesia (Stankovski et al., 2016). This finding suggests that possible relationship between the correlation between the temporal lobe and the insular cortex in the $\alpha$ band seen in Table 5.1 (and the putative insular activity in the $\theta$ band not captured by my analysis) may indeed be related to the cardiac cycle rhythm that is driving my epoching protocol. Less is known about cross-frequency coupling and its relationship to the cardiac cycle in the $\alpha$ and $\beta$ bands, yet I would be remiss not to point out that the lack of consistent patterns across all four participants in the $\beta$ band appears to be intriguing and may be driven by individual differences (see Limitations).

It would be interesting to contrast these select findings of connectivity patterns across neuroimaging modalities, as fMRI findings suggest the reversal of this frequency-distance relationship. For example, Wu and colleagues (2008) report a selective increase in the distance between correlated regions of interest tied to the increase in frequency of fMRI fluctuations— however, their data represent ultra-low-frequency bands not exceeding 1 Hz, which would not be feasible for my research question due to the short duration of epochs dictated by the cardiac cycle. The concordance of my findings with some results obtained from fMRI studies of network dynamics does indeed appear interesting in that regard.

With regard to the core-periphery network structure present in the data of the 4 participants across frequency bands and both cardiac phases, my findings are consistent with previous studies of network behavior at high temporal resolution. In those studies, FC was estimated with methods, such as Pearson correlation of power time series of a truncated parcellation atlas with 400-ms sliding window epochs (De Pasquale et al., 2016), imaginary coherence of power spectra across Destrieux atlas parcels with 1-s epochs (Corsi et al., 2021), and power envelope coupling within 1-s epochs (Iandolo et al., 2021). This method- and time window-agnostic emergence of core-periphery architecture align with my results. Of note is the presence of this type of architecture in both the study which focused on particular frequency bands of interest (De Pasquale et al., 2016) and highlighted the presence of a strong core network in the $\beta$ band, as well as the same finding in studies which analyzed the data with respect to a broader power spectrum (Corsi et al. 2021; Iandolo et al. 2021).

Moreover, this strengthens the assumption of an underlying stable (or quasi-stable) pattern of activation of resting-state networks, where small perturbations within the overarching core-periphery architecture (as seen in my data) would not violate the overarching "small-worldness" of the connectome proper (De Pasquale et al., 2018). This also highlights the importance of the MI estimation I show in the previous section: as has been shown previously in MEG and EEG data (David et al., 2004), MI is sensitive to frequency-specific couplings when considering narrow bands of 2 Hz width. However, as Wilmer et al. (2012) have explored, calculating MI provides the advantage of capturing the complex interactions across a wide frequency range without the need for pre-selecting narrow bands. This approach can offer a comprehensive understanding of functional connectivity that encompasses all frequencies, potentially revealing broader neural dynamics within the broader canonical frequency bands. As such, my findings point to a difference between FC estimations in cardiac cycle-informed systolic and diastolic data than between the average of the cardiac phase-randomized “null” distribution. As the literature remains sparse on empirically meaningful benchmarks for MI values in neurophysiological FC data, the nature of MI computation indicates a lesser degree of similarity between networks in cardiac cycle-informed connectivity matrices, thus confirming prior findings of cardiac cycle-induced differences in brain activity (see, for example, Adelhöfer et al. 2020; Al et al. 2020; Al et al. 2021; Al et al. 2023).

The dynamic nature of these FC changes across the two cardiac phases is well captured in Figures 5.6-5.8. Sankey plots were chosen as the visualization medium to ease interpretation of changes to core-periphery architecture (note that the plots do *not* reflect core versus periphery, but rather show which Destrieux atlas parcels *change their attribution* from core to periphery, or vice versa). This novel approach to data presentation allowed me to succinctly contrast individual differences in the lobar composition of the core and peripheral networks across the two cardiac phases. I defined the core to be represented by up to the three largest communities (thresholded at 10 nodes or more). This was motivated by the understanding that individual differences in network structures may influence the behavior of the Louvain algorithm which determined the group sizes within the given parameters. Thus, the left panels of Figures 5.6-5.8 reflect the stable structure of core and periphery nodes which do *not* change attribution: if they originate in the largest communities in systole, they do not move to smaller groups or become “lone nodes” in diastole, and vice versa. Movement across the two largest communities of the core or change of the arbitrary ordinal number of a lone node was not considered to be a change of attribution.

Within these restrictions, I found interesting individual patterns of dynamic network behavior. For instance, see the difference in the proportional presence of occipital lobe parcels which change their attribution from core to periphery (and vice versa) in S1, as opposed to S2 and S4 in the$\alpha$-band. In turn, S2 and S4 demonstrate a larger proportion of frontal lobe parcels among those which switch their attribution from core to periphery — but not at the expense of the overall broad cortical distribution of the core network in all three participants (Fig. 5.6).

Similarly, I saw the composition of the stable network of core-periphery nodes in both $\beta$ and $\gamma$ bands in all participants, with some notable exceptions (see Figs. 5.7 and 5.8).

Overall, my research points to a pattern of FC differences with respect to cardiac cycle phases, which was observed consistently in four adult participants with a wide age range. This suggests that further studies into the nature of possible cardiac entrainment of brain rhythms and frequency relationships between cardiac and brain activity, as well as a thorough analysis of structural connectivity with FC may be warranted. I discuss this latter point in more detail below with respect to the limitations of my study.

**Limitations**

The present project was realized with several methodological constraints, not the least of which was the size of my sample. That said, some recent studies suggest several advantages to investigations of individual differences in longer datasets as opposed to larger samples. For instance, van Diessen and colleagues (2015) suggest that a deeper analysis of individual participants may offer better insights into FC and network structure, as it is those architectures that tend to have higher levels of variation. Furthermore, individual differences in my case may have influenced the divergence in the anatomical distribution of parcels.

Participant demographic characteristics, such as biological sex, could also play a role. S3 is the only male participant in my study, who, despite being close in age to S1 and S2, may have introduced differences in the computation of across-participant commonalities. In males, reports of higher coherence of EEG $\beta$-band networks and higher excitability of dynamic cortical networks (Jaušovec and Jaušovec, 2010), and differences in microstate duration and dynamics (Tomescu et al., 2018) have been reported. Hence, the variable of biological sex may have contributed to the observed sparseness in the number of coinciding parcels in the higher frequency bands in my participants.

Similarly, S4 as the youngest one is also furthest in age away from the other 3 participants. Tomescu and colleagues (2018) noted that the main effect of age is pronounced in the dynamics of transitions between canonical microstates in EEG when comparing age groups 31-60 and 61-87. Because the typical length of a microstate varies between 80 and 120 ms (see Al Zoubi et al. 2019), this duration allows to compare the results obtained by Tomescu and colleagues to the possible confounding effect of age in the present study. That said, the strategy of binning ages by Tomescu and colleagues may have obscured the gradual shifts happening across aging, as all of the participants in the present study fall in the 31-60 year range. Hoshi & Shigihara (2020) in terms of $\alpha$-band activity suggest that age is a strong predictor of the localization of rostro-caudal dynamics. This suggests that direct $\alpha$-band FC comparison of S1, S2, and S4 may leave only the commonalities outside of the fronto-parietal and fronto-occipital axes of dynamic changes.

Protocols of data acquisition can also be an issue. I followed best practice recommendations made by multiple expert groups (Gross et al. 2013; Puce and Hämäläinen 2017; Pernet et al. 2020). The eyes open resting-state protocol might be suboptimal for recordings as long as ours, as this could prompt decreases in occipital alpha power. Other experts have proposed recommending eyes closed in studies of resting state EEG for the sake of minimizing blinks and eye movements (Van Diessen et al., 2015).

That said, performing long recordings of resting-state activity with eyes closed is a particularly risky practice - as participants can very easily fall asleep and the neurophysiological activity of early stage sleep is quite different to that of someone at quiet rest. In the current study, the recordings were broken up into four blocks of 10 minutes each to minimize the risk of the participant falling asleep - since viewing a black fixation cross in an all white soundproof room is very conducive to inducing slumber. The participant was also visible on camera at all times, so that they would be less likely to take a nap during the study.

In addition to that, my methodological approach to frequency band designation may have followed the canonical band definitions yet did not account for differences in peak frequency slowing due to normal aging (see Puce and Hämäläinen 2017, for more information on frequency band shifts across the lifespan).

Our choice of the null model was constrained by biological factors (such as the impossibility of "removing the heart from the equation"), as well as mathematical feasibility and computational efficiency. As such, I built a null model similar to that recommended by Váša & Mišić (2022), where I compared a distribution of reshuffled labels of my conditions in the estimation of FC. However, as Váša and Mišić (2022) point out, comparisons of empirical and "null" data may not be as important as the predictive utility which the research question bears.

Yet another caveat which relates to the issue of individual differences and applicability of generalized methods is that of source localization fidelity and parcellation. Because this study had as one if its aims an exploration of the anatomical distribution of significant FC differences between the two cardiac phases, it is prudent to discuss the recent findings in the literature. Namely, the study of Samuelsson and colleagues

(2021) compares the methods of source localization and their spatial dispersion, mentioning that while dSPM (the method chosen in the present study) has a relatively low spatial dispersion value, it results in a sharp increase in the localization error sizes. This finding was the primary motivator for my quasi-fuzzy analysis of parcel neighborhoods, as the reported magnitude of localization errors was as high as 5 cm (Molins et al. 2008; Hauk et al. 2019; Samuelsson et al. 2021), especially for regions of SNR>1 (which would account for some mesial wall structure source localization). Potential solutions for these issues may be found in approaches such as hyperedge bundling (Wang et al., 2018). Yet, special consideration must be given to the procedural specifics of network reconstruction when selecting a parcellation schema (for more details, see Zalesky et al. 2010 or Bassett et al. 2018).

Related to that is the nature of attribution to lobes of the cortical structures lying in the mesial wall. Following Irimia and colleagues (2012), I separated parcels into lobes for ease of interpretation of the data. However, the designation of the entirety of the cingulate cortex and the adjacent pericallosal sulcus as one limbic lobe may indeed lead to unfortunate misinterpretation in my analysis of those correlations which correspond to the "limbic" area FC — for example, in the area of the $\alpha$-band frequency coupling with other bands in relation to the cingulate and insular cortical regions, as shown by Munn and colleagues (2017).

Finally, I would like to mention my choice of MI as a measure of network dissimilarity when comparing across cardiac phases. As seen in von Wegner et al. (2018), careful consideration must be given to the possibility of short-range and long-range *temporal* dependence of time-lagged MI investigations. As the authors pointed out, long-range temporal dependence appears to be more reliable in studies of EEG data.

However, as my investigation considered only non-time-lagged power envelope correlation, and MI was computed across the two cardiac phases, the appearance of spurious Hurst phenomena is not of concern.

### Implications and future directions

The importance of the heart-brain axis in interoception is central to the paradigmatic shift in experimentation on the embodied brain. As such, my findings with regard to the functional involvement of the insular cortex in the $\gamma$-band agree with existing literature vis-a-vis the laterality of insular involvement in the regulation of cardiac activity (Tahsili-Fahadan and Geocadin, 2017). It is the left insula correlation with the contralateral temporal cortex which differentiates systole from diastole in all four of my participants. However, I also demonstrate a prominent right insular correlation with the ipsilateral parietal cortex in S1, S2, and S4 in the $\alpha$-band. A replication of my study with a larger cohort of healthy participants could elucidate this intriguing difference with prior research (see also Oppenheimer et al. 1992; Hilz et al. 2001; Macefield 2003; Poppa et al. 2022).

Moreover, I would be remiss not to mention the pertinent discussion of the afferent vagal communication of cardiac activity. As shown by Beaumont and colleagues (2013), the connection between the intrinsic cardiac ganglia and the preganglionic neurons of the nucleus ambiguus and the dorsal motor nucleus of the vagus in the medulla follows a more complex pattern of connectivity than simple relay of information. In addition, efferent communication of neurohumoral nature as it relates to the cerebral cortical, amygdalar, hypothalamic, and overall limbic activity in relation to the activation of cranial nerves IX and X further complicates the possibility of simple bidirectional feedback loop. This underlines the involvement of both long-range autonomic relationships between the cerebral cortex and cardiac tissue, but also highlights the knowledge gap as to the cortical network activity throughout the cardiac cycle. It is also interesting from the perspective of intravagal ephaptic communication and the afferent vagal communication with the cortical areas such as the cingulate (see Shaffer et al. 2023). Further studies of higher spatial resolution may indeed illuminate the important interplay between the central and autonomic nervous systems as they relate to the heart rhythm.

It is also important to address the fundamental FC relationships of the cerebral and cardiac tissues which have been illustrated in the literature. As I alluded to in the Introduction, much work has been done with respect to stimulus-based investigations of heart-evoked potentials and cardiac phase-locked responses to sensory stimuli (Couto et al. 2015; Park and Blanke 2019; Al et al. 2020; Poppa et al. 2022). Yet, studies into task-free paradigm associations with cardiac cycle phases remain sparse. Meanwhile, resting state presents an attractive way of measuring the relationship between cognition (and/or emotion) and embodied processes, as this lack of controlled activity offers a view into the patterns of cognitive dynamics and possible phenotypic differences in behavior between individuals (see, for instance, Diaz et al. 2013). Moreover, disentangling cardiac phase influence on resting state cognitive patterns from other embodied interactions appears to be crucial, as several prior studies have demonstrated stable dynamics of resting state networks in modalities which are more tightly intertwined with cardiac activity, such as blood oxygenation level-dependent signal in fMRI (Damoiseaux et al. 2006; Rosazza and Minati 2011; Brookes et al. 2012).

Studies in neurophysiological modalities demonstrate slow fluctuations in the dynamics of resting state networks (e.g., Honey et al. 2012) which may reflect processes tied to the autonomic nervous system control of sympathetic and parasympathetic efferents — including those tied to the regulation of the cardiac ventricular cycle and heart rate variability. It is thus critical to provide a solid foundation to the investigations of healthy controls across lifespan to consider the temporal and anatomical commonalities driving these types of interactions.

This interaction between heart rate variability and brain network dynamics also carves out space for discussions of cardiac entrainment of higher frequency electrophysiological activity. Some research findings suggest that cognitive processes such as active information sampling (Kunzendorf et al., 2019), cognitive-emotional stimuli such as emotional Stroop task (Adelhöfer et al., 2020), visual processing of emotional stimuli (Park et al., 2014) do indeed demonstrate a strong relationship with the cardiac rhythm. Separating these findings from those focused on subcortical FC to cardiac baroreceptor activity (such as Richter et al. 2009; Rae et al. 2018; Larra et al. 2020) is critical not only in terms of physiological and anatomical differences but also in relation to the ontological architecture of bottom-up processing and more comprehensive approaches to studying embodied processes. At the same time, the question of entrainment of cardiac rhythm is mostly studied from the "top-down" perspective of brain efferents influencing the electrical activity in cardiac tissue (see Sastre et al. 2000 or Pokrovskii 2005for examples of such arguments). At the same time, integrative approaches to studying heart-brain interactions have mostly focused on heart rate variability as the metric of choice in establishing bidirectional relationships (Taylor et al., 2010). Thus, my findings offer a uniquely detailed insight into the physiological link between the cardiac ventricular cycle and neurophysiological dynamics measured with both MEG and EEG.

I propose that my method be replicated with much larger samples to ensure test-retest reliability of the FC links and network architecture changes that I demonstrate. More multimodal investigations of both electro- and magnetophysiological data, as well as studies of anatomical relationships in both gray and white matter will yield more fine-grained results with respect to reliance of cardiac cycle phases on neural activity, and vice versa. In addition, novel methodological approaches in computation may offer better resolution and fewer constraints on spatial fidelity of source localization in both MEG and EEG studies. Finally, novel empirical approaches involving more ecologically valid settings such as ambulatory EEG and ECG could provide me with more insight into idiographic relationships between situated and embodied cognitive and/or emotional processes as they relate to real-life scenarios.

## Conclusion

In this study, I demonstrated that FC and network structure of brain neurophysiological activity measured with MEG-EEG can change with the phases of the cardiac ventricular cycle. These changes spanned three canonical frequency bands of neurophysiological activity and were present in four adult participants of varying ages (30-59). While my results cannot be generalized to the population, or be conclusive as to specific patterns of structural connections leading to the divergence of network connectivity in systole versus diastole, I maintain that further investigations into the bidirectional relationship between heart and brain are needed. Clarifying the complex feedback loop processes which inform not only cardiac rhythm but also brain function will aid in situating multimodal, holistic empirical research within new ecologically valid paradigms of cognitive and neuroscience.

