USING DATA SCIENCE TO UNRAVEL THE EMOTIONAL BODY EXPERIENCE

UTILISATION DE LA SCIENCE DES DONNÉES POUR DÉCOUVRIR L'EXPÉRIENCE ÉMOTIONNELLE CORPORELLE

A thesis submitted
by
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for the degree
of
Philosophiæ Doctor in Psychology

to the
Ecole Doctorale Science de l'Homme et de la Société
SCALab, UMR CNRS 9193
University of Lille

December 9, 2022

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I searched all over the internet for a smart quote.

ABSTRACT

We live in a world where data is considered one of the most valuable of all resources. Data science is a domain of research that is focused on how to (a) collect useful and meaningful data, (b) extract key features and variables contained within the recorded data, and (c) interpret results within a given theoretical framework to give meaning to the findings. My PhD work applied the logic of data science to the case study of emotional body movements in the cognitive field of affective sciences. Emotions are at the cornerstone of human societies; they bind humans together and exert a decisive influence on all aspects of adaptive behavior. Emotions have the ability to modulate heart rate or even voluntary motor actions by making us move faster or slower. Most importantly, emotions change the way we move, offering non-verbal cues on our inner affective states. After an introductory part on data science (Chapter 1), I present an overview of the theoretical frameworks applicable to the concepts of emotion and affect (Chapter 2). Chapter 3 is a methodological section offering a guideline to the good methods in affective sciences. More specifically, I present a step-by-step tutorial on how to collect good data in the study of emotional body experiences in young healthy adults, sitting or moving (questionnaires, physiological measures, kinematic data). The final part of my PhD manuscript presents three show cases. These show cases demonstrate that emotional body experience can be studied from different methodological perspectives but within a common theoretical framework. The first show case (Chapter 4) is centered around the effects of odor molecules on physiological and affective reactions. The analysis techniques used in this show case are heart rate, heart-rate variability analyses, as well as questionnaires (Geneva Emotion and Odor Scale, affect grid). The second show case (Chapter 5) is centered around a complete description of the effects of emotions on whole-body movements in actors. This show case uses kinematics (e.g., speed, jerk) and time-series analysis (cross-wavelet coherence, auto-correlations) to account for the underlying evolutionary meaning of emotional influence on kinematics. The third and final show case (Chapter 6) is centered around the prediction of the emotional state of an actor, solely based on its kinematics. The main analysis technique of this show case is a deep convolutional neural network. Finally, to conclude this PhD thesis, Chapter 7 will provide a general discussion on the results and on the perspective offered by taking a data science perspective to help tackle new theoretical challenges, in the field of emotions.

Keywords: affect; kinematics; evolution; classification; physiology; odors

RÉSUMÉ

La donnée est l'or d'aujourd'hui. La science des données est un domaine de recherche qui répond au besoin de (a) collecter des informations structurées, qualitatives et quantitatives, (b) analyser et extraire des indices clés qui peuvent évoluer au cours du temps, et (c) interpréter les résultats vis-à-vis d'un cadre théorique spécifique dans le but de donner du sens aux donnée collectées. Mon travail de thèse s'est attaché à la question de comment récolter des données utiles et sensées pour caractériser un comportement humain émotionnel, en appliquant la logique des sciences des données à la psychologie. Les émotions sont au cœur des sociétés humaines; elles sont le ciment qui relie les humains et elles exercent une influence certaine sur les aspects adaptatifs du comportement. Les émotions ont la capacité de moduler notre rythme cardiaque ou encore nos actions volontaires en nous faisant marcher plus vite ou plus lentement. Plus important encore, nos émotions modifient la façon dont nous bougeons, offrant ainsi des indices non-verbaux de nos état affectifs interne. Après une introduction sur la science des données (Chapitre 1), je présente un aperçu des cadres théoriques applicables aux concepts d'émotion et d'affect (Chapitre 2). Le Chapitre 3 est une partie méthodologique, offrant des conseils pour une bonne méthodologie en sciences affectives. Plus spécifiquement, je présente un tutoriel étape par étape sur comment collecter de bonnes données lorsque l'on souhaite étudier l'expérience émotionnelle corporelle chez de jeunes adultes sains, assis ou en mouvement (questionnaires, mesures physiologiques, enregistrements cinématique). La dernière partie du manuscrit de thèse présente trois cas d'études. Ces trois études démontrent que l'expérience émotionnelle corporelle peut être étudiée à partir de différentes perspectives méthodologiques, au sein d'un même cadre théorique. Le premier cas d'étude (Chapitre 4) est centré sur les effets des odeurs sur les réactions physiologiques et affectives. Les techniques d'analyse utilisées dans ce cas d'étude sont l'analyse de la fréquence et de la variabilité cardiaque ainsi que des questionnaires (Échelle des Odeurs et des Émotion de Genève, affect grid). Le second cas d'étude (Chapitre 5) est centré sur une description la plus complète possible des effets des émotions sur des mouvements corps entier d'acteurs. Ce cas d'étude utilise des analyses cinématiques (e.g., vitesse, jerk) et temporelles (ondelettes, autocorrélations) pour rendre compte de l'avantage évolutionniste offert par l'influence des émotions sur la cinématique corporelle. Le troisième et dernier cas d'étude (Chapitre 6) est centré autour de la prédiction de l'état émotionnel d'un acteur, de par la modélisation de sa cinématique corporelle. La technique d'analyse principalement utilisée dans ce cas d'étude est un réseau de neurones profond convolutionnel. Pour conclure, le Chapitre 7 présente une discussion générale sur les résultats et les perspectives offertes par une approche science des données dans le but de s'attaquer à de nouveaux challenges théoriques et appliqués dans le domaine des émotions.

Mots-clefs: affect ; cinématique ; évolution ; classification ; physiologie ; odeurs

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MOTIVATIONS

My thesis focused on applying a data science perspective to emotional research to further theoretical advances. This work allowed the development of a strong background in theoretical emotional models. It also helped me to develop new methodologies as well as merging tools from multiple disciplines to expand the range of possibilities. These methodologies include physiological analyses (e.g., HR, HRV), motion capture and deep-learning. During my PhD, I also developed valuable skills in communication to vulgarize and transfer my findings to a wide and diverse audience. My goal is now to use these skills in an applied context, mostly in the private sector to solve real-world problems.

EDUCATION BACKGROUND

4th Modeling Symposium (July 2021)

Organized by Felix Ball
Speaker: Prof. Sebastian Stober

PAISS Summer School (July 2021)

Organized by Inria and the institutes MIAI and PRAIRIE.
Speaker: Dr. Yann LeCun

Master's degree with honors (2017 - 2018)

Sciences Cognitives pour l'Entreprise, University of Lille, France

Thesis: "When Machines Know How You Feel: Automatic Classification of Emotions based on Body Kinematics"

WORK EXPERIENCE

PhD Student (Sept. 2019 - Dec. 2022)

Under the supervision of Pr. Yvonne Delevoye-Turrell, SCALab (UMR CNRS 9193). Funded by the I-Site Consortium. 100 000€ grant + 400€/year for travel

"Using data science to unravel the emotional body experience"
Grounded from psychological theories of emotional processes, I am combining physiology, motion capture and deep learning to unravel the how and why emotions exert their influence on body kinematics.

R&D Engineer (Feb. 2019 - July 2019)

EURA NOVA, Marseille, France

- Design and build ML pipeline
- Assist clients in solving commercial issues through ML
- Build UI to easily interact with trained ML models
- Write and present data analysis reports

SPECIALIZATIONS

- Motion Capture
  - Qualisys ●●●●◐
  - Theia3D ●●●◐○
- Bash ●●●○○
- Inkscape ●●●●○
- Python 3
  - Tensorflow 2 ●●●●○
  - Keras ●●●●◐
  - PyTorch ●●●○○
- Data visualization ●●●●◐

REFERENCES

Romain Trachel (PhD, Senior ML Specialist, Eidos Montréal)

Thomas Peel (PhD, Lead Data Scientist, EURA NOVA)

Costas I. Karageorghis (Professor, Brunel University, London)

OTHER EXPERIENCES

- PhD representatives (2021)
- Member of steering committee and scientific board of the 15th scientifc day of young researchers (Lille, France)
- Scientific animator in an open-lab (Xpérium, 2021-2022)

VICTOR BROSSARD

WORK EXPERIENCES

Both before and during my PhD, I assumed many responsibilities, most of which are listed on this page and in more details than in my resume.

Open-lab scientific animator (2021 - 2022)

Xpérium, directed by Professor Jean Cosléou, PhLAM (UMR CNRS 8523), University of Lille

- 32 days of scientific demonstration of how human visual perception is achieved
- Development of a small demonstration experiment using Python and a Tobii eye-tracker
- Presentations to a diverse audience (e.g., childrens, students, companies, researchers)

Teaching (2020 - 2022)

64 hours of teaching to undergraduate and master students

- "What Data Science is and how it can be used in psychology", 2 hours, 30 students
- "Data analysis project in human social sciences", 2 x 20 h, 2 x 20 students. Basic data analysis concepts in Python and guidances to redact and present the project
- "Data analysis project applied to psychology", 12 h, 15 students. Big Five questionnaire analysis in Python
- "Getting up-to-speed in Python", 9 h, 12 students. Python basics to get new master degree students up-to-speed

DataCamp Classroom Management (2020 - 2022)

Management of the DataCamp classroom account, for 150+ students over 3 years

- Renewal of the account every 6 months
- Inviting students and managing the level groups
- 2 hours course for student to learn how to use it
- Support for teachers to assign tasks to students

Councilling (2020 - 2022)

32 days of council for EURA NOVA Marseille

- Litterature review
- Development of a graph network, in Python
- Versioning of produced code, using Gitlab
- Meeting with clients

Research equipment management (2019 - 2022)

For the team of Professor Yvonne N. Delevoye-Turrell, SCALab (UMR 9193)

- Team of 15 people
- ~20k € worth of equipment
- Motion capture cameras (Qualisys), markerless software (Theia3D, Visual3D), eye-trackers (Pupil Invisible) and physiological sensors (Empatica E4 and Polar V800)
- How to use, store, protect and analyze data from each equipment
- Communications with the manufacturers to order and repair the various equipments

R&D Engineer (Feb. 2019 - July 2019)

EURA NOVA, Marseille, France

- Design and build ML pipeline
- Assist clients in solving commercial issues through ML
- Build UI to easily interact with trained ML models
- Write and present data analysis reports

Junior research engineer (Oct. 2018 - Jan. 2019)

Collaboration SCALab (UMR CNRS 9193) and SATT Nord, Lille, France

- Development of an interactive bike, adapting the sensorial environment to the user
- Developed using Python
- Embarked technology (Raspberry Pi)
- Demonstrator tested in Plaine Image, Tourcoing

Partnership growth (July-Sept. 2018)

3 months to seek and develop partnership with researchers and engineers from the Sheffi eld Hallam University, Sheffi eld, UK and partners in the north of France.

- Presentation of the research themes of Pr. Yvonne N. Delevoye-Turrell, SCALab (UMR CNRS 9193)
- Participation to meetings with engineers and researchers from the various universities
- Exploration of the technical possibilities of collaboration between SCAlab and the various universities

PUBLICATIONS

REFEREED JOURNAL ARTICLES UNDER REVIEW

Brossard, V. P. M., & Delevoye-Turrell, Y. N. (2022). *Remote Recording and Computing of Heart Rate and Heart Rate Variability From Wristband Sensors: A Practical Guidance*. Manuscript submitted for publication.

Brossard, V. P. M., Mathé, C., Monnier, L., Nardello-Rataj, V., & Delevoye-Turrell, Y. N. (2022a). *Effects of Odor Valence on Physiology, Emotions, and Desire to Move*. Manuscript submitted for publication.

Brossard, V. P. M., Ott, L., & Delevoye-Turrell, Y. N. (2022b). *Spatiotemporal Correlations of Whole Body Movements: An Evolutionist Perspective to Reveal the Affective Properties of Human Motor Behavior*. Manuscript submitted for publication.

CONFERENCE AND POSTER SESSION PROCEEDINGS

Brossard, V. P. M., & Delevoye-Turrell, Y. N. (2021, October 29). *Measuring emotions from motion: A markerless motion capture case study* [Conference session]. 19ème Congrès de l'Association des Chercheurs en Activités Physiques et Sportives, Montpellier, France.

Brossard, V. P. M., Nardello-Rataj, V., & Delevoye-Turrell, Y. N. (2019, November 15). *Sentir fait bouger : Influence de la valence des odeurs sur le contrôle postural d'adultes sains* [Poster presentation]. 14e Journée Scientifique des Jeunes Chercheurs, Lille, France.

Brossard, V. P. M., Ott, L., & Delevoye-Turrell, Y. N. (2022, August 30). *Time-series and wavelets to reveal the emotional properties of motor behavior: An evolutionist account* [Poster presentation]. 22nd Conference of the European Society for Cognitive Psychology, Lille, France.

Brossard, V. P. M., Peel, T., & Delevoye-Turrell, Y. N. (2021). *DeeREKt: Deep recognition of emotions using kinematics* [Poster presentation]. Conférence sur l'Apprentissage automatique (CAp), Saint-Etienne, France.

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ACRONYMS

AC autocorrelation

ANS autonomic nervous system

BPM beats per minute

BVP blood volume pulse

CPM Component Process Model

CPU central processing unit

DD-Net Double-feature Double-motion Network

DeeREKt Deep Recognition of Emotions from Kinematics

ECG electrocardiogram

EOS Emotion and Odor Scale

FAS Felt Arousal Scale

FS Feeling Scale

GEOS Geneva Emotion and Odor Scale

GEW Geneva Emotion Wheel

GPU graphics processing unit

HR heart rate

HRV heart-rate variability

IMPPACT Impetus, Motivation, and Prediction in Perception–Action Coordination Theory

LSL lab streaming layer

MoCap motion capture

PPG photoplethysmographic

RM ANOVA repeated-measures analysis of variance

RMSSD root mean square of successive differences

SAM Self Assessment Manikin

SDSD standard deviation of successive differences

SVM support vector machine

TCE Theory of Constructed Emotions

Part I

INTRODUCTION

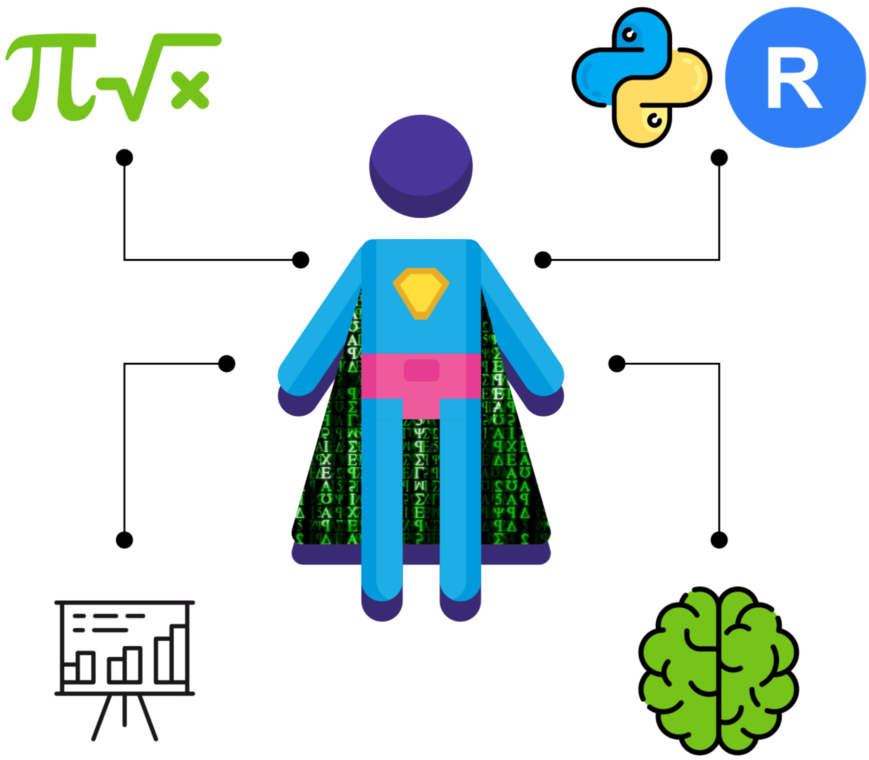
1 DATA SCIENCE

We live in a world were data is considered one of the most valuable of all resources. Data is used everyday to help us avoid traffic on our daily commute, tailor the output of a search query, or answer a research question. In order to use these kind of information, data has to be produced. There are an almost infinite number of ways humans generate data. Sending an email is producing data, as the servers sending and receiving gather a large number of information about the sender, recipient, protocols used, and so on. The amount of data produced each day is gigantic (Vopson, 2021). To help the reader put things into perspective, in 2019 the number of emails sent each day was estimated to be around 294 billion. The number of tweets sent each day was around 500 million. And one connected car was producing around 4 TB of data (Visual Capitalist, 2019). With an estimated growth rate of data production of 61%, the production seems far from decreasing. Therefore, to be able to help us avoid traffic or answer research question, it is necessary to give meaning to this vast amount of data. This is the ultimate goal of data science.

Data science is a relatively new field of research (Cao, 2018). Data science is at the crossroad of statistics, computer science, and domain knowledge. Many different definition exist of what data science really is. My definition of data science is that it is a domain of research focused on giving meaning to data. In my opinion, there is a data-science logic that can be applied to virtually every domain of research or work. The data-science logic starts with data collection, zooming on how to collect useful and meaningful data. Then, data analysis considers the question of how to extract key features and variables contained within the recorded data. Afterwards, there is the need to interpret results within a given theoretical framework to give meaning to the findings. Finally, all these information need to be shared with other researchers, stakeholders, or the general population and data science involves efficient communication of the findings (e.g., creating meaningful and insightful visualization). An illustration of my personal view of a data scientist can be found in Figure 1. To summarize my point of view, a data scientist is a super-hero whose superpowers are mathematics, computer science, domain knowledge (cognitive science in this work), and communication.

Data science has infiltrated many domains, both in research and the private sector. This is why the definition of data science includes "domain knowledge", in addition to the mathematics or computer science aspects. Because data science is fundamentally adaptable to any domain, data science is evolving quickly. We already see the emergence of a diversity of jobs related to data science, such as data analyst, data engineer, data manager, data architect, and so on. Each job is designed for specialists with their own area of expertise. Taken together, all these specialists improve the field of data science and help other domain benefit from data science. In the case of psychology, data science has been used but not so much in research. Large companies (e.g., Google, Apple, Facebook, Amazon or Microsoft) already apply some kind

Figure 1
Personal View of Data Science



Note. A data scientist is a super-hero with skills in mathematics (top-left), computer science (top-right), domain knowledge (e.g., cognitive science; bottom-right), and communication (bottom-left).

of data science for a wide variety of tasks, such as filtering their possible candidates. The companies usually rely on machine learning models to estimate how possible candidate would fit with their current teams, both in term of hard and soft skills. The companies use the output of coding tests for hard skills and psychological tests, such as the Big Five, to test soft skills (John et al., 1991). When designed correctly, coding tests can give companies a good idea of some technical skills of candidates. Psychological tests, once administered, are expected by companies to provide the same kind of information but for the personality of the candidates. Therefore, large firms rely on these tests and on clustering, for example, to predict if a candidate might fit in one of their team, in terms of work ethic, relationship with other employees, or respect of the hierarchy to name a few.

Psychology developed during the first half of the XX$^{\text{th}}$ century with a behavioral point of view (da Silva Neves, 2012). Behaviorism still exists today but is no longer dominating the field. According to behaviorists, all thought mechanisms could be explained by a set of laws guiding and linking human behavior to context. However, according to da Silva Neves (2012), behaviorism have failed to explain human problem solving and understanding abilities. Therefore, another school of thought has emerged through the second half of the XXth century with the idea that the human mind could be simulated within an artificial system (i.e., a computer). This school of thought has given birth to cognitive psychology. Cognitive psychology relies on the idea that cognitive processes are described as a set of processes where information flows between them, guided by predefined rules.

To evolve from behaviorism to cognitivism, psychology has benefited from other disciplines. At the end of the XIXth century, the recent development in physics and biology has allowed scientists such as Paul Broca to understand that some parts of the brain are mostly devoted to certain abilities (e.g., speech production; Changeux, 1983). Physicians and chemists also helped psychologists understand that neurons transmit information through electricity and neuro-transmitters (i.e., chemical molecules). With this knowledge, psychologists, physicians, chemists, and biologists began developing neurosciences. Neuroscientists have, in turn, help psychologists develop new theories about brain representation of cognitive processes. Furthermore, the very fabric of cognitive psychology was born through the help of mathematicians and computer engineers, such as Alan Turing and John Von Neumann. Psychology has a long history of working with other disciplines to evolve and explain human functioning. I believe that data science can help psychology evolve its theories once again.

Psychology has recently suffered from a reproducibility crisis (Baker, 2016; Fanelli, 2018; Pashler & Wagenmakers, 2012). Therefore, we are seeing an increase in the expected number of participants from one study to the next. Especially in order to increase the reliability of the statistical tests performed (Lakens & Evers, 2014). Therefore, researchers are facing the need to collect more data to get a wider picture of the human experience. Data science can provide with some help and guidelines to plan ahead how the data will be collected, stored, and analyzed. By carefully planning and then writing computer code, analyzing 15 participants or 500 is done with a click of the mouse. Even the tedious phase of data collection can be improved. In Chapter 3, section 3.4, and Appendix A, I provide an example of an innovative methodology that we developed to be able to collect data from several participants at once using psychological questionnaires and physiological responses. This innovative methodology was born through a data science perspective. Data science can also help psychological researchers expand their way of thinking through trans-disciplinary education. Data science is fundamentally multi-disciplinary. It forces data scientists to look at a problem from various angles and draw from many disciplines to find the right solution for the current issue. There is no one-size-fits-all solution for every problem. By drawing from different disciplines, the probability that a solution is found increases.

To conclude this section on data science and how it can be applied to psychology, I would like to point out how my PhD work can make a valuable contribution in helping data science reach psychology. In this work, I present three show cases in which the data science logic was applied alongside psychology to help push theories further. Chapter 3 is a methodological section offering a guideline to the good methods in affective sciences. More specifically, I present a step-by-step tutorial on how to collect good data in the study of emotional body experiences in young healthy adults (questionnaires, physiological measures, kinematic data). The final part of the PhD manuscript presents three show cases. These show cases will demonstrate that emotional body experience can be studied from different methodological perspectives but within a common theoretical framework. The first show case (Chapter 4) is centered around the effects of odor molecules on physiological and affective reactions. The analysis techniques used in this show case are heart-rate, heart-rate variability analyses, as well as questionnaires (Geneva Emotion and Odor Scale, affect grid). The second show case (Chapter 5) is centered around a complete description of the effects of emotions on whole-body movements in actors. This show case uses kinematics (e.g., speed, jerk) and cross-wavelet coherence analysis to account for the underlying evolutionary meaning of emotional influence on kinematics. The third and final show case (Chapter 6) is centered around the prediction of the emotional state of an actor, solely based on its kinematics. The main analysis technique of this show case is a deep convolutional neural network. Finally, to conclude this PhD manuscript, Chapter 7 will provide a general discussion on the results and on the perspective offered by taking a data science perspective to help tackle new theoretical challenges, in the field of emotions.

2 EMOTION RESEARCH IN THE ERA OF AFFECTIVISM

In this chapter, I will describe the current major theoretical models of emotions and explain how they can provide answers for other domains of research, willing to integrate emotion in their own research field.

The XXth century has seen major advances in cognitive psychology. Drawing on disciplines such as computer science and physics, psychologists have been able to create computational models of cognitive processes and investigate the neural correlates of these processes. Nonetheless, emotions were considered as some form of a human bug, which needed to be suppressed by logic and reasoning. Research in human psychology was developing through the study of cold cognitive processes (i.e., without the emotional bias). However, and whether we like it or not, emotions play a critical role in decision-making, performance, and overall well-being. It is impossible, undesirable, and detrimental to stop people from experiencing them (Mauss & Gross, 2004; Traue et al., 2016). Considering the role of human emotions has now become vital in all aspects of society, going from the economic value of a worker to the well-being of a child.

2.1 INTRODUCTION

The XXIst century is the century of affectivism. Emotion as a topic is highly popular in the business and management sectors (Fosslien & Duffy, 2020; Motro et al., 2019) as well as in research, with nearly 30,000 papers published on the topic of emotions in 2021 (and more than 500,000 from 1969 to 2022), according to a simple "emotion" PubMed query. Scientific areas that are considering the impact of emotion in their research include, but are not limited to, history (Broomhall et al., 2019), language (Pritzker et al., 2019), and philosophy (Goldie, 2010). This trend in emotion research has recently lead some of the major emotional theorists to consider how psychology as whole will transition from cognitivism to affectivism (Dukes et al., 2021). Affectivism is an emerging current in psychology that considers emotional processes as an important modulator of cognitive processes. The goal of affectivism is to build on the advances made in emotion research to incorporate emotion into other domains of research in order to have a better understanding of human cognitive processes. Only time can tell whether affectivism will be the next defining current in psychology. However, we believe that the increased trend in emotion is an opportunity for emotion research to draw on digital tools available today to continue evolving and guide other disciplines in their integration of emotional concepts.

The XXIst century is also a digital century. Over the past 20 years, computing capacities together with available data sets have grown in importance. The amount of data recorded and shared around the globe, both for research and business is enormous. These data sets and analysis techniques are reaping benefits in artificial intelligence or language processing modeling for instance. They could also be used to improve theoretical emotional framework. Having access to large-scale emotion datasets could provide an opportunity to test and refine theoretical models. Higher computing capacities could translate into easier development of computational models of emotions processes which would, in turn, further our understanding of human emotional experiences. Sharing the codes produced to model these processes would enable researchers from every corner of the world to work on the understanding of these emotional processes.

The goal of this review is, first, to offer a description focused on the behavioral aspects of the current theoretical frameworks used to model emotional processes. Then, we will focus on the constructs of core affects and emotions, setting aside the slower changing construct of mood. Finally, we will describe how the digital tools available nowadays may help push the current boundaries of emotion research in the era of affectivism.

2.2 AFFECTIVE MODELS

Core affect is a neuro-physiological state consciously accessible as a simple primitive non-reflective feeling most evident in mood and emotion (Russell & Feldman-Barrett, 2009). One of its differentiating characteristics from emotion is that it does not need to be directed at anything (Russell & Barrett, 1999). Thus, it is a neuro-physiological state that is always present and that can arise to consciousness to form the basis of what we call an emotion. Its purpose is to orient the organism towards states that will yield positive outcomes (Batson et al., 1992, p.298).

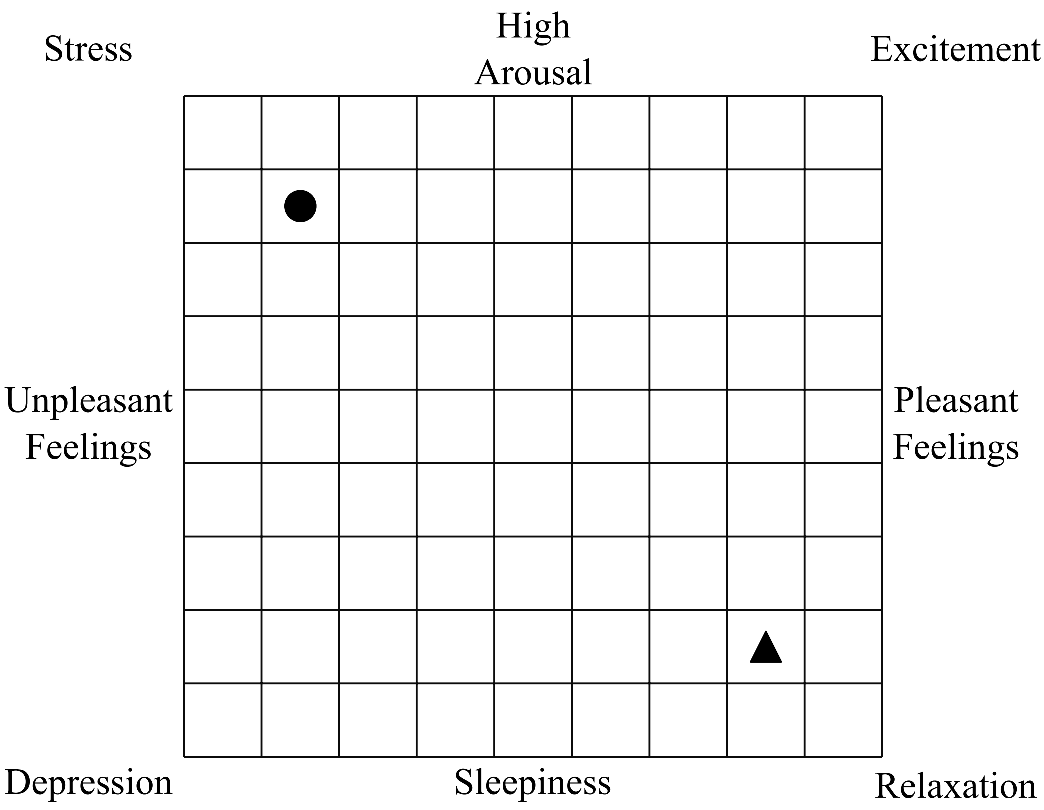
To react adequately to an upcoming stimulus, an organism must have some knowledge about its current state. Furthermore, knowledge about the current state will allow the organism to use it as a baseline reference to assess the contextual significance of the upcoming stimulus. Scientific-based studies were developed to obtain baseline measures to homogenize the experimental groups and gain reference data to create the initial models of affective sciences in healthy adult individuals.

2.2.1 *Modeling affective states*

Core affect can take various forms. It can be seen as variations in heart-rate frequency or changes in core body temperature. Core affect is a state of the body at a given time. Its purpose is also to orient the organism towards states that will yield positive outcomes (Batson et al., 1992). More recent theories in affective neurosciences even claim that core affect is a signal allowing the brain to have a measure of its current state and and to predict if this state is beneficial or harmful to the body (Barrett, 2017). Accordingly, core affect is a phenomenon that should be found in all species as it provides the bases of evolutionary adaptation for species survival.