# Chapter 6

# Conclusion

Presented in this dissertation is an attempt to approach emotion in a manner which would reflect the multifaceted nature of the phenomenon and the history of research into it. Following the historical analysis of advantages and limitations of the listed approaches, I approached the conceptualization of emotions not merely as a theoretical exercise but as a necessary evolution in understanding complex psychological phenomena. The historical and often compartmentalized study of emotions has yielded diverse models, each adding layers of understanding but often failing to bridge the gap between theory and applicability across different contexts and cultures. At the end of Chapter 2, I proposed a framework that views emotions as dynamic, continuous entities, deeply embedded within the cultural and social fabric of human experience. This philosophical standpoint fosters a more holistic and inclusive view, which is crucial for developing models that are not only reflective of real-world complexities but also empirically generalizable — as it contrasts with the existing dicretized view.

By grounding my approach in a robust philosophical framework, I achieve a dual objective: I adhere to the rigorous standards of scientific inquiry while also ensuring that my models are reflective of the complex, often chaotic reality of human emotions. This dual focus not only enhances the generalizability of my findings across different theoretical and applied domains but also sets a precedent for future research frameworks that seek to capture the essence of human emotional complexity without sacrificing empirical integrity.

As I move forward, the integration of this philosophical understanding with empirical methodologies opens new avenues for exploring the vast landscape of human emotions. It invites future researchers to build upon a foundation that appreciates the depth and breadth of emotional experiences, encouraging a continuous dialogue between theoretical innovation and practical application.

To move on to specific points of interest in separate chapters of the dissertation, the following few sections will focus on addressing possible concerns and limitations, as well as future directions in each of Chapters 2-5.

### Chapter 2

Chapter 2 of the dissertation delves into the complex evolution of emotion theories within psychology and neuroscience. It critically examines the transition from traditional paradigms, which often viewed emotions as discrete and static phenomena, to more dynamic and integrated models. This historiographic analysis emphasizes the limitations of earlier models that did not account for the fluidity and cultural variability of emotional expressions, setting the stage for a more comprehensive understanding. As one can see from the literature review, this attempt follows in the footsteps of many esteemed researchers in various subfields of psychology and neuroscience.

Over the last two centuries, emotions have been defined as habitual (Darwin, 1872), discrete (James 1884; Ekman and Friesen 1971), multidimensional (Schlosberg 1954; Plutchik 1960), categorical (Russell, 1980), dynamic (Davidson et al., 2000), and complex (Barrett 2012; Grühn et al. 2013; Berrios 2019). Yet, as shown in the historiographic review, little consensus exists within and between the fields of cognitive and mathematical psychology and affective neuroscience with respect to one unifying framework within which emotions should be viewed. The chapter critically discusses the shift from viewing emotions as mere biological reactions to understanding them as complex constructs influenced by a multitude of factors including social interactions and personal history.

Among some of the more prominent epistemological and methodological gaps identified in the analysis are the prevalence of disciplinary and linguistic narrowness and the discretized approach to emotions, both of which I aim to circumvent in the proposed operationalization of emotion in Definition 1.

Regarding historical narrowness, previous models often failed to integrate interdisciplinary insights that could bridge the gap between emotion theories and their practical applicability across different cultures and contexts. As alluded below, this brings up an important issue of generalizability of existing models with regards to valence. Much can be said about the ontological basis of emotion as a phenomenon, yet many of the researchers to this day refer to valence as a foundational aspect of emotion. Yet, the perceived valence of any emotion may differ between people of varied backgrounds, be they ethnic, cultural, generational, or gender-related (see Jackson et al. 2019 for examples of clustering differences based on semantics).

Another crucial aspect of existing theories which was highlighted as the result of the historiographic review is the overemphasis on discreteness of emotions. Traditional frameworks frequently focused on categorizing emotions into discrete types without considering the continuous nature of emotional experiences. However, little to no explanation is given to this atomization of experiences, and few authors justify the ontological bases of their frameworks — thus, in most sources the understanding of emotion as an isolated event which has a beginning and end is implicit (see the categorical definition given by Ekman 2018 as a foundational one for the entire field of emotion measurement).

In contrast, in the present dissertation I proposed to move away from those factors which may introduce bias into the measurement and investigation of emotion. The linguistic basis of verbal expressions of emotion allows for vagueness in definitions and hinders inter-study generalizability when it comes to valence attribution; meanwhile, the arbitrary temporal borders imposed on any emotion event preclude one from studying emotions which may be assigned "complex" labels when shifting from one to another.

Thus, the reconceptualization of emotions as dynamic, continuous phenomena embedded within cultural and social contexts marks a significant philosophical and methodological advancement. This shift not only challenges the boundaries of psychological research but also enhances the empirical generalizability of emotion theories. By viewing emotions through this broader lens, future research can develop more nuanced models that reflect the complexity of human experience, facilitating better therapeutic and analytical applications. Chapter 2 sets a robust foundation for the models and methodologies discussed in subsequent chapters, advocating for a more inclusive and holistic approach to studying emotions.

**Chapter 3**

Similar to a psychometric network model proposed by Lange and colleagues (2020), the integrative approach I propose in Chapter 3 follows the calls to action expressed by Hoemann and colleagues (2023), as well as Westlin and colleagues (2023). The significance of this reconceptualization lies in its ability to transcend traditional boundaries of psychological research, offering a scaffold that supports both mathematical rigor and practical relevance. The mathematical model introduced in Chapter 3 is predicated on this new understanding. By incorporating principles from network theory and systems dynamics, the scaffold provides a structured yet flexible approach to modeling emotional phenomena. This not only facilitates a deeper analytical exploration but also aligns with the multidimensional and interconnected nature of emotions as explored throughout the dissertation.

The mathematical framework captures the multidimensional nature of emotions as defined to be dynamic embedded and embodied phenomena. This aspect is crucial for understanding how emotional states can be represented within a multidimensional topological space, which reflects the complexity and variability of emotional experiences across individuals.

Because dimensionality is directly related to the number of variables required to represent an emotion in a model accurately, a model which allows for higher dimensionality in an empirical dataset can capture more complex interactions and nuances of emotional states. My model leverages the concept of dimensionality by utilizing a manifold structure with emotional states representing points on said manifold. This approach facilitates the identification of underlying patterns and clusters of emotional states, potentially leading to better predictive models of emotional dynamics.

Moreover, this aspect of exploring the dimensionality and possible expansion upon the number of variables which would be feasible to analyze with computational methods such as that described in the Implications section of Chapter 3, an exploration of a simulated dataset or a toy model would be prudent to perform. Toy models are simplified versions of complex systems that are used to understand or demonstrate specific aspects of these systems without the computational overhead or the need for extensive data collection protocol implementation. To that end, I propose developing toy models to illustrate the theoretical principles underpinning our understanding of emotional dynamics. Such a model could serve as a pedagogical tool to explain complex mathematical concepts in an accessible manner, as well as allow for exploration of other aspects of the topological manifold, such as its Riemannian metric, differential equations describing local transition dynamics, or the shape of a local patch on the underlying global space.

As an example, one could simulate emotional transitions on a three- or four-dimensional surface, helping visualize how emotions evolve over time and interact with each other within a controlled environment across variables similar to those described in Chapter 4, or with the inclusion of several dimensions provided by a simulated ECG or EEG recording to allow for analysis of data with greater temporal resolution (such as those described in Chapter 5). This can facilitate a deeper preliminary testing of hypotheses related to the mathematical properties of the model.

Moreover, with the use of a toy model, a deeper integration of dynamics and differential geometry could be carried out to more accurately describe how emotional states evolve and interact over time. Future investigations should focus on dynamic models that not only capture the static positioning of emotions within a manifold but also describe the trajectories emotions follow over time. This involves the use of differential equations to model the temporal changes in emotional states. As stated above, applying differential geometric techniques can provide insights into the curvature and topology of the emotional manifold, offering clues about the global and local properties of emotion dynamics.

Some aspects in which differential geometric analyses could include the exploration of differences between surfaces of manifold projections. Analyses of metrization and characteristics of the spaces could yield meaningful and interpretable results in terms of emotion classification and clustering — for instance, if we are to move away from valence (as called for in Solomon and Stone 2002 or Shuman et al. 2013) as the defining dimension of interest in assessing emotions, the results of any approximation on a manifold may appear erratic to a human interpreter. However, if one were to assume the existence of equivalence relations (and, by extension, equivalence classes) on a manifold approximated from emotion dynamics data, advanced machine learning techniques could be used to estimate classes of emotions based on an aspect unrelated to valence (but founded on a physiological parameter such as the level of fluctuation of a biomarker like testosterone, or the dynamics of arterial blood pressure, or heart rate variability, etc.).

In addition to the identification of equivalence relations (either from toy data, an empirically acquired set, or derived analytically), such analysis could also lend itself to further investigation of quotient spaces of said equivalence classes. As a quotient space is described through the "gluing together" of all points of an equivalence class, this would allow for the modeling of emotion dynamics as more cohesive entities within the manifold. This approach would potentially simplify the complex high-dimensional data into more manageable subspaces, where each subspace represents a unique emotional state or cluster as defined by similar physiological markers.

Furthermore, the quotient spaces could facilitate a deeper understanding of the underlying structure of emotional spaces by reducing dimensionality and highlighting inherent symmetries and patterns in the data. This reduction could make it more feasible to interpret and visualize the connections between various emotional states, thereby providing a clearer map of how emotions transition from one state to another based on underlying physiological changes. The development and application of differential geometric tools to study these quotient spaces could also enhance the precision of emotional classifications. For instance, clustering techniques applied within these spaces could reveal new categories of emotional states that are not readily apparent when using traditional methods. Such classifications could prove invaluable in fields such as psychometrics and affective computing, where accurate emotion recognition is critical.

Moreover, the exploration of these mathematical constructs might lead to novel insights into the stability and variability of emotional states, offering explanations for phenomena such as mood disorders or emotional resilience. By examining how emotional states cluster and transition within these quotient spaces, researchers could develop more targeted interventions that are tailored to the specific emotional dynamics of individuals.

Overall, by advancing the application of differential geometry in emotion research, we can open up new avenues for understanding the complex landscape of human emotions, leading to more effective tools for monitoring, analysis, and intervention in mental health and behavioral sciences.

In practice, these approaches can be particularly useful in creating models that adapt to real-time emotional data, improving the responsiveness and accuracy of systems used in areas such as affective computing and personalized mental health interventions. For instance, a possible application of current research could be envisioned as a mobile or web application which would monitor and collect continuous user data — both verbal inputs of emotion labels and some aspect of physiological or psychological well-being (e.g. through a smart watch device capable of capturing heart rate information via photoplethysmography). This information would then be passed to a back end server with sufficient encryption to protect privacy, and the data could be processed with relation to the topological characteristics of the emotion dynamics submitted by the user.

The interpretation of such application output would, of course, need to be evaluated for suitability for end-user reporting — it could appear prudent to only allow access to manifold information to a healthcare provider trained in the method as a tool for enrichment of mental health interventions. Yet, a realization of such a tool and addition of other wearable technology (such as that called for by Hoemann and colleagues in 2023) could provide a plethora of possibilities for furthering our understanding of emotion dynamics. It would not only refine the theoretical constructs but also enhance the empirical utility of the models through more sophisticated analyses and interpretations.

Overall, the model proposed in Chapter 3 merits further exploration with both simulated and real-world datasets. The reconceptualized approach to emotions as dynamic entities allows for the development of novel approaches to both the psychology and neuroscience of emotion as phenomena inextricably tied to everyday experiences. Thus, ecologically valid paradigms may yield data better suited for complex mathematical analyses such as the one described in the present dissertation.

**Chapter 4**

The practical implications of this theoretical foundation are vividly demonstrated in the experimental design detailed in Chapter 4. The experiment operationalizes the theoretical constructs into a psychometric network model that captures the dynamic interplay between different emotional states as experienced by individuals. This model's implementation showcases the practical utility of my theoretical reconceptualization, allowing for empirical investigations that can adapt to and reflect the nuanced variations in human emotional experiences.

In this chapter, I also demonstrate the feasibility of a computational model which integrates the *dynamicity* and *continuity* of emotions with the verbal labels used in everyday language. I implemented several criteria of emotion as defined in Chapter 2, one of the most important ones being the notion of dynamics *between* emotions. Moreover, the freedom of emotion label choices, opt-in model of data collection by participants who could log their emotion transitions at will, as well as the use of BPSM as the defining experimental paradigm, all aid in aligning this study more closely with that specified by Hoemann and colleagues (2021a). While the number and nature of experimental variables can be augmented in future research, the findings from my proposed UMAP embedding method demonstrate the practical applicability of computational techniques when exploring emotions as continuous phenomena.

Of course, this practical realization of the paradigm may have also lead to certain drawbacks. For instance, the aforementioned model of opt-in data collection may have introduced a selection bias, limiting the diversity and representativeness of the sample in terms of participants' inclination towards introspection and analysis of their own behavioral patterns. Such participants might have been overrepresented, potentially skewing the emotional dynamics explored. Combine that with the challenges faced by the computational model. While it is robust in exploring the continuity and dynamicity of emotions, the analysis of data coming from participants differing in their levels of interoceptive or introspective sensitivity may have lead to errors in handling and interpreting. Moreover, simplifications necessary for computational feasibility might have overlooked subtle yet critical variations in individual patterns of emotion dynamics.

Future research should expand the number and nature of experimental variables, including physiological measures and environmental contexts, to validate and enrich the emotional models further. The introduction of more objective measures not reliant on self-report could aid in eschewing the issue of individual sensitivity mentioned above; moreover, many measures of physiological dynamics allow for greater temporal resolution of collected data, which could greatly improve the basis of computation for algorithms such as UMAP.

It would also be beneficial to investigate the stability and evolution of emotional manifolds over time to determine if these structures are fixed or change with personal development, aging, or changing social attachments. Of course, it would be beneficial to establish a representative sample with a staged study in which participants would fill out questionnaires such as MAIA-2, SRIS, and IRI prior to enrolment could ensure better distribution of scores and an approximate Gaussian distribution to better reflect the general population trends. Recruitment strategies could also be amended to include targeting of older age groups (as the current sample was limited to a narrow range of 22-35 years of age), so that issues such as the bias of aging positivity or youth negativity (see, for example, Carstensen and DeLiema 2018) may be accounted for.

The augmentation of variables can be performed in multiple ways for the exact teleological purpose of the operational research question (see Schiller et al., 2023 for a review of methods teleology). For instance, one could include a variety of trait measurements as "baseline" measures of the participant's degree of awareness in terms of BPSM (or other model's) dimensions — for instance, a measure of emotion expertise (Hoemann et al., 2021) or emotion understanding (Castro et al., 2016) can be invaluable in assessing therapeutic effects in a computational analysis of interrupted time series of emotion transitions.

Further exploration into how different cultural backgrounds and biological markers (such as hormonal levels or heart rate variability) influence emotional manifolds can provide deeper insights into the universal versus culture-specific aspects of emotions. As alluded to in the Discussion section of Chapter 4, possible causal relationships between ethnic background and emotion dynamic factors may well influence the computational analysis at the stage of manifold shape approximation (if a surface such as a sphere or a torus is chosen) or indeed the results of such projection, perhaps due to differences in the sensitivity to interoceptive or introspective aspects, as well as differences in the perception of social phenomena. It is thus imperative to employ more sophisticated tools of analysis of cultural background into the processing of datasets such as that introduced in Chapter 4.

Moreover, the critique aiming at the need to explore equivalence relations and quotient spaces within the manifold points towards an innovative direction for classifying emotions beyond the traditional valence-focused approaches. Such advancements could revolutionize the way we understand and categorize emotions, aligning classifications more closely with physiological indicators rather than solely psychological constructs.

These insights and directions, emerging from the discussions and analyses presented in Chapter 4, not only pave the way for future research but also enhance the practical applications of emotion theory in fields like psychology, affective computing, and personalized therapy.

**Chapter 5**

Moreover, the framework outlined in Chapters 3 and 4 also allows for reliable integration of multimodal data such as those pertaining to physiological variables of interest, such as recordings of brain activity or cardiac rhythms. As I demonstrate in Chapter 5, integration of multimodal information within embodied processes provides surprising insights into the functional connectivity and network architecture of the brain; however, additional measures of a psychometric nature collected from participants simultaneously with the collection of MEG-EEG and other physiological data could elucidate the phenomenon of dynamic emotions even further. A joint study with fMRI and body signal sensing could also illustrate the structural relationships between behavior, body, and social environments.

The data analysis presented in the chapter revealed significant differences in resting-state functional connectivity associated with different phases of the cardiac cycle. This emphasizes the heart-brain interaction and suggests that cardiac cycles may influence brain dynamics. The use of simultaneous recording techniques allowed for a detailed examination of how physiological states, like those during systole and diastole, correlate with changes in network structures within the brain. This demonstrates that the incorporation of multimodal data into complex analytical frameworks yields meaningful results and may be further explored with relation to the manifold approximation method.

That said, the study outlined in Chapter 5 was conducted with a small sample size, which may limit the generalizability of the findings. This small cohort size necessitates cautious interpretation of the data and its applicability to broader populations. It is especially prudent to address the possible influence of individual differences, such as biological sex and age, which may have introduced variability that could affect the consistency of findings across participants. It is worth noting here that individual differences may also be introduced by such parameters as the height of the individual, which would affect the distance between the heart and the brain, and thus the timing of cardiac cycle-related pulsatile activity of cerebral vasculature (see Manea et al. 2015).

Moreover, as was alluded to in Chapter 5, the two separate sources of cardiac artifact are attributed to volume conduction of the electromagnetic field from the heart to the brain (faster transmission typically not exceeding 5 ms) and vascular transfer of wavelike patterns on the order of hundreds of milliseconds (typically 200 ms). However, as described by Debener and colleagues (2010), this time-locked pattern appears to be tied to individual cardiovascular parameters and thus would not affect timing strategies such as that employed in Chapter 5. Nonetheless, differences across participants would be pronounced more if the stability of such cerebrovascular coupling is inconsistent due to age or health parameters.

It is logical to assume that future studies should aim to include a larger and more diverse sample to enhance the robustness and generalizability of the findings. However, the more important aspect of further deepening of the experimental paradigm concerns the exploration of how these patterns of cardiac cycle influence on neurophysiological signals change over longer periods or across different developmental stages. Longitudinal studies could provide deeper insights into the temporal stability of heart-brain interactions.

In contrast, analyses of the existing dataset (as well as other multimodal datasets available in open-source spaces) with respect to intra-subject dynamics could be beneficial for establishment of dynamics in these patterns, too. As the current dataset presents 40 minutes of data recorded in 4 10-minute runs, comparing across these recording snippets could provide insight as to the stability of this heart-brain relationship.

As for the usability of these findings, applying them in clinical settings could allow to test interventions aimed at modulating heart-brain interactions. Possible extension of paradigms might include biofeedback or other techniques to influence cardiac rhythms and observe consequent changes in brain activity, or perhaps a test of existing behavioral breathing interventions (due to the relationship of the cardiac cycle to breathing rate) and subsequent shifts in patterns of frequency band-based changes in brain network dynamics.

Finally, utilizing advanced computational models to analyze the complex datasets could further elucidate the underpinnings of physiological and emotional interactions.

Exploring the role of differential geometry and topological data analysis could provide new methods for classifying and understanding these interactions more deeply. At the mechanistic level of emotion dynamics, the level of resolution provided by neuroimaging and neurophysiological modalities (as well as other modalities of biological sensing) appears to be invaluable for furthering the practical usability of the model in both clinical and research settings.

### General conclusion

This dissertation represents a comprehensive effort to reconceptualize emotions not merely as transient states but as dynamic, continuous phenomena that are deeply embedded within the cultural and social fabric of human experience. By advancing a novel framework that views emotions through the lens of dynamic systems theory, I have demonstrated how such an approach not only addresses but also leverages the complexities inherent in emotional processes to offer richer insights and more robust models.

From the perspective of theoretical significance, I proposed a model that breaks away from traditional, discrete categorizations of emotions, instead presenting them as continuous states within a multidimensional space. This approach aligns better with the fluid and often complex nature of human emotions as they interact with cultural and social dynamics. Moreover, I demonstrated the empirical utility of said model through the integration of multimodal data from physiological signals to behavioral expressions. This provided a robust method to empirically test and validate the theoretical propositions. The method revealed new patterns and connections that were previously obscured by less dynamic models of emotion.

I suggest that further studies using the proposed method should expand the types of data incorporated into the study of emotions. This expansion could include genetic, hormonal, or deeper neurological data which would further elucidate the biological underpinnings of emotion dynamics. As there is a compelling need for longitudinal studies that track emotion dynamics over significant periods, studies conducted over weeks or months with minimal effort required of participants would offer invaluable insights into how emotional landscapes evolve with age, life experiences, or cultural shifts.

I would also like to posit that the models developed here have practical implications for both mental health interventions and the design of affective computing systems. Future work should explore how these models can be operationalized in real-world settings to support emotional well-being and enhance human-computer interaction.

To conclude, my work underscores the importance of considering emotions as complex systems that are integral to human experience and interaction. By adopting this view, we can develop more sensitive and specific tools for understanding and managing emotional states, ultimately leading to better outcomes in both personal and societal contexts. It is my hope that this dissertation will inspire further exploration and innovation at the intersection of emotion research and technology, driving forward our collective understanding of what it means to experience and interpret emotions.

**Appendix A: Table of participant cultural identities in Chapter 4**

| PIN ID | Original Identity as Typed In | Final Categorization |
|---|---|---|
| 93714 | Black | Black |
| 82247 | Luo | Black |
| 40708 | Black american | Black |
| 30680 | Kikuyu | Black |
| 31786 | Kisii | Black |
| 38898 | Black american | Black |
| 13386 | Black | Black |
| 3068 | African american | Black |
| 51018 | White | White |
| 48666 | White | White |
| 95540 | latino | Hispanic |
| 91339 | Native American | Native American |
| 41116 | Black | Black |
| 62658 | N/A | Other |
| 79774 | Black american | Black |
| 502 | Black | Black |

Continued on next page

**Table 1 – continued from previous page**

| PIN ID | Original Identity as Typed In | Final Categorization |
|---|---|---|
| 35052 | Black american | Black |
| 80698 | White caucasian | White |
| 97124 | Black British | Black |
| 81050 | African American | Black |
| 10658 | Afro Carobbean | Black |
| 87753 | African American | Black |
| 10969 | Black american | Black |
| 53512 | Black | Black |
| 41571 | White | White |
| 11891 | Black American | Black |
| 45463 | Middle East | Middle Eastern |
| 91018 | Black British | Black |
| 77420 | Afro Caribbean | Black |
| 86893 | African American | Black |
| 90499 | Black | Black |
| 14380 | Native American | Native American |

Continued on next page

**Table 1 – continued from previous page**

| PIN ID | Original Identity as Typed In | Final Categorization |
|---|---|---|
| 89263 | Black American | Black |
| 62766 | Indian | Asian |
| 54323 | Asian | Asian |
| 17747 | African American | Black |
| 30781 | Black | Black |
| 4528 | Native American | Native American |
| 28903 | Black | Black |
| 52913 | Alaska | Other |
| 88520 | African American | Black |
| 68674 | African American | Black |
| 56571 | Alamba | Black |
| 25206 | Alaska | Other |
| 93465 | Native American | Native American |
| 27406 | American | Other |
| 96921 | African American | Black |
| 09087 | Black American | Black |

Continued on next page

**Table 1 – continued from previous page**

| PIN ID | Original Identity as Typed In | Final Categorization |
|---|---|---|
| 32603 | Alaska | Other |
| 23398 | African American | Black |
| 44576 | African American | Black |
| 53352 | Florida | Other |
| 171 | African American | Black |
| 61463 | N/A | Other |
| 88828 | Black American | Black |
| 87019 | Black American | Black |
| 46166 | Black British African | Black |
| 49198 | Black African | Black |
| 15051 | Black American | Black |
| 89718 | African American | Black |
| 76697 | Asian-American | Asian |
| 57014 | Caucasian | White |
| 35580 | Chinese | Asian |
| 65131 | Caucasian | White |

Continued on next page

**Table 1 – continued from previous page**

| PIN ID | Original Identity as Typed In | Final Categorization |
|---|---|---|
| 96541 | Asian | Asian |
| 63443 | Caucasian | White |
| 69407 | Asian | Asian |
| 77367 | white/caucasian | White |

Table 1: **Participant cultural identities in study conducted in Chapter 4.** Original orthography preserved.

## Appendix B: Questionnaires used in Chapter 4

# Multidimensional Assessment of Interoceptive Awareness

## Version 2
## (MAIA-2)
(2018)

Contact: Wolf E. Mehling, MD
Osher Center for Integrative Medicine
University of California, San Francisco
1545 Divisadero St., 4th floor
San Francisco, CA 94115
Phone: 01 (415) 353 9506
mehlingw@ocim.ucsf.edu
http://www.osher.ucsf.edu/maia/

# MAIA-2

## Multidimensional Assessment of Interoceptive Awareness (Version 2)

### Permission and Copyright



### Scoring Instructions

Take the average of the items on each scale.
**Note: (R): reverse-score (5 – x) items 5, 6, 7, 8, 9 and 10 on Not-Distracting, and items 11, 12 and 15 on Not-Worrying.**

1. **Noticing:** Awareness of uncomfortable, comfortable, and neutral body sensations

   Q1______ + Q2______ + Q3______ + Q4______ / 4 = ___________

2. **Not-Distracting:** Tendency not to ignore or distract oneself from sensations of pain or discomfort

   Q5(**R**)____ + Q6(**R**)____+ Q7(**R**)____+ Q8(**R**)____+Q9(**R**)____+Q10(**R**) / 6 = ___________

3. **Not-Worrying:** Tendency not to worry or experience emotional distress with sensations of pain or discomfort

   Q11(**R**)______ + Q12(**R**)______ + Q13______ + Q14______ + Q15 (**R**) / 5 = ___________

4. **Attention Regulation:** Ability to sustain and control attention to body sensations

   Q16_____ + Q17_____ + Q18_____ + Q19_____ + Q20_____ + Q21_____ + Q22_____ / 7 = ________

5. **Emotional Awareness:** Awareness of the connection between body sensations and emotional states

   Q23_____ + Q24_____ + Q25_____ + Q26_____ + Q27_____ / 5 = ___________

6. **Self-Regulation:** Ability to regulate distress by attention to body sensations

   Q28_____ + Q29_____ + Q30_____ + Q31_____ / 4= ___________

7. **Body Listening:** Active listening to the body for insight

   Q32_____ + Q33_____ + Q34_____ / 3= ___________

8. **Trusting:** Experience of one's body as safe and trustworthy

   Q35_____ + Q36_____ + Q37_____ / 3= ___________

# MAIA-2

**Below you will find a list of statements. Please indicate how often each statement applies to you generally in daily life.**

| . | **Circle one number on each line** | | | | | |
|---|---|---|---|---|---|---|
| | **Never** | | | | | **Always** |
| 1. When I am tense I notice where the tension is located in my body. | 0 | 1 | 2 | 3 | 4 | 5 |
| 2. I notice when I am uncomfortable in my body. | 0 | 1 | 2 | 3 | 4 | 5 |
| 3. I notice where in my body I am comfortable. | 0 | 1 | 2 | 3 | 4 | 5 |
| 4. I notice changes in my breathing, such as whether it slows down or speeds up. | 0 | 1 | 2 | 3 | 4 | 5 |
| 5. I ignore physical tension or discomfort until they become more severe. | 0 | 1 | 2 | 3 | 4 | 5 |
| 6. I distract myself from sensations of discomfort. | 0 | 1 | 2 | 3 | 4 | 5 |
| 7. When I feel pain or discomfort, I try to power through it. | 0 | 1 | 2 | 3 | 4 | 5 |
| 8. I try to ignore pain | 0 | 1 | 2 | 3 | 4 | 5 |
| 9. I push feelings of discomfort away by focusing on something | 0 | 1 | 2 | 3 | 4 | 5 |
| 10. When I feel unpleasant body sensations, I occupy myself with something else so I don't have to feel them. | 0 | 1 | 2 | 3 | 4 | 5 |
| 11. When I feel physical pain, I become upset. | 0 | 1 | 2 | 3 | 4 | 5 |
| 12. I start to worry that something is wrong if I feel any discomfort. | 0 | 1 | 2 | 3 | 4 | 5 |
| 13. I can notice an unpleasant body sensation without worrying about it. | 0 | 1 | 2 | 3 | 4 | 5 |
| 14. I can stay calm and not worry when I have feelings of discomfort or pain. | 0 | 1 | 2 | 3 | 4 | 5 |
| 15. When I am in discomfort or pain I can't get it out of my mind | 0 | 1 | 2 | 3 | 4 | 5 |
| 16. I can pay attention to my breath without being distracted by things happening around me. | 0 | 1 | 2 | 3 | 4 | 5 |
| 17. I can maintain awareness of my inner bodily sensations even when there is a lot going on around me. | 0 | 1 | 2 | 3 | 4 | 5 |
| 18. When I am in conversation with someone, I can pay attention to my posture. | 0 | 1 | 2 | 3 | 4 | 5 |

# MAIA-2

**How often does each statement apply to you generally in daily life? Circle one number on each line**

| | Never | | | | | Always |
|---|---|---|---|---|---|---|
| 19. I can return awareness to my body if I am distracted. | 0 | 1 | 2 | 3 | 4 | 5 |
| 20. I can refocus my attention from thinking to sensing my body. | 0 | 1 | 2 | 3 | 4 | 5 |
| 21. I can maintain awareness of my whole body even when a part of me is in pain or discomfort. | 0 | 1 | 2 | 3 | 4 | 5 |
| 22. I am able to consciously focus on my body as a whole. | 0 | 1 | 2 | 3 | 4 | 5 |
| 23. I notice how my body changes when I am angry. | 0 | 1 | 2 | 3 | 4 | 5 |
| 24. When something is wrong in my life I can feel it in my body. | 0 | 1 | 2 | 3 | 4 | 5 |
| 25. I notice that my body feels different after a peaceful experience. | 0 | 1 | 2 | 3 | 4 | 5 |
| 26. I notice that my breathing becomes free and easy when I feel comfortable. | 0 | 1 | 2 | 3 | 4 | 5 |
| 27. I notice how my body changes when I feel happy / joyful. | 0 | 1 | 2 | 3 | 4 | 5 |
| 28. When I feel overwhelmed I can find a calm place inside. | 0 | 1 | 2 | 3 | 4 | 5 |
| 29. When I bring awareness to my body I feel a sense of calm. | 0 | 1 | 2 | 3 | 4 | 5 |
| 30. I can use my breath to reduce tension. | 0 | 1 | 2 | 3 | 4 | 5 |
| 31. When I am caught up in thoughts, I can calm my mind by focusing on my body/breathing. | 0 | 1 | 2 | 3 | 4 | 5 |
| 32. I listen for information from my body about my emotional state. | 0 | 1 | 2 | 3 | 4 | 5 |
| 33. When I am upset, I take time to explore how my body feels. | 0 | 1 | 2 | 3 | 4 | 5 |
| 34. I listen to my body to inform me about what to do. | 0 | 1 | 2 | 3 | 4 | 5 |
| 35. I am at home in my body. | 0 | 1 | 2 | 3 | 4 | 5 |
| 36. I feel my body is a safe place. | 0 | 1 | 2 | 3 | 4 | 5 |
| 37. I trust my body sensations. | 0 | 1 | 2 | 3 | 4 | 5 |

# Self-reflection and Insight Scale

**(Factors, reverse scoring and scoring instructions shown)**

Please read the following questions and circle the response that indicates the degree to which you agree or disagree with each of the statements. Try to be accurate, but work quite quickly. Do not spend too much time on any question

**THERE ARE NO "WRONG" OR "RIGHT" ANSWERS – ONLY YOUR OWN PERSONAL PERSPECTIVE**

**BE SURE TO ANSWER EVERY QUESTION          ONLY CIRCLE ONE ANSWER FOR EACH QUESTION**

| Item | Factor | Disagree Strongly | Disagree | Disagree Slightly | Agree Slightly | Agree | Agree Strongly |
|---|---|---|---|---|---|---|---|
| **1. I don't often think about my thoughts (R)** | **(E)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **2. I am not really interested in analyzing my behaviour (R)** | **(N)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **3. I am usually aware of my thoughts** | **(I)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **4. I'm often confused about the way that I really feel about things (R)** | **(I)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **5. It is important for me to evaluate the things that I do** | **(N)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **6. I usually have a very clear idea about why I've behaved in a certain way** | **(I)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **7. I am very interested in examining what I think about** | **(N)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **8. I rarely spend time in self-reflection (R)** | **(E)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **9. I'm often aware that I'm having a feeling, but I often don't quite know what it is (R)** | **(I)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **10. I frequently examine my feelings** | **(E)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **11. My behaviour often puzzles me (R)** | **(I)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **12. It is important to me to try to understand what my feelings mean** | **(N)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **13. I don't really think about why I behave in the way that I do (R)** | **(E)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **14. Thinking about my thoughts makes me more confused (R)** | **(I)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **15. I have a definite need to understand the way that my mind works** | **(N)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **16. I frequently take time to reflect on my thoughts** | **(E)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **17. Often I find it difficult to make sense of the way I feel about things (R)** | **(I)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **18. It is important to me to be able to understand how my thoughts arise** | **(N)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **19. I often think about the way I feel about things** | **(E)** | 1 | 2 | 3 | 4 | 5 | 6 |
| **20. I usually know why I feel the way I do** | **(I)** | 1 | 2 | 3 | 4 | 5 | 6 |



E = Engagement in self-reflection: N = Need for self-reflection: I = Insight: R = Reverse scored

Grant, A. M., Franklin, J., & Langford, P. (2002). The Self-reflection and Insight Scale: A new measure of private self-consciousness. Social Behavior and Personality, 30, 821-836. – *Permission is freely granted to use this scale for research and therapeutic/coaching purpose. Commercial use of this*

## Scoring Instructions

**The scoring process is very simple. Summed scores are used. There is no scaling or scale transformation required other than basic reverse scoring for four items.**

**Step 1.**
**Reverse score those items marked (R).**
An original score of "1" would become "6"; "2" would become "5"; "3" becomes "4" and visa versa.