The model of core affect is today accepted by most researchers in the field of affective sciences. In this model, core affect is defined as a state, not a trait (Russell, 2003; Russell & Barrett, 1999). It is valued in terms of valence (positive or negative) and arousal (high or low). Over the years, a number of questionnaires have been created to qualify and quantify core affect through the means of declarative statements. Hence, the investigation of changes in core affect can be conducted through

Figure 2
Affect Grid



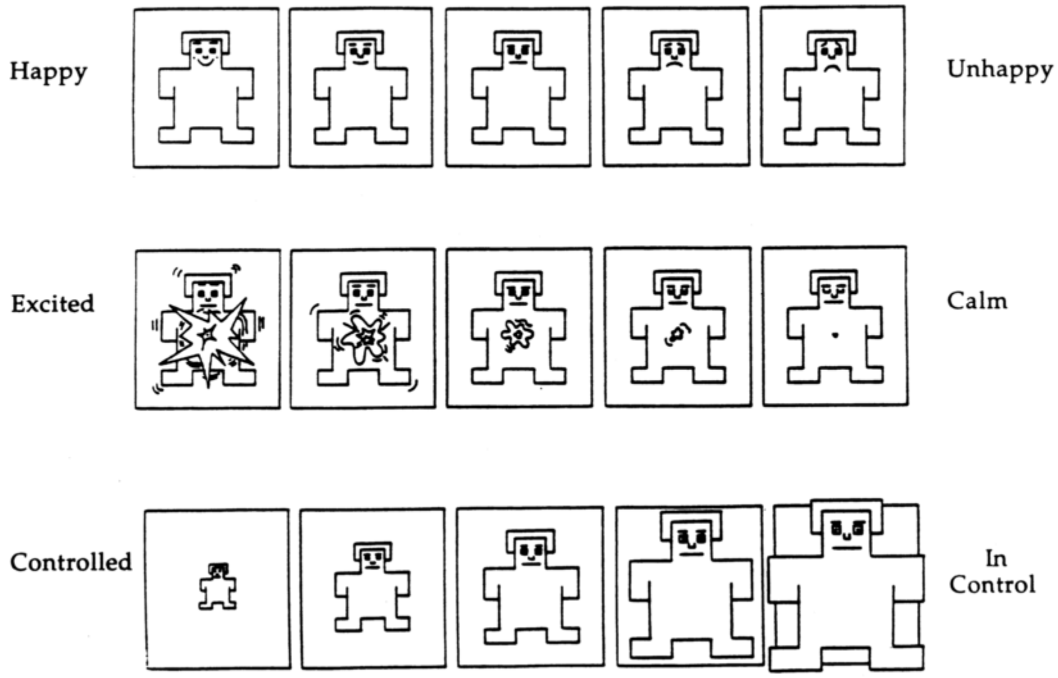
Note. Affect Grid representing two evaluations of two different states of core affect. Black circle represents a negative state of high arousal (imagine hearing a gunshot close to you). Black triangle represents a positive state of low arousal (imagine enjoying a relaxing massage). Adapted from Russell et al. (1989).

the use of validated tools. Four of such tools will be described below: the Affect Grid (Russell et al., 1989), the Self Assessment Manikin (SAM; Bradley & Lang, 1994), the Feeling Scale (FS; Hardy & Rejeski, 1989) and the Felt Arousal Scale (FAS; Svebak & Murgatroyd, 1985).

The Affect Grid (Figure 2) is a two-dimensional grid that provides the means to collect self-reported subjective indicators of affect with a single answer. Participants are invited to draw a cross on the grid to report their feelings, both in terms of valence (positive to negative) and arousal (high arousal to sleepiness). Valence is often on the horizontal axis whereas arousal is commonly led on the vertical axis. Recently, a numerical version of the affective grid was developed to promote the measure of affective experiences in individuals performing leisure physical activity (Batistatou et al., 2022).

To help participants familiarize themselves with the Affect Grid, Russell et al. (1989) prepared a set of instructions and examples. Two opposite examples are as follows: "Imagine hearing a gunshot close to you. How would you rate your feel-

Figure 3
Self Assessment Manikin



Note. The Self Assessment Manikin (Bradley & Lang, 1994) is a three-dimensional tool used to score valence, arousal, and dominance. The SAM is a tool consisting in drawings depicting a character ranging from unhappy to happy for the valence dimension, from sleepy to aroused for the arousal dimension, and from non-dominant to dominant for the dominance dimension.

ings? One possible answer would be the black circle in Figure 2. Now, imagine that you are enjoying a relaxing massage. How would you rate your feelings now? One possible answer would be the black triangle in Figure 2."

The SAM (Figure 3) is a three-dimensional tool, sharing its first two dimensions with the Affect Grid. The third dimension codes for dominance. The SAM is a tool consisting in drawings depicting a character ranging from unhappy to happy for the valence dimension, from sleepy to aroused for the arousal dimension, and from non-dominant to dominant for the dominance dimension. The participant is invited to choose the drawing that corresponds best to their feelings, in each of the three dimensions. Although the article introducing the SAM was entitled "Measuring emotion: The self-assessment manikin and the semantic differential" (Bradley & Lang, 1994), the authors might have been referring to core affect rather than emotions. At that time, it was common for authors to use emotion and affect as interchangeable terms (Ekkekakis, 2013, p.33).

The FS and the FAS are both one-dimensional scales designed to measure one component of core affect. The FS is used to measure perceived valence. It is composed of an 11-point scale ranging from *I feel very bad* (-5) to *I feel very good* (+5). The FAS is used to measure felt arousal (hence the name). It is composed of a 6-point scale ranging from *low arousal* (1) to *high arousal* (6). The FS and FAS are the most used questionnaires in sport and exercise sciences as they provide a simple measure with a clear distinction between the two dimensions (e.g., Carlier et al., 2017).

2.2.2 *Examples of studies investigating core affect*

An example of a study using measures of core affect is one conducted by Bird et al. (2016). In this study, the effects of music, music-video, and no stimulation (control condition) on core affect was investigated while participants were exercising on an ergocycle at a pre-defined exercise intensity. The FS and the FAS were used to score valence and arousal components of core affect. In the introduction of the paper, the authors carefully defined the term of core affect to highlight the choice of the affective construct and physiological model. The authors also specified the scientific bases of their choice of using FS and FAS tools. With the objective to assess the changes in felt affect every two minutes during a 20-minute practice session, participants were invited to indicate out loud the quadrant most representative of their state of the moment, on both scales. The scores obtained in each experimental condition (i.e., music, music-video, control) were compared with the pre-task measures implemented as covariates. Results showed that, when exercising with music or music-video, participants felt better than when they were exercising without audio stimulation. Participants were also significantly more aroused as the exercise went on and more relaxed immediately after the end of practice in the presence of a musical environment.

Another example of a study investigating changes in core affect is one conducted by de Groot et al. (2018). Here, the Affect Grid was used as a validation tool to assess the success of their procedure. The aim of the study was to investigate emotional communications through body odors among Western Caucasians and East Asians. To assess changes in core affect in their adult participants, the Affect Grid was used (Russell et al., 1989). The study consisted in two phases. The first phase was to collect body odors from "senders" who followed a procedure of emotional induction by watching movie clips (e.g., horror or comedy movies). The second phase consisted in recruiting another sample of participants. These receivers smelled the odor samples of the "senders" and the Affect Grid was used to assess the impact of the odor stimuli on felt affective states. Results showed that the Affect Grid was sensitive enough to confirm that (a) the inductive procedure worked in the "senders" and (b) the affective impact on the "senders" was transmitted through body odors and detectable by the naive receivers.

2.2.2.1 *Conclusion*

Core affect is a widely investigated construct. This affective phenomena is being studied in many different research fields, such as cognitive psychology, behavioral neurosciences, and sport sciences. Studies are targeting core affect for different theoretical reasons, with the aid of various types of tools (e.g., paper and digital questionnaires, internet surveys). However, they all share a common set of features: (a) use of a validated version of the measurement tools, (b) acceptance of the theoretical background and implications of the core affect model, and (c) knowledge of the hypotheses justifying the choice of the measurement tools. Overall, core affect is the model to adopt if one is seeking to study whether an element is good or bad for maintaining internal sensorial allostasis[1]. If a situation is bad, one will have the urge to leave; if it is good, the urge will be to stay. The intensity of the trigger event will code the force with which one will tend to move. Nevertheless, we will see in the following section that the decision to move or not may be more complex than what is proposed in the original core-affect models.

2.3 THE COGNITIVE MODELS OF EMOTION

Humans are complex organisms that have evolved to adapt to their environment. Thanks to appraisal processes, individuals have the means to quantify the significance of an upcoming stimulus for allostasis and prolonged well-being. With such knowledge, humans can decide (albeit unconsciously most of the time) what course of action to engage in. For example, a person can decide to *approach* or to *avoid* another person that seems from a distance threatening (Cartaud et al., 2018).

With the evolution in the 90's of scientific tools and methods, and specifically with the arrival of brain imaging techniques, researchers were encouraged to investigate the role of cognitive processing in the emergence of emotions. Through the years, the cognitive theories developed a number of assumptions and in particular that emotions arise from the synchronized changes over a number of functional components (Sander et al., 2005; Scherer, 1984). An example of a cognitive component is the relevance component that gives sense to a perceived stimulus. However, these components do not need to be cognitive per se. An example of a non-cognitive component is the coping component that triggers motor adjustments. In the following paragraphs we will consider in more detail the commonalities that can be extracted from the appraisal models.

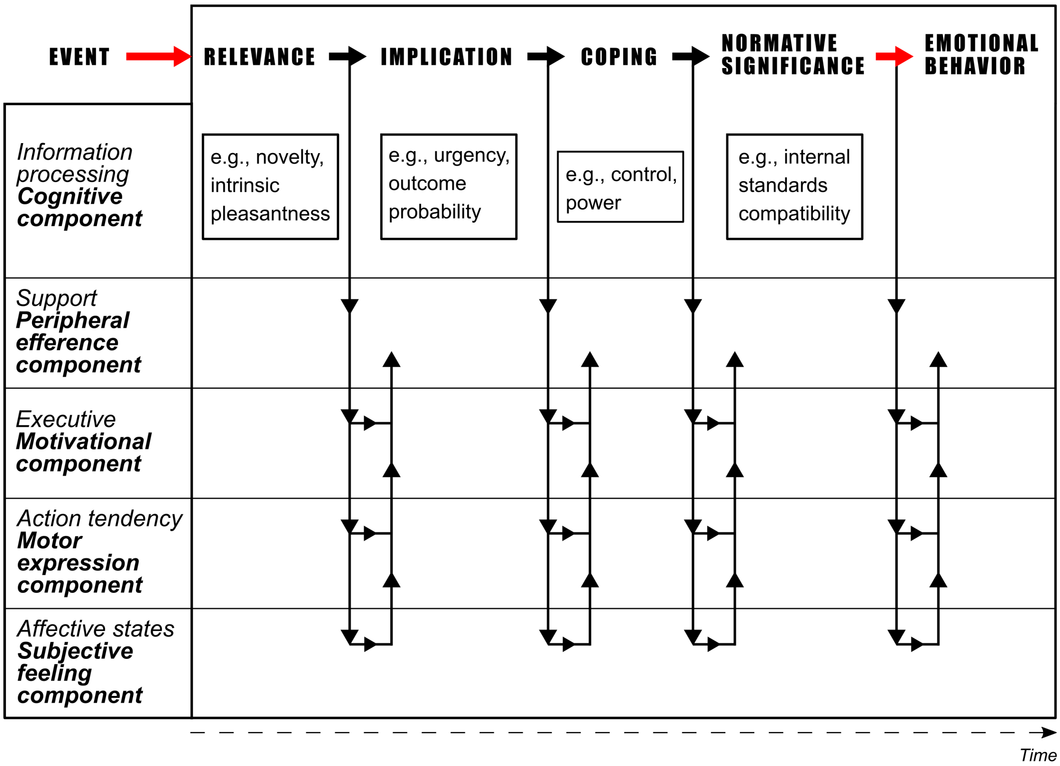
2.3.1 *The appraisal theories*

The term *appraisal* appeared in 1960, with the release of a book titled *Emotion and Personality* by Magda Arnold (1960). It is defined as a process that detects and assesses the significance of the environment for well-being (Moors et al., 2013)[2]. Over the last decades, many authors have written about appraisal and different theories have been elaborated and tested. Overall, appraisal theories are theoretical constructs that postulate that emotions are a serial combination of appraisals (Ellsworth & Scherer, 2003). Accordingly, appraisal processes are necessary for an emotion to emerge. Lazarus goes even further by stating that this is necessary and sufficient (Lazarus, 1991; Smith et al., 1993). Models differ especially in the number and nature of appraisal components. The work by Klaus Scherer (1984, 2005) and Nico Frijda (1986, 2006) may be considered as key contributions.

1 Allostasis is the phenomenon that provides stability through change. It refers particularly to the idea that parameters of most physiological-regulatory systems change to accommodate environmental demands (Sterling, 2012)

2 Well-being can be defined here as the satisfaction or obstruction of concerns referring to an individual's needs, attachments, values, current goals, and beliefs (Moors et al., 2013)

Figure 4
Component Process Model



Note. In the CPM, the emotions are seen as episodes emerging from the synchronized changes of five organismic subsystems (Sander et al., 2005). The five organismic subsystems - and their corresponding emotional components are: information processing (cognitive component), support (peripheral efference component), executive (motivational component), action (motor expression component), and monitor (subjective feeling component). It is the coordination of these subsystems that give rise to the emotional episodes. Adapted from Scherer (1984).

2.3.1.1 *The Component Process Model*

Scherer (1984) developed a model to describe specifically a possible mechanism explaining the emergence of an emotion in humans. The Component Process Model (CPM, see Figure 4) describes an emotion as an episode of interrelated, synchronized changes in the states of all, or most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event, as relevant to major concerns of the organism (Sander et al., 2005). The subsystems are coordinated to trigger an emotional experience.

The role of appraisal in the CPM is to code the relevance of an incoming stimulus vis-a-vis each of the five emotional components/organismic subsystems. Hence, the appraisal theory is based on the idea that there are continuous and recursive processes evaluating each component successively (Sander et al., 2005). The five organismic subsystems - and their corresponding emotional components are: information processing (cognitive component), support (peripheral efference component), executive (motivational component), action (motor expression component), and monitor (subjective feeling component).

Everything starts with a stimulus (i.e., an event). Figure 4 provides a detailed example of the CPM mechanistic process. A stimulus is first appraised based on its relevance (e.g., is it new or familiar? Is it pleasant?). Following this first appraisal, changes might be observed in the peripheral efference, motivational, motor expression, or subjective feeling components. Once the first appraisal has been executed, the following appraisal component can proceed, the implication (e.g., is it an urgent stimulus that must be dealt with now?), the coping (e.g., can I control what is happening?), and the normative significance of the stimulus (e.g., is the stimulus compatible with my standards?). Each appraisal can trigger both the next appraisal and the organismic subsystems serving the changes in autonomic physiology, action tendencies, body posture, and affective states at a given moment. Hence, the CPM is not an entirely linear model. Furthermore, once a component has been appraised, it can be reappraised. Such reappraisal can happen because the incoming stimulus has changed or because the effects of one appraisal has modified previous appraisals. In addition, not all components need to be appraised for the emotion to emerge. That being said, the more components are appraised, the more the emotion is differentiated (i.e., the more it is specific in its expression).

One of the organismic subsystems of the CPM model is action tendency. This concept of action tendency stems from the concept of action readiness, which is at the heart of another appraisal model by Nico Frijda who developed the theory of *action readiness*. This model postulates that emotions are necessary only to help humans react to the world (Frijda, 1986, 2006). Emotions exist for the sake of signaling states of the world that need to be responded to (Frijda, 2006). This cornerstone idea inspired the writing of two major books: *The Emotion* to describe emotions (Frijda, 1986) and *The Laws of Emotions* (Frijda, 2006) in which definitions of emotions, appraisal as well as the concepts of action readiness and action tendencies for emotional reactions are presented, defined, and discussed.

Frijda (2006) defines a total of eleven laws that guide human experiences of any given emotion. These laws are defined to decode the causes, the nature, and properties of the experiences as well as the outcomes of the global emotional experience. In this theoretical framework, emotions exist only to help humans act and react for sustained well-being within an ever changing world. This is why the concepts of action readiness and action tendency are here the corner stones of what is an emotion. Action readiness is the readiness to achieve a particular aim. The aim that is evoked here can be anything from avoiding walking in a dark alley at night to eating a juicy fruit. Action tendencies are states of motor and cognitive preparation to achieve the aims. Thus, action tendencies happen before action readiness. And these states of action readiness are what is meant by emotions.

Action readiness arise through appraisal. Frijda, Scherer, and a great number of emotion researchers consider that appraisal is necessary for an action readiness (and an emotion) to emerge. In Frijda's model 2006, the first law –the *law of situational meaning* –states that emotions arise in response to patterns of information, and that it is the meanings and the individual's appraisals that count; not the stimuli or events per se. Hence, a dark alley at night is not scary in itself. It is scary because one appraises it as scary, given that dark alley may be used by criminals to assault civilians. This is an example of the second law –the *law of concern*. Here, emotions arise in response to events that are important to an individual's concerns. If one is a special operations military, one might not appraise the dark alley as scary.

These first two laws offer a better view of how an emotion can emerge. Most importantly, they offer an answer to the question why does an emotion emerge when it does. The theory of Frijda inspired Scherer notably, but also Ridderinkhof who developed more recently a dynamical model of emotion, presented in section 2.4.3 of this chapter.

2.3.2 *Measurement tools*

Psychologists sometimes ask participants to describe their feelings in their own words. While this procedure may yield interesting insights, it is fraught with limitations. For example, people differ with respect to their verbal ability and richness of vocabulary. Hence, psychologists generally use forced-choice self-reports of emotional experience. There are two major approaches: (a) the discrete emotion labels approach and (b) the dimensional rating approach.

2.3.2.1 *Discrete emotion labels*

The discrete-emotion labels approach is based on the theoretical idea that there exists a finite set of basic emotions. Thus, the measurement tools invite participants to rate how they feel for each of the labeled emotion.

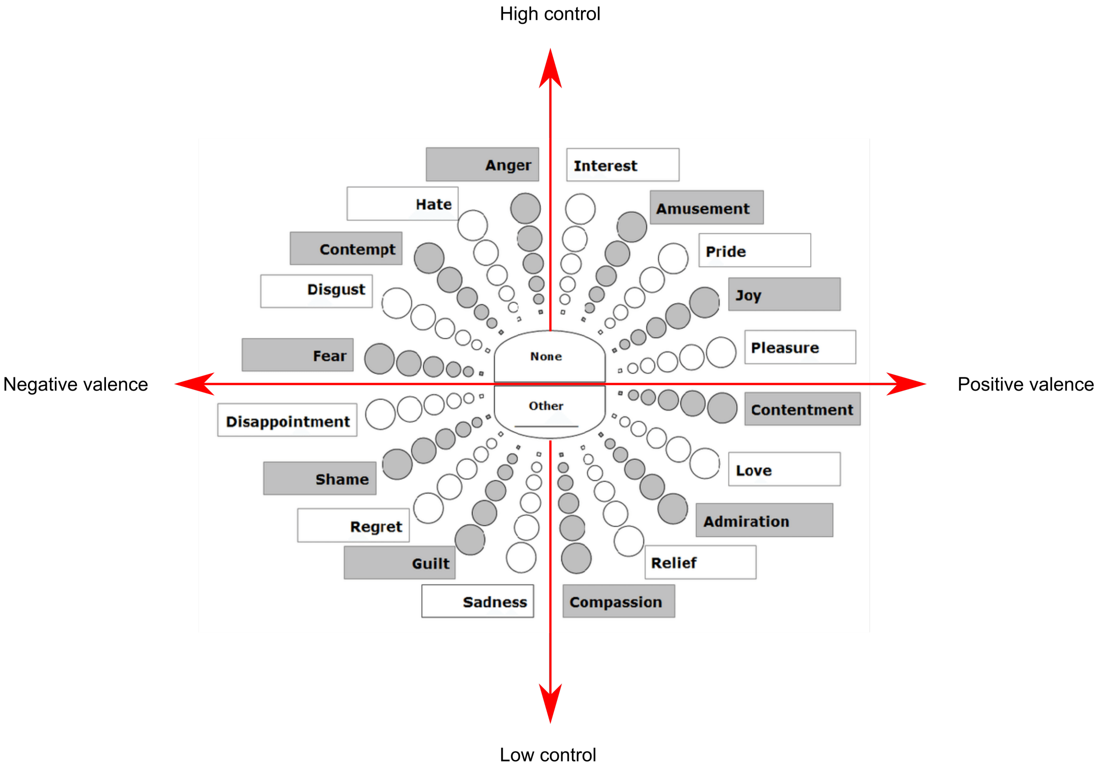
A good example of such a tool is the fourth version of the Differential Emotional Scale (Izard et al., 1993). This tool consists of labels presenting 12 distinct emotions. Participants are instructed to rate if they feel (or not) each of the twelve emotions. To rate the intensity of the appraisal, a 5-point scale is presented ranging from 1 (*rarely, never, weak*) to 5 (*very often; strong*).

2.3.2.2 *Dimensional rating*

The dimensional rating approach, on the other hand, is based on the theoretical idea that emotional experience is supported by a number of dimensions (usually two or three). The measurement tools based on this approach require participants to rate how they feel in each dimension.

One of these measurement tool is the Geneva Emotion Wheel (GEW; Scherer, 2005, see Figure 5). This tool consists of 20 emotion families arranged around a circle. Participants are instructed to rate if they feel one, several, or none of the 20 emotional categories and how intensely their experience is. Thus, the GEW enables researchers to investigate three dimensions of emotional experience: valence, control/power, and intensity. Valence is evaluated along the horizontal axis. Control/power is evaluated along the vertical axis. Intensity is coded by the size of the selected circle.

Figure 5
Geneva Emotion Wheel



Note. The Geneva Emotion Wheel offers the means to measure three dimensions of emotional experience: valence, control/power, and intensity. Positive emotions are presented on the right side of the GEW. Emotions with high control/power are presented on the top. Intensity is coded by the size of the circles (the bigger the circle, the more intense the perceived emotion). Adapted from Scherer (2005).

2.3.3 *Examples of studies investigating emotions*

This section will explore examples of studies using the GEW and the Emotion and Odor Scale (EOS) to investigate emotions in relation to art and odors.

The first study is one conducted by Tinio and Gartus (2018) at the Whitney Museum of American Art in New York City. Researchers wanted to investigate the emotional responses of visitors to two exhibitions. The GEW was used as it provides participants with a large choice of emotions (and the ability to report an absence of emotion) but mainly because the theoretical framework was that of appraisal. Participants were recruited at the end of their tour in the museum. They were invited to answer four questionnaires, with the GEW being the first. The experimenter correlated the data with the time spent in the exhibitions and the number of art labels read. Results revealed that the more time the participants spent in the exhibitions, the more they reported feeling involvement, interest, enjoyment, and pleasure. Concerning the number of art labels read, the results were similar. The more labels participants read, the more they reported feeling involvement, interest, enjoyment, and pleasure.

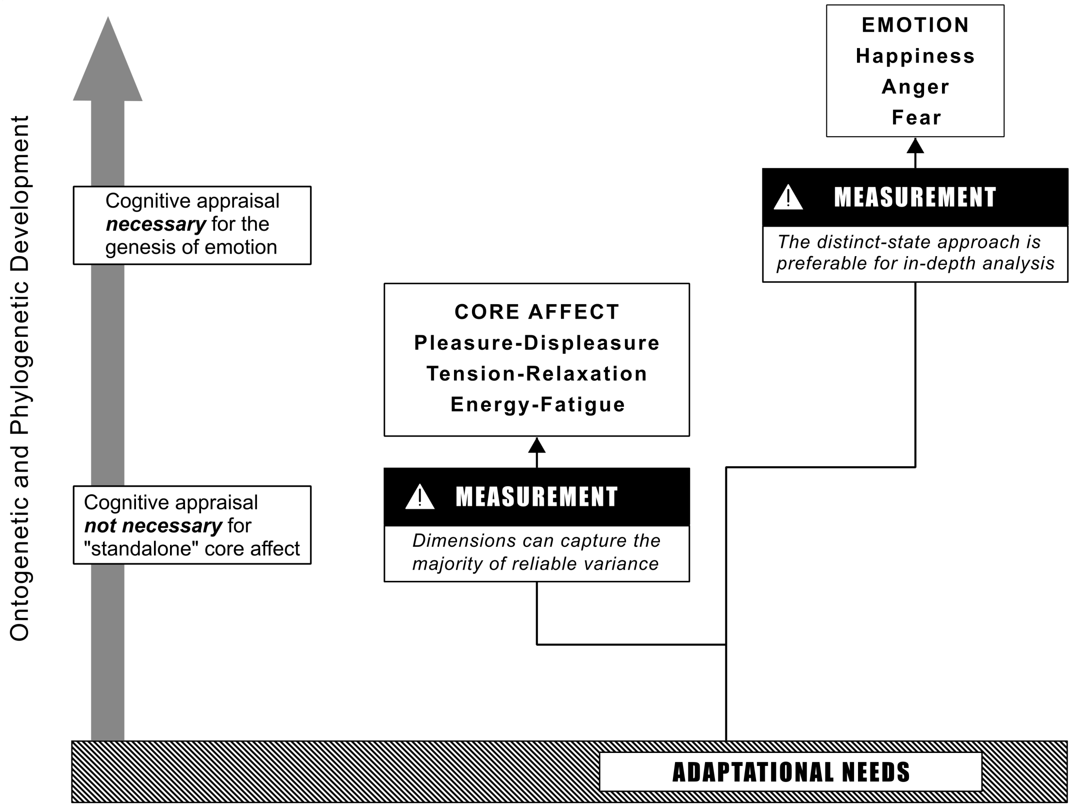
Another study investigating emotions is one conducted by Guillet et al. (2017). This study focused on the impact of odors on customers in luxury hotels in Hong Kong. Hotels that developed their own scented environments were chosen. The EOS (Chrea et al., 2009; Ferdenzi et al., 2013a) was adopted within the theoretical context of appraisal. The EOS is a list of emotions and participants were invited to rate on a 10 cm continuous scale how intense they feel each emotion word. The anchors are *not at all intense* and *extremely intense*. Participants were asked to rate their perception of the hotel scent using the EOS (Guillet et al., 2017). Results indicated that the hotel scent elicited happiness, delight and sensuality. The scent was also rated as being of a mild intensity (6.15 on a scale ranging from 1 to 10).

2.3.4 *Conclusion*

Emotions are today at the heart of virtually every scientific field of research. As with affect, each study investigating emotion adopts a particular measurement tool, for a specific reason. Hence, the importance of agreeing on a common set of theories and methodological principles. Such a consensus has been reached for the physiological aspect of affective states but has not yet been reached for emotions.

Definitions are rarely universally agreed. They cannot be proven (Scherer, 2005). Thus, definitions must be considered universally as useful by a research community in order to guide research and make research comparable across laboratories and disciplines (Scherer, 2005, p.724). Mood, affect, and emotion are three constructs that have been tentatively defined. Due to considerable convergence among scientific disciplines, a workable classification scheme has started to emerge and is being adopted by an increasing number of researchers (Ekkekakis, 2013). Figure 6 illustrates the general idea. Depending on the research question, one or other of the affective/emotion branch will be used. The key point to bare in mind is that the choice of a method must be guided by the theoretical model from which the method emerged.

Figure 6
Structure of Core Affect and Emotion



Note. Adapted from Ekkekakis (2013).

2.4 EMOTIONAL MOTOR BEHAVIOR

Affective responses can be generated without an antecedent cognitive appraisal. Russell (2003) emphasized that as consciously experienced, core affect is mental but not cognitive or reflective. Hence, a bodily movement can in itself induce changes in core affect (e.g., simply imagine running a 10 km race). But once an affective state has emerged, sensorial consequences can be predicted, processed cognitively, and become an emotion (Lazarus, 1991). Accordingly, thoughts alone are capable of producing emotions. For example Kunst-Wilson and Zajonc (1980) reported data indicating that participants could form preferences for meaningless visual stimuli that were superimposed on images of happy and angry faces, at a speed faster than the threshold for conscious awareness. Hence, core affect may be a neuro-physiological state consciously accessible as a simple primitive, a non-reflective feeling that can in a second step, trigger or modulate an emotion that is available to consciousness when payed attention to (Russell & Feldman-Barrett, 2009). This dynamical view of emotion is at the heart of most recent models, which will be presented in the following section.

2.4.1 *Rooted from biological models*

In an effort to bridge the gap between psychologists and neuro-biologists, Marc D. Lewis (2005) proposed a theory of emotion based on Dynamic System (DS) modeling, which is used to describe and predict the interactions over time between multiple components of a phenomenon that are viewed as a system (Irwin & Wang, 2017). In this framework, an emotional episode is a system that arises from multiple interacting components. This is consistent with the aforementioned models of emotions, such as the CPM for which organismic subsystems are continuously and recursively appraised to give rise to the emotional episode. This non-static consideration of emotion has given birth to a new line of research that embraces the importance of assessing changes over time. Whether stemming from the appraisal or the affective models, current theories argue for a dynamic view of emotional human behavior, with a need to embrace new technical tools and methodological approaches in experimental human sciences.

2.4.2 *Rooted from affective models*

Rooted from affective models, Lisa Feldman Barrett (2017) has developed a neurobiological theory of emotion based on predictive coding (Friston, 2005). The idea at the heart of her Theory of Constructed Emotions (TCE) is that all humans (as every living organisms) thrive to maintain allostasis (i.e., regulating the body by anticipating physiological needs and preparing to meet them before they arise; Barrett, 2017). To achieve such a goal, organisms must run an internal model of their world (Barrett, 2017). Using this internal model, organisms can then predict the impact of their actions both on their inner and outer worlds. Thus, emotions may simply be a construct used to label the emergence of attitudes that need to be perceived and recognized by others. The recognition process would be reached trough cognitive mechanisms that would compute the discrepancies between simulations and actual sensory inputs.

The complexity of the brain raises nevertheless the question of the selection process that must undergo from real world elements and percepts to simulations. Following the TCE model, the brain selects simulation candidates memorized from past experiences, which are similar to incoming sensory inputs. Through bayesian probabilities, a prediction error is calculated between simulation and actual input. Selection is then made to minimize computed errors by contrasting or tweaking series of simulations. Once this error is minimized, the simulation becomes a perception (i.e., an emotional percept; Barrett, 2017). The percept becomes an emotion as soon as a human observer calls it an emotion. Indeed, the brain does not give names to its simulations and perceptions. Only humans – gifted with language abilities – can infer conceptual categories. It is in this sense that Barrett believes that emotions are born the same way as other perceptions. "Emotion categories are as real as any other conceptual categories that require a human perceiver for existence, such as *money*." (Barrett, 2017, p.13).