**Step 2.**
**Sum the scores for each subscale**

Engagement in Self-reflection Sub-scale – Items: 1 (R) , 8 (R), 10, 13 (R), 16, 19

N = Need for Self-reflection Sub-scale – Items: 2 (R),  5, 7, 12, 15, 18

I = Insight Sub-scale – Items: 3, 4 (R) , 6, 9 (R), 11 (R), 14 (R), 17 (R), 20

# INTERPERSONAL REACTIVITY INDEX (IRI)

**Reference:**

Davis, M. H. (1980). A multidimensional approach to individual differences in empathy. *JSAS Catalog of Selected Documents in Psychology, 10*, 85.

**Description of Measure:**

Defines empathy as the "reactions of one individual to the observed experiences of another (Davis, 1983)."

28-items answered on a 5-point Likert scale ranging from "Does not describe me well" to "Describes me very well". The measure has 4 subscales, each made up of 7 different items. These subscales are (taken directly from Davis, 1983):

*Perspective Taking* – the tendency to spontaneously adopt the psychological point of view of others

*Fantasy* – taps respondents' tendencies to transpose themselves imaginatively into the feelings and actions of fictitious characters in books, movies, and plays

*Empathic Concern* – assesses "other-oriented" feelings of sympathy and concern for unfortunate others

*Personal Distress* – measures "self-oriented" feelings of personal anxiety and unease in tense interpersonal settings

**Abstracts of Selected Related Articles:**

Davis, M. H. (1983). Measuring individual differences in empathy: Evidence for a multidimensional approach. *Journal of Personality and Social Psychology, 44*, 113–126.

The past decade has seen growing movement toward a view of empathy as a multidimensional construct. The Interpersonal Reactivity Index (IRI; Davis, 1980), which taps four separate aspects of empathy, is described, and its relationships with measures of social functioning, self-esteem, emotionality, and sensitivity to others is assessed. As expected, each of the four subscales displays a distinctive and predictable pattern of relationships with these measures, as well as with previous unidimensional empathy measures. These findings, coupled with the theoretically important relationships existing among the four subscales themselves, provide considerable evidence for a multidimensional approach to empathy in general and for the use of the IRI in particular.

Pulos, S., Elison, J., & Lennon, R. (2004). Hierarchical structure of the Interpersonal Reactivity Index. *Social Behavior and Personality, 32*, 355-360.

The hierarchical factor structure of the Interpersonal Reactivity Index (IRI) (Davis, 1980) inventory was investigated with the Schmid-Leiman orthogonalization procedure (Schmid & Leiman, 1957). The sample consisted of 409 college students. The analysis found that the IRI could be factored into four first-order factors, corresponding to the four scales of the IRI, and two second-order orthogonal factors, a general empathy factor and an emotional control factor.

**Scale (taken from** mailer.fsu.edu/~cfigley/Tests/**IRI**.RTF)**:**

## INTERPERSONAL REACTIVITY INDEX

The following statements inquire about your thoughts and feelings in a variety of situations. For each item, indicate how well it describes you by choosing the appropriate letter on the scale at the top of the page: A, B, C, D, or E. When you have decided on your answer, fill in the letter next to the item number. READ EACH ITEM CAREFULLY BEFORE RESPONDING. Answer as honestly as you can. Thank you.

ANSWER SCALE:

| A | B | C | D | E |
|---|---|---|---|---|
| DOES NOT DESCRIBE ME ME WELL | | | | DESCRIBES VERY WELL |

1. I daydream and fantasize, with some regularity, about things that might happen to me. (FS)

2. I often have tender, concerned feelings for people less fortunate than me. (EC)

3. I sometimes find it difficult to see things from the "other guy's" point of view. (PT) (-)

4. Sometimes I don't feel very sorry for other people when they are having problems. (EC) (-)

5. I really get involved with the feelings of the characters in a novel. (FS)

6. In emergency situations, I feel apprehensive and ill-at-ease. (PD)

7. I am usually objective when I watch a movie or play, and I don't often get completely caught up in it. (FS) (-)

8. I try to look at everybody's side of a disagreement before I make a decision. (PT)

9. When I see someone being taken advantage of, I feel kind of protective towards them. (EC)

10. I sometimes feel helpless when I am in the middle of a very emotional situation. (PD)

11. I sometimes try to understand my friends better by imagining how things look from their perspective. (PT)

12. Becoming extremely involved in a good book or movie is somewhat rare for me. (FS) (-)

13. When I see someone get hurt, I tend to remain calm. (PD) (-)

14. Other people's misfortunes do not usually disturb me a great deal. (EC) (-)

15. If I'm sure I'm right about something, I don't waste much time listening to other people's arguments. (PT) (-)

16. After seeing a play or movie, I have felt as though I were one of the characters. (FS)

17. Being in a tense emotional situation scares me. (PD)

18. When I see someone being treated unfairly, I sometimes don't feel very much pity for them. (EC) (-)

19. I am usually pretty effective in dealing with emergencies. (PD) (-)

20. I am often quite touched by things that I see happen. (EC)

21. I believe that there are two sides to every question and try to look at them both. (PT)

22. I would describe myself as a pretty soft-hearted person. (EC)

23. When I watch a good movie, I can very easily put myself in the place of a leading character. (FS)

24. I tend to lose control during emergencies. (PD)

25. When I'm upset at someone, I usually try to "put myself in his shoes" for a while. (PT)

26. When I am reading an interesting story or novel, I imagine how I would feel if the events in the story were happening to me. (FS)

27. When I see someone who badly needs help in an emergency, I go to pieces. (PD)

28. Before criticizing somebody, I try to imagine how I would feel if I were in their place. (PT)

## Appendix C: Link to the GitHub Repository

Due to a large volume of data from participants in the study in Chapter 4, a GitHub repository was created to ease access to the data: https://github.com/KSalibay/diss-emo-topology-networks-interoception.

In addition to the illustrations of UMAP embeddings across 68 participants (see folder Figures_AppC), the repository also contains examples of the trapezoidal algorithm code for ECG analysis in Chapter 5, as well as the code for the preprocessing pipelines and other miscellaneous code snippets for data analysis.

# BIBLIOGRAPHY


Achaibou, A., Pourtois, G., Schwartz, S., and Vuilleumier, P. (2008). Simultaneous recording of eeg and facial muscle reactions during spontaneous emotional mimicry. *Neuropsychologia*, 46(4):1104–1113.

Adelhöfer, N., Schreiter, M. L., and Beste, C. (2020). Cardiac cycle gated cognitive-emotional control in superior frontal cortices. *NeuroImage*, 221:11718.

Adelmann, P. K. and Zajonc, R. B. (1989). Facial efference and the experience of emotion. *Annual Review of Psychology*, 40(1):249–280.

Adolphs, R. (2016). How should neuroscience study emotions? by distinguishing emotion states, concepts, and experiences. *Social Cognitive and Affective Neuroscience*, 12(1):24–31.

Adolphs, R. and Anderson, D. J. (2018). *The neuroscience of emotion: A new synthesis*. Princeton University Press.

Al, E., Iliopoulos, F., Forschack, N., Nierhaus, T., Grund, M., and Motyka, P. & Villringer, A. (2020). Heart–brain interactions shape somatosensory perception and evoked potentials. *Proceedings of the National Academy of Sciences*, 117(19):10575–10584.

Al, E., Iliopoulos, F., Nikulin, V. V., and Villringer, A. (2021). Heartbeat and somatosensory perception. *Neuroimage*, 238(11824):7.

Al, E., Stephani, T., Engelhardt, M., Haegens, S., Villringer, A., and Nikulin, V. V. (2023). Cardiac activity impacts cortical motor excitability. *PLoS Biology*, 21:11.

Al Zoubi, O., Mayeli, A., Tsuchiyagaito, A., Misaki, M., Zotev, V., Refai, H., Paulus, M., Bodurka, J., and Investigators, T. . (2019). Eeg microstates temporal dynamics differentiate individuals with mood and anxiety disorders from healthy subjects. *Frontiers in human neuroscience*, 13:56.

Arnold, M. B. (1968). *The Nature of Emotion (1st ed.)*. Penguin Books Ltd.

Arnold, M. B. and Gasson, J. A. (1954). Feelings and emotion as dynamic factors in personality integration. In *The Human Person: An Approach to an Integral Theory of Personality*, page 294–313. Ronald.

Association, A. P. (2020). *Publication manual of the American Psychological Association 2020: the official guide to APA style (7th ed.)*. American Psychological Association.

Avery, J. A., Gotts, S. J., Kerr, K. L., Burrows, K., Ingeholm, J. E., Bodurka, J., Martin, A., and Kyle Simmons, W. (2017). Convergent gustatory and viscerosensory processing in the human dorsal mid-insula. *Human Brain Mapping*, 38(4):2150–2164.

Azzalini, D., Rebollo, I., and Tallon-Baudry, C. (2019). Visceral signals shape brain dynamics and cognition. *Trends in cognitive sciences*, 23(6):488–509.

Babo-Rebelo, M., Wolpert, N., Adam, C., Hasboun, D., and Tallon-Baudry, C. (2016). Is the cardiac monitoring function related to the self in both the default network and right anterior insula? *Philosophical Transactions of the Royal Society B: Biological Sciences*, 371(1708):20160004.

Bain, A. (1855). *The senses and the intellect*. John W. Parker and Son.

Bain, A. (1859). *The emotions and the will*. John W. Parker and Son.

Bain, A. (1873). *Mind and body: The theories of their relation*. D. Appleton & Company.

Bard, P. (1928). A diencephalic mechanism for the expression of rage with special reference to the sympathetic nervous system. *American Journal of Physiology*, 84(3):490–515.

Barrett, L. F. (2012). Emotions are real. *Emotion*, 12(3):413–429.

Barrett, L. F. (2016). Functionalism cannot save the classical view of emotion. *Social Cognitive and Affective Neuroscience*, 12(1):34–36.

Barrett, L. F., Adolphs, R., Marsella, S., Martinez, A. M., and Pollak, S. D. (2019). Emotional expressions reconsidered: Challenges to inferring emotion from human facial movements. *Psychological Science in the Public Interest*, 20(1):1–68.

Barrett, L. F., Mesquita, B., Ochsner, K. N., and Gross, J. J. (2007). The experience of emotion. *Annual Review of Psychology*, 58:373–403.

Barrett, L. F. and Satpute, A. B. (2013). Large-scale brain networks in affective and social neuroscience: Towards an integrative functional architecture of the brain. *Current Opinion in Neurobiology*, 23(3):361–372.

Barrett, L. F. and Satpute, A. B. (2019). Historical pitfalls and new directions in the neuroscience of emotion. *Neuroscience Letters*, 693:9–18.

Barrett, L. F. and Simmons, W. K. (2015). Interoceptive predictions in the brain. *Nature Reviews Neuroscience*, 16(7):419–429.

Bassett, D. S., Zurn, P., and Gold, J. I. (2018). On the nature and use of models in network neuroscience. *Nature Reviews Neuroscience*, 19(9):566–578.

Bastiaansen, J. A. C. J., Thioux, M., and Keysers, C. (2009). Evidence for mirror systems in emotions. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1528):2391–2404.

Battiston, F., Guillon, J., Chavez, M., Latora, V., and de Vico Fallani, F. (2018). Multiplex core–periphery organization of the human connectome. *Journal of the Royal Society Interface*, 15(146):20180514.

Bazett, H. C. and Penfield, W. G. (1922). A study of the sherrington decerebrate animal in the chronic as well as the acute condition. *Brain*, 45(2):185–265.

Beaumont, E., Salavatian, S., Southerland, E. M., Vinet, A., Jacquemet, V., Armour, J. A., and Ardell, J. L. (2013). Network interactions within the canine intrinsic cardiac nervous system: implications for reflex control of regional cardiac function. *The Journal of physiology*, 591(18):4515–4533.

Bechterew, W. (1905). Über die sensible und motorische rolle des sehhügels. *European Neurology*, 17(3):224–231.

Bell, S. C. (1806). *Essays on the anatomy of expression in painting*. Longman, Hurst, Rees, and Orme.

Benedict, C., Hahn, A. L., Diefenbach, M. A., and Ford, J. S. (2019). Recruitment via social media: advantages and potential biases. *Digital health*, 5(2055207619867223).

Berent, I., Barrett, L. F., and Platt, M. (2019). *Essentialist biases in reasoning about emotions*. Center for Open Science.

Berger, H. (1935). Über das elektrenkephalogramm des menschen. *Archiv Für Psychiatrie Und Nervenkrankheiten*, 103(1):444–454.

Bernard, C. (1878). *Leçons sur les phénomènes de la vie communs aux animaux et aux végétaux*. J.-B. Baillière et fils.

Berntson, G. G. and Khalsa, S. S. (2021). Neural circuits of interoception. *Trends in neurosciences*, 44(1):17–28.

Berrios, R. (2019). What is complex/emotional about emotional complexity? *Frontiers in psychology*, 10:428224.

Bhole, L. and Ingle, M. (2019). Eeg based emotion classification using nonlinear features. *International Journal of Research in Advent Technology*, 7(5):628–635.

Birznieks, I., Boonstra, T. W., and Macefield, V. G. (2012). Modulation of human muscle spindle discharge by arterial pulsations - functional effects and consequences. *PLoS ONE*, 7(4):e35091.

Boddice, R. (2017). *The history of emotions*. Manchester University Press.

Boddice, R. (2020). History looks forward: Interdisciplinarity and critical emotion research. *Emotion Review*, 12(3):131–134.

Boiger, M., Ceulemans, E., De Leersnyder, J., Uchida, Y., Norasakkunkit, V., and Mesquita, B. (2018). Beyond essentialism: Cultural differences in emotions revisited. *Emotion*, 18(8):1142.

Bolger, N. and Laurenceau, J. P. (2013). *Intensive longitudinal methods: An introduction to diary and experience sampling research*. Guilford press.

Borgatti, S. P. and Everett, M. G. (2000). Models of core/periphery structures. *Social networks*, 21(4):375–395.

Brookes, M. J., Woolrich, M. W., and Barnes, G. R. (2012). Measuring functional connectivity in meg: A multivariate approach insensitive to linear source leakage. *NeuroImage*, 63(2):910–920.

Busch, E. L., Huang, J., Benz, A., Wallenstein, T., Lajoie, G., Wolf, G., and Turk-Browne, N. (2023). Multi-view manifold learning of human brain-state trajectories. *Nature computational science*, 3(3):240–253.

Buzsáki, G., Anastassiou, C. A., and Koch, C. (2012). The origin of extracellular fields and currents — eeg, ecog, lfp and spikes. *Nature Reviews Neuroscience*, 13(6):407–420.

Buzsáki, G. and Draguhn, A. (2004). Neuronal oscillations in cortical networks. *Science*, 304(5679):1926–1929.

Cabral, J., Luckhoo, H., Woolrich, M., Joensson, M., Mohseni, H., Baker, A., Kringelbach, M. L., and Deco, G. (2014). Exploring mechanisms of spontaneous functional connectivity in meg: how delayed network interactions lead to structured amplitude envelopes of band-pass filtered oscillations. *Neuroimage*, 90:423–435.

Calvo, R. A. and D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Transactions on affective computing*, 1(1):18–37.

Candia-Rivera, D., Catrambone, V., Valenza, G., and Lanata, A. (2021). The role of electroencephalography electrical reference in the assessment of functional brain–heart interplay: From methodology to user guidelines. *Journal of Neuroscience Methods*, 353:10908.

Canli, T. and Amin, Z. (2002). Neuroimaging of emotion and personality: Scientific evidence and ethical considerations. *Brain and cognition*, 50(3):414–431.

Cannon, W. B. (1926). Physiological regulation of normal states: some tentative postulates concerning biological homeostatics. In Pettit, A., editor, *A Charles Richet: ses amis, ses collègues, ses élèves*. Les Éditions Médicales.

Cannon, W. B. (1927). The james-lange theory of emotions: A critical examination and an alternative theory. *The American journal of psychology*, 39(1/4):106–124.

Cannon, W. B. (1931). Again the james-lange and the thalamic theories of emotion. *Psychological Review*, 38(4):281.

Carstensen, L. L. and DeLiema, M. (2018). The positivity effect: A negativity bias in youth fades with age. *Current opinion in behavioral sciences*, 19:7–12.

Castro, V. L., Cheng, Y., Halberstadt, A. G., and Grühn, D. (2016). Eureka! a conceptual model of emotion understanding. *Emotion Review*, 8(3):258–268.

Cechetto, D. F. and Saper, C. B. (1987). Evidence for a viscerotopic sensory representation in the cortex and thalamus in the rat. *Journal of Comparative Neurology*, 262(1):27–45.

Chang, C., Metzger, C. D., Glover, G. H., Duyn, J. H., Heinze, H.-J., and Walter, M. (2013). Association between heart rate variability and fluctuations in resting-state functional connectivity. *Neuroimage*, 68:93–104.

Chang, Y., Hu, C., Feris, R., and Turk, M. (2006). Manifold based analysis of facial expression. *Image and Vision Computing*, 24(6):605–614.

Chen, C. N. H. C. H. and Chung, H. Y. (2004). The review of applications and measurements in facial electromyography. *Journal of Medical and Biological Engineering*, 25(1):15–20.

Chouchou, F., Mauguière, F., and Mazzola, L. (2023). Central control of cardiac activity as assessed by intra-cerebral recordings and stimulations. *Neurophysiologie Clinique*, 53(1):27–34.

Choudhury, S. and Slaby, J. (2011). Introduction: Critical neuroscience—between lifeworld and laboratory. In *Critical neuroscience: A handbook of the social and cultural contexts of neuroscience*, pages 1–26. Wiley.

Choudhury, S. and Slaby, J., editors (2016). *Critical neuroscience: A handbook of the social and cultural contexts of neuroscience*. John Wiley & Sons.

Clark, J. E., Watson, S., and Friston, K. J. (2018). What is mood? a computational perspective. *Psychological medicine*, 48(14):2277–2284.

Coan, J. A. and Allen, J. J. B. E. (2007). *Handbook of emotion elicitation and assessment*. Oxford University Press.

Coll, M.-P., Hobson, H., Bird, G., and Murphy, J. (2021). Systematic review and meta-analysis of the relationship between the heartbeat-evoked potential and interoception. *Neuroscience & Biobehavioral Reviews*, 122:190–200.

Contreras-Rodríguez, O., Cano, M., Vilar-López, R., Rio-Valle, J. S., Verdejo-Román, J., Navas, J. F., Martín-Pérez, C., et al. (2019). Visceral adiposity and insular networks: associations with food craving. *International Journal of Obesity*, 43(3):503–511.

Cooper, S. J. (2008). From claude bernard to walter cannon. emergence of the concept of homeostasis. *Appetite*, 51(3):419–427.

Corsi, M.-C., Chavez, M., Schwartz, D., George, N., Hugueville, L., Kahn, A. E., Dupont, S., Bassett, D. S., and Fallani, F. D. V. (2021). Bci learning induces core-periphery reorganization in m/eeg multiplex brain networks. *Journal of Neural Engineering*, 18(5):056002.

Cory, G. A. (2003). Maclean's evolutionary neuroscience and the conflict systems neurobehavioral model: Some clinical and social policy implications. *In Human Nature and Public Policy (p*, 161.

Coutinho, E., Gentsch, K., van Peer, J., Scherer, K. R., and Schuller, B. W. (2018). Evidence of emotion-antecedent appraisal checks in electroencephalography and facial electromyography. *PLOS ONE*, 13(1):e0189367.

Couto, B., Adolfi, F., Velasquez, M., Mesow, M., Feinstein, J., Canales-Johnson, A., Mikulan, E., et al. (2015). Heart evoked potential triggers brain responses to natural affective scenes: a preliminary study. *Autonomic Neuroscience*, 193:132–137.

Cowen, A. S. and Keltner, D. (2021). Semantic space theory: A computational approach to emotion. *Trends in Cognitive Sciences*, 25(2):124–136.

Critchley, H. D. and Garfinkel, S. N. (2017). Interoception and emotion. *Current opinion in psychology*, 17:7–14.

Critchley, H. D., Wiens, S., Rotshtein, P., Öhman, A., and Dolan, R. J. (2004). Neural systems supporting interoceptive awareness. *Nature neuroscience*, 7(2):189–195.

Dale, A. M., Liu, A. K., Fischl, B. R., Buckner, R. L., Belliveau, J. W., Lewine, J. D., and Halgren, E. (2000). Dynamic statistical parametric mapping: combining fmri and meg for high-resolution imaging of cortical activity. *Neuron*, 26(1):55–67.

Dalmia, A. and Sia, S. (2021). Clustering with umap: Why and how connectivity matters. arxiv. preprint.

Damasio, A. R. (1994). *Descartes' Error: Emotion, Reason, and the Human Brain.* Avon Books, New York.

Damasio, A. R. (2003). *Looking for Spinoza: Joy, sorrow, and the feeling brain.* Houghton Mifflin Harcourt.

Damasio, A. R. (2005). *Descartes' error: Emotion, reason, and the human brain.* Penguin.

Damoiseaux, J. S., Rombouts, S. A., Barkhof, F., Scheltens, P., Stam, C. J., Smith, S. M., and Beckmann, C. F. (2006). Consistent resting-state networks across healthy subjects. In *Proceedings of the national academy of sciences*, pages 13848–13853. 103(37.

Darwin, C. (1871). *The Descent of man.* D. Appleton & Company.

Darwin, C. (1872). *The expression of the emotions in man and animals.* John Murray.

David, O., Cosmelli, D., and Friston, K. J. (2004). Evaluation of different measures of functional connectivity using a neural mass model. *Neuroimage*, 21(2):659–673.

Davidson, R. J., Jackson, D. C., and Kalin, N. H. (2000). Emotion, plasticity, context, and regulation: Perspectives from affective neuroscience. *Psychological Bulletin*, 126(6):890–909.

Davies, K. J. A. (2016). Adaptive homeostasis. *Molecular Aspects of Medicine*, 49:1–7.

Davis, M. H. (1980). *Interpersonal Reactivity Index (IRI) [Database record].* APA PsycTests.

Davitz, J. R. (1969). *The Language of Emotion.* Academic Press.

de Cyon, E. (1873). *Principes d'électrothérapie.* Baillière.

De Pasquale, F., Corbetta, M., Betti, V., and Della Penna, S. (2018). Cortical cores in network dynamics. *Neuroimage*, 180(Part B):370–382.

De Pasquale, F., Penna, D., S., S., O., R., L., G., and Corbetta, M. (2016). A dynamic core network and global efficiency in the resting human brain. *Cerebral Cortex*, 26(10):4015–4033.

Debener, S., Kranczioch, C., and Gutberlet, I. (2010). Eeg quality: origin and reduction of the eeg cardiac-related artefact. *EEG-FMRI: Physiological basis, technique, and applications*, pages 135–151.

Dejonckheere, E., Mestdagh, M., Houben, M., Rutten, I., Sels, L., Kuppens, P., and Tuerlinckx, F. (2019). Complex affect dynamics add limited information to the prediction of psychological well-being. *Nature human behaviour*, 3(5):478–491.

Delis, I., Chen, C., Jack, R. E., Garrod, O. G., Panzeri, S., and Schyns, P. G. (2016). Space-by-time manifold representation of dynamic facial expressions for emotion categorization. *Journal of Vision*, 16(8):14–14.

Delplanque, S. and Sander, D. (2021). A fascinating but risky case of reverse inference: From measures to emotions! *Food Quality and Preference*, 92(104183).

Desmidt, T., Lemoine, M., Belzung, C., and Depraz, N. (2014). The temporal dynamic of emotional emergence. *Phenomenology and the Cognitive Sciences*, 13(4):557–578.

Destrieux, C., Fischl, B., Dale, A., and Halgren, E. (2010). Automatic parcellation of human cortical gyri and sulci using standard anatomical nomenclature. *Neuroimage*, 53(1):1–15.

Diaz, B. A., Sluis, V. D., S., M., S., B., J. S., M., F., S., D., D. B., A., P., S. S., H., R., Van't Ent, D., and Boomsma, D. I. (2013). The amsterdam resting-state questionnaire reveals multiple phenotypes of resting-state cognition. *Frontiers in human neuroscience*, 7:446.

Dimberg, U. (1990). Facial electromyographic reactions and autonomic activity to auditory stimuli. *Biological psychology*, 31(2):137–147.

Dimberg, U. and Thunberg, M. (2012). Empathy, emotional contagion, and rapid facial reactions to angry and happy facial expressions. *PsyCh Journal*, 1(2):118–127.

Dror, O. E. (2001). Techniques of the brain and the paradox of emotions, 1880–1930. *Science in Context*, 14:04.

Dror, O. Y. (1999). The scientific image of emotion: Experience and technologies of inscription. *Configurations*, 7(3):355–401.

Duchenne, G.-B. (1862). *Mécanisme de la physionomie humaine, ou, Analyse électro-physiologique de l'expression des passions*. Jules Renouard.

Duchenne, G.-B. (2006). *The mechanism of human facial expression (R.* A. Cuthbertson, Trans.). Cambridge University Press.

Duffy, E. (1941). An explanation of "emotional" phenomena without the use of the concept "emotion". *The Journal of General Psychology*, 25(2):283–293.

Eisler, H., Eisler, A. D., and Hellstrom, A. (2008). Psychophysical issues in the study of time perception. *Psychology of time*, 1:75–110.

Ekman, P. (1973). Universal facial expressions in emotion. *Studia Psychologica*, 15(2):140–147.

Ekman, P. (1999). Basic emotions. In Dalgleish, T. and Power, M. J., editors, *Handbook of Cognition and Emotion*. John Wiley & Sons, Ltd.

Ekman, P. (2018). How emotions might work. In Fox, A. S., Lapate, R. C., Shackman, A. J., and Davidson, R. J., editors, *The Nature of Emotion: Fundamental Questions*. Oxford University Press.

Ekman, P. and Friesen, W. V. (1971). Constants across cultures in the face and emotion. *Journal of personality and social psychology*, 17(2):124.

Ekman, P. and Friesen, W. V. (1978). *Facial action coding system*. PsycTESTS Dataset.

Ekman, P. and Heider, K. G. (1988). The universality of a contempt expression: A replication. *Motivation and emotion*, 12(3):303–308.

Engel, A. K. and Fries, P. (2010). Beta-band oscillations—signalling the status quo? *Current opinion in neurobiology*, 20(2):156–165.

Engel, G. L. (1977). The need for a new medical model: a challenge for biomedicine. *Science*, 196(4286):129–136.

Erickson, K. and Schulkin, J. (2003). Facial expressions of emotion: a cognitive neuroscience perspective. *Brain and Cognition*, 52(1):52–60.

Escofier, B. and Pagès, J. (1994). Multiple factor analysis (afmult package). *Computational Statistics and Data Analysis*, 18:121–140.

Fardo, F., Vinding, M. C., Allen, M., Jensen, T. S., and Finnerup, N. B. (2017). Delta and gamma oscillations in operculo-insular cortex underlie innocuous cold thermosensation. *Journal of Neurophysiology*, 117(5):1959–1968.

Favela, L. H. (2020). Dynamical systems theory in cognitive science and neuroscience. *Philosophy Compass*, 15(8):e12695.

Feldman, M. J., Siegel, E., Barrett, L. F., Quigley, K. S., and Wormwood, J. B. (2022). Affect and social judgment: The roles of physiological reactivity and interoceptive sensitivity. *Affective Science*, 3(2):464–479.

Ferri, R., Rundo, F., Bruni, O., Terzano, M. G., and Stam, C. J. (2008). The functional connectivity of different eeg bands moves towards small-world network organization during sleep. *Clinical Neurophysiology*, 119(9):2026–2036.

Field, D. T. and Inman, L. A. (2014). Weighing brain activity with the balance: a contemporary replication of angelo mosso's historical experiment. *Brain*, 137(2):634–639.

Fischl, B., Van Der Kouwe, A., Destrieux, C., Halgren, E., Ségonne, F., Salat, D. H., Busa, E., Seidman, L. J., Goldstein, J., Kennedy, D., et al. (2004). Automatically parcellating the human cerebral cortex. *Cerebral cortex*, 14(1):11–22.

Ford, D. H. and Lerner, R. M. (1992). *Developmental systems theory: An integrative approach*. SAGE Publications, Incorporated.

Ford, T. W. and Kirkwood, P. A. (2018). Cardiac modulation of alpha motoneuron discharges. *Journal of Neurophysiology*, 119(5):1723–1730.

Foundation, N. S. (2018). Science and engineering indicators 2018. Technical report, National Science Foundation.

Fox, A. S., Lapate, R. C., Shackman, A. J., and Davidson, R. J. (2018). *The nature of emotion: Fundamental questions*. Oxford University Press.

Freitas-Magalhães, A. (2021). *Facial Action Coding System 4.0 - Manual of Scientific Codification of the Human Face (42nd ed.)*. Leya.

Fridlund, A. J. (1991). Evolution and facial action in reflex, social motive, and paralanguage. *Biological psychology*, 32(1):3–100.

Fridlund, A. J. and Cacioppo, J. T. (1986). Guidelines for human electromyographic research. *Psychophysiology*, 23(5):567–589.

Furedy, J. J., Shulhan, D. L., and Scher, H. (1986). Effects of electrode placement on direction of t-wave amplitude changes in psychophysiological studies. *Physiology & behavior*, 36(5):983–986.

Gao, Y., Sun, X., Meng, M., and Zhang, Y. (2022). Eeg emotion recognition based on enhanced spd matrix and manifold dimensionality reduction. *Computers in biology and medicine*, 146:105606.

Garcia-Casado, J., Martinez-de Juan, J. L., and Ponce, J. L. (2003). Effect of abdominal layers on surface electroenterogram spectrum. In *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE Cat No.03CH37439)*.

Geary, J. W. (2002). *The evolutionary neuroethology of Paul MacLean: Convergences and frontiers*. Greenwood Publishing Group.

Gendron, M., Mesquita, B., and Barrett, L. F. (2020). The brain as a cultural artifact: Concepts, actions, and experiences within the human affective niche. In Kirmayer, L. J., Worthman, C. M., Kitayama, S., Lemelson, R., and Cummings, C., editors, *Culture, mind, and brain: Emerging concepts, models, and applications*. Cambridge University Press.

Gera, R., Alonso, L., Crawford, B., House, J., Mendez-Bermudez, J. A., Knuth, T., and Miller, R. (2018). Identifying network structure similarity using spectral graph theory. *Applied network science*, 3(1):1–15.

Gerrards-Hesse, A., Spies, K., and Hesse, F. W. (1994). Experimental inductions of emotional states and their effectiveness: A review. *British journal of psychology*, 85(1):55–78.

Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., et al. (2013). Meg and eeg data analysis with mne-python. *Frontiers in neuroscience*, 7:70133.

Grant, A. M., Franklin, J., and Langford, P. (2002). The self-reflection and insight scale: A new measure of private self-consciousness. *Social Behavior and Personality: an international journal*, 30(8):821–835.

Griffiths, P. and Hochman, A. (2015). Developmental systems theory. *eLS*, pages 1–7.

Griffiths, P. E. and Scarantino, A. (2008). Emotions in the wild: The situated perspective on emotion. In *The Handbook of Situated Cognition*. Cambridge University Press, Cambridge.

Gross, C. T. and Canteras, N. S. (2012). The many paths to fear. *Nature Reviews Neuroscience*, 13(9):651–658.

Gross, D. M. (2008). *The Secret History of Emotion: From Aristotle's Rhetoric to modern brain science*. University of Press, Chicago.

Gross, J., Baillet, S., Barnes, G. R., Henson, R. N., Hillebrand, A., Jensen, O., Jerbi, K., et al. (2013). Good practice for conducting and reporting meg research. *Neuroimage*, 65:349–363.

Gross, J. J. (1998). The emerging field of emotion regulation: An integrative review. *Review of General Psychology*, 2(3):271–299.

Gruzelier, J. (2009). A theory of alpha/theta neurofeedback, creative performance enhancement, long distance functional connectivity and psychological integration. *Cognitive Processing*, 10(S1):S101–S109.

Grühn, D., Lumley, M. A., Diehl, M., and Labouvie-Vief, G. (2013). Time-based indicators of emotional complexity: interrelations and correlates. *Emotion*, 13(2):226.

Hamaker, E. L., Ceulemans, E., Grasman, R. P. P. P., and Tuerlinckx, F. (2015). Modeling affect dynamics: State of the art and future challenges. *Emotion Review*, 7(4):316–322.

Hammer, M., Schwale, C., Brankačk, J., Draguhn, A., and Tort, A. B. (2021). Theta-gamma coupling during rem sleep depends on breathing rate. *Sleep*, 44:12.