The theory of constructed emotion challenges the cognitive-centered views of emotion that emphasize the central role of appraisal processes. In Barrett's words, meaning may simply be a resultant of action, whereas for the following authors, actions stem from meaning.

2.4.3 *Rooted from appraisal models: The IMPPACT model*

Starting from a decidedly Frijdian perspective, Ridderinkhof developed a theoretical model to explain and predict the links between emotions and actions (Ridderinkhof, 2014, 2017). The Impetus, Motivation, and Prediction in Perception–Action Coordination Theory (IMPPACT) was first designed to describe how humans coordinate their actions, their perceptions and the interactions between action and perceptual processes (Ridderinkhof, 2014). In 2017, the model evolved to include an emotional aspect of voluntary motor behaviors.

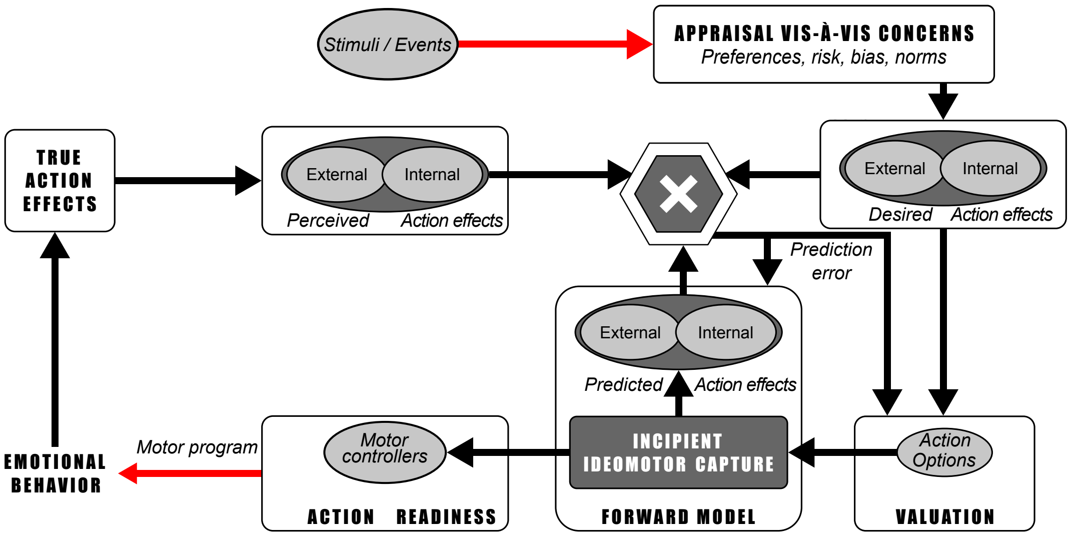
Emotions are percepts that signal the need for action, to maintain or retrieve one's well-being. However, an action does not always imply a movement. Sometimes it might be best to produce the action of not moving, to avoid being hit by a car for instance. Therefore, an emotional action, or rather an emotional act, is produced by motives to alter the current state of the self and of the world so as to approximate a more optimal state of being (Ridderinkhof, 2017). Another characteristic of an emotional act is that it is determined by its ultimate or proximate end (Ridderinkhof, 2017). In simpler terms, an emotion is an act produced to achieve a certain end, which is to maintain or retrieve a state of well-being. Take the following example: Mary is returning home after a hard day of work, along with her daughter. While walking towards the front door, she smells a strong odor of gas. The emotional act of Mary would be to turn back and keep away from the house while calling the emergency services. Only then will she be able to put words on what she felt. The act is to keep away from the house and call the emergency services. The end goal of the act is to regain safety both for here and for her daughter.

An illustration of the cognitive process that may have taken place in Mary's brain and body is presented in Figure 7. Following the IMPPACT logic, emotional actions are produced by a six-step process: appraisal, pragmatic idea, incipient ideomotor capture, changes in action readiness, valuation of action options, production of emotional behavior.

The first step, appraisal, serves the purpose of determining the significance of a stimulus with regards to the organism appraising the stimulus. Ridderinkhof (2017) adds that an emotion needs an event to be elicited but that an emotional act needs an event "as appraised" to be elicited. In other words, actions stem from an emotional percept that contains meaning.

Once an event has been appraised, the formation of a "pragmatic idea" is required to trigger an emotional act. More specifically, a pragmatic idea consists of images of kinesthetic sensations associated with the action and its anticipated effects on the world and one's own body (Ridderinkhof, 2017). This pragmatic idea is the prediction action effects, the anticipated consequences of a possible forthcoming action. Note that this pragmatic idea is, most of the time, unconscious. The pragmatic idea of Mary is that she and her daughter should be safe (effects on the body) and that their house should not explode (effect on the world).

Figure 7
IMPPACT Model



Note. The Impetus, Motivation, and Prediction in Perception–Action Coordination Theory model reproducing the schematic architecture for ideomotor action, supplemented with a forward model (i.e., turning action selection into an action–effect prediction-and-valuation cycle). The forward model calculates the predicted action effects (for exteroceptive, interoceptive and proprioceptive action effects); these predictions are fed into a comparator (symbolized by the central hexagon). Predicted action effects are compared to actual action effects, giving rise (in case of discrepancy) to a prediction error which is fed back into the forward model so as to optimize its predictions. Predicted action effects are compared to desired action effects, in which case a prediction error is used to reevaluate and adjust the chose action option, which is then fed into the forward model in its turn; the cycle continues until the prediction error is minimized and the appropriate action can be programmed (action readiness module) and executed. Adapted from Ridderinkhof (2017).

The formation of a pragmatic idea does not lead directly to action. It leads to the retrieval of a motor program that produces the desired effects, issued from the pragmatic idea. Indeed, the ideomotor principle holds that any activation of the pragmatic idea of an action's effect may awaken the corresponding action (Ridderinkhof, 2017). Mary's ideomotor actions are any action that achieves the goal of feeling safe (e.g., running away to safety, shielding behind another house) and any action that prevents her house from exploding (e.g., calling the emergency services, or running inside the house to find the gas leak). The ideomotor action leads to a change in action readiness. In this step, the organism gets ready (although not always consciously) to engage in one of the ideomotor actions. Mary is now ready to engage in either two of her four ideomotor actions: run or shield.

How can the organism select the right one? The various action alternatives differ in their values with respect to both their cost and their benefit (Ridderinkhof, 2017). Through the valuation of action options, the brain selects the action that has the lowest cost/benefit ratio for the individual. This cost/benefit ratio is specific to the organism. This processing step might appear to be costly for the organism. If ratios for virtually all actions had to be computed every time, it would indeed be too costly for the organism. Fortunately, humans are a remarkably well designed machinery. Through evolution and learning, most of human actions have a given cost/benefit ratio (Ridderinkhof, 2014). These ratios are created, refined with experience, learning, and then anchored within the valuation module of the brain. Mary's brain now computes and compares the cost/benefit ratio for each of her four ideomotor actions, within a split second.

It is only when the ratios for all possible actions are computed that the final action processing step of the model is carried out. The brain now compares the predicted effect of the optimal action (selected at the previous valuation processing step) to the desired effect of the action. This comparison takes into account the true perceived internal and external action effects to calculate a prediction error that is then used by the brain to determine whether the selected action is the optimal one. If the selected action is not optimal, then another action is selected and the forward model loop is ran a second time. This internal loop process is repeated until the prediction error is minimal. Only then is the corresponding motor program sent to the effectors (i.e., muscles) in order to carry out the selected motor behavior. Mary's brain has computed and compared the different effects of her four ideomotor actions and has selected the most adapted in reference to her past experiences. Mary now grabs her daughter, runs to safety, and calls the emergency services. She and her daughter are safe and their house has not exploded! All of these processing steps happened in a fraction of a second, and without Mary even being aware of it.

A good theory is one that provides answers and means to test them. The IMPPACT model is a well accepted model that stems from Frijda's work on action readiness (Frijda et al., 1989) and Wolpert's work on forward modeling (Wolpert & Flanagan, 2001). Hence, it provides a trans-disciplinary approach of emotional motor behavior. Most importantly, it offers a testable framework in the experimental fields of motor behavior, cognitive psychology, and affective sciences. Humanoid robotic systems can also be implemented with the proposed control loops, another meaningful way to test experimentally the IMPPACT model. Nevertheless, questionnaires and scales are not sufficient. Indeed, to take into account the recursive and dynamic aspect of the model, derived paradigms are needed that take essence in new technologies.

2.5 EMOTION RESEARCH IN THE ERA OF AFFECTIVISM

The COVID-19 pandemic has made humans realize how technology was changing our way of communicating our emotions. Today, emotions are not limited to human–human contacts. We have built, through technology, human–human contacts via computer screens for example. Video-conference tools allow to communicate but only by displaying a static view of the world. Not being able to see the context or the body of our interlocutor can impair our emotional recognition abilities (Meeren et al., 2005). This change of communication medium is having an influence on various cognitive processes, such as creativity (Brucks & Levav, 2022) for instance, not just emotional processes. Furthermore, technological advances in robotics have lead to the development of highly developed robots. Humans have now been found to feel emotions towards robots, objects or avatars (Hortensius et al., 2018). Considering the recent development both in robotics and virtual reality, there is a high probability of more artificial agents entering our lives. Therefore, emotion theories need to continue evolving to account for and understand the changes that technology exert on humans. Doing so will provide emotion research with the mean to guide other disciplines wishing to integrate emotion in their research.

Emotion research has been continuously evolving. It has evolved from measuring physiological reactions in sitting tasks (Droit-Volet et al., 2013; Nummenmaa et al., 2006; Ruiz-Padial & Thayer, 2014) to measurements of emotions in whole-body movements (Daoudi et al., 2017; Hicheur et al., 2013), due to technological advances. Motion capture (MoCap) technologies have enabled researchers to investigate how the whole-body was reacting to emotions, by placing reflective markers on participants. Today, further advances in computer vision have offered the means to continue doing so, without ever touching the participant. The markerless MoCap systems are now as accurate as the traditional marker-based systems (Kanko et al., 2021a, 2021b). Emotion research needs to continue its evolution and we believe that adopting a data science perspective can help part of the evolution.

Data science is a relatively new field of research, fundamentally multi-disciplinary (Cao, 2018). It promotes the integration of experts in various domains to help them all grow and create new advances. Taking into consideration the impact of the emotional content of a stimulus while controlling the affective state of a participant is challenging. It requires that physiologists and cognitive psychologists work together. Integrating the methodologies of several domains can be achieved through a data science perspective. Furthermore, embracing a data science perspective might allow researchers to ask theoretical questions and design new experiments without being blocked by technical limitations (e.g., synchronizing multiple equipment). To be more specific, measuring emotional experience during whole-body movements requires the synchronization of motor control measures and emotional perception before, during and after the task. Hence, such synchronization would enable new experimental designs to investigate the dynamics of emotional processes that might be hard to investigate at the moment (Carlier et al., 2017). New avenues in emotion research can be opened by removing technological barriers. A holistic data science perspective can help achieve this goal.

2.6 CONCLUSION

The rise of affectivism that is emerging in psychology is bringing emotion in all other domains of research. Together with the extensive use of technology, it raises many theoretical questions for emotion research. Embracing a data science perspective can offer a holistic point of view. It can allow to remove many technical constraints on experimental designs, such as dealing with large amount of data, synchronizing equipments, or measuring the dynamics of emotional processes. This holistic perspective can help emotion research continue its evolution, as emotion research will have a defining role in guiding other research domains in their integration of emotions. It is only by understanding emotional processes that it will be possible to integrate them in other domains.

Part II

A GOOD METHOD TO MEASURE COMPLEX HUMAN PROCESSES

3 MEASURING BODILY REACTIONS TO EMOTIONS

3.1 AT A SUBJECTIVE LEVEL

Affect and emotions can trigger changes in the physiology, kinematics, and perception of a person. To get a complete understanding of these changes, it is necessary to ask participants to report how they feel. To collect self-declared experiences, many questionnaires have been developed. There are questionnaires where participants are presented with emotional words and they need to select the words matching their feelings (e.g., GEW; Scherer, 2005). There are also questionnaires with small characters depicting different emotions and participants are asked to circle the ones matching their feelings (e.g., SAM; Bradley & Lang, 1994). Each questionnaire is designed to evaluate a specific construct, such as the emotion, the intensity of the emotion, the affective state, or a combination of constructs. Hence, as is the case for all methodology, the selection of a questionnaire must be made in accordance with the theoretical framework in which the work is included. This is why during my PhD work, the affect grid was selected to measure the affective responses of the participants (Russell et al., 1989).

The affect grid is a two-dimensional grid designed to have a measure of both valence and arousal with a single response from the participant. The measure is based on the circumplex model of affect (Russell, 1980). This theoretical model posit that affect can be measured in terms of valence (how positive is what I am feeling?) and arousal (how intense is what I am feeling?). Both valence and arousal are scored on a 9-point Likert scale, with valence on the horizontal axis and arousal on the vertical. In the studies of my PhD work, I decided to add numbers to the original affect grid so that participants would have an easier time at reporting their feelings verbally (see Figure 8), during seating, walking, and cycling tasks.

3.1.1 *Difficulties and limits*

The choice of the affect grid was not straightforward and it led to some difficulties, for which we managed to find solutions. When we first used the affect grid in one of our studies, we were pre-testing an experiment where the participants were expected to run at a low intensity on an electrical treadmill. We wanted to investigate how they would react to the presence of an odor during their run. We had printed the affect grid on an A0-poster format which was presented before, during, and after the run. During the activity, we noticed that participants would try to point at the squares in the affect grid to give their response and how this movement destabilized them. If the speed was to be increased, their was a real risk of falling. I took a marker and started adding numbers in the squares to help participants respond. We decided to keep this version because it did not make a profound modification of the scale, and

Figure 8
Adapted Version of the Affect Grid

Stress					High Arousal					Excitement
	1	2	3	4	5	6	7	8	9	
	10	**11**	12	13	14	15	16	17	18	
	19	20	21	22	23	24	25	26	27	
	28	29	30	31	32	33	34	35	36	
Unpleasant Feelings	37	38	39	40	41	42	43	44	45	Pleasant Feelings
	46	47	48	49	50	51	52	53	54	
	55	56	57	58	59	60	61	62	63	
	64	65	66	67	68	69	70	**71**	72	
	73	74	75	76	77	78	79	80	81	
Depression					Sleepiness					Relaxation

Note. Adapted version of the affect grid (Russell et al., 1989). Numbers were added to make verbal report of affect easier when participants perform the experimental tasks. The bold numbers represent two of expected answer to the questions "how would you describe your affective state in terms of valence and arousal if you were to hear a gunshot close to you (number 11) or if you were enjoying a relaxing massage (number 71)?"

thus did not impair the scientific validity of the scale while making verbal responses easier and safer in the case of exercise studies.

The second difficulty we faced was that, to us researchers, used to manipulating the psychological concepts of affect, valence, and arousal, the affect grid is easy to use. However, for participants, the use of a grid to describe unconscious and often unnoticed affective states, was difficult and strange. No one has ever had to describe their feelings in terms of valence or arousal outside a laboratory. First, it was necessary to explain to our participants what we meant with valence and arousal. In our words, valence describes how positive your affective state is. The more positive you feel, the more you are expected to respond on the right-hand side of the affect grid (toward the anchor *Pleasant Feeling* in Figure 8). Arousal describes how aroused, or energized your affective state makes you feel. The more you feel aroused or energized, the more you are expected to respond on the top of the affect grid (toward the anchor *High Arousal* in Figure 8). Depending on the participants, the explanations could be repeated more than once. To further help participants familiarize with the grid, Russell et al. (1989) developed two examples. The first one is "imagine hearing a gunshot behind you, how would you describe your affective state in terms of valence and arousal?" (this example is depicted with the bold number 11 in Figure 8). The second one is "imagine enjoying a relaxing massage, how would you describe your affective state in terms of valence and arousal?" (this is the bold number 71 in Figure 8). These two examples are critical if we want to be sure that the participants used the grid adequately.

3.2 AT A PHYSIOLOGICAL LEVEL

The cardiac activity is one of the most vital organism in the human living being. Therefore, understanding its functioning and being able to measure its activity is crucial. However, the mechanism by which the heart sends blood throughout the organism is complex and adapts as a function of the ongoing behavior. Hence, a good methodology is key to modeling the human physiological system especially in remote psychological testing.

The cardiovascular system is responsible for transporting nutrients and removing gaseous waste from the body. This system is comprised of the heart and the circulatory system. Hence, heart rate (HR) and heart-rate variability (HRV) are the physiological indicators that can be used to describe how the cardiovascular system is regulated over time. HR, usually measured as the number of heart beats per minute (BPM), reflects how the heart is responding to the current demand in blood and oxygen of the body. When exercising, for example, the muscles are in need of more energy and oxygen to accommodate the demand. Therefore, the heart beats faster to increase the amount of oxygen sent via the blood vessels to the muscles. This would be visible as an increase in the number of BPM within a couple of seconds after the occurrence of an event. HRV is more subtle as it reflects the changes in the interval of time between successive heartbeats (Shaffer & Ginsberg, 2017). HRV is influenced by many core mechanisms of the human function (e.g., respiratory system, circadian rhythms), and most notably by the autonomic nervous system (ANS).

Broadly speaking, HRV is a measure of how good the heart is at adapting its functioning to match bodily requirements.

Time-domain measurements of HRV reflect the variance in the amount of time between successive heartbeats. These measurements are easy to compute as they can be calculated on short trials (< 5 min.). However, they do not provide a complete description of the underlying physiological mechanisms. Time-domain measurements include, but are not limited to, the standard deviation of successive differences (SDSD) and the root mean square of successive differences (RMSSD). The RMSSD is one of the most reported metric in scientific literature and is used to estimate the vagally mediated changes reflected in HRV (Shaffer & Ginsberg, 2017). In my PhD work, we were limited to trials of maximum 4-min in length, in individuals that were not immobilized (possible occurrence of motion artifacts). Hence, the RMSSD, expressed in milliseconds, was used to measure HRV. The RMSSD can be computed on most of the physiological recordings, even those ranging from 30–60 s (referred to as ultra-short recordings; Munoz et al., 2015).

Now that we knew which indicator of HRV would be computed, we could select a recording device. The important thing to consider is the sampling frequency (i.e., the number of recordings made per seconds). The higher the frequency, the more precise the analysis. The Nyquist-Shannon theorem states that the sampling frequency must be at least two times superior to the frequency of what is measured. A healthy human has a HR between 42 and 210 BPM (0.7–3.5 Hz; Opthof, 2000). Thus, to record accurately the HR of a healthy human, it is necessary to have a sampling frequency of at least 7 Hz. But to measure time differences in heart beats of the order of 10 ms (100 Hz), one must use a sampling frequency of at least 200 Hz. This is why prior studies on HRV have shown that the minimum sampling frequency of an HRV recording device should be above 200 Hz without efficient pre-processing. Nevertheless, in recent times, it has been shown that this limit can be tuned down to below 100 Hz if a strong pre-processing approach is adopted to offer the means to mathematically enhance the R-peak detection prior to HRV computation (Laborde et al., 2017).

A wide range of sensors are available to record cardiac activity. The most used and most reliable of all is the electrocardiogram (ECG). With a high sampling frequency of typically 1,000 Hz, the ECG is the optimal indicator from which to extract both time- and frequency-domain measurements of HRV. The ECG measures the electrical activity of the heart via electrodes positioned on the skin. The electrodes are wired to the recorder, positioned within close proximity of the electrodes. However, when using an ECG, the participants or patients are limited in their movements. When we decided which recording device we were going to use in my PhD work, we tested a wireless version of an ECG (Biopac, Biopac Systems, Goleta, CA), a commercial smartwatch (Apple Watch Series 3, Apple, Cupertino, CA), a Polar V800 (Polar Electro, Kempele, Finland), and the Empatica E4 wristband (Empatica, Cambridge, MA). Our criterion were to have the best device that could be used both inside and outside the lab, so as to maximize the reusability of the algorithms we were going to develop. The wireless ECG was the best in term of sampling frequency and signal quality, as expected. However, even wirelessly, the participant needed to remain within several meters from the recorder, which was quite heavy and connected to a computer. The Apple Watch Series 3 satisfied our criterion to be used inside and outside the lab but only gave the values of HRV, without access to the raw signal. The Polar V800 also satisfied our freedom of movement criterion and gave the R–R intervals, which can be used to compute all time-domain measurements of HRV. The only downside of the Polar V800 was that it used a chestband to monitor HR. The Empatica E4 wristband is lightweight and records data via a photoplethysmographic (PPG) sensor, so directly on the wrist of participants. It has a quite low sampling frequency of 64 Hz but gives access to the raw signal. Therefore, we chose the Empatica E4 wristband because (a) it satisfied our freedom of movement criterion and (b) we could use cutting-edge pre-processing algorithms on the raw signal to make up for the low sampling frequency.

When we first looked at the data obtained in Chapter 4, we saw a high number of motion artifacts for a task that required almost no movement (the participant was seated and invited to smell odors as well as respond to scales on the computer). Fortunately, the motion artifacts were not too big as we had positioned the wristband on the non-dominant hand of the participant and asked them to avoid moving their hand. To remove these artifacts, a visual inspection of the signal of every trial of every participant was necessary. When the artifacts were too big, we followed the guidelines of the scientific community and removed that portion of the signal (Laborde et al., 2018). Then, a filter was applied to remove most of the artifacts. To avoid removing potentially informative data, we set the bounds of the filter to 0.7–3.5 Hz (i.e., 42–210 BPM, the normal range of BPM in humans; Opthof, 2000). Only then were we able to compute both the number of BPM and RMSSD. The full detail of the procedure can be found in the submitted manuscript, in Appendix A.

In my PhD work, changes in either the number of BPM or RMSSD were interpreted as reflecting the impact of a stimulus on the ability of the body to regulate itself. Studies have found that odors and induced emotions modulate physiological parameters (Alaoui-Ismaili et al., 1997; Appelhans & Luecken, 2006; Vernet-Maury et al., 1999; Wang et al., 2018). The direction of this influence is generally that positive odors and emotions trigger a decrease in HR and an increase in HRV. This influence has been interpreted in my PhD thesis as an evolutionary advantage provided by the stimulus. If a positive stimulus decreases your HR, your heart will need less energy to maintain its functioning and you will need less energy intake. Furthermore, by increasing your HRV, the positive stimulus will enhance the capacities of your body to regulate itself to respond to the environmental demand. Therefore, your body will be able to react faster and better, providing you with a significant evolutionary advantage.

3.2.1 *Difficulties and limits*

When I first looked at the data of Chapter 4, I was very satisfied with their quality until I saw the data coming from the Empatica E4 wristband. Or some of it. For one participant in particular, the data was not analyzable due to motion artifacts. For most participant there were none but for others we could see minor but numerous motion artifacts. Our participants were asked to sit on a chair, their head placed on a chin rest, the wristband was positioned on their non-dominant hand, and they were asked not to move their non-dominant hand. This is why I was quite surprised to find even minor motion artifacts in the data. At least two reasons can explain these artifacts. The first is that, contrary to my belief, participants were not behaving exactly as we expected them to. Even if asked not to move, participants still moved, consciously or not. The second reason is that the wristband is using light to measure cardiac activity. If there are other sources of light entering the receptor, then the measure is not accurate. This is why we added a dark cloth around the wrist to limit light infiltration. Furthermore, the position of the wristband must be made very carefully to ensure data quality. If the wristband is displaced due to movement, then this part of the recorded data might suffer from artifacts.

Wristband cardiac sensors provide a lot of benefits for out-of-the-lab research, notably. Their utility could even be improved by enhancing the quality of the signal. One possibility would be to use the data coming from the accelerometer of the wristband and then perform some kind of source separation to remove part of the noise in the signal. I had thought about using source separation over the course of my PhD. However, doing so requires both time and advanced skills in signal processing. If I had done source separation, I would not have been able to complete my PhD in three years. Which is why we decided to acknowledge this problem, follow the guidelines of the scientific community, and remove parts of the signal that were too noisy.

3.3 AT A KINEMATICS LEVEL

Kinematics is "the study of motion of the body or parts of the body in terms of limb and joint position, velocity, and acceleration" (American Psychological Association, n.d.). It is studied in itself and in a wide range of research domains such as psychology for example. Kinematics data collection is conducted in various ways, using MoCap technologies or electromyographs most notably. In my PhD work, I decided to use MoCap technologies to record human kinematics because of its reliability, relative ease of use, and because I had experience with this technology during my Master thesis.

3.3.1 *Recording kinematics*

MoCap systems are a set of tools designed to record the kinematics of either humans or animals. It is used to study the influence of a pathology on gait, to enhance the performance of an athlete, or to model the interpretation of an actor in an Hollywood movie. The underlying technologies can vary but the most used in research and industry today are based on cameras. Optical MoCap can either be marker-based or markerless.

Marker-based MoCap uses markers and infrared cameras to record in real-time the location of each marker in space. The markers are usually positioned on major joints of the body but can be placed on any surface, allowing to record the motion of manipulable objects for instance. The markers can either be passive retro-reflective made of plastic or active LEDs emitting light at specific intervals. The active markers are less prone to occlusions but are much more expensive and complicated in their design as they are made of tiny LEDs. Therefore, almost only passive markers are now in use (both in research and industry). This technology is widely used in research as its measurement error (i.e., the difference between the measurement and the reality) can drop even below 0.2 mm.

Markerless MoCap has been developed for several years, mostly in computer science and especially in computer vision. The goal of markerless MoCap is to record the kinematics without placing markers on the participant. The technology is now accurate enough to be used in scientific research (for a validation of one system, see Kanko et al., 2021a, 2021b). In my PhD, one markerless system was used, Theia3D (Theia Markerless Inc., Kingston, ON), to record the emotional kinematics of laymen. Theia3D uses eight synchronized Qualisys (Qualisys AB, Gothenburg, Sweden) video cameras to record different views of the participant. Then, the deep-learning algorithms behind Theia3D identifies the participant, extracts its major joints position, and computes the inverse kinematics to be able to infer the exact position of each joint.

The advantages offered by markerless MoCap are numerous. Indeed, the time-consuming phase of marker placement is no longer needed and participants are free to be dressed however they desire, further increasing the possibility of ecological research. Nevertheless, no system is perfect and markerless MoCap has its set of drawbacks. First of all, it requires a large amount of storage on the recording computer. As an illustration, in one of the studies of my PhD work, participants had to walk for 1 min and 30 s, repeated 20 times. A total of 300 GB was necessary for each participant. Thirty participants were recorded. Hence, this one study required 9 TB of storage space. The second drawback is related to the computing power and time necessary to process the data. Theia3D, as nearly all computer vision deep-learning algorithms, rely on graphics processing unit (GPU) rather than traditional central processing unit (CPU) to perform faster computations. GPUs can be costly but they provide a significant increase in computing power (around 2.5 times faster than CPUs; Lee et al., 2010). Even with such added power, the markerless analysis is still time-consuming. For the experiment mentioned above, with the minimal requirements of Theia3D (NVIDIA RTX 2060 Super GPU, 32 GB RAM), it required 18 hours to extract the 3D position for a single participant. Again, 30 participants were recruited which led to 540 hours of data extraction to simply obtain the 3D positions of the markers.

3.3.2 *Analyzing kinematics*

The recording of the kinematics is only part of the study of human kinematics. Once the data has been collected, it is necessary to analyze it to be able to confirm or reject the research hypotheses. Traditional measurements of kinematics include velocity, acceleration, jerk, and joint angles. These measurements are now easy to compute yet convey sufficient information for a number of studies, including most of my PhD work.

Velocity, acceleration, and jerk are all computed from the 3D position of the joints. They are the 1^{st}, 2^{nd}, and 3^{rd} derivative of the position, respectively. While velocity and acceleration are concept familiar to virtually all researchers, jerk might need more explanation. As the 3^{rd} derivative of position and 1^{st} derivative of acceleration, the jerk is a measure of the instantaneous changes in acceleration. Therefore, it is a measure of motion smoothness and is expressed in meter per second cubed (m/s^3).

The lower the jerk, the smoother the movement. However, 3D position can also be used to compute more complex time-series measurements, such as autocorrelation (AC) or cross-wavelet coherences (as was the case in Chapter 5). Furthermore, the 3D position was also used to train a deep neural network in Chapter 6.

3.3.3 *Difficulties and limits*

Research on human kinematics can pose a lot of difficulties and my PhD work did not differ in that regard. The first difficulty I faced at the beginning of my PhD was with the use of marker-based MoCap. We had access to a shared experimental room with shared Qualisys cameras. We had to compromise on their positioning. During our pre-tests, we had too many marker loss and not enough space for our participants to perform the tasks (e.g., walking around a 5-m diameter circle). We had difficulties in finding the optimal solution to our problem. But then, COVID-19 came. Thankfully, it afforded us time to think and plan our solution. After many discussions, online demos with manufacturers, and scientific article readings, we decided to give a shot at markerless MoCap. Our lab also gave us another room to perform our experiments. Naively, I believed that all my problems had vanished.

As was implied in the previous sections, markerless MoCap solves many of the problems posed by marker-based systems while also posing new ones. First of all, I had to learn how to connect the cameras to the recording computer. This step might seem trivial. It is not. We had eight cameras recording at 120 Hz with a resolution of 1280×720 pixels. We did not realize how much data each camera was producing and simply chaining the cameras (as we did with the marker-based technology) lead to some files having less data than other. It took me a few days to understand that there was too much data flowing through the Ethernet cables and that the cables could not safely carry everything. A phone call later with our camera provider and I was ordering a new network card for the computer and a 10 Gb/s network router. It took me a full hour to understand how to wire all the cameras to the router and then to the computer. Basically, I could chain at most 4 cameras before the cables would be overwhelmed. Once that was done, I again believed I had solved all problems. Then I discovered that our computer needed slightly less than an hour (54 min, to be precise) to extract the kinematics of a 1 min and 30 s recording. The only solution to decrease the processing time would have been to buy a new computer. Therefore, I put a schedule into place to collect the data then have one full day and night to extract the kinematics before including the next participant.

The last two difficulties we had with the markerless system were the required disk space and the data format. The format in which the system exported the kinematics did not match what we used. I had to write a small code snippet to automatically export the data to our format so that we could still use all our previous analysis tools. It took me a full day to understand how to write this code because I had never worked with Visual3D and it was the only format in which the markerless system exported the data. Then came the problem of storage. As I have mentioned in the previous sections, the amount of storage required for one participant was 300 GB. Our computer had 4 TB of available storage. Of which we could use less than 80% since the disks were solid state drives. Therefore, we bought two external 5TB hard drives to store the data. The data remained on the computer for processing purposes only. Once the kinematics extraction was done, I would transfer the data to the external drives. I also made a backup of the data to a cloud owned by the University. All these difficulties are just the ebb and flow of research but they offered me a better understanding of the markerless technology. It also confirmed the need of computer science know-hows to include new technology in psychological human testing.

3.4 SYNCHRONIZATION OF EQUIPMENT

Over the course of my PhD, many different equipment were used. The necessity rapidly came of finding a way to synchronize these various tools. I chose to run with a program called lab streaming layer (LSL), used mainly in research experiments.

Imagine an experimental session for which the participant has to smell an odor, then score the pleasantness of the odor while wearing a wristband monitoring their cardiac frequency. How can the experimenter separate the cardiac frequency during the smelling phase and during the scoring phase? Several possibilities exists. The experimenter could record on a piece of paper the time at which the participant started smelling and the time at which the participant stopped smelling the odor. Afterwards, the experimenter would need to report these two events in the cardiac frequency data. While theoretically feasible, this possibility is prone to errors. Scenarios like this one are familiar to virtually all experimenters in psychology. LSL offers another elegant solution. The program acts as a lightweight interface between the computer sending the visual stimuli, receiving the input from the participant and the wristband. When an event is sent to LSL (e.g., stimulus on-set, cardiac frequency measurement), a timestamp is associated based on the computer clock. When the experiment is completed, LSL saves all data to a single file, on a unified time series.

The COVID-19 pandemic caught everyone by surprise. From one day to the next, the world stopped. We had data in our hands so we modified our schedules and carried on with research, differently. When the world started to come back to normal, restrictions were still in place to protect us all. Participants had to wear masks during the experimental sessions, continuous ventilation of the room was done, and all materials were disinfected. For some researchers it was only a minor setback. For researchers working on olfaction, it posed a completely different problem. We had to rethink our way of designing experiments. It was a hard but good time. During this period, my coworkers and I developed a whole new way of experimenting with odors. I imagined an experimental setup that allowed for remote data collection.

The setup was made of a recording computer, audio instructions, a wristband to measure cardiac activity, a chin rest, and different vials containing the odors. The wristband was connected to the computer and the instructions are programmed via PyschoPy (Peirce et al., 2019). Everything was synchronized using LSL. The participant was equipped with an auditory headset and the instructions were recordings of a unique person talking at a moderate, soft speaking voice. Audio tracks are now used in most of our in-lab studies, to avoid possible bias in case the experimenters are not always the same person. The recordings were made with the most neutral voice tone possible. The odor vials were marked with numbers on top of them so that the participant knew which one to place in front of them. A chin-rest and an vial holder were provided to ensure that the distance between the vial and the nose of the participant remained constant from one trial to the next. Only the height of the chair was adapted for each participant. The different psychological scales used to record the perception of the participants were implemented on the computer. All the answers were directly recorded and synchronized with the wristband data. At the end of the experiment, the file was uploaded to a NextCloud server owned by the University of Lille. Then, I developed a Python code to process and analyze the relevant dependent variables. The output of the analysis scripts was also uploaded to the NextCloud server, to safeguard against possible data loss. The analysis scripts were ran whenever needed and without the need of having access to the recording computer, since the data were stored on the NextCloud server. During the months of 2021, the access to our lab was somewhat difficult. This innovating procedure offered us the means to collect data from other campuses while I was working remotely.

3.5 CONCLUSION

In this section, we have seen how different tools such as MoCap and physiological sensors can be used to measure the emotional body experience. The perfect tool does not exist and each one of them has its own limitations and difficulties that I managed to overcome thanks to a fruitful collaboration with the lab engineers. My background in cognitive science and, albeit short, experience in the private sector allowed me to develop a multi-disciplinary reflection to apply data science to a theoretical question: how can we characterize the emotional body experience. In the following chapters, I will present three experiments to showcase how the intersection of emotional perception, physiology, and movement has allowed us to witness the evolutionary nature of emotional behavior as a whole.

Part III

SHOWCASES AROUND BODY EXPERIENCES

4 INFLUENCE OF ODOR DILUTION ON PERCEIVED VALENCE

4.1 METHODOLOGICAL INTERLUDE

Experimenting with odors in humans is not an easy feet. Humans have between 300 and 400 olfactory receptors (Glusman et al., 2000, 2001). Each one of them reacts to one or several odor molecules but not every human reacts to the same molecules. These differences lead to different olfactory perception among participants. Furthermore, the more complex a molecule is, the more likely participants are to experience it as pleasurable (Kermen et al., 2011). However, this is only part of the problems one might encounter when experimenting with odors. Some molecules can degrade rapidly and should be kept in airtight, light-protected containers and stored in refrigerators for a limited amount of time (usually 24–48h when prepared). The preparation required before each experiment should be done by trained chemists to ensure the quality of the samples. This is why, during my PhD work, we have collaborated with the team of Professor Véronique Nardello-Rataj from the Unité de Catalyse et Chimie du Solide (UMR CNRS 8181) lab at the University of Lille. The chemists helped us prepare the samples that were presented to the participants. Each sample was prepared at most 24h before the experiment. Olfaction is not like other sensorial modalities, like vision for example. Experimenting with odors require careful selection, preparation, storage, and presentation of molecules to be confident in the data collected.

Dealing with the odor molecules is not the only issue raised by olfaction research. Since humans have some differences in their olfactory receptors, they also have some differences in their perception of odors. Androstenone, for example, is a pig pheromone that is perceived as unpleasant, even disgusting to an extent, for most people (Araneda & Firestein, 2003). For the large majority of individuals, it smells like urine or sweat. However, for some individuals, androstenone is perceived as pleasant and adjectives to describe the odor have been reported to be in the family of the following words: floral, pleasant, sweet. Researchers even reported that for another small portion of the sample population, the androstenone pheromone presented no smell at all, as the participants were anosmic to the molecule. Therefore, to study the perception of odors it is necessary to ask participants how the odor makes them feel and assess their olfactory abilities. With this aim in mind, one particular questionnaire has been developed by olfactory researchers: the EOS.

The EOS is a scale composed of 35 words describing emotional reactions to odors (e.g., pleasant, revitalized, disgusted). The participants are expected to rate on a linear scale how intensely they feel the emotional word (from *not at all intense* to *extremely intense*). Because participants should respond to every word, the time taken to answer the questionnaire can be long. Therefore, researchers have developed a shorter version of the EOS, the Geneva Emotion and Odor Scale (GEOS; Porcherot et al., 2010). This shorter version is using triplets of words, created by aggregating words from the EOS (e.g., happiness – well-being – pleasantly surprised). Again, participants are expected to rate on a linear scale how intensely they feel the emotional word (from *not at all intense* to *extremely intense*).

In the following study, we used the GEOS and the Affect Grid (Russell et al., 1989) to have a complete description of the changes in the affective states induced by the odors. Furthermore, we used an Empatica E4 wristband to understand the physiological changes triggered by the odors. This work was submitted in Quarterly Journal of Experimental Psychology and provides a description of the method used to measure physiological responses. Only the section about the selection of the scales used was left outside the paper as it is only of interest in this manuscript.

4.2 INTRODUCTION

We live in a world full of odors. These odors are powerful signals to make humans and animals move (Takahashi et al., 2005). However, not all odors are created equal when it comes to making people act. Food odors, for example, have been shown to elicit faster responses than other odors (Boesveldt et al., 2010). In the previously mentioned experiment, the authors contrasted between unpleasant and pleasant odors as well as food and non-food odors. Only the unpleasant food odor (i.e., fish) elicited faster reaction times compared to all other odors. From an evolutionary standpoint, it makes sense that humans have evolved to react faster and stronger to unpleasant food odors. Indeed, one single ingestion of a dangerous food can be enough to kill an adult. Generally speaking, evolutionary meaningful negative stimuli have been hypothesized to be signals of danger, at least in the olfactory (Boesveldt et al., 2010) and visual system (Mineka & Öhman, 2002).

Putrescine, for example, an odor molecule produced by the decomposition of a dead body, has been found to increase the walking speed of participants to escape the odor (Wisman & Shrira, 2015). Furthermore, certain odor molecules have the ability to modulate cognitive or physiological components of human functioning. Peppermint essential oil (mostly constituted of menthol and eucalyptol) has been found to increase cognitive abilities by reducing reaction times and increasing alertness (Lwin et al., 2020; Mahachandra et al., 2015; Tang et al., 2020). On the other hand, rosemary essential oil (mostly constituted of camphor and eucalyptol) has been found to raise physiological arousal by reducing sleepiness and increasing energy levels of participants (Moss et al., 2003; Nasiri & Boroomand, 2021). These modulations of human functioning might be triggered by cognitive emotional processes arising after odor perception.

The perception of an odor is created by the brain after the binding of odor molecule on the olfactory receptors in the nose. Humans have between 300 and 400 olfactory receptors (Glusman et al., 2000, 2001). Each odor molecule can bind to one or several receptor and it is from their combined activation that the perception is created. One might think of it as an organ, where the combined activation of multiple keys would produce a delightful melody. This olfactory melody will be processed cognitively by a mechanism called appraisal (Arnold, 1960). It is defined as a process that detects and assesses the significance of the environment for well-being (Moors et al., 2013). For example, the putrescine odor will be assessed as unpleasant and potentially dangerous for well-being. Therefore, the appraisal will trigger a set of reaction to protect the organism (e.g., walk away faster). This appraisal mechanism is also thought to be at the root of all emotional processes (Ellsworth & Scherer, 2003).

The component process model (Sander et al., 2005; Scherer, 1984) is the dominant model of emotional appraisal. This model describes how an emotional stimulus (e.g., an odor) can be appraised, give rise to an emotional processing, then modulate physiological and behavioral responses. In the component process model, humans appraise the stimulus based on a number of components (e.g., is it new to me? Is it dangerous? Do I like it?), and each appraisal check can trigger a reaction. Based on this, when an odor is appraised as being unpleasant and/or threatening, a physiological reaction is triggered. This phenomenon, seen as a change in HR for example, will then, and only then, spark the desire to move and the participant will have the true experience of having the urge to move.

Experimental studies with emotional stimuli use questionnaires to better understand how participants feel when presented with the stimuli. Participants are usually asked to describe their feelings in terms of valence (how good is what I am feeling) and arousal (how energizing is what I am feeling). Valence and arousal are thought to be at the core of affective reactions (Russell, 1980). However, researchers have argued that olfactory perception is a highly complex mechanism that can not be accounted for simply by valence and arousal. This is why the GEOS has been developed, within the theoretical framework of appraisal (Chrea et al., 2008; Ferdenzi et al., 2013b; Porcherot et al., 2010). This scale is composed of words or triplets of words. Participants are asked to rate how intensely they feel the corresponding words. The GEOS allows to have a more complete description of the emotional perception triggered by smelling an odor molecule.

In this work, we used these scales, in combination with physiological measures to test the effect of three different molecules on creating the urge to move in healthy adults. These three molecules were chosen because findings suggest that they activate the cognitive (menthol), physiological (camphor), or motor (cadaverine) components of human functioning. The following hypotheses were made: as cadaverine has a molecular structure very close to putrescine, it should be rated as less pleasant and more unpleasant than menthol and limonene (H_1; Wisman & Shrira, 2015); camphor and menthol have been shown to increase alertness and arousal, and should be rated as more arousing than cadaverine (H_2; Lwin et al., 2020; Mahachandra et al., 2015; Moss et al., 2003; Nasiri & Boroomand, 2021; Tang et al., 2020); as being more arousing, camphor and menthol should also increase the HR frequency of participants when compared to cadaverine (H_3); if the predictions of the component process model are accurate for olfactory processing, we should observe a positive correlation between physiological response (HR or HRV) and desire to move, while observing no correlation between unpleasantness and desire to move (H_4).

Table 1
Odorant Molecule Description

Structure	CAS Number	Manufacturer	Activates
cadaverine 95%	462-94-2	Sigma Aldrich	Motor function (Wisman & Shrira, 2015)
DL-menthol 98+%	89-78-1	N/A	Cognition (Lwin et al., 2020; Mahachandra et al., 2015; Tang et al., 2020)
(1R)-(+)-camphor 98%	464-49-3	Alfa Aesar	Physiology (Moss et al., 2003; Nasiri & Boroomand, 2021)

Note. Chemical structure, CAS number, manufacturer and human component activated for each of the three odorant stimuli used in the present work.

4.3 METHOD

4.3.1 *Participants*

A total of 45 healthy adults took part in the experiment (all aged between 18 and 35; 27 women). The sense of smell of each participant was assessed using the Sniffin' Sticks Screening 12 Test (Burghart; Wedel, Germany; Hummel et al., 1997). A score below 11 was set as the cut-off threshold (Hummel et al., 2001). This led to the rejection of 10 participant (6 women). Out of the remaining 35 participants, 4 were removed due to a failure of the recording computer. Therefore, all the following analyses were conducted on 31 participants.

4.3.2 *Odorant stimuli*

Three odorant stimuli were selected: cadaverine, camphor, and menthol (see Table 1 for more information on the molecules). These stimuli were chosen to activate either the cognitive (menthol; Lwin et al., 2020; Mahachandra et al., 2015; Tang et al., 2020), physiological (camphor; Moss et al., 2003; Nasiri & Boroomand, 2021), or motor (cadaverine; Wisman & Shrira, 2015) component of human functioning. Although putrescine was used by Wisman and Shrira (2015), this molecule is dangerous to inhale. This is why, cadaverine was used in the present study as it has a similar chemical structure to putrescine and should elicit the same response (Wisman & Shrira, 2015). Each odorant were single molecule rather than mixes of different molecules (as essential oils for example; see Table 1 for details on the molecules).

Odors were presented to the participants in 30 mL glass vial: each vial contained a 1.5 cm × 1.5 cm square of chromatographic paper (Whatman 1CHR 3001-653, Whatman Article No. 28419181) on which had been dropped 0.15 mL of the odorant. The samples were prepared (odorant dropped on the paper) at least 20 min and at most 24h before the test, to have a similar chemical composition of the headspace of the flask (molecule evaporated from the paper to the air in the flask) for each participant.

Each vial of odorant was coded with a random code. The vials were sorted by molecule and stored in plastic containers to avoid contamination between molecules.

4.3.3 *Measures*

To collect an objective measure of the impact of odors concentrations on physiological, emotional, and behavioral responses, the following equipment was used.

4.3.3.1 *Circumplex model of affect to score arousal and valence*

The changes in affective states of the participants was measured with two scales, based on the circumplex model of affect (Russell, 1980). These two scales, one for valence and one for arousal, are discrete and ranging from 1 (negative affect or low arousal) to 9 (positive affect or high arousal). The valence scale was presented horizontally, while the arousal scale was presented vertically to be as close as possible as the affect grid (Russell et al., 1989).

4.3.3.2 *Geneva Emotion and Odor Scale*

The GEOS (Chrea et al., 2008; Porcherot et al., 2010) was used to record the changes in emotional perception induced by the various odor concentrations. The scale is composed of eight triplets of words. The participant was invited to rate, for each triplet separately, the extent to which their feelings matched the triplet, on a linear scale without anchoring. The order of presentation of the triplets was randomized to avoid a possible learning of the order and avoid biases in the responses. The scale was presented as a linear scale ranging from 0 to 200 and the value was hidden from the participants.

4.3.3.3 *Desire to move*

The desire to move was measured by asking the participant to rate their desire to stay or leave the room. To answer, the participant was provided with a linear scale internally ranging from 0 to 200, whose anchors were *stay* and *leave*. The anchors were randomly assigned to the left- or right-hand side of the scale. Using a similar procedure as with the GEOS, the exact value of the response was hidden from the participant. The participant was simply asked to indicate how strongly they desired to either stay or leave the room after smelling the odor.

4.3.3.4 *Empatica to measure heart rate*

The Empatica E4 wristband (Empatica S.r.l, Milano, Italy) was used to record PPG data and electrodermal activity. The PPG sensor records changes in blood volume pulse and thus, is used to compute HR and HRV. The E4 was used in the present study to measure changes in HR (in BPM) and HRV. HRV was computed through the use of the RMSSD. The RMSSD is a time-domain measurement of HRV based on the differences between successive heartbeats (Shaffer & Ginsberg, 2017). It is expressed in milliseconds.

4.3.4 *Procedure*

Each participant was tested on the three odors, repeated five times. Odor molecules were not mixed, which means that all repetitions of one odors had to be completed before moving to the next odor. The participant was not informed that each odor was repeated five times. Each trial lasted approximately 3 min.

The participant was invited to sit in front of a desk. A computer and two boxes were placed on the same desk, each box containing five glass vials. Prior to smelling the odor, the participant was trained to perform a specific respiratory pattern (i.e., cued-sniffing procedure; Ischer et al., 2021). Each trial started with a countdown from four to zero and the participant was invited to hold their breath until the number "1" appeared on the screen, then they could breath normally. Afterwards, an instruction on the computer invited the participant to remove the cap of the odor vial, close their eyes and smell for 35 s. Then, the participant was asked to close the vial and rest for 60 s. Following this period, the participant was invited to rate the odor using: (a) a 9-point intensity scale, (b) a double-anchored leave or stay scale, (c) a 9-point familiarity scale, (d) a 9-point valence scale, (e) a 9-point arousal scale, (f) the GEOS (Porcherot et al., 2010). Finally, the participant was invited to repeat the procedure for the next odor, as indicated by the computer. All vials were similar, except for a number marked on the vial (ranging from one to five).

This whole procedure was performed without the experimenter being present in the room. The experimenter was just outside the room to monitor and assist the participant if needed. All the instructions were voice-recorded and everything was automatized (see (Brossard & Delevoye-Turrell, 2022) for a full description of the procedure).

4.3.5 *Preprocessing*

Before any preprocessing step, the Sniffin' Sticks Screening 12 Test results were examined to reject participants not meeting the required criteria (i.e., a score < 10 for men and < 11 for women). This procedure lead to the rejection of 10 participants. Another 4 participants were rejected due to a technical failure of the recording computer.

Raw data was filtered between 0.7 and 3.5 Hz with a 3^{rd} order Butterworth band-pass filter. Cut-off frequencies were chosen as they correspond to 42 and 210 BPM, covering the normal range of heart rate found in humans (Opthof, 2000). Finally, the photoplethysmographic data was filtered by the use of an outlier rejection pass (van Gent et al., 2019). The chosen method was the quotient filter. This phase is designed to automatically detect and remove R–R intervals that are unlikely to reflect parasympathetic activity. Details about this procedure can be found in Section 4.4, page 44 of Piskorski and Guzik (2005). Once all R-R intervals were correctly annotated, the BPM and RMSSD were computed. BPM was computed as the number of heartbeats per minute. RMSSD was computed as the root mean square of successive R–R intervals. All these phases were conducted using the Python HeartPy toolbox (van Gent et al., 2019).

4.3.6 *Dependent variables*

The dependent variables were computed as the difference between the value obtained during baseline and the value obtained during 60 s after the end of the odor presentation. The dependent variables were HR (Δ BPM), HRV (Δ RMSSD), pleasant feeling, unpleasant feeling, valence, arousal, and desire to move. For each of the dependent variables, an outlier rejection pass was ran using the interquartile range. A lower and upper bounds were calculated as:

$$\text{lower} = Q1 - (1.5 \times [Q3 - Q1]) \tag{1}$$

$$\text{upper} = Q3 + (1.5 \times [Q3 - Q1]) \tag{2}$$

With Q1 and Q3 being the 1st and 3rd quartile, respectively. All data points that fell out of the lower and upper-bound ranges were considered outliers and removed from further analyses.

4.3.7 *Statistical analyses*

Data normality assumption was assessed using Shapiro–Wilk test. Data sphericity assumption was assessed using the Mauchly test. Greenhouse–Geiser corrections were applied when sphericity assumption were violated.

A Kruskal–Wallis test was conducted with odor as the only factor (camphor, cadaverine, menthol) for each of the discrete dependent variable (valence and arousal). Alpha level was set at .05 and Dunn post-hoc tests were conducted when necessary. Partial eta squared (η_p^2) were calculated to report effect sizes.

A one-way repeated-measures analysis of variance (RM ANOVA) was conducted with odor (camphor, cadaverine, menthol) as the only factor, for each of the continuous dependent variable (HR, RMSSD, and desire to move). Alpha level was set at .05 and *t* tests with Bonferroni correction for multiple comparisons were conducted when necessary. Partial eta squared (η_p^2) were calculated to report effect sizes.

Pearson's correlation coefficient was used to measure the linear correlations between Δ BPM and desire to move, as well as between perceived unpleasantness and desire to move. Alpha level was set at .05 and the normality of the distributions was assessed by a visual inspection of the quantile-quantile plots. The magnitude of the correlation was interpreted based on fixed criterion ($r < 0.19$,no correlation; $0.2 < r < 0.39$, low correlation; $0.4 < r < 0.59$, moderate correlation; $0.6 < r < 0.79$, moderately high correlation; $r > 0.8$, high correlation; Zhu, 2012).

4.4 RESULTS

4.4.1 *Δ BPM*

The RM ANOVA showed a statistically significant main effect of odor, $F(2, 285) = 8.00, p < .001, \eta_p^2 = .05$, with lower Δ BPM for menthol (M = 2.50, SD = 3.95) than for cadaverine (M = 4.03, SD = 4.62, $p = .033, d = 0.35$) and camphor (M = 4.82, SD = 3.66, $p < .001, d = 0.61$). Overall, the results indicated that camphor and cadaverine increased the HR frequency more than menthol.

4.4.2 *Subjective ratings results*

4.4.2.1 *Perceived pleasantness*

The RM ANOVA showed a statistically significant main effect of odor $F(2, 296) = 31.79, p < .001, \eta_p^2 = .18$, with lower pleasantness ratings for cadaverine (*M* = 32.30, *SD* = 39.44) than for camphor (*M* = 83.47, *SD* = 64.26, $p < .001, d = 0.96$) and menthol (*M* = 92.62, *SD* = 60.71, $p < .001, d = 1.18$). Overall, the results indicated that cadaverine reduced the feeling of pleasantness compared to camphor and menthol.

4.4.2.2 *Perceived unpleasantness*

The RM ANOVA showed a statistically significant main effect of odor $F(2, 297) = 57.32, p < .001, \eta_p^2 = .28$, with higher unpleasantness ratings for cadaverine (*M* = 120.87, *SD* = 63.78) than for camphor (*M* = 60.40, *SD* = 63.25, $p < .001, d = 0.95$) and menthol (*M* = 33.59, *SD* = 42.56, $p < .001, d = 1.61$). Overall, the results indicated that cadaverine increase the feeling of unpleasantness compared to camphor and menthol.

4.4.2.3 *Perceived arousal*

The Kruskal–Wallis test showed a statistically significant main effect of odor $\chi^2 = 50.95, df = 4, p < .001, \eta_p^2 = .103$, with lower arousal ratings for cadaverine (*med* = 4, *IQR* = 3.5) than for camphor (*med* = 6, *IQR* = 2, $p < .001, d = 1.05$) and menthol (*med* = 5, *IQR* = 2, $p = .010, d = 0.55$). Results also showed statistically significant lower arousal ratings for menthol than for camphor ($p = .005$, $d = 0.48$). See Figure 9, panel B for a visual description of the results.

4.4.2.4 *Desire to move*

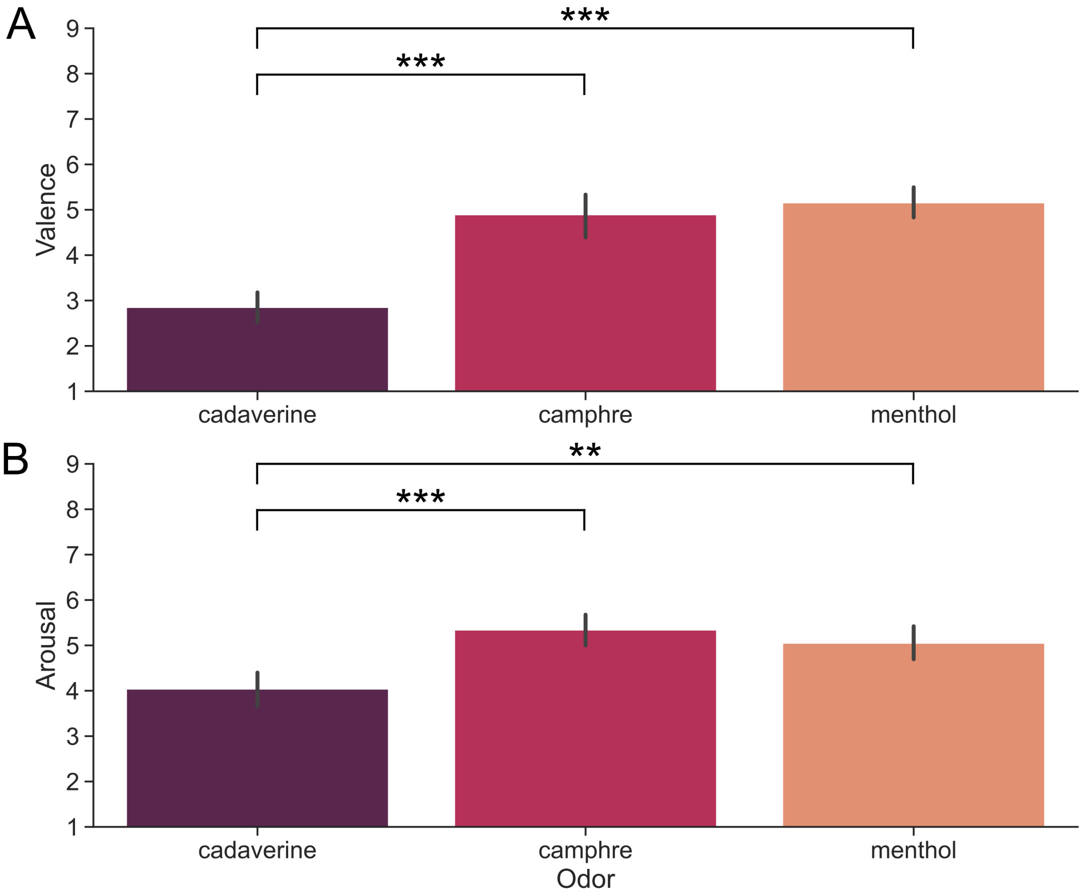
The RM ANOVA showed a statistically significant main effect of odor $F(2, 297) = 55.42, p < .001, \eta_p^2 = .27$, with higher desire to move for cadaverine (*M* = 141.94, *SD* = 58.81) than for camphor (*M* = 86.45, *SD* = 63.88, $p < .001, d = 0.90$) and menthol (*M* = 54.79, *SD* = 48.74, $p < .001, d = 1.61$). Post-hoc results also showed a higher desire to move for camphor than for menthol ($p < .001$, $d = 0.56$). Overall, the results indicated that cadaverine increased the desire to move compared to other odors. See Figure 10 for a visual description of the results.

4.4.3 *Correlations*

To understand if a physiological reaction was needed to trigger the urge to move, the linear correlation between Δ BPM and desire to move was computed. The correlation was not statistically significant ($r = .10$, $t(293) = 1.70$, $p = .090$, see Figure 11).

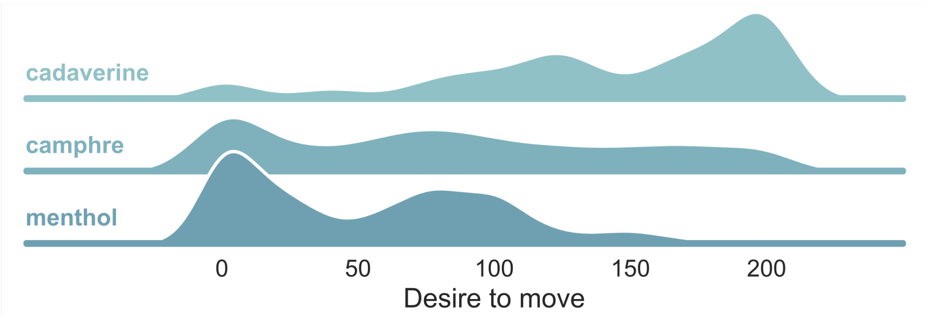
An additional Pearson's correlation coefficient was computed between the perceived unpleasantness and desire to move. The correlation was statistically significant ($r = .78$, $t(298) = 21.63$, $p < .001$, see Figure 12). This correlation coefficient is considered as a moderately high correlation (Zhu, 2012).

Figure 9
Perceived Valence and Arousal as a Function of Odor



Note. Perceived valence (panel A) and arousal (panel B) ratings as a function of the odor presented. Error bars denote 95% confidence interval. The number of stars denotes the statistical significance of the comparison. $^{**}p < .01$, $^{***}p < .001$.