Harari, G. M., Müller, S. R., Aung, M. S., and Rentfrow, P. J. (2017). Smartphone sensing methods for studying behavior in everyday life. *Current opinion in behavioral sciences*, 18:83–90.

Hari, R., Baillet, S., Barnes, G., Burgess, R., Forss, N., Gross, J., Hämäläinen, M., Jensen, O., Kakigi, R., Mauguière, F., et al. (2018). Ifcn-endorsed practical guidelines for clinical magnetoencephalography (meg). *Clinical Neurophysiology*, 129(8):1720–1747.

Hari, R. and Puce, A. (2023). *Meg-EEG Primer*. Oxford University Press.

Harrison, N. A., Gray, M. A., Gianaros, P. J., and Critchley, H. D. (2010). The embodiment of emotional feelings in the brain. *Journal of Neuroscience*, 30(38):12878–12884.

Hashimoto, T., Kitajo, K., Kajihara, T., Ueno, K., Suzuki, C., Asamizuya, T., and Iriki, A. (2015). Neural correlates of electrointestinography: Insular activity modulated by signals recorded from the abdominal surface. *Neuroscience*, 289:1–8.

Hauk, O., Stenroos, M., and Treder, M. (2019). Towards an objective evaluation of eeg/meg source estimation methods: The linear tool kit. *BioRxiv*, 672956.

Head, H. and Holmes, G. (1911). Sensory disturbances from cerebral lesions. *Brain*, 34(2-3):102–254.

Hejjel, L. and Roth, E. (2004). What is the adequate sampling interval of the ecg signal for heart rate variability analysis in the time domain? *Physiological measurement*, 25(6):1405.

Hektner, J. M., Schmidt, J. A., and Csikszentmihalyi, M. (2007). *Experience sampling method: Measuring the quality of everyday life*. Sage.

Heller, M., LeDoux, J., Debiec, J., and Brozek, B. (2014). *The Emotional Brain Revisited*. Copernicus Center Press.

Hess, U., Arslan, R., Mauersberger, H., Blaison, C., Dufner, M., Denissen, J. J. A., and Ziegler, M. (2016). Reliability of surface facial electromyography. *Psychophysiology*, 54(1):12–23.

Hess, U. and Blairy, S. (2001). Facial mimicry and emotional contagion to dynamic emotional facial expressions and their influence on decoding accuracy. *International journal of psychophysiology*, 40(2):129–141.

Hess, U., Kappas, A., McHugo, G. J., Lanzetta, J. T., and Kleck, R. E. (1992). The facilitative effect of facial expression on the self-generation of emotion. *International Journal of Psychophysiology*, 12(3):251–265.

Hilz, M. J., Dütsch, M., Perrine, K., Nelson, P. K., Rauhut, U., and Devinsky, O. (2001). Hemispheric influence on autonomic modulation and baroreflex sensitivity. *Annals of neurology*, 49(5):575–584.

Hipp, J. F., Hawellek, D. J., Corbetta, M., Siegel, M., and Engel, A. K. (2012). Large-scale cortical correlation structure of spontaneous oscillatory activity. *Nature Neuroscience*, 15(6):884–890.

Hoemann, K., Barrett, L. F., and Quigley, K. S. (2021a). Emotional granularity increases with intensive ambulatory assessment: Methodological and individual factors influence how much. *Frontiers in psychology*, 12(70412):5.

Hoemann, K., Nielson, C., Yuen, A., Gurera, J. W., Quigley, K. S., and Barrett, L. F. (2021b). Expertise in emotion: A scoping review and unifying framework for individual differences in the mental representation of emotional experience. *Psychological Bulletin*, 147(11):1159.

Hoemann, K., Wormwood, J. B., Barrett, L. F., and Quigley, K. S. (2023). Multimodal, idiographic ambulatory sensing will transform our understanding of emotion. *Affective Science*, 4(3):480–486.

Honey, C. J., Thesen, T., Donner, T. H., Silbert, L. J., Carlson, C. E., Devinsky, O., Doyle, W. K., Rubin, N., Heeger, D. J., and Hasson, U. (2012). Slow cortical dynamics and the accumulation of information over long timescales. *Neuron*, 76(2):423–434.

Honnibal, M. and Montani, I. (2017). *spaCy 2: Natural language understanding with Bloom embeddings, convolutional neural networks and incremental parsing*. To appear.

Hoshi, H. and Shigihara, Y. (2020). Age-and gender-specific characteristics of the resting-state brain activity: a magnetoencephalography study. *Aging (Albany NY)*, 12(21):21613.

Hua, Y., Zhong, X., Zhang, B., Yin, Z., and Zhang, J. (2021). Manifold feature fusion with dynamical feature selection for cross-subject emotion recognition. *Brain Sciences*, 11(11):1392.

Iadecola, C. (2017). The neurovascular unit coming of age: A journey through neurovascular coupling in health and disease. *Neuron*, 96(1):17–42.

Iandolo, R., Semprini, M., Sona, D., Mantini, D., Avanzino, L., and Chiappalone, M. (2021). Investigating the spectral features of the brain meso-scale structure at rest. *Human Brain Mapping*, 42(15):5113–5129.

Icenhour, A., Witt, S. T., Elsenbruch, S., Lowén, M., Engström, M., Tillisch, K., Mayer, E. A., and Walter, S. (2017). Brain functional connectivity is associated with visceral sensitivity in women with irritable bowel syndrome. *NeuroImage: Clinical*, 15:449–457.

Irimia, A., Chambers, M. C., Torgerson, C. M., and Van Horn, J. D. (2012). Circular representation of human cortical networks for subject and population-level connectomic visualization. *Neuroimage*, 60(2):1340–1351.

Jackson, J. C., Watts, J., Henry, T. R., List, J.-M., Forkel, R., Mucha, P. J., Greenhill, S. J., Gray, R. D., and Lindquist, K. A. (2019). Emotion semantics show both cultural variation and universal structure. *Science*, 366(6472):1517–1522.

James, W. (1884). What is an emotion? *Mind, os-IX(*, 34:188–205.

Janbakhshi, P. and Shamsollahi, M. B. (2018). Ecg-derived respiration estimation from single-lead ecg using gaussian process and phase space reconstruction methods. *Biomedical Signal Processing and Control*, 45:80–90.

Jas, M., Engemann, D. A., Bekhti, Y., Raimondo, F., and Gramfort, A. (2017). Autoreject: Automated artifact rejection for meg and eeg data. *NeuroImage*, 159:417–429.

Jaušovec, N. and Jaušovec, K. (2010). Resting brain activity: differences between genders. *Neuropsychologia*, 48(13):3918–3925.

Jaworski, W. (2017). Mind-body theories and the emotions. In Naar, H. and Teroni, F., editors, *The Ontology of Emotions*. Cambridge University Press.

Jebb, A. T., Tay, L., Wang, W., and Huang, Q. (2015). Time series analysis for psychological research: examining and forecasting change. *Frontiers in psychology*, 6(14457):5.

Jensen, O. and Colgin, L. L. (2007). Cross-frequency coupling between neuronal oscillations. *Trends in Cognitive Sciences*, 11(7):267–269.

Jensen, O. and Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: gating by inhibition. *Frontiers in human neuroscience*, 4:186.

Jeub, L. G., Sporns, O., and Fortunato, S. (2018). Multiresolution consensus clustering in networks. *Scientific reports*, 8(1):3259.

Ji, L. J., Guo, T., Zhang, Z., and Messervey, D. (2009). Looking into the past: cultural differences in perception and representation of past information. *Journal of personality and social psychology*, 96(4):761.

Joshi, V. M. and Ghongade, R. B. (2021). Eeg based emotion detection using fourth order spectral moment and deep learning. *Biomedical Signal Processing and Control*, 68(10275):5.

Kano, M., Muratsubaki, T., Yagihashi, M., Morishita, J., Mugikura, S., Dupont, P., Takase, K., Kanazawa, M., Van Oudenhove, L., and Fukudo, S. (2019). Insula activity to visceral stimulation and endocrine stress responses as associated with alexithymia in patients with irritable bowel syndrome. *Psychosomatic Medicine*, 82(1):29–38.

Karatsoreos, I. N. and McEwen, B. S. (2011). Psychobiological allostasis: Resistance, resilience and vulnerability. *Trends in Cognitive Sciences*, 15(12):576–584.

Kastaun, S., Gerriets, T., Tschernatsch, M., Yeniguen, M., and Juenemann, M. (2016). Psychosocial and psychoneuroendocrinal aspects of takotsubo syndrome. *Nature Reviews Cardiology*, 13(11):688–694.

Kehri, V., Ingle, R., Patil, S., and Awale, R. N. (2019). Analysis of facial emg signal for emotion recognition using wavelet packet transform and svm. In *Machine intelligence and signal analysis*, pages 247–257. Springer Singapore.

King, D. B., O'Rourke, N., and DeLongis, A. (2014). Social media recruitment and online data collection: A beginner's guide and best practices for accessing low-prevalence and hard-to-reach populations. *Canadian Psychology/Psychologie canadienne*, 55(4):240.

Kleckner, I. R., Zhang, J., Touroutoglou, A., Chanes, L., Xia, C., Simmons, W. K., Quigley, K. S., Dickerson, B. C., and Barrett, L. F. (2017). Evidence for a large-scale brain system supporting allostasis and interoception in humans. *Nature human behaviour*, 1(5):0069.

Kleinginna Jr, P. R. and Kleinginna, A. M. (1981a). A categorized list of emotion definitions, with suggestions for a consensual definition. *Motivation and emotion*, 5(4):345–379.

Kleinginna Jr, Paul, R. and Kleinginna, A. M. (1981b). A categorized list of emotion definitions, with suggestions for a consensual definition. *Motivation and emotion*, 5(4):345–379.

Knief, U. and Forstmeier, W. (2021). Violating the normality assumption may be the lesser of two evils. *Behavior Research Methods*, 53(6):2576–2590.

Kreibig, S. D., Samson, A. C., and Gross, J. J. (2013). The psychophysiology of mixed emotional states. *Psychophysiology*, 50(8):799–811.

Kuang, B., Li, X., Li, X., Lin, M., Liu, S., and Hu, P. (2021). The effect of eye gaze direction on emotional mimicry: A multimodal study with electromyography and electroencephalography. *NeuroImage*, 226(11760):4.

Kunzendorf, S., Klotzsche, F., Akbal, M., Villringer, A., Ohl, S., and Gaebler, M. (2019). Active information sampling varies across the cardiac cycle. *Psychophysiology*, 56(5):e13322.

Kuppens, P. (2015). It's about time: A special section on affect dynamics. *Emotion Review*, 7(4):297–300.

Kövecses, Z. (2018). Metaphor, cognition, culture. In *Handbook of Advances in Culture and Psychology*. Routledge.

Lakoff, G. and Johnson, M. (1980). *Metaphors we live by*. University of Chicago Press.

Lange, C. G. and James, W. (1922). *The emotions*. Williams & Wilkins Co.

Lange, J., Dalege, J., Borsboom, D., van Kleef, G. A., and Fischer, A. H. (2020). Toward an integrative psychometric model of emotions. *Perspectives on Psychological Science*, 15(2):444–468.

Larra, M. F., Finke, J. B., Wascher, E., and Schächinger, H. (2020). Disentangling sensorimotor and cognitive cardioafferent effects: A cardiac-cycle-time study on spatial stimulus-response compatibility. *Scientific Reports*, 10(1):4059.

Larson, R. and Csikszentmihalyi, M. (2014). The experience sampling method. *Flow and the foundations of positive psychology: The collected works of Mihaly Csikszentmihalyi*, pages 21–34.

Larsson, M. B. O., Tillisch, K., Craig, A. D., Engström, M., Labus, J., Naliboff, B., Lundberg, P., Ström, M., Mayer, E. A., and Walter, S. A. (2012). Brain responses to visceral stimuli reflect visceral sensitivity thresholds in patients with irritable bowel syndrome. *Gastroenterology*, 142(3):463–472.

Ledoux, J. (1998). *The Emotional Brain: The mysterious underpinnings of emotional life*. Simon & Schuster.

LeDoux, J. (2012). Rethinking the emotional brain. *Neuron*, 73(5):1052.

LeDoux, J. E. (1996). *The Emotional Brain: The Mysterious Underpinnings of Emotional Life*. Simon & Schuster, New York.

Leeuwen, M. V. (2005). Questions for the dynamicist: The use of dynamical systems theory in the philosophy of cognition. *Minds and Machines*, 15:271–333.

Lewis, M. D. and Liu, Z. (2011). Three time scales of neural self-organization underlying basic and nonbasic emotions. *Emotion Review*, 3(4):416–423.

Leys, R. (2011). The turn to affect: A critique. *Critical Inquiry*, 37(3):434–472.

Li, G., Li, Y., Zhang, Z., Geng, Y., and Zhou, R. (2010). Selection of sampling rate for emg pattern recognition based prosthesis control. In *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, pages 5058–5061. IEEE.

Liberati, G., Klöcker, A., Algoet, M., Mulders, D., Safronova, M. M., Santos, S. F., Vaz, J.-G. R., Raftopoulos, C., and Mouraux, A. (2018). Gamma-band oscillations preferential for nociception can be recorded in the human insula. *Cerebral cortex*, 28(10):3650–3664.

Liégeois, R., Yeo, B. T., and Van De Ville, D. (2021). Interpreting null models of resting-state functional mri dynamics: Not throwing the model out with the hypothesis. *NeuroImage*, 243:118518.

Limonero, J. T., Fernández-Castro, J., Soler-Oritja, J., and Álvarez Moleiro, M. (2015). Emotional intelligence and recovering from induced negative emotional state. *Frontiers in psychology*, 6:140382.

Lindquist, K. A., Wager, T. D., Kober, H., Bliss-Moreau, E., and Barrett, L. F. (2012). The brain basis of emotion: A meta-analytic review. *Behavioral and Brain Sciences*, 35(3):121–143.

Liu, J., Meng, H., Li, M., Zhang, F., Qin, R., and Nandi, A. K. (2018). Emotion detection from eeg recordings based on supervised and unsupervised dimension reduction. *Concurrency and Computation: Practice and Experience*, 30(23):e4446.

Liu, M., Wang, R., Li, S., Shan, S., Huang, Z., and Chen, X. (2014a). Combining multiple kernel methods on riemannian manifold for emotion recognition in the wild. In *Proceedings of the 16th International Conference on multimodal interaction*, pages 494–501.

Liu, M., Wang, R., Li, S., Shan, S., Huang, Z., and Chen, X. (2014b). Combining multiple kernel methods on riemannian manifold for emotion recognition in the wild. In *Proceedings of the 16th International Conference on multimodal interaction*, pages 494–501.

Liégeois, R., Yeo, B. T., and Van De Ville, D. (2021). Interpreting null models of resting-state functional mri dynamics: not throwing the model out with the hypothesis. *NeuroImage*, 243(11851):8.

Lundqvist, L.-O. (1995). Facial emg reactions to facial expressions: A case of facial emotional contagion? *Scandinavian journal of psychology*, 36(2):130–141.

Lélut, L. F. (1862). *Physiologie de la pensée: Recherche critique des rapports du corps à l'esprit*. Didier et Co.

Ma-Kellams, C. (2014). Cross-cultural differences in somatic awareness and interoceptive accuracy: a review of the literature and directions for future research. *Frontiers in psychology*, 5:117196.

Macefield, V. G. (2003). Cardiovascular and respiratory modulation of tactile afferents in the human finger pad. *Experimental Physiology*, 88(5):617–625.

Macefield, V. G., James, C., and Henderson, L. A. (2013). Identification of sites of sympathetic outflow at rest and during emotional arousal: concurrent recordings of sympathetic nerve activity and fmri of the brain. *International journal of psychophysiology*, 89(3):451–459.

MacLean, P. D. (1949). Psychosomatic disease and the" visceral brain": Recent developments bearing on the papez theory of emotion. *Psychosomatic medicine*, 11(6):338–353.

MacNamara, A. and Phan, K. L. (2016). *Prefrontal-Limbic brain circuitry and the regulation of emotion*. Oxford University Press.

Mahjoory, K., Nikulin, V. V., Botrel, L., Linkenkaer-Hansen, K., Fato, M. M., and Haufe, S. (2017). Consistency of eeg source localization and connectivity estimates. *Neuroimage*, 152:590–601.

Maiese, M. (2017). Can the mind be embodied, enactive, affective, and extended? *Phenomenology and the Cognitive Sciences*, 17(2):343–361.

Manea, M., Comsa, M., Minca, A., Dragos, D., and Popa, C. (2015). Brain-heart axis-review article. *Journal of medicine and life*, 8(3):266.

Matsumoto, D. and Ekman, P. (2009). Basic emotions. In *Oxford Companion to Emotion and the Affective Sciences*. OUP Oxford.

Mazzola, L., Mauguière, F., and Isnard, J. (2019). Functional mapping of the human insula: Data from electrical stimulations. *Revue Neurologique*, 175(3):150–156.