Figure 10
Desire to Move as a Function of Odor



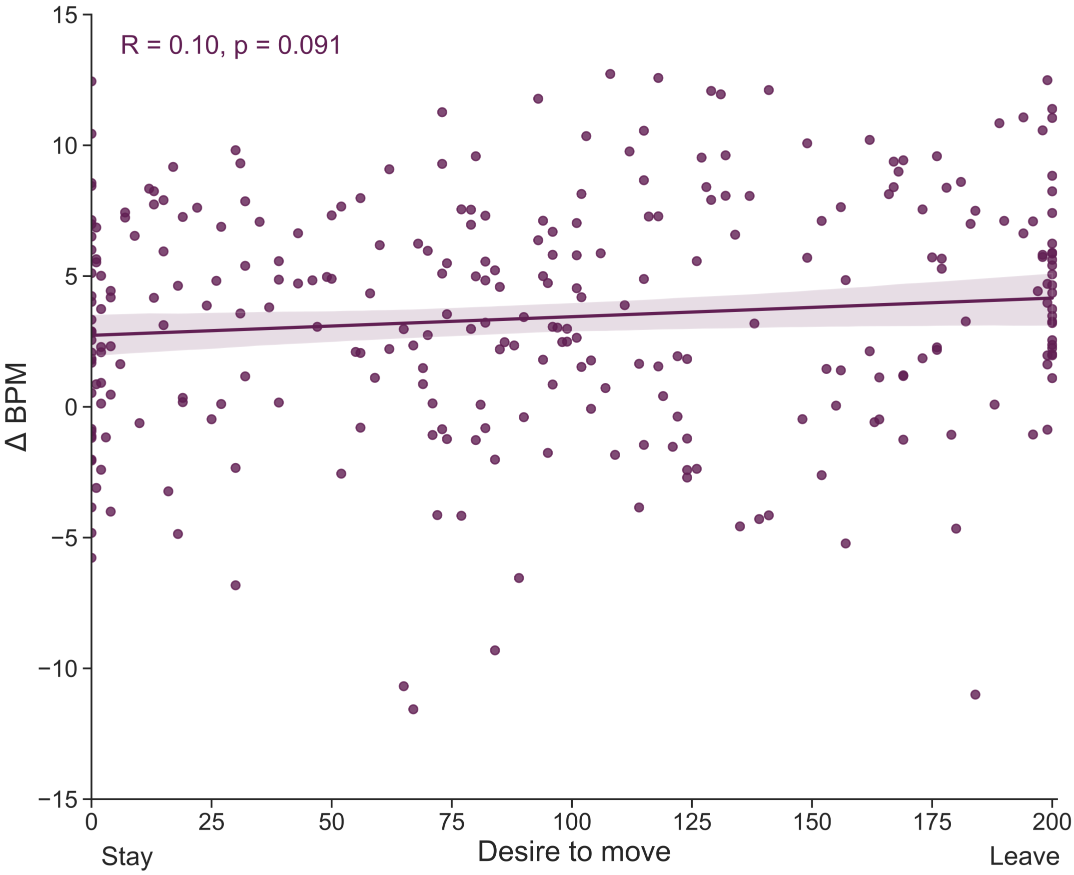
Note. Desire to move as a function of the odor presented. The larger the value, the more the desire to move was felt.

4.4.4 *Exploratory analyses*

This section presents further analyses conducted on variables outside the primary hypotheses but that can bring new insights in the understanding of the results.

Figure 11

Linear Regression Between Δ BPM and Desire to Move



Note. Pearson's correlation coefficient was used to estimate the correlation between the change in BPM and the desire to move. The correlation was not statistically significant ($r = .10$, $t(293) = 1.70$, $p = .090$).

4.4.4.1 Δ *RMSSD*

The RM ANOVA did not show a statistically significant main effect of odor $F(2, 288) = 0.14$, $p = .867$, $\eta_p^2 < .01$.

4.4.4.2 *Perceived valence*

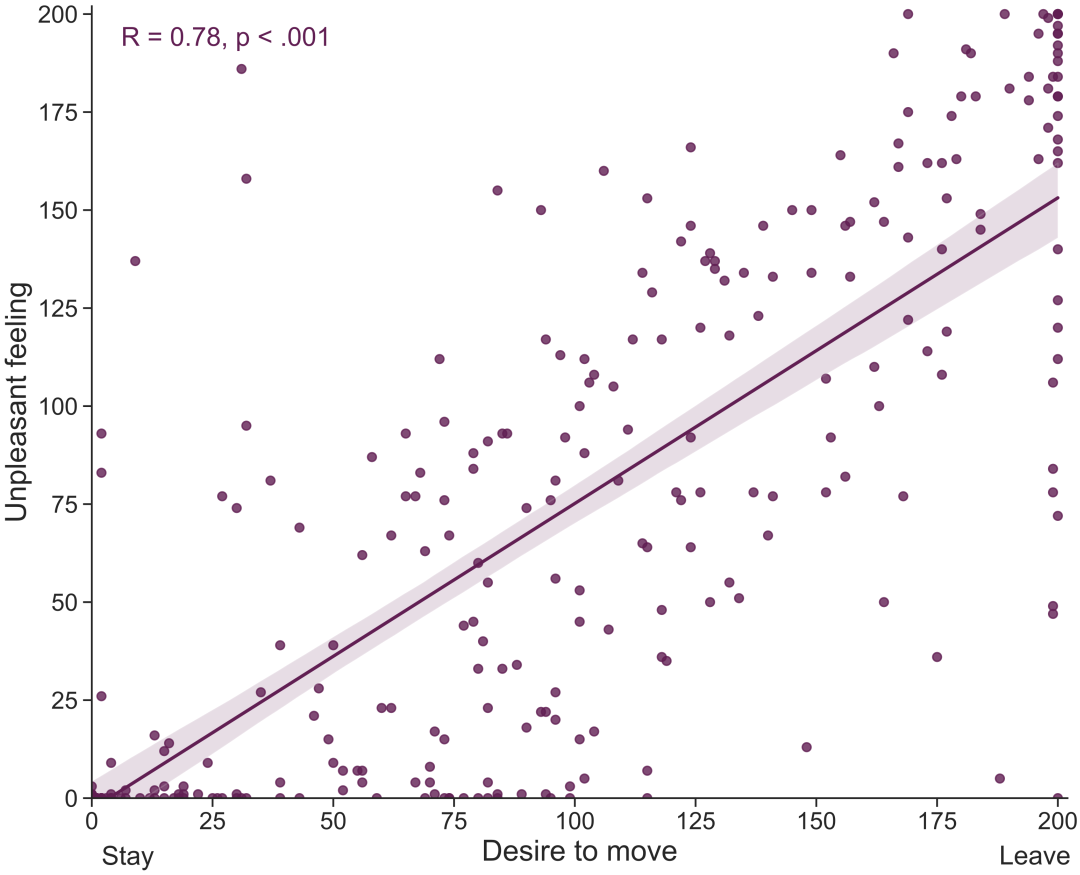
The Kruskal–Wallis test showed a statistically significant main effect of odor $\chi^2 = 61.19, df = 2, p < .001, \eta_p^2 = .20$, with lower valence ratings for cadaverine (*med* = 3, *IQR* = 3) than for camphor (*med* = 6, *IQR* = 3, $p < .001, d = 0.93$) and menthol (*med* = 5, *IQR* = 3, $p < .001, d = 1.38$). See Figure 9, panel A for a visual description of the results.

4.4.4.3 *Correlations*

To understand how the participants used both the GEOS and valence scale, the linear correlation between valence and unpleasant feelings was computed. The correlation

Figure 12

Linear Regression Between Unpleasantness and Desire to Move



Note. Pearson's correlation coefficient was used to estimate the correlation between the felt unpleasantness and the desire to move. The correlation was statistically significant ($r = .78$, $t(298) = 0.78$, $p < .001$), with a moderately high coefficient (Zhu, 2012).

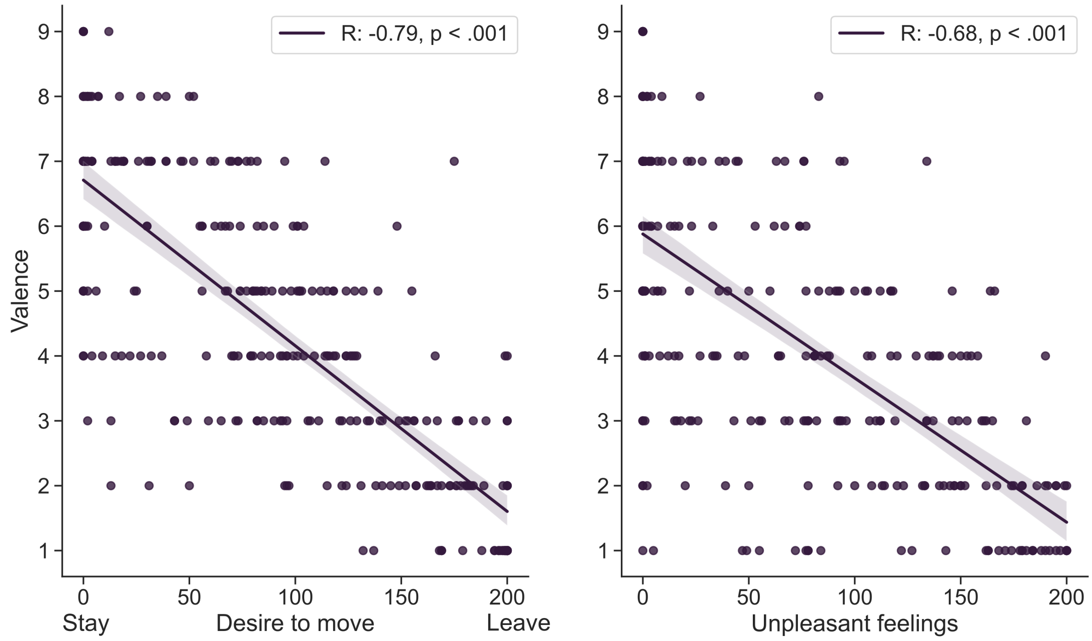
was statistically significant ($r = -.68$, $t(298) = -16.19$, $p < .001$; see Figure 13, right panel). This correlation coefficient is considered as a moderately high correlation (Zhu, 2012).

4.5 DISCUSSION

Odors are powerful stimuli to trigger behavioral changes. In this particular study, our goal was to test the effect of three molecules on creating the urge to move among healthy young adults. These three molecules are menthol, camphor, and cadaverine. They were chosen as they have been shown to activate the cognitive (menthol; Lwin et al., 2020; Mahachandra et al., 2015; Tang et al., 2020), physiological (camphor; Moss et al., 2003; Nasiri & Boroomand, 2021), or motor (cadaverine; Wisman & Shrira, 2015) component of human functioning. We used physiological analyses and psychological scales to understand how each molecule was affecting the urge to move and whether a change in physiology was a necessary condition to the desire to move. The results

Figure 13

Linear Regressions Between Valence and Desire to Move or Unpleasant Feelings

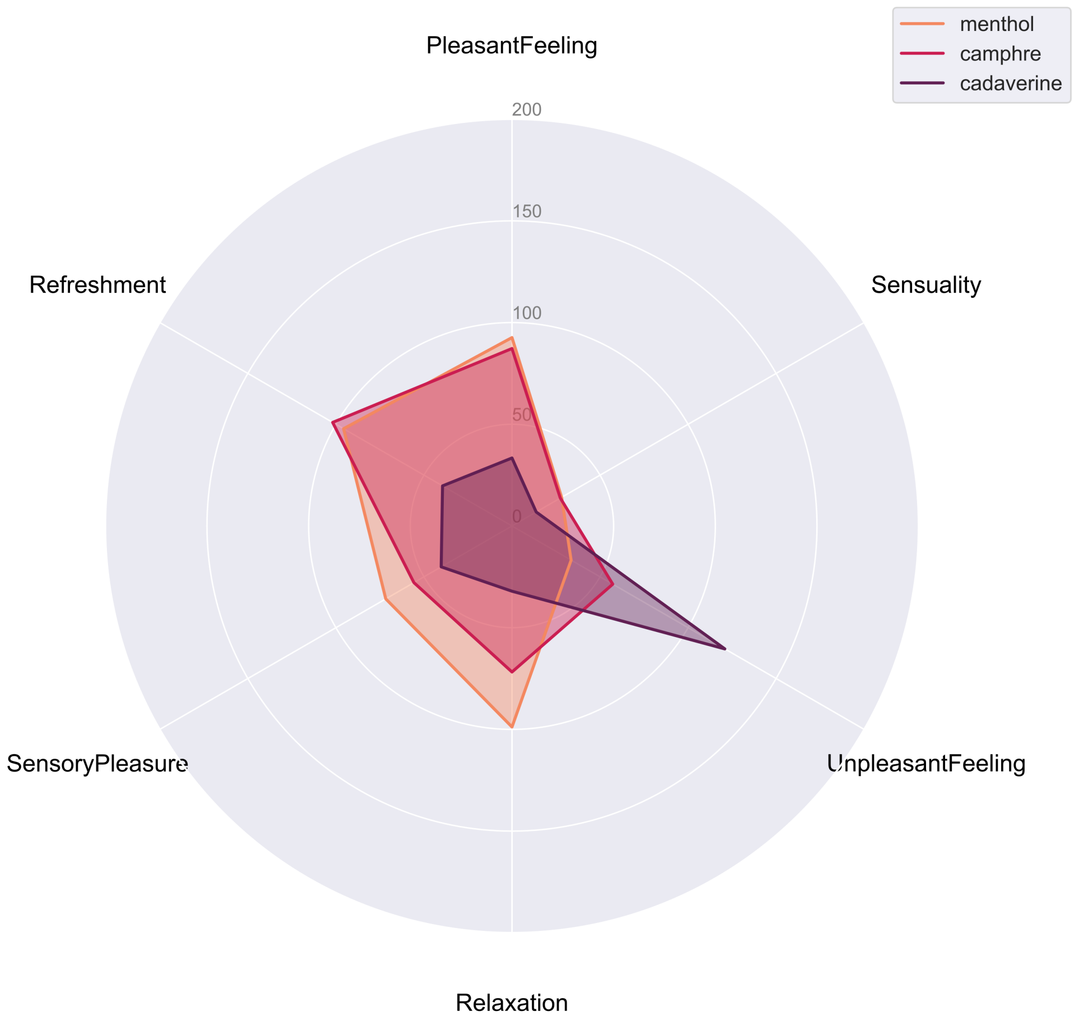


Note. Left panel represents the linear regression between valence ratings and desire to move. Right panel is the linear regression between valence ratings and unpleasant feelings ratings.

have shown that cadaverine was rated as less pleasant and more unpleasant than camphor and menthol, confirming H1. The results have also shown that menthol and camphor have been perceived as more arousing than cadaverine, confirming H2. However, cadaverine and camphor elevated the HR of the participants when compared to menthol, contrary to H3. Furthermore, there was no correlation between physiological response and desire to move, but there was a moderately high positive correlation between felt unpleasantness and desire to move, contrary to H4.

The results on the emotional perception provoked by each odor were in line with the hypotheses. Cadaverine, which is a molecule structurally close to putrescine (Wisman & Shrira, 2015), seems to have a similar effect as putrescine. It triggered highly unpleasant feelings among all participants and made them want to leave the room. This result was expected as it is a molecule produced by the decomposition of a dead body. Thus, this molecule holds a powerful evolutionary meaning and it is possible that the reaction to this smell has been shaped by evolution. All three odors were rated in a similar manner for the GEOS and the valence scale. However, what is interesting is that the correlation between the responses from the GEOS and valence is not 1 ($r = -0.68$; see Figure 13, right panel). This correlation coefficient is considered as moderately high but only accounts for around 68% of the variance. This could mean that a third of the participants used the two scales differently. One possible explanation for this would be that they used the GEOS to describe how they perceived the odor while using the valence scale to describe how the smell made them feel. Imagine the smell of gasoline. For some people, this odor is perceived as rather pleasant.

Figure 14
GEOS Results For Each Odor



Note. Results for each dimension of the Geneva Emotion and Odor Scale of all participants and for each odor. For each of these dimensions, participants were presented with a triplet of words and a linear scale (ranging from 0 to 200 and hidden from the participants). Participants were asked to rate how much their feelings matched the triplet of words. See Chrea et al. (2008) and Porcherot et al. (2010) for the complete description and validation of the scale.

Nevertheless, gasoline odor can be detrimental for health (Sousa-Santos et al., 2020). Therefore, it is possible to imagine that some participants would respond with high ratings of pleasantness on the GEOS but low values with the valence when presented with a gasoline odor. That being said, these results are only exploratory and more investigations are needed to fully understand how participants use both scales and what the possible theoretical implications would be.

The results obtained on the perceived arousing properties of the three molecules were also in line with both the hypotheses and previous literature. Camphor and menthol were found to increase arousal, alertness, reduce sleepiness, and reaction times (Lwin et al., 2020; Mahachandra et al., 2015; Moss et al., 2003; Nasiri & Boroomand, 2021; Tang et al., 2020). Nevertheless, an increased perceived arousal does not seem to be linked with physiological reactions to odors, contrary to our hypothesis. Indeed, it was hypothesized that the level of perceived arousal would be linked with physiological changes, such as an increase in BPM. However, only menthol reduced the increase in BPM observed across participants. This effect, while unanticipated, can be explained by the molecules themselves. All three molecules have been found to stimulate the trigeminal nerve (Frasnelli & Manescu, 2017). Stimulation of the trigeminal nerve is responsible for sensations of burning or stinging for example. Four receptors are notably activated by odor molecules (TRPA1, TRPM8, TRPV3, TRPV1). Both cadaverine and camphor have been found to activate receptor TRPV1, mostly responsible for the perception of tingling (and even pain if the odor is very intense; Frasnelli & Manescu, 2017). Menthol, on the other hand, has been found to activate receptor TRPM8, mostly responsible for the perception of cooling, never being painful (Frasnelli & Manescu, 2017). Therefore, the defining factor in modifying HR could be the type of trigeminal receptors stimulated by the odor. Furthermore, the exploratory analyses have shown that HRV seems to not be affected by the molecule in this study. This could be because the participants did not actually move. HRV is a marker of regulation mechanisms (or of an influence of the parasympathetic nervous system). However, there is very little to regulate in this experiment, since the participants could not perform the action of leaving. Future studies should try to investigate if similar effects arise when participants are offered to actually leave the room for a minute if the smell is highly unpleasant.

Accounting for all these findings can prove to be complex. The component process model, described in the introduction, seemed to indicate that for the desire to move to arise, a physiological reaction due to appraisal was necessary. Nonetheless, there was no correlation between Δ BPM and desire to move, contrary to our hypothesis. Furthermore, there was a moderately high correlation between perceived unpleasantness and desire to move. These results seem to indicate that a physiological reaction is not a necessary condition for the urge to move to arise, contrary to the prediction made with the component process model. Therefore, another appraisal model could help explain these results. The IMPPACT model (Ridderinkhof, 2017), is based on the idea of motor control loops taking place after an appraisal phase, similar to the component process model. If an odor is appraised as being unpleasant and/or threatening, then the urge to move will be triggered by the prediction of the future physiological and psychological consequences of staying close to the odor source. In the current experiment, the participant was seated on a chair, presented with an unpleasant odor and asked to rate his desire to move but without the possibility to actually move. According to the IMPPACT model, the participant could wish to move, even if he does not have a physiological response, because his brain would not predict a physiological change since he can not really perform the movement.

4.5.1 *Conclusion*

This study has yielded the first bricks of knowledge towards an understanding of how an odor can trigger the urge to move. However, it should be noted that further investigations are needed to (a) confirm that evolutionary negative odors (e.g., cadaverine) can trigger the urge to move, (b) find other molecules capable of triggering the urge to move, and (c) test the influence of being able to perform a movement to get away from an unpleasant odor. To conclude, it is not the sensation provoked by the odor, but rather the perception of unpleasantness that triggers the urge to move.

5

SPATIOTEMPORAL CORRELATIONS OF WHOLE BODY MOVEMENTS

This article has been submitted for publication in Journal of Experimental Psychology: General.

5.1 INTRODUCTION

Adaptation is crucial for survival. Humans have developed protective and defensive behavior to shield their bodies from outside threats (e.g., fight or flight response, yelling for help; Blanchard et al., 2001). But threats can also come from within, e.g., overheating and undernourishment. Hence, individuals have also developed internal mechanisms to regulate body functioning and optimize energy consumption. Allostasis is one of such internal mechanisms that provides stability through change and refers particularly to the idea that parameters of most physiological regulatory systems change to accommodate environmental demands. For this regulation system to perform efficiently, a signaling mechanism is however vital. Affects and more generally emotions, have in the last decade been proposed to play such a role. Defined in terms of valence (i.e., positive or negative) and arousal (i.e., energetic or sleepy), core affect would reflect the sensory consequences of allostatic changes (Barrett, 2017, p.9). Hence, core affect may be a powerful signal used to detect significant risks to allostasis dysregulation throughout the course of a day, allowing the brain to maintain optimal functioning of the moving body in a constantly changing world (Barrett, 2017; Russell, 2003).

Emotions signal contrasting messages depending on the affective valence. Negative emotions are especially informative of allostasis dysregulation, increasing the risks of cardiac diseases (Mostofsky et al., 2014), noncommunicable mental disorders (Fowler et al., 2011; Klippel et al., 2021) and may be the cause of one of many health issues of the 21st century (Bloom et al., 2012). But even without considering these extreme cases, negative affective states modify body functioning. Frequent situations of anger or anxiety lead to increased levels of impulsive eating behaviors (Macht, 1999) and an intensification of oxygen consumption (Dudley et al., 1964). In the context of physical activity, and in cycle riders for example, Lane and collaborators reported that the outbreak of a negative emotion increased oxygen consumption by 10 to 20 liters per minute compared to that observed in the cycle riders experiencing positive emotions while performing the identical task of cycling for 2 hours, at lactate threshold (Lane et al., 2011). Negative emotions would hence be the signal that something threatening to the system is occurring and a change is required. As a protective measure, the body would tense up leading to a general greater levels of muscle co-contraction. Such overall high sets in muscle tone lead to an increase in energy needs. Physiological modifications through food consumption and oxygen intake would be the first mechanisms to regulate internal allostasis. However, when the internal resources are not sufficient, body movement is required in search of solutions. Consequently, emotions would have the additional power of triggering changes in body position and dynamics.

Imagine walking down a calm street at mid-day. Without a worry in mind, the spontaneous pace of walking is around 2 Hz, i.e., close to two meters per second (Moelants, 2002). This pace is rather constant across ages and cultures (Bobin-Bègue & Provasi, 2008; McAuley et al., 2006; Van Noorden & Moelants, 1999) probably because it is the pace at which the cognitive cost of motor adjustment is the lowest (Delevoye-Turrell et al., 2014; Guérin et al., 2021a). It is also the pace at which the metabolic energy cost of controlling body motion is minimal (Alexander, 2002). However, individuals can modulate their movement speed to facilitate smooth interaction with others and objects. Slowing the hand movement to fit a key in a lock; run to catch a train. Adaptive behavior emerges in the first years of life (Bobin-Bègue et al., 2006) with the maturation of cortical networks required to control the ability to modulate the spontaneous pace of movement as a function of contextual demands (Guérin et al., 2021b). But the urge to walk faster can also be triggered by unconscious affective sources signaling the need to move. Imagine now walking down the same calm street but at night, alone, with the difficulty to step over trash and broken bottles. If one is a war veteran with good defensive skills, one might not even notice the potential threat. Nevertheless, if a civilian, one might adopt a protective posture: body tensed up, head low and hunched back in position for defense or attack. This attitude is thought to emerge from past evolutionary experiences, providing the means to adopt a rigid body, with the additional physical consequence of protecting the throat from external threat. Walking pace may increase to limit the time spent in the unpleasant environment; one could even break into a soft jog or a sprint depending on the intensity of the unpleasantness. The changes in body posture and walking pace may be slightly different from one individual to another, especially depending on the perceived nature of the life-taking threat and its associated risk. Nevertheless, changes in body kinematics all originate from internal afferences, which signal that action must be taken to maintain allostasis integrity and preserve the body from external threat.

Internal afferences constitute a vital branch of the motor control loops (Wolpert & Flanagan, 2001). When preparing to act, the brain predicts both the timing and the content of the sensory afferences that will be experienced by the body as a direct consequence of the execution of the planned motor command. Once the movement is executed, the memory traces of the predicted afferences are compared to the true sensory feedback that is received from the effectors. The discrepancy that may exist is coded as a prediction error, which is then used, in a trial–error fashion, to modulate and adapt body tone, posture and movement patterns. The vital goal of the brain is here to minimize the prediction error to maintain allostasis, i.e., avoid using too much energy while producing the goal directed behavior. Control loops are efficient as they are ingrained at various levels of the motor system. At a reflex level, reafferences can modulate muscle tone by facilitating motor co-contraction. At the cerebral level, sensory and affective sources of information can modulate automatic motor responses and trigger pre-cabled organized patterns of complex motor outputs. Obviously, with activation of the cerebral brain areas, goal-directed motor actions can be initiated, inhibited and/or modulated as a function of more cognitive-based decisions. It is the changes made to how a motor behavior is expressed through posture and types of body gestures that is referred to as an emotional action. Indeed, in classic motor control, body kinematics (e.g., position, acceleration, jerk) is studied in reference to the goal of a voluntary body movement (e.g., move the hand to grasp a cup). However, actions can be taken with the intention to trigger positive or negative changes in the world (e.g., waving at a friend, signaling a pedestrian to stop crossing the road). Motor behavior can also be modulated to change the inner pleasantness state of the body (e.g., walk slower to avoid sweating vs. walk faster to be out of harm's way). Hence, what makes a motor action emotional is the fact that the action is produced to achieve a desired affective effect on the world and on the body (Ridderinkhof, 2017). An emotional outbreak should thus have a visible impact on the kinematics of an expressive body but only as a secondary signature ingrained within the primary properties of the goal-directed movement.

In movement science, studies have reported the impact of emotional states on body kinematics. A certain number of studies have described that anger and joy increase the speed of execution of motor actions whereas sadness and fear decrease motion speed. This effect has been reported in various actions, from simple arm movements (Pollick et al., 2001) to more complex gait patterns (Crane & Gross, 2007; Roether et al., 2009). Speed is not the only parameter to be influenced by emotions. The jerkiness of the motion, for instance, is greater after inducing states of anger and joy compared to the cases of contentment, neutral and sadness (Pollick et al., 2001). Emotions also have the power to change body postures. Wamain et al. (2015) found that when listening to emotional music, head position lowered by 3 degrees when cycling for 30 s bouts of leisure exercise. Roether et al. (2009) had individuals imagine emotional scenarios and reported that head position dropped with negative and raised with positive memories. Even if small in absolute terms, these micro changes in body postures and dynamics are sufficient for naive observers to categorize the emotional state of the actor, simply by watching video clips of the motion, i.e., without facial expressions (Atkinson et al., 2004; Pollick et al., 2001) or with point-light displays (Roether et al., 2009). Recent studies have even quantified the performance of human classifiers reporting over 72% of good classification when 5 emotional categories were presented under a force-choice procedure (Daoudi et al., 2017). However, while these studies provide solid evidence that emotions impact the expression of voluntary motor programs, the findings do not provide the means to map emotions to kinematics on a one-to-one correspondence.

In the present work, we propose that emotional expression is a by-product of body states and goal-directed body movements. Humans do not move to express emotions - language has taken over for that purpose. Changes in body kinematics are the consequences of inner variations in muscle tone and physiological activity that translate as levels and intensities of unpleasantness, threatening allostasis integrity.

Following this idea, we applied time series analyses to decode the changes through time of body tension and energy, in relation to the degree of unpleasantness of the experience. Indeed, time series analysis is an important tool for medical diagnostic purposes (Pascolo & Carniel, 2009) and thus, can be used to monitor the time evolution of body control and tension (Zhipeng et al., 2014). Building on previous

Table 2
General Demographics of the Eight Actors

	Age (years)	Experience (years)	Height (m)	Weight (kg)
Women	27.0 ± 2.71	6.5 ± 2.65	1.63 ± 6.14	58.5 ± 5.69
Men	26.0 ± 1.14	5.6 ± 1.11	1.82 ± 8.12	66.8 ± 7.8

Note. General demographics for the eight actors participating in the study. An analysis of variance indicated that Group differences reached significance for Height only $F(1,6) = 14.672, p = 0.008$.

lines of research (Dione & Delevoye-Turrell, 2015; Guérin et al., 2021a), we first applied serial auto-correlations on the interval between foot steps, to distinguish differences in control strength between emotions with positive and negative valences. More specifically, negative emotions that trigger an increase in control applied to the body should be associated with significant negative auto-correlations. In a second step, we decomposed the time series into time–frequency space to perform a cross-wavelet analysis (Grinsted et al., 2004). This wavelet analysis provided the means to determine localized variations of power across left-toe and right-wrist time series. Statistical significance testing was included to contrast low and high energy levels as a function of the affective states. More specifically, we hypothesized that high-energy emotions (anger, joy) will be characterized by shorter and jerkier gait patterns compared to that observed in low-energy emotions (sadness, fear, neutral; H_1). Negative emotions (anger, fear, sadness) will be characterized by lower head positions compared to that observed in positive emotions (joy; H_2). Control through time of rigid body parts will be more visible for negative emotions and will be characterized by negative auto-correlations (H_3). Finally, the four categories of emotions will yield specific wavelet 2D patterns when taking into account both tension and energy levels across the time series of the left-toe and right-wrist parts of the moving body (H_4).

5.2 MATERIAL AND METHODS

5.2.1 *Participants*

Eight healthy, well-experienced professional actors (four males) were paid for their participation in the experiment. They gave informed consent prior to inclusion in the study. Experiments complied with the Declaration of Helsinki. The general demographics for the actors are presented in Table 2, with the men being significantly taller than the female actors.

5.2.2 *Task*

The actors were required to walk back and forth along a ten-meter lane under five different emotional conditions: fear, sadness, anger, joy and neutral. Five trials for each emotion were recorded per participant. However, for some participants, only two trials were exploitable due to marker loss. Therefore, a total of 156 trials were used in the following analyses.

5.2.3 *Inducing emotional states*

Emotional induction is the most rigorous means of testing the causal influence of affective states on the motor system. In the present study, an autobiographical recall technique was used to help actors summon personal emotional memories to reactivate the original affective experience (Prkachin et al., 1999). In a preliminary experiment, some actors started to run in the fear condition. Hence, in the specific case of fear, participants were instructed to perform the task as if they were walking down a dark and dangerous alley (for more details on the procedure, see Hicheur et al., 2013). For each trial, participants were instructed to imagine a past experience to feel the recalled emotion before initiating gait. The 3D recording of body movements was initiated when the participant initiated the first step.

5.2.4 *Equipment*

Three-dimensional positions of light reflexive markers were recorded using an opto-electronic Vicon V8 motion capture system wired to 24 cameras, running at a sampling frequency of 120 Hz. The Vicon Plug in Gait model was used to reconstruct gait dynamics (VICON, Oxford Metrics Limited, Oxford, United Kingdom) and data were filtered with a 4^{th} order Butterworth low-pass filter at 15 Hz.