McDonald, G. C. (2009). Ridge regression. *Wiley Interdisciplinary Reviews: Computational Statistics*, 1(1):93–100.

McEwen, B. S. and Wingfield, J. C. (2003). The concept of allostasis in biology and biomedicine. *Hormones and Behavior*, 43(1):2–15.

McInnes, L., Healy, J., and Melville, J. (2018). Umap: Uniform manifold approximation and projection for dimension reduction. preprint.

Mehling, W. E., Acree, M., Stewart, A., Silas, J., and Jones, A. (2018). The multidimensional assessment of interoceptive awareness, version 2 (maia-2). *PloS one*, 13(12):e0208034.

Meilă, M. (2007). Comparing clusterings—an information based distance. *Journal of multivariate analysis*, 98(5):873–895.

Meiselman, H. L. (2021). *Emotion measurement*. Woodhead Publishing.

Melnikoff, D. E., Carlson, R. W., and Stillman, P. E. (2022). A computational theory of the subjective experience of flow. *Nature communications*, 13(1):2252.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., and Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *In Advances in Neural Information Processing Systems (p*, pages 3111–3119.

Mishra, S., Srinivasan, N., and Tiwary, U. S. (2022). Cardiac–brain dynamics depend on context familiarity and their interaction predicts experience of emotional arousal. *Brain Sciences*, 12(6):702.

Molenaar, P. C. M., Lerner, R. M., and Newell, K. M. (2009). *Handbook of developmental systems theory and methodology*. Guilford Publications.

Molins, A., Stufflebeam, S. M., Brown, E. N., and Hämäläinen, M. S. (2008). Quantification of the benefit from integrating meg and eeg data in minimum l2-norm estimation. *Neuroimage*, 42(3):1069–1077.

Mosso, A. (1880). *Sulla circolazione del sangue nel cervello dell'uomo: recherché sfigmografiche*. Coi Tipi Del Salviucci.

Mosso, A. (1890). *Die Temperatur des Gehirns*. Verlag von Veit.

Mosso, A. (1896). *Fear*. Longmans, Green, and Co.

Mulcahy, J. S., Larsson, D. E. O., Garfinkel, S. N., and Critchley, H. D. (2019). Heart rate variability as a biomarker in health and affective disorders: A perspective on neuroimaging studies. *NeuroImage*, 202(11607):2.

Munkres, J. (2015). *Topology*. Pearson, 2nd edition edition.

Munn, R. G., Hardcastle, K., Porter, B., and Bilkey, D. (2017). Circadian-scale periodic bursts in theta and gamma-band coherence between hippocampus, cingulate and insular cortices. *Neurobiology of Sleep and Circadian Rhythms*, 3:26–37.

Nguyen, H., Chen, F., Kotani, K., and Le., B. (2014). Human emotion estimation using wavelet transform and t-rois for fusion of visible images and thermal image sequences. In Science, C. and Applications–ICCSA, I., editors, *14th International Conference, Guimarães, Portugal, June 30–July 3, 2014, Proceedings, Part VI 14*, pages 224–235, International Publishing. Springer.

Niedenthal, P. M., Winkielman, P., Mondillon, L., and Vermeulen, N. (2009). Embodiment of emotion concepts. *Journal of Personality and Social Psychology*, 96(6):1120–1136.

Nikolaou, F., Orphanidou, C., Papakyriakou, P., Murphy, K., Wise, R. G., and Mitsis, G. D. (2016). Spontaneous physiological variability modulates dynamic functional connectivity in resting-state functional magnetic resonance imaging. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 374(2067):20150183.

Nummenmaa, L., Glerean, E., Hari, R., and Hietanen, J. K. (2014). Bodily maps of emotions. *Proceedings of the National Academy of Sciences*, 111(2):646–651.

Oatley, K. (2008). *Emotions: A Brief History*. Blackwell Publishing.

Ogarkova, A. (2021). Cross-lingual translatability of emotion terms: a review. In *Emotion Measurement*, page 909–935. Woodhead Publishing.

Oosterwijk, S. and Barrett, L. F. (2014). Embodiment in the construction of emotion experience and emotion understanding. In Shapiro, L., editor, *Routledge Handbook of Embodied Cognition*. Routledge.

Oppenheimer, S. M., Gelb, A., Girvin, J. P., and Hachinski, V. C. (1992). Cardiovascular effects of human insular cortex stimulation. *Neurology*, 42(9):1727–1727.

Ortony, A. (2022). Are all “basic emotions” emotions? a problem for the (basic) emotions construct. *Perspectives on psychological science*, 17(1):41–61.

Ortony, A. and Clore, G. (2015). Can an appraisal model be compatible with psychological constructionism. *The psychological construction of emotion*, pages 305–333.

Ortony, A., Clore, G. L., and Collins, A. (1990). *The cognitive structure of emotions*. Cambridge University Press.

Overton, W. F. (2013). Relational developmental systems and developmental science: A focus on methodology. In Molenaar, P. C. M., Lerner, R. M., and Newell, K. M., editors, *Handbook of Developmental Systems Theory and Methodology*. Guilford Publications.

Oyama, S. (2000). Causal democracy and causal contributions in developmental systems theory. *Philosophy of Science*, 67:S332–S347.

O'Rorke, P. and Ortony, A. (1994). Explaining emotions. *Cognitive Science*, 18(2):283–323.

Panksepp, J. (1996). *Affective neuroscience: The foundations of human and animal emotions*. Oxford University Press.

Panksepp, J. and Smith-Pasqualini, M. (2004). The search for the fundamental brain/mind sources of affective experience. In Nadel, J. and Muir, D., editors, *Emotional Development*, page 5–30. Oxford University Press.

Papez, J. W. (1937). A proposed mechanism of emotion. *Archives of Neurology And Psychiatry*, 38(4):725.

Park, H.-D. and Blanke, O. (2019). Heartbeat-evoked cortical responses: Underlying mechanisms, functional roles, and methodological considerations. *NeuroImage*, 197:502–511.

Park, H. D., Correia, S., Ducorps, A., and Tallon-Baudry, C. (2014). Spontaneous fluctuations in neural responses to heartbeats predict visual detection. *Nature neuroscience*, 17(4):612–618.

Pavlovia. (retrieved 24 July 2021).

Penfield, W. and Rasmussen, T. (1950). *The Cerebral Cortex of Man; a clinical study of localization of function*. Macmillan.

Peng, Y., Zhu, J.-Y., Zheng, W.-L., and Lu, B.-L. (2014). Eeg-based emotion recognition with manifold regularized extreme learning machine. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 974–977. IEEE.

Pernet, C., Garrido, M. I., Gramfort, A., Maurits, N., Michel, C. M., Pang, E., Salmelin, R., Schoffelen, J. M., Valdes-Sosa, P. A., and Puce, A. (2020). Issues and recommendations from the ohbm cobidas meeg committee for reproducible eeg and meg research. *Nature Neuroscience*, 23(12):1473–1483.

Pessoa, L. (2013). *The cognitive-emotional brain: From interactions to integration*. MIT Press.

Pessoa, L., Medina, L., and Desfilis, E. (2021). Refocusing neuroscience: Moving away from mental categories and toward complex behaviors.

Plamper, J. (2015). *The history of emotions: An introduction*. Oxford OUP.

Plutchik, R. (1960). The multifactor-analytic theory of emotion. *The Journal of Psychology*, 50(1):153–171.

Plutchik, R. and Kellerman, H. (1980). *Theories of emotion*. Academic Press.

Pokrovskii, V. M. (2005). Integration of the heart rhythmogenesis levels: heart rhythm generator in the brain. *Journal of integrative Neuroscience*, 4(02):161–168.

Poppa, T., Benschop, L., Horczak, P., Vanderhasselt, M.-A., Carrette, E., Bechara, A., Baeken, C., and Vonck, K. (2022). Auricular transcutaneous vagus nerve stimulation modulates the heart-evoked potential. *Brain Stimulation*, 15(1):260–269.

Prats-Boluda, G., Garcia-Casado, J., Martinez-de Juan, J. L., and Ponce, J. L. (2007). Identification of the slow wave component of the electroenterogram from laplacian abdominal surface recordings in humans. *Physiological Measurement*, 28(9):1115–1133.

Protevi, J. (2009). *Political Affect: Connecting the Social and the Somatic*. University of Minnesota Press.

Puce, A. and Hämäläinen, M. S. (2017). A review of issues related to data acquisition and analysis in eeg/meg studies. *Brain sciences*, 7(6):58.

Puce, A. and Perrett, D. (2003). Electrophysiology and brain imaging of biological motion. *Philosophical Transactions of the Royal Society of London (Series B: Biological Sciences)*, 358(1431):435–445.

Quadt, L., Critchley, H. D., and Garfinkel, S. N. (2018). The neurobiology of interoception in health and disease. *Annals of the New York Academy of Sciences*, 1428(1):112–128.

Rae, C. L., Botan, V. E., van Praag, C. D. G., Herman, A. M., Nyyssönen, J. A. K., Watson, D. R., Duka, T., Garfinkel, S. N., and Critchley, H. D. (2018). Response inhibition on the stop signal task improves during cardiac contraction. *Scientific Reports*, 8(1):9136.

Raimondo, F., Rohaut, B., Demertzi, A., Valente, M., Engemann, D. A., Salti, M., Fernandez Slezak, D., Naccache, L., and Sitt, J. D. (2017). Brain–heart interactions reveal consciousness in noncommunicating patients. *Annals of neurology*, 82(4):578–591.

Rebollo, I., Devauchelle, A.-D., Béranger, B., and Tallon-Baudry, C. (2018). Stomach-brain synchrony reveals a novel, delayed-connectivity resting-state network in humans. *ELife*, 7.

Rebollo, I., Wolpert, N., and Tallon-Baudry, C. (2021). Brain–stomach coupling: Anatomy, functions, and future avenues of research. *Current Opinion in Biomedical Engineering*, 18:10027.

Reddy, M. J. (1979). The conduit metaphor: A case of frame conflict in our language about language. In Ortony, A., editor, *Metaphor and Thought*, page 164–201. Cambridge University Press.

Reisenzein, R. (2009). Emotions as metarepresentational states of mind: Naturalizing the belief–desire theory of emotion. *Cognitive Systems Research*, 10(1):6–20.

Richter, S., Schulz, A., Port, J., Blumenthal, T. D., and Schächinger, H. (2009). Cardiopulmonary baroreceptors affect reflexive startle eye blink. *Physiology & behavior*, 98(5):587–593.

Robert, J. S., Hall, B. K., and Olson, W. M. (2001). Bridging the gap between developmental systems theory and evolutionary developmental biology. *BioEssays*, 23(10):954–962.

Rosazza, C. and Minati, L. (2011). Resting-state brain networks: literature review and clinical applications. *Neurological sciences*, 32:773–785.

Roseman, I. J. (1996). Appraisal determinants of emotions: Constructing a more accurate and comprehensive theory. *Cognition & Emotion*, 10(3):241–278.

Rosenwein, B. H. and Cristiani, R. (2017). *What is the History of Emotions?* Wiley, John & Sons.

Rosopa, P. J., Schaffer, M. M., and Schroeder, A. N. (2013). Managing heteroscedasticity in general linear models. *Psychological methods*, 18(3):335.

Rubinov, M. and Sporns, O. (2010). Complex network measures of brain connectivity: uses and interpretations. *Neuroimage*, 52(3):1059–1069.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6):1161–1178.

Russell, J. A. and Carroll, J. M. (1999). On the bipolarity of positive and negative affect. *Psychological Bulletin*, 125(1):3–30.

Saarimäki, H., Ejtehadian, L. F., Glerean, E., Jääskeläinen, I. P., Vuilleumier, P., Sams, M., and Nummenmaa, L. (2018). Distributed affective space represents multiple emotion categories across the human brain. *Social Cognitive and Affective Neuroscience*, 13(5):471–482.

Sadler, T. W. (2020). *Langman's Medical Embryology*. Wolters Kluwer, 14th edition edition.

Salomon, R., Ronchi, R., Dönz, J., Bello-Ruiz, J., Herbelin, B., Faivre, N., Schaller, K., and Blanke, O. (2018). Insula mediates heartbeat related effects on visual consciousness. *Cortex*, 101:87–95.

Salomon, R., Ronchi, R., Dönz, J., Bello-Ruiz, J., Herbelin, B., Martet, R., Faivre, N., Schaller, K., and Blanke, O. (2016). The insula mediates access to awareness of visual stimuli presented synchronously to the heartbeat. *The Journal of Neuroscience*, 36(18):5115–5127.

Samuelsson, J. G., Peled, N., Mamashli, F., Ahveninen, J., and Hämäläinen, M. S. (2021). Spatial fidelity of meg/eeg source estimates: A general evaluation approach. *Neuroimage*, 224:11743.

Sandman, C. A. (1984). Augmentation of the auditory event related potentials of the brain during diastole. *International Journal of Psychophysiology*, 2(2):111–119.

Sastre, A., Graham, C., and Cook, M. R. (2000). Brain frequency magnetic fields alter cardiac autonomic control mechanisms. *Clinical neurophysiology*, 111(11):1942–1948.

Satpute, A. B. and Lindquist, K. A. (2021). At the neural intersection between language and emotion. *Affective Science*, 2(2):207–220.

Schachter, S. and Singer, J. (1962). Cognitive, social, and physiological determinants of emotional state. *Psychological Review*, 69(5):379–399.

Scherer, K. R. (2005). What are emotions? *And how can they be measured? Social Science Information*, 44(4):695–729.

Scherer, K. R. (2009). The dynamic architecture of emotion: Evidence for the component process model. *Cognition and emotion*, 23(7):1307–1351.

Schiller, D., Alessandra, N. C., Alia-Klein, N., Becker, S., Cromwell, H. C., Dolcos, F., Eslinger, P. J., et al. (2023). The human affectome. *Neuroscience & Biobehavioral Reviews*, 105450.

Schlosberg, H. (1954). Three dimensions of emotion. *Psychological Review*, 61(2):81–88.

Schulkin, J. (2003). Allostasis: A neural behavioral perspective. *Hormones and Behavior*, 43(1):21–27.

Schulz, A., Vögele, C., Bertsch, K., Bernard, S., Münch, E. E., Hansen, G., Naumann, E., and Schächinger, H. (2020). Cardiac cycle phases affect auditory-evoked potentials, startle eye blink and pre-motor reaction times in response to acoustic startle stimuli. *International Journal of Psychophysiology*, 157:70–81.

Schumann, N. P., Bongers, K., Guntinas-Lichius, O., and Scholle, H. C. (2010). Facial muscle activation patterns in healthy male humans: A multi-channel surface emg study. *Journal of Neuroscience Methods*, 187(1):120–128.

Sennesh, E., Theriault, J., Brooks, D., van de Meent, J. W., Barrett, L. F., and Quigley, K. S. (2022). Interoception as modeling, allostasis as control. *Biological Psychology*, 167:108242.

Shaffer, C., Barrett, L. F., and Quigley, K. S. (2023). Signal processing in the vagus nerve: hypotheses based on new genetic and anatomical evidence. *Biological Psychology*, 108626.

Shamay-Tsoory, S. G. and Mendelsohn, A. (2019). Real-life neuroscience: An ecological approach to brain and behavior research. *Perspectives on Psychological Science*, 14(5):841–859.

She, Q., Shi, X., Fang, F., Ma, Y., and Zhang, Y. (2023). Cross-subject eeg emotion recognition using multi-source domain manifold feature selection. *Computers in Biology and Medicine*, 159:106860.

Sherrington, C. S. (1903). *The Integrative Action of the Nervous System.* Yale University Press.

Shokri-Kojori, E., Tomasi, D., and Volkow, N. D. (2018). An autonomic network: synchrony between slow rhythms of pulse and brain resting state is associated with personality and emotions. *Cerebral Cortex*, 28(9):3356–3371.

Shuman, V., Sander, D., and Scherer, K. R. (2013). Levels of valence. *Frontiers in psychology*, 4:40619.

Siegel, E. H., Sands, M. K., Van den Noortgate, W., Condon, P., Chang, Y., Dy, J., Quigley, K. S., and Barrett, L. F. (2018). Emotion fingerprints or emotion populations? a meta-analytic investigation of autonomic features of emotion categories. *Psychological bulletin*, 144(4):343.

Šimić, G., Tkalčić, M., Vukić, V., Mulc, D., Španić, E., Šagud, M., Olucha-Bordonau, F. E., Vukšić, M., and R. Hof, P. (2021). Understanding emotions: origins and roles of the amygdala. *Biomolecules*, 11(6):823.

Smith, R., Varshney, L. R., Nagayama, S., Kazama, M., Kitagawa, T., and Ishikawa, Y. (2022). A computational neuroscience perspective on subjective wellbeing within the active inference framework. *International Journal of Wellbeing*, 12:4.