Continuous 3D position data were encoded from the 18 points of the participant's body. (1) The two shoulder markers were located on left and right acromion; (2) The two wrist markers were located on the external face of the lower arms; (3) Four markers were located on the pelvis with front markers placed on left and right anterior superior iliac spines. (4) Left and right ankle markers were located on the lateral malleolus and (5) the left and right toe markers were placed at the top of the foot (participants were allowed to wear shoes), between toes 2 and 3; (6) the heel markers were placed on the back of the heel, at the same height as the toe markers. Finally, (7) four markers were directly placed on a pair of light glasses without lenses to gain a better reliability of marker-placements across participants, without affecting the quality of the data obtained from the head markers. An illustration of marker placements is available in Figure 20. From these 18 physical markers, the Vicon Plug in Gait model provides the means to create a set of 43 virtual markers that were used to compute a certain number of indices.

The emotional gait patterns were analyzed in two steps. As classically reported, the kinematics patterns of whole body movements are first presented. Time series are then presented to reveal the specific effects of emotional induction on body control, energy and rigidity.

5.2.5 *Data analysis of emotional gait: Kinematics*

Prior to further computations, 3D data were translated to a new semi egocentric frame of reference with the X-axis and Y-axis following body orientation pointing forward and leftward from the body, respectively. The original vertical Z-axis set by the 3D capture calibration was kept as it was defined as pointing upwards. The origin of this new reference frame was anchored to the mean of the 3 pelvis-marker positions for the X and Y axes but the Z-axis was maintained at its origin. By keeping the original direction and location for the Z component of the 3D data, information about vertical position variations that could manifest during emotional walking movements was retained. An example of such variation could be a bouncing walk when excited. From these recalibrated data sets, a total of three dependent variables were computed.

5.2.5.1 *Cycle duration*

The identification of the period of stance is typically done with force plates but in their absence, kinematics data can be employed (Zeni et al., 2008). An automatic detection algorithm was applied to determine when the marker of the right toe crossed the anatomical frontal plane. The intervals between these events constituted the right-step interval series. The cycle duration was computed as the median time of the right-step intervals and is expressed in seconds (s).

5.2.5.2 *Mean jerk*

Motion smoothness was assessed through jerk of motion. Absolute jerk of the right toe marker was obtained by taking the norm of the vector defined by the third time derivative of the position of a marker on each axis. Mean value was obtained by averaging the absolute jerk across the entire time series of a trial. Mean jerk is expressed in meter per second cubed (m/s^3).

5.2.5.3 *Head angle*

Head angle was computed from the 4 head markers placed on the pair of glasses. It was defined with reference to the horizontal plane obtained during calibration of the system. A negative angle coded for head drop, while a positive angle coded for head raise. Head angle is expressed in degrees.

5.2.6 *Data analysis of emotional gait: Time Series*

Two types of time series analyses were applied to reveal (a) the level of control exerted on the body and (b) the level of energy and rigidity existing between selected joints.

5.2.6.1 *Auto-correlation Function*

The auto-correlation function is a mathematical tool used frequently in signal processing for analysing functions or series of values. It is the cross-correlation of a signal with itself and offers an indication of how well a signal matches a time-shifted version of itself. Auto-correlation is useful for finding repeating patterns in a signal. In the case of psychological human sciences, we have used auto-correlations to reveal the use of predictive timing mechanisms in the control of sequential voluntary movements (Dione & Delevoye-Turrell, 2015; Guérin et al., 2021a). In the present study, the auto-correlation function at lag 1 (denoted as ACF(1)) was computed on the detrended right-step interval time series.

5.2.6.2 *Cross-Wavelet Transformation*

The position vectors of the time series of the right toe and left wrist were processed using a cross wavelet transformation (Grinsted et al., 2004), which provided the means to reveal the regions in time frequency space for which the time series showed high common power. For a given time scale and a specific point in time, the coherence magnitudes and relative phases were denoted by the color and the orientation of an arrow (pointing right: in phase; pointing left: anti phase). Finally, the group average of these values at a period of 0.5 were extracted to compare between emotions. This period of 0.5 was chosen as it corresponds to 2 Hz, i.e., the preferred pace at which humans tend to perform spontaneous voluntary motor actions (Moelants, 2002).

5.2.7 *Statistical analysis*

An outlier-removal procedure was first conducted independently for each of the dependent variables based on the interquartile range method. Lower and upper bounds were calculated as:

$$\mathrm{lower} = Q1 - (1.5 \times (Q3 - Q1)) \tag{3}$$

$$\mathrm{upper} = Q3 + (1.5 \times (Q3 - Q1)) \tag{4}$$

with Q1 and Q3 being the 1st and 3rd quartile, respectively. Data points that fell outside the lower and upper-bound ranges were removed from further analysis.

To test H_1, a one-way repeated-measures analysis of variance (Emotion [fear, sadness, anger, joy, neutral]) was conducted on both the cycle duration and the mean jerk of the right toe. Two trials were detected as outliers and removed from the analysis.

To test H_2, two one-sided t tests against zero (i.e., < 0 for negative emotions, > 0 for positive emotions) were conducted on mean head angle. Two trials were detected as outliers and removed from the analysis.

To test H_3, a one-way repeated-measures analysis of variance (Emotion [fear, sadness, anger, joy, neutral]) was conducted on the auto-correlation function at lag 1. A one-sided t test against zero was conducted for significant results. Four trials were detected as outliers and removed from the analysis.

To test H_4, a one-way repeated-measures analysis of variance (Emotion [anger, joy]) was conducted on the wavelet coherence. One trial was detected as outlier and removed from the analysis.

Shapiro–Wilk's test was used to assess data normality. Data sphericity assumption was assessed using Mauchly's test. Greenhouse–Geiser's correction was applied when sphericity assumption was violated. Alpha level was set at .05 and t tests with

Bonferroni correction for multiple comparisons were conducted when necessary. Effect sizes were computed and reported as η_p^2 for the repeated measures ANOVA and as Cohen's *d* for the *t* tests.

5.3 RESULTS

The results of the emotional gait patterns are presented following our two-step analysis outline. The kinematic patterns of whole body movements are first reported. The findings for the auto-correlation and the wavelet coherence analyses are presented in a second section.

5.3.1 *Emotional gait kinematics*

Results for cycle duration, jerk and head angle are reported in Figures 15, 16 and 17 and Table 3 for means and standard deviations, as a function of emotion.

5.3.1.1 *Cycle duration*

The RM ANOVA on mean cycle duration showed a significant main effect of emotion, $F(2.11, 12.69) = 18.98, p < .001, \eta_p^2 = .76$, with shorter cycle duration for anger (*M* = 0.87, *SD* = 0.09) than for joy (*M* = 1.14, *SD* = 0.20, $p = .006, d = 2.68$), neutral (*M* = 1.09, *SD* = 0.08, $p < .001, d = 3.62$), fear (*M* = 1.58, *SD* = 0.43, $p = .002, d = 2.68$) and sadness (*M* = 1.52, *SD* = 0.28, $p < .001, d = 3.48$). Results also showed significantly lower cycle duration for joy than for fear ($p = .030, d = 1.91$) and sadness ($p = .008, d = 2.30$), as well as significantly lower cycle duration for neutral than for fear ($p = .030, d = 1.78$) and sadness ($p = .007, d = 2.14$). Refer to Figure 15 and Table 3 for detailed results.

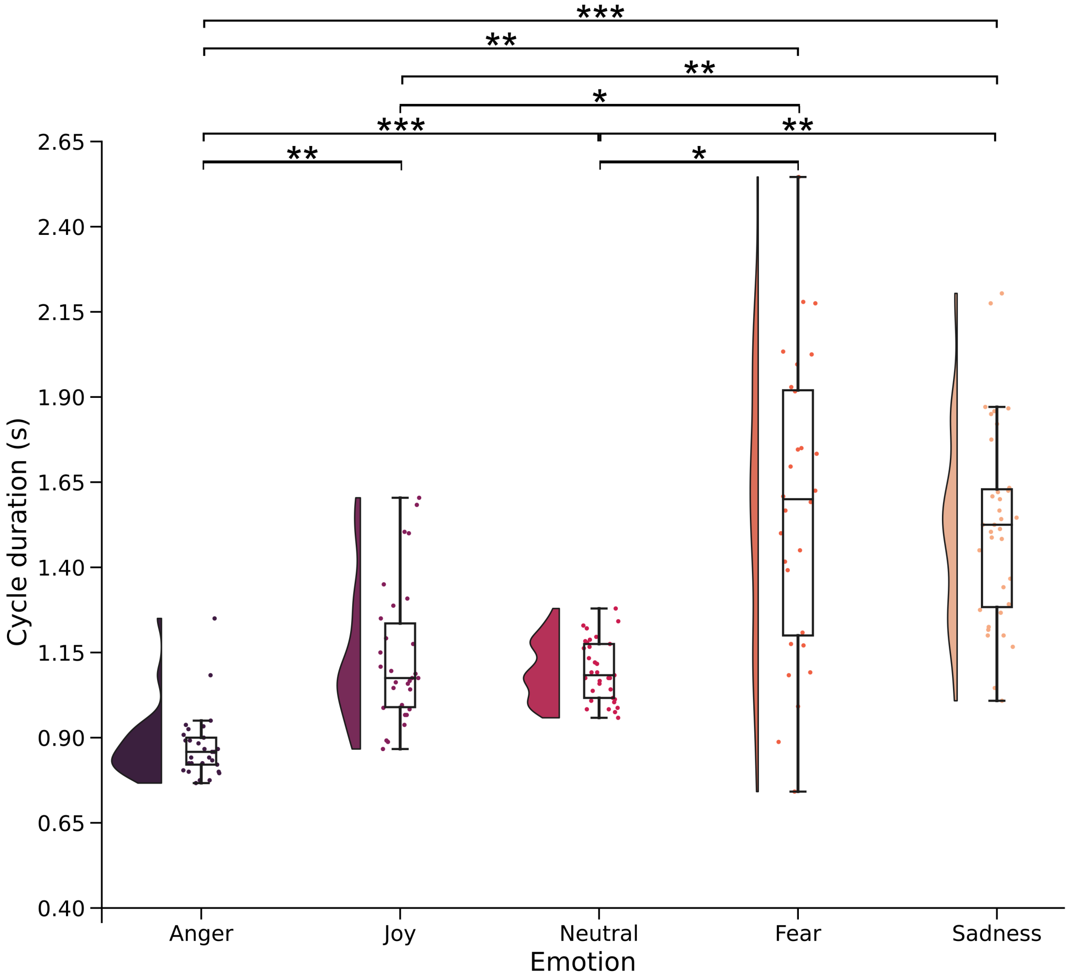
5.3.1.2 *Mean jerk*

The RM ANOVA on the mean jerk of the right toe indicated a significant main effect of emotion, $F(4, 20) = 61.14, p < .001, \eta_p^2 = .92$, with higher mean jerk for anger (*M* = 471.15, *SD* = 111.04) than for joy (*M* = 264.45, *SD* = 109.13, $p = .030, d = 1.78$), neutral (*M* = 252.90, *SD* = 64.51, $p = .004, d = 2.69$), fear (*M* = 112.11, *SD* = 89.34, $p < 0.001, d = 9.60$) and sadness (*M* = 121.41, *SD* = 69.51, $p < .001, d = 5.01$). Results also showed significantly higher mean jerk for joy than for fear and sadness, as well as a higher mean jerk for neutral than for fear and sadness. Refer to Figure 16 and Table 3 for detailed results on means and standard deviations.

5.3.1.3 *Head angle*

The one-sided *t* test against zero on mean head angle was significant for anger, $t(5) = -10.70, p < .001, d = 4.36$, confirming a negative head angle (*M* = -13.77, *SD* = 9.49). Similar findings were found for sadness : $t(7) = -2.87, p = .012, d = 1.01$, with a significantly negative head angle (*M* = -14.68, *SD* = 14.80). The one-sided *t* test against zero for fear was not significant.

Figure 15
Cycle Duration as a Function of Induced Emotion



Note. The cycle duration in seconds is presented for the five emotions. Each point on the figure corresponds to a trial. The number of stars denotes the statistical significance of the comparison. $^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

The one-sided *t* test against zero on mean head angle was significant for joy, $t(7) = 2.17, p = .033, d = 0.76$, indicating a positive head angle (*M* = 5.83, *SD* = 9.28). The one-sided *t* test against zero on mean head angle for neutral was not significant.

5.3.2 *Emotional gait time series*

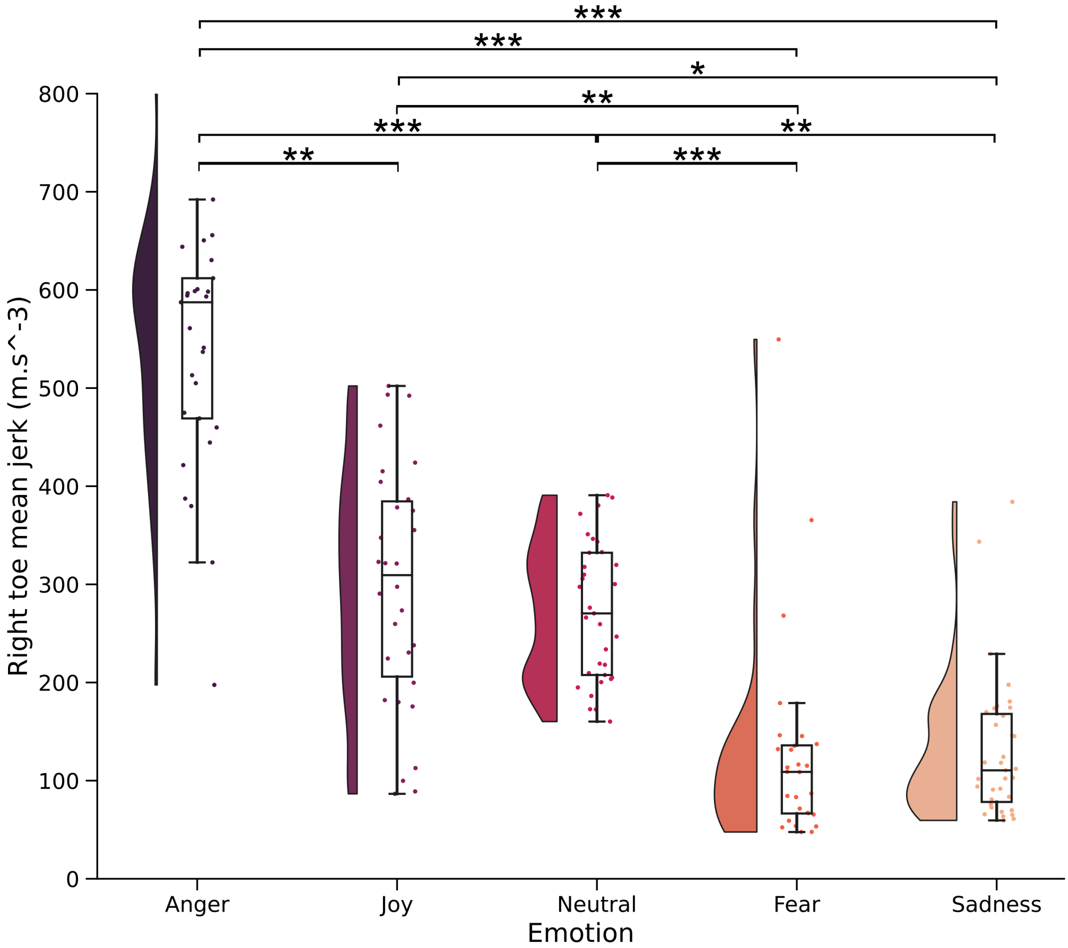
Detailed results for means and standard deviations are presented in Table 4 for both the auto-correlation and the wavelet coherence results. Figures 18 to 20 present illustrations of these findings.

5.3.2.1 *Auto-correlations*

The RM ANOVA on the auto-correlation at lag 1 of the series of right-step time intervals showed a significant main effect of emotion, $F(2.23, 8.92) = 9.93, p = .005, \eta_p^2 =$

Figure 16

Mean Jerk as a Function of Induced Emotion



Note. The mean jerk in meter per seconds cubed is presented for the five emotions. Each point on the figure corresponds to a trial. The number of stars denotes the statistical significance of the comparison. *p < .05. **p < .01. ***p < .001.

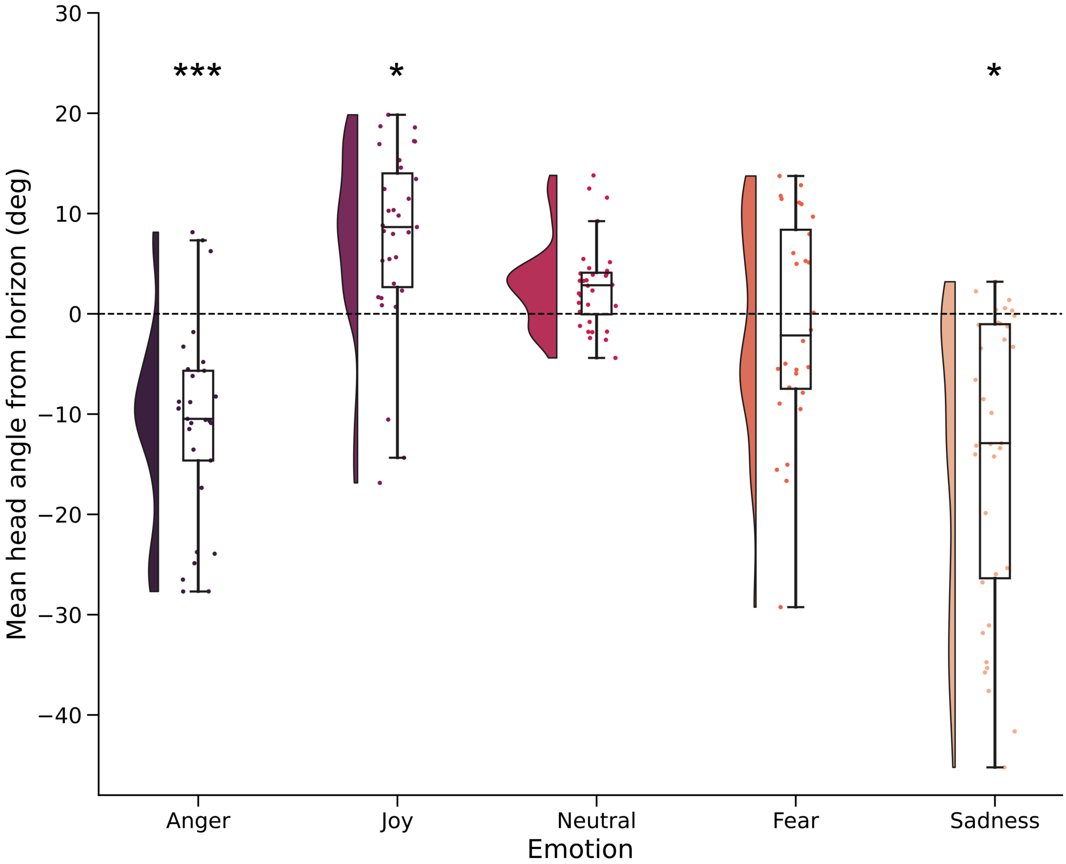
Table 3

Descriptive Statistics of the Kinematics Variables

	Cycle duration (s)		Mean jerk (m/s^3)		Head angle (deg)	
Emotion	*M*	*SD*	*M*	*SD*	*M*	*SD*
Anger	0.87	0.09	471.15	111.04	-13.77	9.49
Joy	1.14	0.20	264.45	109.13	5.83	9.28
Neutral	1.09	0.08	252.90	64.51	1.59	4.13
Fear	1.58	0.43	112.11	89.34	-0.85	10.82
Sadness	1.52	0.28	121.41	69.51	-14.68	14.80

Note. Group means and standard deviations for the five emotions and the three kinematic dependent variables.

Figure 17
Head Angle as a Function of Induced Emotion



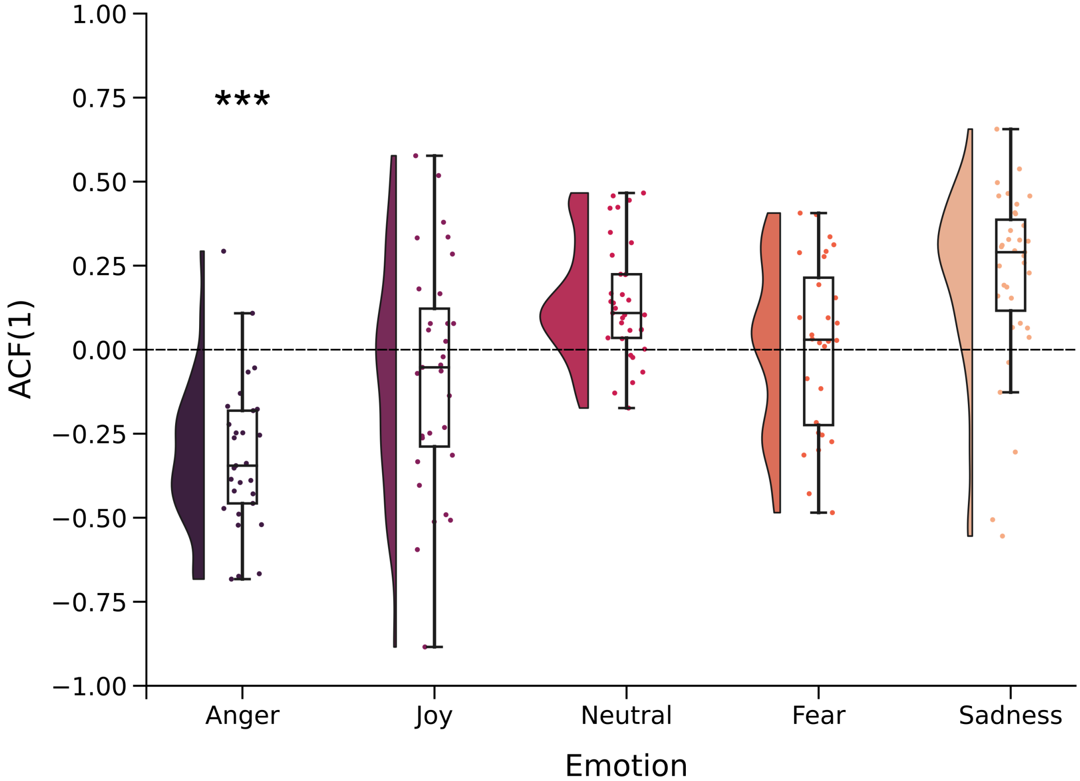
Note. The mean head angle in degrees is reported for the five emotions. Each point on the figure corresponds to a trial. The number of stars denotes the significance when compared to zero. $^{*}p < .05$. $^{***}p < .001$.

.71. Results indicated more negative auto-correlations for anger (*M* = -0.31, *SD* = 0.22) than for neutral (*M* = 0.14, *SD* = 0.17, $p = .007, d = 2.04$) and sadness (*M* = 0.21, *SD* = 0.26, $p = .01, d = 2.76$). Results also showed significantly smaller values of auto-correlations for fear (*M* = 0.01, *SD* = 0.25) when compared to sadness ($p = .002, d = 5.83$). The one-sided *t* test against zero confirmed significant negative auto-correlation for anger only, $t(5)$ = -5.04, p < .001, d = 1.78.

5.3.2.2 *Cross-wavelet analysis of emotional spontaneous walking*

The RM ANOVA on the cross-wavelet coherences between right toe and left wrist showed a significant main effect of emotion, $F(4, 12) = 12.17, p < .001, \eta_p^2 = .80$, with smaller magnitudes of coherences for fear when compared to anger ($p < .001, d = 5.69$), joy ($p < .001, d = 2.06$), neutral ($p < .001, d = 3.33$) and sadness ($p = .020, d = 2.05$). Post hoc analysis also showed a significantly lower coherence for joy when compared to anger ($p = .020, d = 2.19$).

Figure 18
Auto-correlation as a Function of Induced Emotion



Note. The auto-correlation function at lag 1 is presented for the five emotions. Each point on the figure corresponds to a trial. A negative auto-correlation implies that the motion was under cognitive control. The more negative the auto-correlation, the more controlled the movement. The number of stars denotes the significance when compared to zero. $^{***}p < .001$.

Table 4
Descriptive Statistics of the Time-Series Variables

	Auto-correlation function (lag1)		Wavelet coherence right toe - left wrist	
Emotion	*M*	*SD*	*M*	*SD*
Anger	-0.31	0.22	0.56	0.24
Joy	-0.07	0.34	0.45	0.19
Neutral	0.14	0.17	0.48	0.22
Fear	0.01	0.25	0.33	0.10
Sadness	0.21	0.26	0.47	0.22

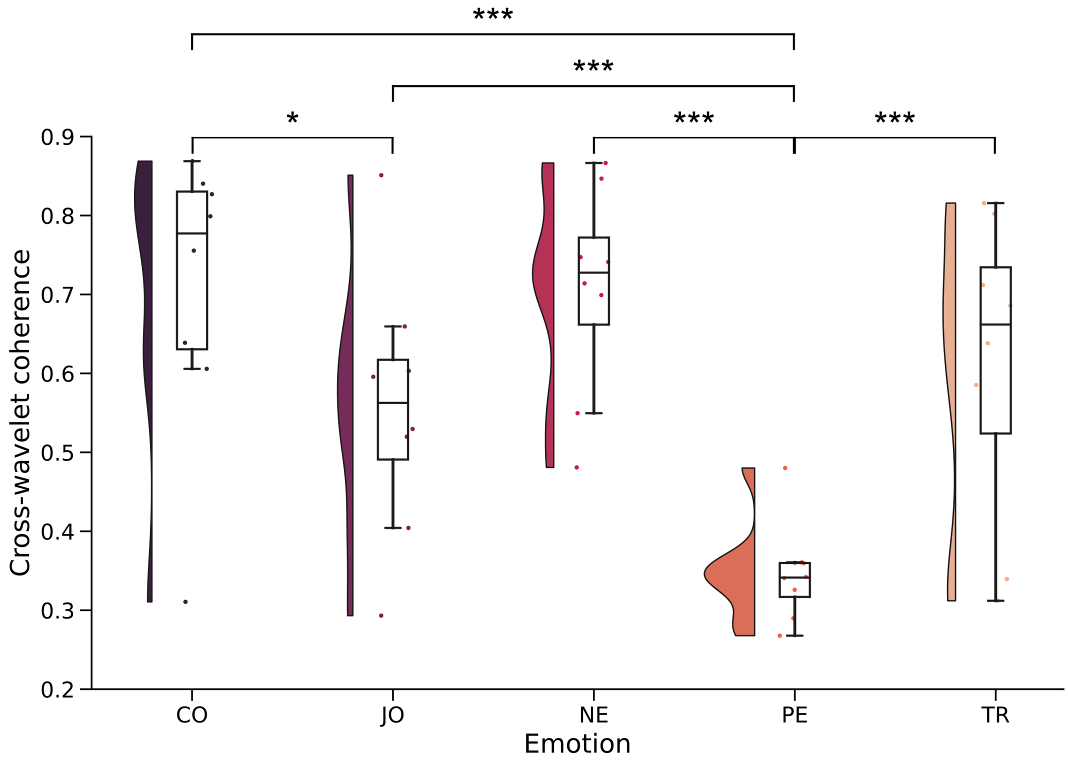
Note. Group means and standard deviations for all emotions and each of the two time series dependent variables (i.e., auto-correlation at lag 1 and wavelet coherence).

5.4 DISCUSSION

Allostasis is the core mechanism used by the brain to control body functioning (Barrett, 2017; Sterling, 2012). To optimize energy consumption, the brain modifies the

Figure 19

Mean Magnitudes of the Cross-Wavelet Coherence Between Right Toe and Left Wrist



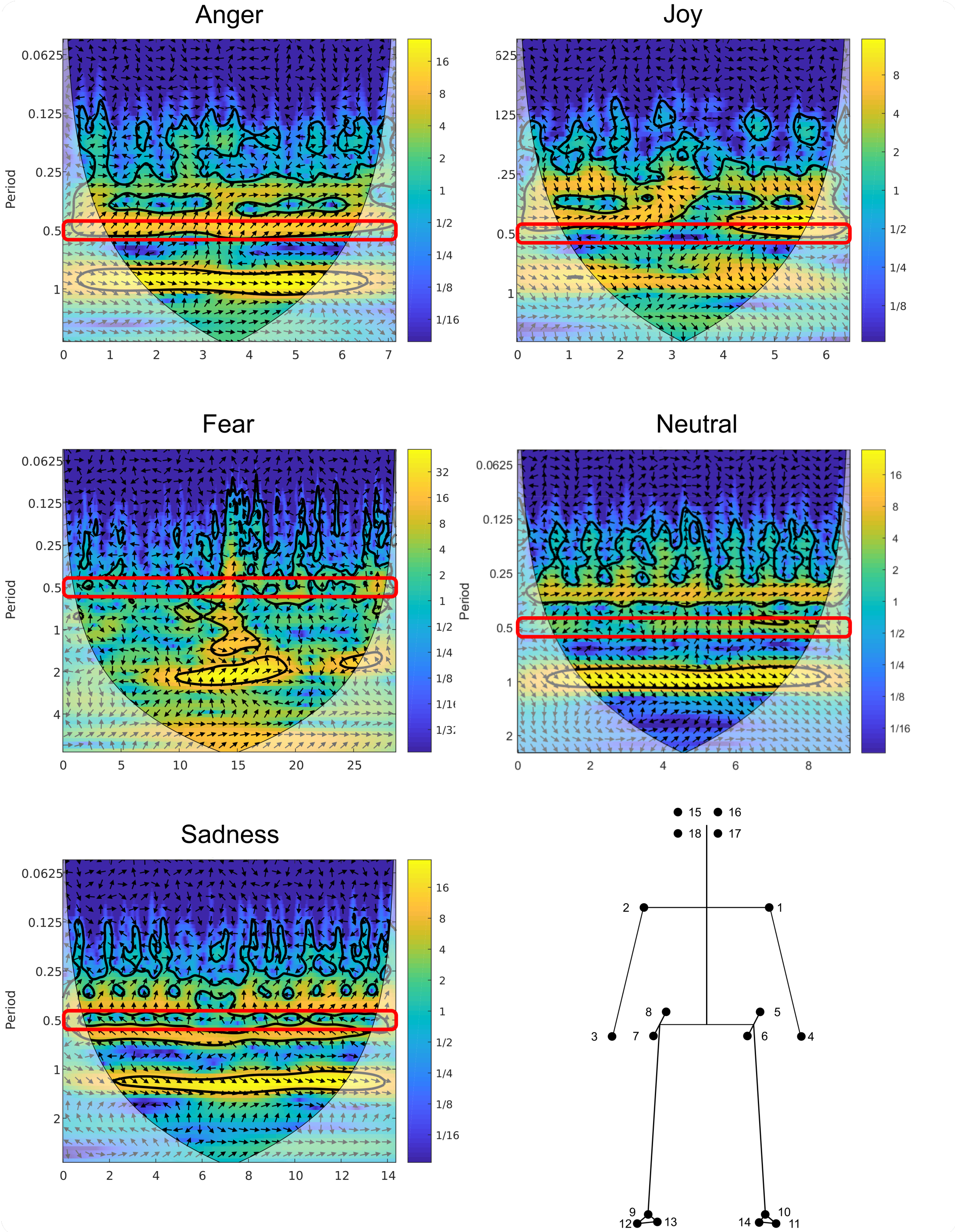
Note. Mean cross-wavelet coherence between the right toe and the left wrist, at a period of 0.5 (i.e., 2Hz).

way the body operates as a function of needs and predicted resources. One of such modification is done at the level of the 3D-joint kinematics, by controlling the style and shape of body movement. The brain adapts notably the speed of movement, and the amount of cognitive control exerted on the ongoing action. This strategy would provide the possibility to interact with the ever-changing environment while continuously regulating energy expenditure. The aim of the present study was to use an in-lab experimental paradigm to report data plebisciting this evolutionary perspective of emotional body movements. We report a study assessing how five induced emotional states modulate the expression of a common gait motor program. To achieve this, eight professional actors were asked to recall an autobiographical memory tagged with an emotional component, before initiating a walking sequence along a ten-meter lane.

To characterize the emotional side of walking, we computed a series of spatial indices: cycle duration to quantify walking speed as an indicator of energy expenditure, jerk to measure motion smoothness, and head angle to unravel the presence of a protective tendency (openness vs. closeness). By applying spatio-temporal analysis on gait cycle (Dione & Delevoye-Turrell, 2015), an index of the amount of cognitive control applied to the ongoing movement was obtained. We observed specifically when moving with anger, a significant negative auto-correlation suggesting greater

Figure 20

Cross-wavelet Coherence as a Function of Emotion



Note. The cross-wavelet coherence is represented for one participant for each emotional condition (fear, sadness, neutral, anger and joy). The red rectangles highlight the period of interest (i.e., 0.5) that was used to compute the mean magnitudes of coherence and conduct the statistical analyses.

cognitive control to exert tension and rigidity in the motor system. This information was finally used to map out wavelet coherence patterns to characterize the amount of coordination existing between the upper- and lower-parts of a person when walking in different states of emotion.

The main results of our work are here outlined. Anger and joy (i.e., high energy emotions) were characterized by shorter cycles and jerkier gait patterns compared to fear and sadness (i.e., low energy emotions), which confirm H_1. These findings replicate previous results on the matter (Crane & Gross, 2007; Roether et al., 2009). Sad and angry negative emotions had a strong effect on head angle, with the head bowing towards the ground within a few seconds whereas positive emotions had a tendency to release head constraints. These results offer a partial confirmation of H_2. The findings from the time series analyses indicated that anger only increased the amount of negative auto correlations, which partially confirm H_3. The cross-wavelet analyses indicated that anger yielded higher coherence between the right-bottom side (toe) and the left top-side (wrist) of the body, when compared to joy. Fear yielded the lowest coherence of all, offering contrasting degrees of body coherence, which confirm H_4.

5.4.1 *Evolutionary advantage of emotions*

Nonverbal expression and perception of emotions are based on multiple channels of communication. Little research regarding the association between body movements and basic human emotions has been conducted, as it is regarded as a weak channel compared to other nonverbal communication such as facial expressions (Cowie & Cornelius, 2003; Ekman, 1999; Izard, 1994). On the other hand, with the absence of facial expressions (COVID-obliged mask use), we have discovered the importance of emotional body postures to engage in natural social interactions. Because of the numerous degrees of freedom, the 3D motion analysis of free movement is difficult. We take advantage of the advances in data sciences to report a new understanding of how and why emotions may influence motor behavior.

5.4.1.1 *Positive emotions*

Emotions are what ties humans together. Emotions provide many benefits and have helped shape human evolution. Three major benefits can be highlighted from the results of the present work. Positive emotions would increase openness to the surrounding world and thus, optimize the likelihood of seeing positive stimulus (e.g., food, shelter, social contacts). In the present study, we showed that with joy, the participants had the unconscious tendency to release the head, which triggered an upward head-tilt to increase the line of sight. When looking up, one also tends to grow taller. Hence, a second benefit to head release is a behavior entailing the search of a suitable partner to transmit genes onto the next generation. The tendency to bring the head up and appear taller might increase the attractiveness towards individuals of the opposite sex. It has been found that height is a defining factor when searching for a mate, especially among women (Brewer & Riley, 2009; Courtiol et al., 2010). In the present study, participants walked faster in joy than in neutral trials. This increased speed could potentially be a signal of vigor and good health, which would again reinforce the appearance of being a suitable partner to individuals of the opposite sex (Buss & Schmitt, 2019). Finally, the third major benefit of positive emotions is a reduction of the control set upon the system. Mean jerk was lower in joy than in anger; autocorrelations were null in joy and negative in anger trials. Fluency of movement is elegant and consumes less energy. Hence, when moving in a positive affective state, the system codes that there is an absence of (tension) stress and thus, it can perform for longer periods of time without further energy intake. Such reduction in stress would also lead to an increase in overall well-being and feelings of pleasure (Delevoye-Turrell et al., 2014).

5.4.1.2 *Negative emotions*

While negative emotions are generally avoided, they do serve crucial evolutionary purposes and have also helped human survive through the course of evolution. The first advantage of negative emotions, and especially negative emotions with high energy (anger) is to escape from danger or appear more threatening to scare danger away all together. The results on cycle duration showed an increase in walking speed for anger when compared to other negative emotions. This increased walking speed could provide the means to escape from a threatening situations. Brisk walking also suggests vigor and energy, which could be a sign of strength to redirect threat to other individuals (Blanchard et al., 2001). The second advantage of negative emotions is to protect vulnerable parts of the body from an imminent danger. The results on the head angle showed that when induced with anger or sadness, participants had a tendency to lower the head. This behavior can be seen as a defensive posture designed to protect the throat, which is a highly vulnerable part of the body. The protection of the body might also be achieved by tensing the muscles to withstand an attack. Auto-correlation results were significantly more negative for anger than for any other emotion, confirming that with anger there were greater levels of control applied during motor execution (Lemoine & Delignières, 2009), which would have the benefit in addition to switch from one action to another to further withstand attacks on the body.

It is not always possible to escape or fight an imminent threat. This is where negative emotions with low energy would come into play. Their role might be to make humans seem nonthreatening and unnoticed. Bowing down when in fear or sadness would be a sign of capitulation; it would also make a person appear smaller and less threatening, therefore increasing the likelihood of the threat fading away. The same is true for the results on cycle duration. The speed of gait was slow when participants were walking in low negative states of emotion. This phenomenon could be seen as an attitude similar to the freezing behavior displayed by rodents to suggest illness, an attitude that has also been reported in humans (Blanchard et al., 2001). Slow movements and released control would help reduce the energy consumption of the system to a bare minimum. In the present study, we confirmed these changes in control settings by reporting the auto-correlation values. Our findings confirmed more positive auto-correlations for sadness than anger, indicating that during sadness there is a release in cognitive control exerted on the motor program, perhaps to further increase the energy savings. However, maintaining a reduced energy consumption is detrimental to the overall functioning of the system and could explain why prolonged feelings of negative emotions is dangerous for humans both for physical and mental health. Just like a too low regime on a motor might damage the engine of car, a too low regime in the body might impair feelings of wellbeing.

5.4.2 *Wavelet coherence*

Wavelet coherence analysis is a time-domain analysis of two time series. It offers the means to compute and investigate the changes in cross-correlations between two time series, at different time scales (Grinsted et al., 2004). It was used in the present work to understand how the upper- and lower-body parts are being coordinated during spontaneous gait under different emotion inductions. The results on the wavelet coherence between the right toe and the left wrist indicated a significantly higher coherence for anger compared to all other emotions. This increased coherence suggested that opposite body sides are highly synchronized in space and time, i.e., planned by the brain to move as one. Such synchronization would suggest an enhanced cognitive control applied to both upper- and lower-body parts. The fact that only anger (a negative emotion with high energy) was found to significantly increase the coherence, further supports the hypothesis that anger tenses the body to prepare future direct threat. The absence of enhanced movement coherence in negative emotions with low energy (fear and sadness) seems to further support the idea that negative emotions with low energy reduce the energy consumption of the system to a minimum, so as to keep low profile until the need arises.

5.4.3 *Limitations and future directions*

The present work presents certain limitations that are now considered. First, our participants were trained professional actors. It is well-known that the work of actors is to exaggerate the expression of emotions to convey a story line to spectators. It would be interesting to conduct a similar study with non-professional actors to investigate whether these results are generalized to the general population. A full study conducted in non-actor adults would also offer the opportunity to investigate the differences that may exist in how people express their emotions as a function of age and social-economical background. Current emotional theories (e.g., Barrett, 2017) posit that every human has its own way of expressing emotions. Consequently, it would be of great interest to conduct a similar study with participants from different cultures and investigate both the similarities and differences that might exist in their emotional body expressions. Lastly, we report the findings for one positive emotion (joy) only. Future work should include positive emotions with low energy, such as contentment. This would allow to contrast and compare the relative evolutionary benefits provided by both high and low energy positive emotions. This added condition would also offer the means to confirm that gait energy and cross wavelet coherence are sufficient alone to decode the inner emotional states of a person while spontaneously moving through space and time.

5.4.4 *Conclusion*

Core affect may be a powerful signal used to detect significant risks to allostasis dysregulation throughout the course of a day, allowing the brain to maintain optimal functioning of the moving body in a constantly changing world (Barrett, 2017; Russell, 2003).

An emotion is a complex state of feeling that results in physical and psychological changes that influence the way a motor action is executed. Our work has confirmed previously published results on the effects of high energy emotions (anger and joy) in increasing the speed of motor execution. But it has in addition shown that considering the changes in control levels through space and time opens the window in decoding between positive and negative states of emotion. Applying our methods to different types of movements (cycling, running) would confirm that cross wavelet analysis can capture the tension and energy in a moving body fostering the indices for decoding the inner states of emotion in real-life activities.

6 DEEP-LEARNING AT THE SERVICE OF EMOTIONAL PSYCHOLOGY

6.1 Methodological interlude

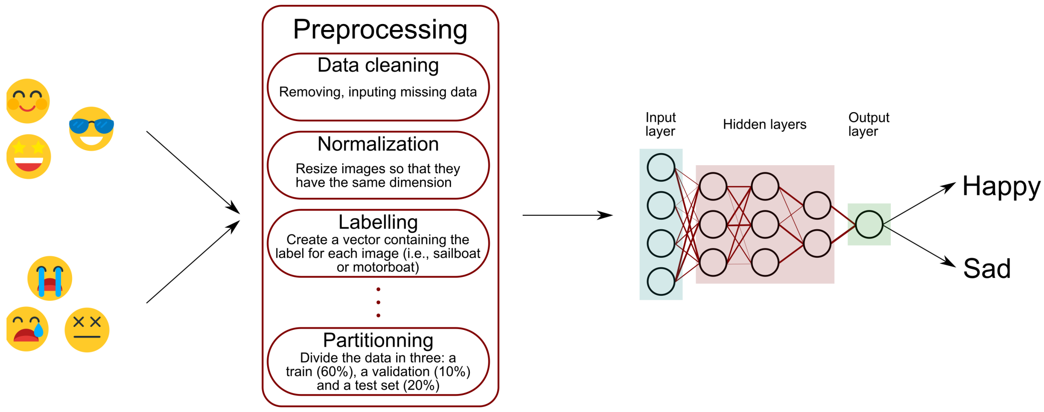
Training a deep-learning model might be seen as a straightforward task, where one simply needs to give the data to a black-box that will output a result. This is, of course, far from the reality of training a deep-learning model. An illustration of a simplified training procedure can be found in Figure 21. Before diving into this section, interested readers might need a fresh reminder on various methods and terms that are considered "business as usual" among machine-learning specialists and that are not thoroughly detailed in the present chapter. This section will cover two of these methods: hyper-parameter tuning, or how to find the optimal set of parameters for the network (e.g., how fast will it learn, how big will the network be), and temperature scaling, or how to reduce the overconfidence of a network.

6.1.1 *Lexicon*

Objective	The quantity to monitor during training (usually either the loss or the accuracy)
Training set	Selected portion of the data only used during the training procedure
Validation set	Selected portion of the data only used during the optimization procedure
Testing set	Remainder of the data, only used during the evaluation of the model
Learning rate	Size of the steps toward the objective, usually seen as how fast the network will learn
Loss	How bad the network was on average over the training set; the goal is to minimize this quantity when set as the objective
Accuracy	How good the network was on average over the training set; the goal is to maximize this quantity when set as the objective
Epoch	One pass across all training data

Figure 21

Simplified Classifier Training Procedure



Note. Simplified illustration of a deep-learning classifier training procedure. The pre-processing step is one of the most vital step when training a network. Some pre-processing steps have been described in this illustration. However, other steps can be conducted, depending on the task.

6.1.2 *Hyper-parameter tuning*

To ensure that the performance of a model is optimal, it is crucial to select the right combination of parameter. A deep-learning model might contain a various parameters to optimize, such as the learning rate or the number of layers in the network. These two parameters were optimized throughout this work, using a random-search method. This method was selected as the search space (i.e., the number of parameter combination) was quite high and our available computing power quite low. After selecting the search space (i.e., the number of parameter combination), the tuning requires to set two more values: the objective and maximum number of combinations that should be tested. The objective guides the optimization by choosing a measure to compare the combinations. In this case, the objective was to minimize the loss on the validation data set. Finally, limiting the maximum number of combinations is useful when the search space is vast.

In the case of random search, the search is conducted by randomly selecting one value for each of the parameter; then the network is trained. At the end of the training, the final value of the objective (e.g., validation loss) is recorded and the training restarts with other values randomly selected. When all combination have been exhausted or the maximum number of tested combination has been reached, the search ends. At this phase, the combination yielding the best value with regards to the objective are returned and the final model can be trained.

To help the reader put things into perspective, the tuning phase for two parameters only took approximately eight hours to complete on a laptop computer running with Ubuntu 18.04, powered by an Intel Core Xeon E2176M cadenced at 2.7 GHz. However, it took 30 min to complete on a desktop computer running Windows 10, powered by an NVIDIA RTX 2060 graphic card.

6.1.3 *Temperature scaling*

When using deep-learning algorithms to make a prediction, one might believe that the algorithm will return a single output. The network will instead return a probability associated with each of the possible outputs. In the case of a deep-learning model designed to recognized emotions from kinematics, the possible outputs are the emotions that the model should learn to recognize. If the model was trained on seven emotions, for each trial it would return the probability internally associated to each emotion category. If the model is faced with the kinematics of a happy person, a possible output would be 1% sadness, 1% fear, 1.5% neutral, 85% happiness, 9.5% anger, 1.5% surprise, and 0.5% disgust. The final prediction of the model will be the output with the highest probability (i.e., happiness). However, how can one be sure that the probabilities returned by the model are to be trusted?

Guo et al. (2017) showed that modern neural networks are poorly calibrated. These neural networks tend to be overconfident in their returned probabilities. Coming back to the previous example, in the case where 100,000 happiness trials are passed on to a poorly calibrated emotional classifier, the computed prediction confidence (e.g., 85%) would not represent the outcome of 85% of trials classified as happiness over all the trials analyzed – it might actually predict that only 78% of them are indeed happiness. Such overconfidence can lead to serious problems in applications where predictions from deep-learning models are used to make important decisions (e.g., self-driving cars, medical care).

To tackle this challenge, Guo et al. (2017) proposed various methods. One of the simplest and most efficient one is called *temperature scaling*. This calibration method, as many others, is done after the network has been trained. Temperature scaling does not affect the accuracy of the model. If the previous emotional classifier predicted happiness, it will still predict happiness but not with the same probability. Temperature scaling is computed on a validation set not used during training to reduce the influence of possible biases. This method is conducted in two steps. First, one needs to train the network and recover the values (called logits) that are fed to the final layer of the network (i.e., a softmax layer in classification tasks). Then, one needs to find the temperature value (i.e., T) that minimize the negative-log likelihood, using the logits as input to this optimization step. Once the optimization is complete, calibrated probabilities are obtained by scaling them with a factor T.

6.2 INTRODUCTION

Emotions are the fabric on which human relationships are woven. The study of facial-expressions initiated the experimental approach to the better understanding of emotion recognition. In 1969, Ekman et al. (1969) created short stories and asked American students to display facial-expressions of these emotions. They then asked other American students to read the emotional stories and to select the facial-expressions corresponding to the emotions of the stories. As they were issued from the same cultural background, students found it easy to match the facial-expressions to the stories. However, the researchers set out to Papua New Guinea to unravel the universality principle of facial emotional recognition. At that time, the Fore tribe members of Papua New Guinea had little exposure to the Western culture. Ekman and Friesen (1971) had translators tell the stories to the Fore tribe members, who where then invited to select the facial expression that corresponded best to the emotion contained in the story. What they found was quite striking. The Fore tribe members selected almost the same facial-expressions as the American students. Thus, it was concluded that facial-expressions of emotions may be universal and that their recognition does not result from social cultural experience.

The research and technological advances made today offer the possibility to train a computer to recognize facial-expressions (for an up-to-date review on the available methods, see e.g., Li & Deng, 2020). Such methods allow for a quick and accurate recognition of emotional facial-expressions and can even be embedded into smart devices such as smartphones, surveillance cameras, and robot carers for the elderly. However, facial-expressions recognition software have three major drawbacks. First, access to video recordings of the faces is required, which poses serious threats to a person's privacy as such recordings can be used to infer identity. The second limiting factor is that facial-expression recognition software mostly rely on deep-learning methods, which require vast amounts of computing power and data. Finally, the abilities of deep-learning models are limited by the data they are trained on. Most datasets used to train models of facial expression recognition fail to include sufficient data for gender, race, and corpulence variety (Xu et al., 2020), which leads to ethical issues. A third limiting factor that has recently appeared concerns the use of face masks, which severely impairs the recognizing abilities of facial expression software, as large areas of the face are covered. Fortunately, research on emotions has not been limited to the study of facial-expressions and studies (e.g., in movement sciences) have focused on other informative parts of whole-body behaviors.

Pollick et al. (2001) studied the perception of emotions from arm movements. Actors were instructed to perform two actions (drinking and knocking) and the 3D movements of the upper joints were recorded. Later on, the point-light displays were shown to naive participants (i.e., video clips with only major joints displayed) and they were asked to categorize the affective state of the actor, simply by looking at the point-light display. The authors reported that participants were able to recognize correctly the emotion of the actor at a rate greater than three times chance level.

Atkinson et al. (2004) built on the findings of Pollick et al. (2001) and developed a set of static and dynamic body expression of emotions. A total of 10 actors participated in the recording of the data set. Actors were told to play five different emotions (disgust, sadness, happiness, fear, and anger). Their faces were blurred on the videos to avoid emotion recognition from facial-expressions. Static- and dynamic-body expressions with blurred faces were created and presented to naive volunteers in an emotional categorization task. Results showed that participants were able to achieve close to 75% correct recognition on the least recognized emotion (i.e., disgust) and 81% for the best recognized emotion (i.e., happiness). The accuracy of the volunteers decreased when they were presented with still images of the body expressions, but remained significantly above chance level. Overall, these results confirmed those reported by Pollick et al. (2001).

Building on the previous research, Dael et al. (2012) extracted a list of 16 "behavior variables" involved in emotion display (e.g., shoulder action, elbow action) which allowed further confirmation that emotions can be recognized from body dynamics. In their work, they highlighted the importance of joint angles, and changes through time when recognizing emotions from body expressions. A complexity difficult to account for with comparative statistics. Consequently, there is a need for new algorithmic strategies to capture the micro-variants of emotional body movements.

Related work on automatic recognition of emotions from body movements can be found in the literature. Karg et al. (2010) used kinematics data of four portrayed emotions (neutral, anger, sadness, happiness) to compare the performance of three types of network (i.e., nearest neighbor, naive-Bayes, and support vector machine (SVM)). They used data from 13 adult males wearing 35 markers across their bodies. From these 35 markers, the authors were able to compute the stride length, cadence, velocity, as well as minimum, mean, and maximum values of neck, shoulder, and thorax angles. This wealth of data allowed them to perform dimensionality reduction techniques (e.g., Principal Component Analysis) to select only the relevant features. Their results showed that the best accuracy (69%) was achieved with the SVM algorithm when all angles were fed to the classifier. Even greater accuracy was achieved (95%) when taking into account the individual performance of each participant.

More recently, Daoudi et al. (2017) developed a new architecture to classify five portrayed emotions (neutral, anger, sadness, happiness, and fear). Their approach was quite different from previous works. They created a prototype emotional movement for each emotion category, from the kinematics. Then, for each trial to be classified, the authors computed the distances between each prototype emotional movement and the current trial. Thus, the classifier returned the emotion corresponding to the shortest distance. Their architecture achieved an overall accuracy of 71% where humans achieved 74%. But the difficulty in these decoding methodologies is the fact that, even if characterized by biological motion, human bodies come in different shapes. Hence, classification algorithms need to focus on the motor-variants between emotional states without needing to take into account the physical cues of the human actors (i.e., body height, weight, and shape).

In this chapter, I describe Deep Recognition of Emotions from Kinematics (DeeREKt), a novel model that was made to classify emotions solely using body kinematics. The proposed model is efficient as it can be trained and ran on a simple laptop, without requiring the use of a dedicated GPU. Additionally, the proposed model is embedded with a so-called "discriminant head" to avoid relying upon physical cues for emotion decoding. If informative cues have been well selected, our model should categorize emotional states above chance level (H_1). From an evolutionary standpoint, humans have evolved to react vigorously to negative stimuli. Consequently, we hypothesize that negatively valenced emotion (e.g., anger, fear) should be better recognized compared to other emotions (e.g., surprise, happiness; H_2). Finally, the discriminant head will help the network both in its generalizing abilities and training time (H_3).

6.3 METHOD

6.3.1 *Dataset 1*

Kinematics data coming from 22 actors (Zhang et al., 2020) were used to create and train the DeeREKt model. Actors were instructed to perform emotional scenarios of six emotions (happiness, sadness, anger, fear, disgust, surprise). A neutral condition was also added. Actors had six seconds to perform the given scenario. An example of a scenario for sadness and happiness are "Zhang's father dies in a car accident" and "Zhang's favorite basketball team wins the NBA championship". Actors performed between two to three repetitions of each scenario in a semi-random order, yielding a total of 1,402 recordings across actors.

Data was sampled at 125 Hz and contained information about 58 joints, with a majority targeting the hands. As the present work focused on emotion recognition from whole-body kinematics, only the 21 joints representing body space were kept.

6.3.1.1 *Preprocessing*

. Before being able to feed the data to the model, a number of pre-processing steps were needed.

REFERENCING This first step consisted in computing the world coordinates of the joints. The data was in the Biovision Hierarchy file format, which was used to store both motion-capture data and joint hierarchy. The origin joint (called root) was the hips. Then, each joint was defined with regards to the root and its parent-joints. The root was a parent joint to all joints directly connected to it. Then, all connected joints were parents to joints directly connected to them, and so forth. A similar principle held for the coordinates of the joints, which were defined with regards to the position of their parents. This was applied to the data through the use of an offset and coordinates were thereafter referred to as local coordinates. To compute the world coordinates of a joint, it was necessary to find all parents for that joint, up until the root, as it required taking into account all offsets by adding them to the local coordinates.

DETERMINING TRIAL LENGTH . After computing the world coordinates, the length of each trial was examined. As trials differed in length, not all trials were selected. Only trials lasting for at least five seconds were kept for further analyses. Then, to further improve consistency, the first five seconds of each trial were kept. Following this selection phase, trials were resampled at 120 Hz. Finally, all trials were merged into a single file for a given actor with the corresponding emotional label.

6.3.1.2 *Partitioning*

The construction of the two data sets used for training and testing of the model were then created. The actors and trials in the training set were selected pseudo-randomly. A total of 70% of the actor – emotion pairs were allocated to the training set and the remaining 30% were reserved for the testing set. A rule was set specifying that, once an actor – emotion pair was selected to be part of the training set, this pair could not be used in the testing set. This was done to avoid a learning bias by the model training while insuring that all actors and trial types (actors × emotions) were present in both sets.

6.3.2 *Dataset 2*

A second dataset was used to further test the predictive accuracies of the network. This dataset was built by recording the 3D kinematics of eight professional actors, who were instructed to portray five different emotional states (joy, fear, anger, neutral, and sadness) while walking back and forth, across a ten-meter lane. Kinematics data was recorded using 24 Vicon V8 motion-capture cameras, at a sampling frequency of 120 Hz. The system recorded the position of 43 joints of the actors, using passive reflective markers. Care was taken to lose as little markers as possible during data collection. Nevertheless, the trials containing at least 6 s of exploitable recorded data were kept, which led to the rejection of three trials, over a total of 160 trials.

6.3.2.1 *Preprocessing*

During each trial, the actor was asked to follow a line traced on the floor. The moment at which the actor turned around was removed to avoid passing irrelevant emotional information to the network. The turn-around was detected by finding the minimum of the dot product of a vector spanning from the right to the left hip ($\overrightarrow{H_R H_L}$, Equation 5) with a unit vector ($\vec{u}$, Equation 6), following Equation 7:

$$\overrightarrow{H_R H_L} = \begin{pmatrix} x_{H_R} - x_{H_L} \\ y_{H_R} - y_{H_L} \\ z_{H_R} - z_{H_L} \end{pmatrix} \tag{5}$$

$$\vec{u} = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \tag{6}$$

$$\overrightarrow{H_R H_L} \cdot \vec{u} = \left\| \overrightarrow{H_R H_L} \right\| \times \left\| \vec{u} \right\| \times \cos(\overrightarrow{H_R H_L}, \vec{u}) \tag{7}$$

After detecting the moment of the turn-around, half a second was removed before and after the vector interval. For some trials (approximately 20%), the recording was started before the initiation of the movement. To detect the start of the motion, the second derivative of the position of the right hip was computed over the first 4 s of the recording. Then, the maximum of the second derivative, over this time window, was taken as the initiation of the movement. Data was inspected by a human observer to ensure that the trial contained relevant motion information. Finally, to augment the number of trials, trials were partitioned in two. Three seconds of movement were obtained from the beginning of the trial and three seconds were obtained before the end. Therefore, the dataset contained 312 trials.

After selecting the relevant frames, the data was re-referenced. A new three dimensional coordinate frame (*xyz*) was defined. The *z* axis was directed upwards along the vertical plane but was kept as the original *z* axis. The *y* axis was oriented leftward perpendicular to the z axis and computed by averaging the two markers from the left pelvis. The x axis was aligned with walking direction and computed as the cross product of the y and z axis. All markers were re-referenced to this new xyz coordinate frame.

6.3.2.2 *Partitioning*

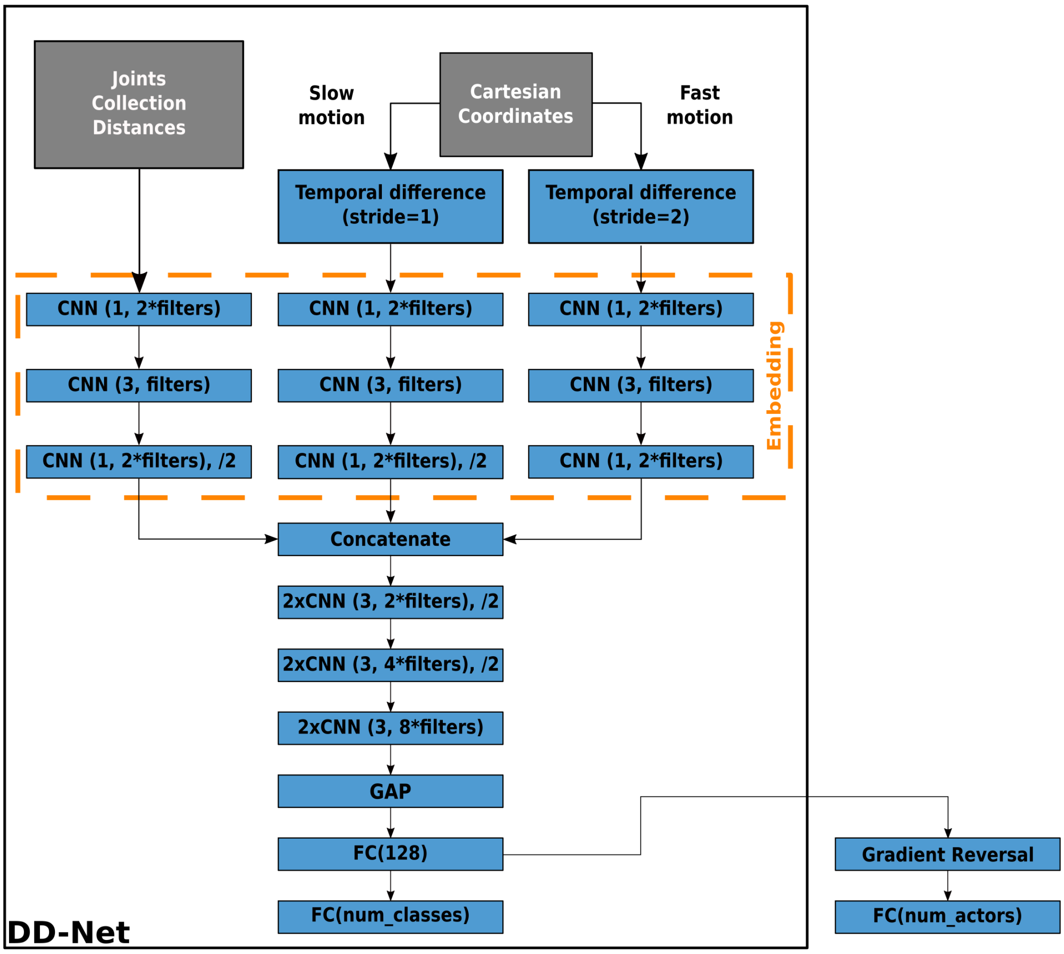
Close to 70% of the trials were kept for training and the remaining 30% were set aside for testing. The training set contained the following amount of trials: 22 for joy, 20 for fear, 20 for anger, 23 for neutral, and 25 for sadness. The partitioning was also designed so that each actor was equally represented in both sets. The most represented actor had 16 trials in the training set while the least represented actor had 11 trials. This is because not all actors performed the same number of trials and once an actor – emotion pair was in the training set, the same actor – emotion pair could not be in the testing set.