Smith, S. T. (1993). *Geometric optimization methods for adaptive filtering*. Harvard University.

Sokolov, E. N. and Boucsein, W. (2000). A psychophysiological model of emotion space. *Integrative Physiological and Behavioral Science*, 35(2):81–119.

Solomon, R. C. and Stone, L. D. (2002). On "positive" and "negative" emotions. *Journal for the Theory of Social Behaviour*, 32(4):417–435.

Spunt, R. P. and Adolphs, R. (2019). The neuroscience of understanding the emotions of others. *Neuroscience Letters*, 693:44–48.

Stam, C. J., Nolte, G., and Daffertshofer, A. (2007). Phase lag index: Assessment of functional connectivity from multi channel eeg and meg with diminished bias from common sources. *Human Brain Mapping*, 28(11):1178–1193.

Stanisławski, K., Cieciuch, J., and Strus, W. (2021). Ellipse rather than a circumplex: A systematic test of various circumplexes of emotions. *Personality and Individual Differences*, 181(2021):111052.

Stankovski, T., Petkoski, S., Raeder, J., Smith, A. F., McClintock, P. V., and Stefanovska, A. (2016). Alterations in the coupling functions between cortical and cardio-respiratory oscillations due to anaesthesia with propofol and sevoflurane. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 374(2067):20150186.

Steenbergen, L., Maraver, M. J., Actis-Grosso, R., Ricciardelli, P., and Colzato, L. S. (2021). Recognizing emotions in bodies: Vagus nerve stimulation enhances recognition of anger while impairing sadness. *Cognitive, Affective, & Behavioral Neuroscience*, 21:1246–1261.

Sterling, P. (2012). Allostasis: A model of predictive regulation. *Physiology & Behavior*, 106(1):5–15.

Sterling, P. and Eyer, J. (1988). Allostasis: A new paradigm to explain arousal pathology. In Fisher, S. and Reason, J., editors, *Handbook of Life Stress, Cognition and Health*. Wiley, John & Sons.

Tahsili-Fahadan, P. and Geocadin, R. G. (2017). Heart–brain axis: effects of neurologic injury on cardiovascular function. *Circulation research*, 120(3):559–572.

Tantardini, M., Ieva, F., Tajoli, L., and Piccardi, C. (2019). Comparing methods for comparing networks. *Scientific reports*, 9(1):1–19.

Taulu, S. and Kajola, M. (2005). Presentation of electromagnetic multichannel data: the signal space separation method. *Journal of Applied Physics*, 97(12).

Taylor, A. G., Goehler, L. E., Galper, D. I., Innes, K. E., and Bourguignon, C. (2010). Top-down and bottom-up mechanisms in mind-body medicine: development of an integrative framework for psychophysiological research. *Explore*, 6(1):29–41.

Thatcher, R. W., Biver, C. J., and North, D. M. (2007). Spatial-temporal current source correlations and cortical connectivity. *Clinical EEG and Neuroscience*, 38(1):35–48.

Toivonen, R., Kivelä, M., Saramäki, J., Viinikainen, M., Vanhatalo, M., and Sams, M. (2012). Networks of emotion concepts. *PLoS ONE*, 7(1):e28883.

Tomescu, M. I., Rihs, T. A., Rochas, V., Hardmeier, M., Britz, J., Allali, G., Fuhr, P., Eliez, S., and Michel, C. M. (2018). From swing to cane: sex differences of eeg resting-state temporal patterns during maturation and aging. *Developmental cognitive neuroscience*, 31:58–66.

Tomkins, S. S. (1991). *The negative affects: Anger and fear*, volume III of *Affect imagery consciousness*. Springer Publishing Company.

Tomkins, S. S. and McCarter, R. (1964). What and where are the primary affects? some evidence for a theory. *Perceptual and Motor Skills*, 18(1):119–158.

Townsend, J. T., Solomon, B., and Spencer Smith, J. (2005). The perfect gestalt: Infinite dimensional riemannian face spaces and other aspects of face perception. In *Computational, Geometric, and Process Perspectives on Facial Cognition: Contexts and Challenges*. Psychology Press.

Trnka, R., Balcar, K., and Kuška, M. (2011). *Re-constructing emotional spaces: From experience to regulation*. Prague Psychosocial Press.

Trnka, R., Lačev, A., Balcar, K., Kuška, M., and Tavel, P. (2016). Modeling semantic emotion space using a 3d hypercube-projection: An innovative analytical approach for the psychology of emotions. *Frontiers in Psychology*, 7:522.

Trofimov, I., Cherniavskii, D., Tulchinskii, E., Balabin, N., Burnaev, E., and Barannikov, S. (2022). Learning topology-preserving data representations. In *The Eleventh International Conference on Learning Representations*.

Uhlirova, H., Kılıç, K., Tian, P., Thunemann, M., Desjardins, M., Saisan, P. A., Sakadžić, S., Ness, T. V., Mateo, C., Cheng, Q., et al. (2016). Cell type specificity of neurovascular coupling in cerebral cortex. *elife*, 5:e14315.

Ulloa, J. L., Puce, A., Hugueville, L., and George, N. (2012). Sustained neural activity to gaze and emotion perception in dynamic social scenes. *Social Cognitive and Affective Neuroscience*, 9(3):350–357.

Uusitalo, M. A. and Ilmoniemi, R. J. (1997). Signal-space projection method for separating meg or eeg into components. *Medical and biological engineering and computing*, 35:135–140.

Van Diessen, E., Numan, T., Dellen, E. V., Kooi, A. W. V. D., Boersma, M., Hofman, D., Lutterveld, R. V., et al. (2015). Opportunities and methodological challenges in eeg and meg resting state functional brain network research. *Clinical Neurophysiology*, 126(8):1468–1481.

van Gent, P., Farah, H., van Nes, N., and van Arem, B. (2019). Heartpy: A novel heart rate algorithm for the analysis of noisy signals. *Transportation Research Part F: Traffic Psychology and Behaviour*, 66:368–378.

Varcin, K. J., Grainger, S. A., Richmond, J. L., Bailey, P. E., and Henry, J. D. (2019). A role for affectivity in rapid facial mimicry: An electromyographic study. *Social Neuroscience*, 14(5):608–617.

Varon, C., Morales, J., Lázaro, J., Orini, M., Deviaene, M., Kontaxis, S., Testelmans, D., Buyse, B., Borzée, P., Sörnmo, L., Laguna, P., Gil, E., and Bailón, R. (2020). A comparative study of ecg-derived respiration in ambulatory monitoring using the single-lead ecg. *Scientific Reports*, 10:1.

Vázquez-Seisdedos, C. R., Neto, J. E., Marañón Reyes, E. J., Klautau, A., and Limão de Oliveira, R. C. (2011). New approach for t-wave end detection on electrocardiogram: Performance in noisy conditions. *Biomedical engineering online*, 10:1–11.

Vera-Baceta, M.-A., Thelwall, M., and Kousha, K. (2019). Web of science and scopus language coverage. *Scientometrics*, 121(3):1803–1813.

Volynets, S., Glerean, E., Hietanen, J. K., Hari, R., and Nummenmaa, L. (2020). Bodily maps of emotions are culturally universal. *Emotion*, 20(7):1127–1136.

Von Stein, A. and Sarnthein, J. (2000). Different frequencies for different scales of cortical integration: from local gamma to long range alpha/theta synchronization. *International journal of psychophysiology*, 38(3):301–313.

Von Wegner, F. H. L. and Tagliazucchi, E. (2018). Mutual information identifies spurious hurst phenomena in resting state eeg and fmri data. *Physical Review E*, 97(2):022415.

Váša, F. and Mišić, B. (2022). Null models in network neuroscience. *Nature Reviews Neuroscience*, 23(8):493–504.

Wagner, W., Hansen, K., and Kronberger, N. (2014). Quantitative and qualitative research across cultures and languages: Cultural metrics and their application. *Integrative Psychological and Behavioral Science*, 48(4):418–434.

Walker, B. B. and Sandman, C. A. (1982). Visual evoked potentials change as heart rate and carotid pressure change. *Psychophysiology*, 19(5):520–527.

Wang, S. H., Lobier, M., Siebenhühner, F., Puoliväli, T., Palva, S., and Palva, J. M. (2018). Hyperedge bundling: A practical solution to spurious interactions in meg/eeg source connectivity analyses. *NeuroImage*, 173:610–622.

Wells, F. L. and Forbes, A. (1911). *On certain electrical processes in the human body and their relation to emotional reactions*. The Science Press.

Westlin, C., Theriault, J. E., Katsumi, Y., Nieto-Castanon, A., Kucyi, A., Ruf, S. F., Brown, S. M., et al. (2023). Improving the study of brain-behavior relationships by revisiting basic assumptions. *Trends in cognitive sciences*, 27(3):246–257.

Widmaier, E., Raff, H., and Strang, K. T. (2022). *Vander's human physiology*. McGraw-Hill US Higher Ed USE.

Widmann, A., Schröger, E., and Maess, B. (2015). Digital filter design for electrophysiological data–a practical approach. *Journal of neuroscience methods*, 250:34–46.

Wilmer, A., de Lussanet, M., and Lappe, M. (2012). Time-delayed mutual information of the phase as a measure of functional connectivity. *PLOS ONE*, 7:1–22.

Wolpert, N., Rebollo, I., and Tallon-Baudry, C. (2020). Electrogastrography for psychophysiological research: Practical considerations, analysis pipeline, and normative data in a large sample. *Psychophysiology*, 57(9).

Wood, P. and Brown, D. (1994). The study of intraindividual differences by means of dynamic factor models: Rationale, implementation, and interpretation. *Psychological Bulletin*, 116(1):166.

Woodworth, R. S. and Sherrington, C. S. (1904). A pseudaffective reflex and its spinal path. *The Journal of Physiology*, 31(3-4):234–243.

Wróbel, M. and Imbir, K. K. (2019). Broadening the perspective on emotional contagion and emotional mimicry: The correction hypothesis. *Perspectives on Psychological Science*, 14(3):437–451.

Wu, C. W., Gu, H., Lu, H., Stein, E. A., Chen, J. H., and Yang, Y. (2008). Frequency specificity of functional connectivity in brain networks. *Neuroimage*, 42(3):1047–1055.

Wu, M., Hu, S., Wei, B., and Lv, Z. (2022). A novel deep learning model based on the ica and riemannian manifold for eeg-based emotion recognition. *Journal of Neuroscience Methods*, 378:109642.

Wu, M., Ouyang, R., Zhou, C., and Li, P. (2024). A study on the combination of functional connection features and riemannian manifold in eeg emotion recognition. *Frontiers in Neuroscience*, 17:1345770.

Xing, M., GadElkarim, J., Ajilore, O., Wolfson, O., Forbes, A., Phan, K. L., Klumpp, H., and Leow, A. (2018). Thought chart: tracking the thought with manifold learning during emotion regulation. *Brain Informatics*, 5:1–9.

Xu, X., Liang, T., Zhu, J., Zheng, D., and Sun, T. (2019). Review of classical dimensionality reduction and sample selection methods for large-scale data processing. *Neurocomputing*, 328:5–15.

Yang, Y., Sun, H., Gong, J., Du, Y., and Yu, D. (2022). Interpretable dimensionality reduction by feature preserving manifold approximation and projection. arxiv. preprint.

Younis, E. M., Mohsen, S., Hussein, E. H., and Ibrahim, O. A. S. (2024). Machine learning for human emotion recognition: a comprehensive review. *Neural Computing and Applications*, pages 1–47.

Zalesky, A., Fornito, A., Harding, I. H., Cocchi, L., Yücel, M., Pantelis, C., and Bullmore, E. T. (2010). Whole-brain anatomical networks: does the choice of nodes matter? *Neuroimage*, 50(3):970–983.

Zemack-Rugar, Y., Bettman, J. R., and Fitzsimons, G. J. (2007). The effects of nonconsciously priming emotion concepts on behavior. *Journal of Personality and Social Psychology*, 93(6):927–939.

Zhang, Y., Zhang, J., Xie, M., Ding, N., Zhang, Y., and Qin, P. (2023). Dual interaction between heartbeat-evoked responses and stimuli. *NeuroImage*, 266:119817.

Zhong, W., Ciatipis, M., Wolfenstetter, T., Jessberger, J., Müller, C., Ponsel, S., Yanovsky, Y., Brankačk, J., Tort, A. B. L., and Draguhn, A. (2017). Selective entrainment of gamma subbands by different slow network oscillations. *Proceedings of the National Academy of Sciences*, 114(17):4519–4524.

Zhou, P., Critchley, H., Garfinkel, S., and Gao, Y. (2021). The conceptualization of emotions across cultures: a model based on interoceptive neuroscience. *Neuroscience & Biobehavioral Reviews*, 125:314–327.

Zou, Q. (2022). Learning emotion representations on a manifold. In *2022 IEEE Conference on Telecommunications*, pages 1431–1435, IEEE. Optics and Computer Science (TOCS).

CURRICULUM VITAE

# Kamilya Salibayeva

## EDUCATION

- Ph.D. in Neural Science, Indiana University, Bloomington, IN, May 2024
- Ph.D. in Psychology, Indiana University, Bloomington, IN, May 2024
- B.S. in Neuroscience, with Honors, Indiana University, Bloomington, IN, 2014

## WORKING EXPERIENCE

- **Graduate Teaching Assistant,** Department of Psychological and Brain Sciences, Indiana University, Bloomington (2019-2022, 2023-2024)

  *Courses assisted in:* PSY P386 (Social Neuroscience), PSY P472 (Lab in Brain Electrical Activity), PSY P460 (Psychology of Women), PSY P155 (Introduction to Psychological and Brain Sciences), PSY P546 (Graduate Laboratory in Neurophysiological Techniques), PSY X150 (Exploring Brain Function)

- **Instructor of Record**, Department of Psychological and Brain Sciences, Indiana University Bloomington (Spring 2022)

  PSY P472 — Lab in Brain Electrical Activity

  Senior-level laboratory hands-on course in EEG data acquisition, preprocessing, and analysis

- **Predoctoral trainee**, CRCNS: US-France Data Sharing Proposal: Open science & cloud computing of MEEG, NIH / NIBIB / CENIR (2022-2023)

Joint US-France grant project focusing on bringing MEG/EEG data analytical tools onto https://www.brainlife.io cloud platform.

Code development, data analysis, quality assurance, documentation, preparation of white paper for publication.

- **Lead Scientific Consultant**, SmartSoft, LLC, Astana, Kazakhstan (2015-2019)

  Conducted preliminary literature reviews and personnel debriefing on gold standard practices in neuroimaging and neurophysiological data acquisition. Assisted in further development of clinical software pertaining to said modalities of neurological examinations.

- **Information Specialist/Deputy Director of the Department of Technology**, HealthCity, LLC, Almaty, Kazakhstan (2014-2015)

  Worked on transition, expansion, and reformatting of Hospital Information Systems (HIS) in the network of HealthCity clinics. Assisted medical engineering teams in the integration of MRI, CT, ultrasound, and EEG systems in the personal medical charting modules of the chosen HIS.

- **Undergraduate Research Assistant**, Mathematical Psychology Laboratory, Department of Psychological and Brain Sciences, Indiana University Bloomington (2011-2014)

  Assisted on multiple research projects and presentations (literature surveys, preparation of psychophysical stimuli, carrying out pilot runs, etc.), conducted independent research leading up to Honors Thesis.

SELECT PUBLICATIONS

- *A topological approach to evaluating the dynamics of human emotions*

  **Configural Processing Consortium 2023** (November 2023), San Francisco, CA, USA

  Proposal for a novel differential geometric and topological analysis as applied to behavioral experimental paradigms when studying human emotions as continuous variables across multiple dimensions.

- *MEG-EEG resting-state functional connectivity and brain networks change with the cardiac cycle*

  **Organization for Human Brain Mapping 2023** (July 2023), Montreal, QC, Canada

  An investigation of how resting-state MEG-EEG activity changes as a function of the cardiac cycle in a multimodal data set.

- *Mind-body relationships and neuroscientific frameworks:a pluralistic proposal based on cultural anthropology*

  **Neuromatch 3.0 Conference**, online (2020)

  https://www.youtube.com/watch?v=_Zs6KsblJOY

- *Let's face it: Attempted incipient unification of differential geometric and dynamic concepts of facial expressions*

  James T. Townsend and Kamilya Salibayeva

  **Fechner Day 2013** (Annual Meeting of the International Society for Psychophysics)

Presentation of a proposal related to the mathematical model of a perceptual face space.

- *Revisiting simultanagnosia: new classification based on existing lesion studies and cognitive models*

  **Lomonosov-2013**, Moscow, Russia

  Conference talk focused on assessing existing cognitive models of simultanagnosia in relation to gestalt processing and General Recognition Theory.