6.3.3 *DeeREKt model*

The DeeREKt model is based on the Double-feature Double-motion Network (DD-Net; Yang et al., 2019b). The DD-Net model has been designed to achieve action recognition from skeleton-based data (i.e., kinematics data from major joints of a person in two or three dimensions). The successfulness of the DD-Net lies both in the design of the model and processing of the data. The principle is the following: First, the skeleton data is used to compute the Euclidean distances between pairs of joints. The output of this step is a symmetric matrix and only the lower half of the triangular matrix is kept to "avoid redundancy", and especially to decrease data size and memory consumption (Yang et al., 2019b, p.2). Second, the model computes the temporal differences between frames. This allows the DD-Net to learn to differentiate between fast and slow goal-directed motions. Last, once the temporal difference has been computed, the network automatically captures the correlations between joints through an embedding procedure. This is a key addition as in traditional action-recognition models, these correlations are part of the input of the model. Since the DD-Net is highly efficient and accurate in distinguishing action from motion, it forms the basis of the DeeREKt model.

Every human body is different and the network should not rely on physical cues to predict emotional states, otherwise it would have poor generalizing abilities. Hence, on top of the DD-Net, a discriminant head was added based on the Domain-Adversarial Training of Neural Networks (Ganin et al., 2016). The more this head is able to recognize the actor, the more it disrupts the network. To do so, the head reverses the gradient used to compute the training error. The gradient is a measure of the performance of the network. Hence, if the head correctly identifies the actor, the gradient should be small. By reversing the gradient, the head informs the network that it should not rely on the actor to perform the task. A visualization of the architecture of the model is presented in Figure 22.

Figure 22
Architecture of the DeeREKt Model



Note. DeeREKt: Deep Recognition of Emotions from Kinematics. Architecture of the DD-Net is based on (Yang et al., 2019b).

6.3.3.1 *Training parameters*

Several parameters were set in order for the model to learn how to recognize efficiently the emotions. Only the two most crucial parameters were selected via random search and will be described in the following section.

Hyperparameter optimization was done using Keras–Tuner library (O'Malley et al., 2019). The first parameter to be optimized was the learning rate and it was set to 10^{-4}. The greater this parameter, the faster the model learns. Possible values during random search were 10^{-2}, 10^{-3}, and 10^{-4}. The second parameter is referred to as lambda, that controls the strength of the disruption caused by the discriminant head. The greater the value, the more disruptive is the head. This parameter was set to 1.0. Possible values for lambda during random search were 0.1, 1.0, and 10.0.

6.3.3.2 *Implementation details*

The DeeREKt model uses Python (version 3.7) code from the original Github repository of the DD-Net (Yang et al., 2019a). The discriminant head of the model was also coded using Python (version 3.7). Training of the model was done on a laptop computer running Ubuntu 18.04, powered by an Intel Core Xeon E2176M cadenced at 2.7 GHz. Training time for each epoch was < 1 s, maintaining the performance of the original DD-Net.

6.3.4 *Comparison with simpler models*

To contrast the performance of DeeREKt, two simple classifiers were trained and tested on the same splits. These two classifiers were taken from the scikit-learn Python library (v0.23.1; Pedregosa et al., 2011). The first one was the Gaussian Naive Bayes classifier and the second was the Linear support vector machine classifier.

6.3.5 *Ablation study*

In order to test the influence of the discriminant head on the generalizing abilities of DeeREKt, an ablation study was conducted. The ablated network consisted of the network, without the discriminant head. The training procedure was conducted using the exact same splits than for training DeeREKt.

6.4 RESULTS

6.4.1 *Dataset 1*

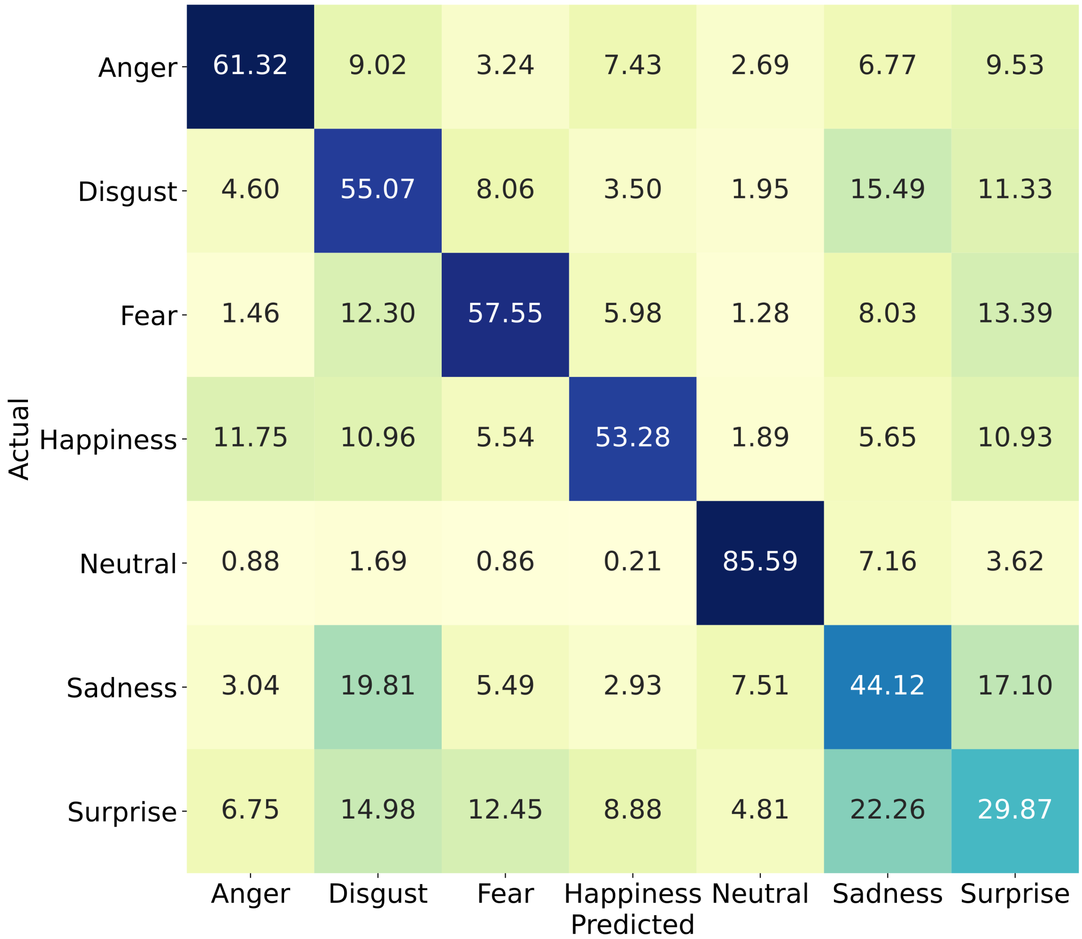
After training, DeeREKt achieved an accuracy score of 54.00% across the seven emotions (see Figure 23 for the confusion matrix). Training time was around 76 ms/step. The highest accuracy was reached in the neutral emotion, with a score of 85.59%. The lowest accuracy was obtained in the surprise emotion, 29.87%. Concerning individual emotions, anger was correctly recognized in 61.32% of the cases while disgust was accurately identified in 55.07% of the cases. In fear and happiness emotions, recognition rates were 57.55% and 53.28%, respectively. Finally, accuracy score for the sadness emotion was 44.12%. See Table 5 for a comparison of the results with other classifiers.

6.4.1.1 *Comparison with simple classifiers*

To compare the performance of DeeREKt, two simple classifiers were trained on the same splits. Across the seven emotions, the Naive Bayes classifier (Figure 24, Panel A) achieved an accuracy score of 19.32%. The highest accuracy was reached in the surprise emotion, with a recognition rate of 68.4%. The lowest accuracy was obtained in the disgust emotion with 0%. Concerning other emotions, anger was correctly classified in 2.8% of the cases while fear was correctly recognized in 40.7% of the

Figure 23

Confusion Matrix for DeeREKt Trained on the 1st Dataset



Note. DeeREKt: Deep Recognition of Emotions from Kinematics. Confusion matrix for DeeREKt when trained on the 1st dataset. Overall, DeeREKt achieved an accuracy of 54.00%.

cases. Regarding the happiness and neutral emotions, recognition rates were 25.0% and 6.3%, respectively. Finally, accuracy score int the sadness emotion was 23.9%.

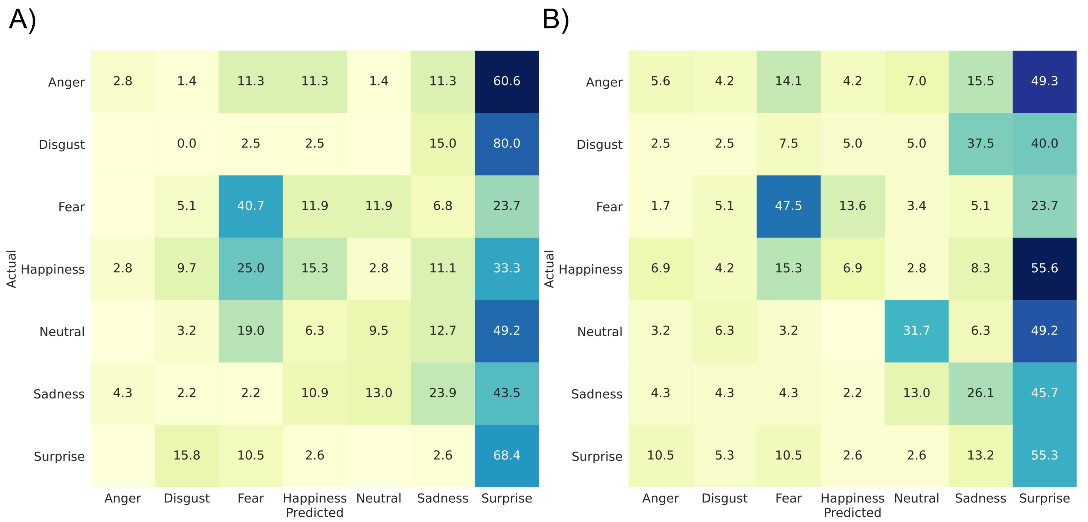
The SVM classifier (Figure 24, Panel B) achieved an accuracy score of 26.71% across the seven emotions. The highest accuracy was reached in the surprise emotion, at 26.1%. The lowest accuracy was obtained in the disgust emotion, at 2.5%. Concerning other emotions, anger was correctly classified in 5.6% of the cases while fear was correctly recognized in 47.5% of the cases. Regarding the happiness and sadness emotions, recognition rates were 15.3% and 26.1%, respectively. Finally, accuracy score in the neutral emotion was 31.7%.

6.4.1.2 *Ablation study*

The same pattern of accuracy can be seen on both the ablated network and DeeREKt (Figure 25). Concerning the performance of the ablated network, it reached an accuracy of 54.51% across all seven emotions. The highest accuracy of the ablated network

Figure 24

Confusion Matrices for Naive Bayes and SVC on the 1^{st} Dataset



Note. Confusion matrices for Naive Bayes classifier (Panel A) and Support Vector Classifier (Panel B).

was reached in the neutral emotion, at 88.45%. The lowest accuracy was obtained in the surprise emotion, at 32.19%. Concerning other emotions, anger was correctly classified in 59.57% of the cases while disgust was correctly recognized in 57.64% of the cases. Regarding the fear and happiness emotions, recognition rates were 57.45% and 52.24%, respectively. Finally, accuracy score in the sadness emotion was 44.82%.

Table 5

Results For All Networks And All Emotions on Dataset 1

Network	Anger	Disgust	Fear	Happiness	Neutral	Sadness	Surprise	All
NB	2.80	0.00	40.70	25.00	6.30	23.9	**68.40**	19.32
SVM	5.60	2.50	47.50	15.30	31.70	26.10	26.10	26.71
Ablation	59.57	**57.64**	57.45	52.24	**88.45**	**44.82**	32.19	**54.51**
DeeREKt	**61.32**	55.07	**57.55**	**53.28**	85.59	44.12	29.87	54.00

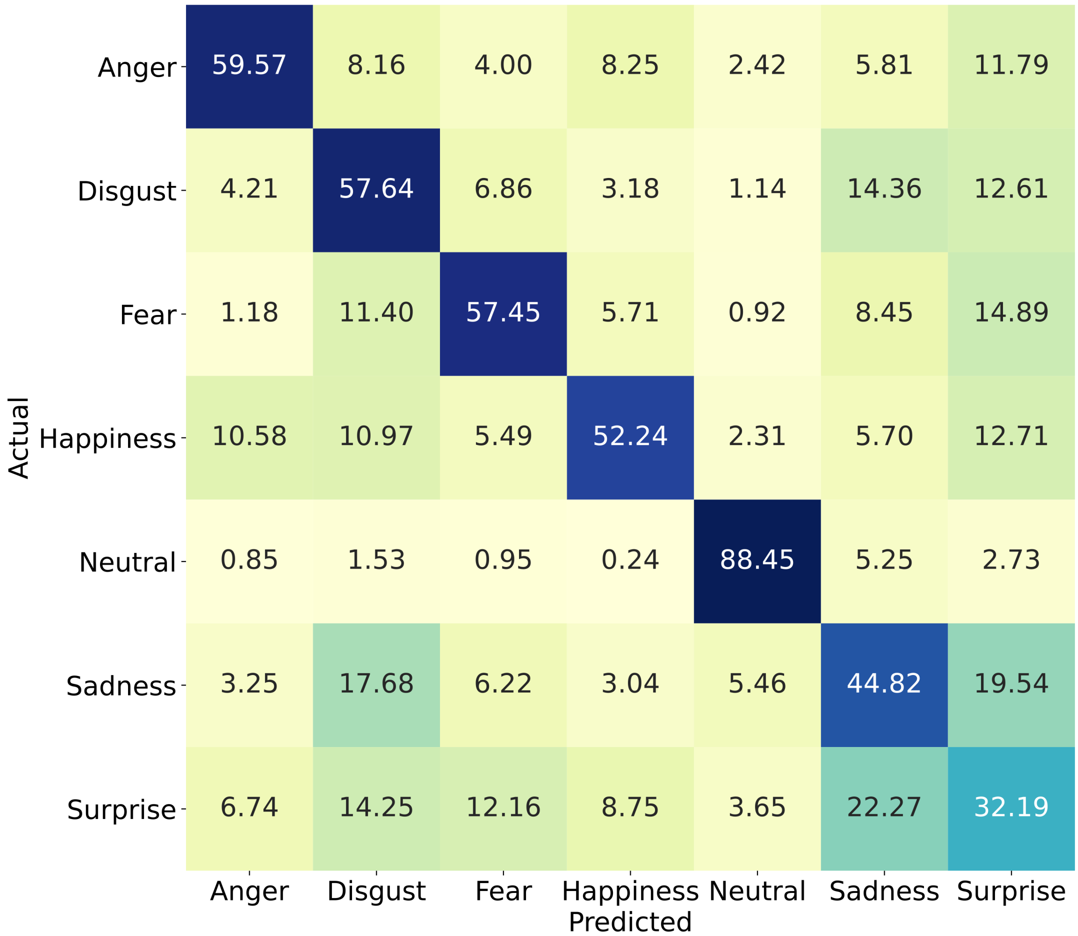
Note. NB: naive-Bayes; SVM: Support Vector Machine. Accuracies are expressed in percentage. Bold numbers represent the maximum accuracy for each column. DeeREKt: Deep Recognition of Emotions from Kinematics

6.4.2 *Dataset 2*

When trained on the 2^{nd} dataset, DeeREKt achieved an accuracy score of 84.80% across the five emotions (see Figure 26 for the confusion matrix). The highest accuracy was reached in the anger emotion, with a score of 100.00%. The lowest accuracy was obtained in the sadness emotion, 75.00%. Concerning other emotions, joy was correctly recognized in 88.89% of the cases while fear was accurately identified in

Figure 25

Confusion Matrix for the Ablated Network on the 1st Dataset



Note. DeeREKt: Deep Recognition of Emotions from Kinematics. The ablated network is DeeREKt without the discriminant head. The training was performed with the exact same splits as for the training of the full network. Overall accuracy was 54.51%.

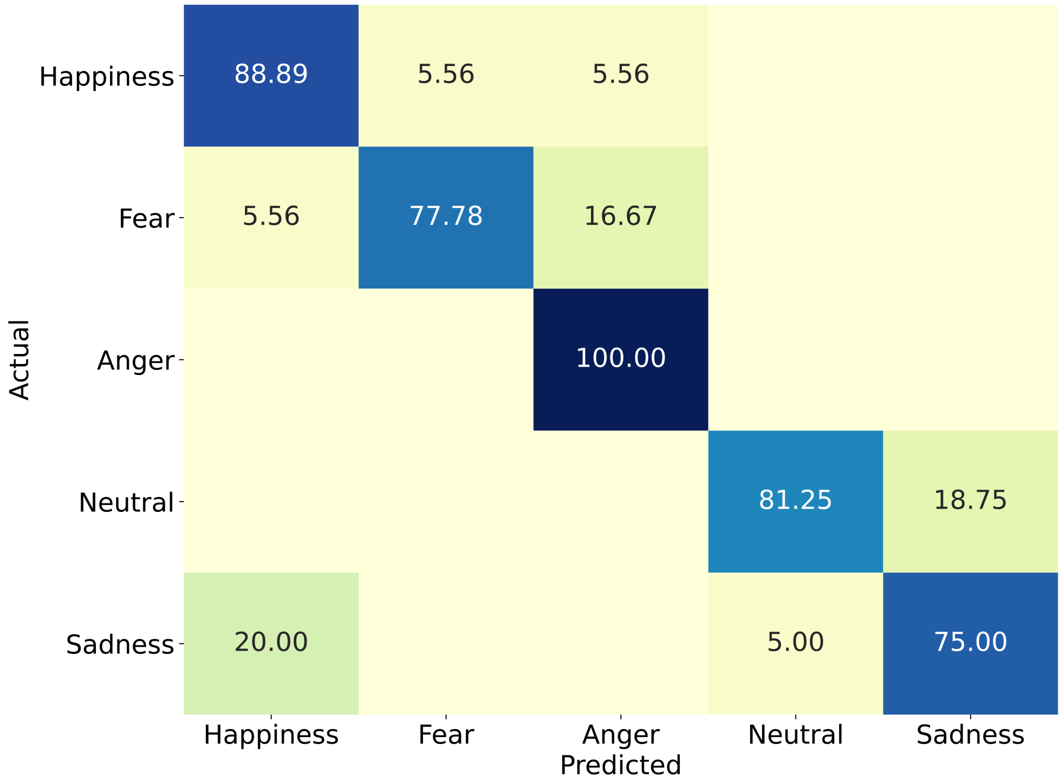
77.78% of the cases. Finally, accuracy score for the neutral emotion was 81.25%. See Table 6 for a comparison of the results with other classifiers.

6.4.2.1 *Comparison with simple classifiers*

To compare the performance of DeeREKt, two simple classifiers were trained on the same splits. Across the five emotions, the naive-Bayes classifier (Figure 27, Panel A) achieved an accuracy score of 27.17%. The highest accuracy was reached in the joy emotion, with a recognition rate of 44.44%. The lowest accuracy was obtained in the sadness emotion, 5.00%. Concerning other emotions, anger was correctly classified in 40.00% of the cases while fear was correctly recognized in 22.22% of the cases. Finally, accuracy score in the neutral emotion was 25.00%.

The SVM classifier (Figure 27, Panel B) achieved an accuracy score of 50.00% across the five emotions. The highest accuracy was reached in the joy emotion, at 66.67%.

Figure 26
Confusion Matrix for DeeREKt on 2^{nd} *Dataset*



Note. DeeREKt: Deep Recognition of Emotions from Kinematics. Overall accuracy was 84.80%.

The lowest accuracy was obtained in the sadness emotion, at 35.00%. Concerning other emotions, anger was correctly classified in 60.00% of the cases while fear was correctly recognized in 38.89% of the cases. Finally, accuracy score in the neutral emotion was 50.00%.

6.4.2.2 *Ablation study*

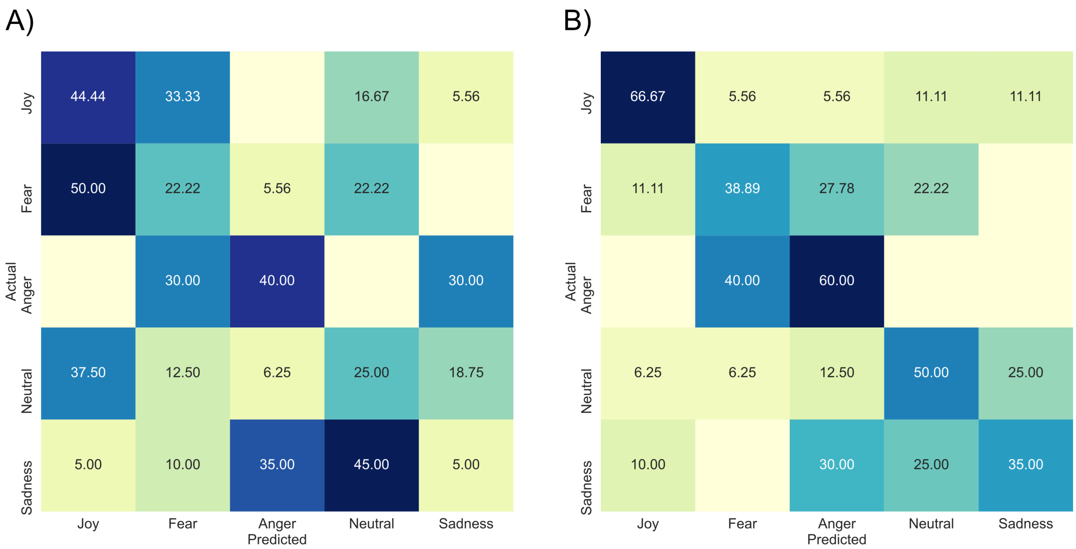
The ablated network achieved an accuracy of 67.39% across the five emotions (see Figure 28). The highest accuracy was reached in the joy emotion, with a score of 88.89%. The lowest accuracy was obtained in the fear emotion with 44.44%. Concerning other emotions, anger was correctly recognized in 65.00% of the cases while neutral was accurately identified in 56.25% of the cases. Finally, accuracy score for the sadness emotion was 80.00%.

6.5 DISCUSSION

The objective of the reported study was to test the accuracy of a lightweight emotional classification algorithm. We combined knowledge from psychology and computer science to achieve the project of using a relatively small dataset for a deep-learning task (22 and 8 human bodies only, for two datasets). DeeREKt achieves better

Figure 27

Confusion Matrices for Naive Bayes and SVC on 2^{nd} *Dataset*



Note. Confusion matrices for naive-Bayes classifier (Panel A) and Support Vector Classifier (Panel B). Both networks were trained on the same splits as Deep Recognition of Emotions from Kinematics, for the 2^{nd} dataset. Overall accuracies were 27.17% and 50.00% for naive-Bayes and SVC, respectively.

Table 6

Results For All Networks And All Emotions on Dataset 2

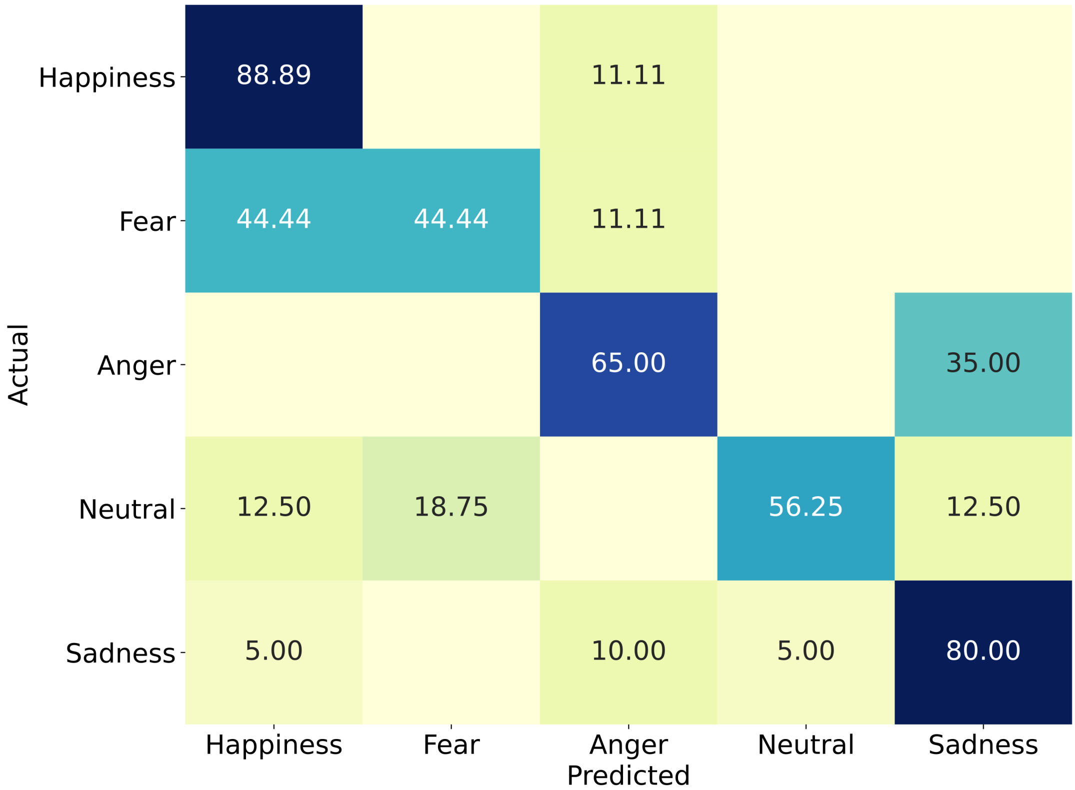
Network	Anger	Fear	Happiness	Neutral	Sadness	All
NB	40.00	22.22	44.44	25.00	35.00	27.17
SVM	60.00	38.89	66.67	50.00	26.10	50.00
Ablation	65.00	44.44	**88.89**	56.25	**80.00**	54.51
DeeREKt	**100**	**77.78**	**88.89**	**81.25**	75.00	**84.80**

Note. NB: naive-Bayes; SVM: Support Vector Machine. Accuracies are expressed in percentage. Bold numbers represented the maximum accuracy for each column.

performance accuracy than naive classifiers and is best when fed with emotional relevant body markers. Our results suggest that DeeREKt can categorize the emotional states of spontaneous human motor behavior at a rate greater than twice chance level. This is similar to that found in human classifiers of facial-expressions and provides first evidence for the power of machine learning in classifying emotional states even in individuals wearing face masks.

The results obtained from the two datasets confirm that the first hypothesis has been corroborated. To have an estimate of the performance of DeeREKt, the proportion of the most represented emotion was used as a baseline. For the first dataset, given that there were 941 examples in the training set and that the most represented emotion had 168 examples, the baseline score was approximately 17.85%. The worst classification score was 29.87% for surprise. When considering the results presented

Figure 28
Confusion Matrices for the Ablated Network on 2$^{\text{nd}}$ *Dataset*



Note. DeeREKt: Deep Recognition of Emotions from Kinematics. The ablated network is DeeREKt without the discriminant head. The training was performed with the exact same splits as for the training of the full network. Overall accuracy was 67.39%.

in Table 5, it is possible to conclude that all emotions were classified at a rate slightly below two times chance level. Concerning the second dataset, there were 110 training examples and the most represented emotion had 25 examples. Hence, the baseline score was 22.73%. The worst classification score was 75.00%, when classifying sadness. Therefore, all emotions were classified at a rate, at least, three times above chance level. These results are similar to that reported in the literature from facial-expressions of emotion. In addition, our results confirm the hypothesis that body kinematics alone are sufficient to train a deep classifier to recognize emotions.

The performance comparison with more naive classifiers points toward the fact that the abilities of DeeREKt are not due to random variations. The accuracy for the naive-Bayes classifier on the surprise emotion was not expected (19.32%). The naive-Bayes classifier predicted surprise only, explaining the poor accuracy across other emotions. These more naive classifiers still seem to be able to recognize some emotions, most notably surprise and neutral. They do not reach very high recognition rate or when they do, it comes at a price of high variability and their accuracies are far below those of DeeREKt. This comes as a confirmation that the recognition of emotions from kinematics is a complex task. To achieve such a task, it is necessary to have a deep understanding of both the psychological factors behind emotional recognition and a deep understanding of neural network to be able to design and use complex networks.

Existing classification algorithm have been used to decode body language. Indeed, in most reported studies, scenarios were used to induce different motor actions depending on the emotional category (e.g., closed fist for anger, arms up for joy). Nevertheless, in everyday situations, one can perceive the affective state of a person simply by observing the way that person is moving (Pollick et al., 2001). Daoudi et al. (2017) first reported the possibility to classify emotional state from actors when performing a simple walking task. However, their algorithm was quite complex and required large computing capacities. Hence, another approach was selected to conduct the present work. In a previous work, we have demonstrated that emotions modulate the spatio-temporal coordination of participants (Brossard et al., 2022). This modulation is hypothesized to emerge from evolution as it may have provided significant advantages for survival (e.g., demonstrate that one is dangerous and should not be trifled with when in anger).

The performance for the anger emotion was expected as anger is an important emotion from an evolutionary standpoint and is often expressed in a distinctive manner. The two top scores were achieved for neutral and anger (85.60% and 61.30%, respectively). Therefore, the second hypothesis was validated. That being said, the performance for the neutral condition was not expected. Nonetheless, it can be accounted for by the fact that the scenarios used by the actors to express the neutral emotion has limited room for variability. One of those scenario for neutral was "imagine that you are taking a key to open a door". Humans tend to express their emotions with a certain degree of variability in their movements but when it comes to opening a door, humans tend to perform the same gestures. Therefore this would help DeeREKt in classifying these trials which were stereotyped. Karg et al. (2010) showed that taking into account the individual characteristics of the participants led to a drastic increase in classifying performances. This issue was addressed in this work by adding the discriminant head and trying to force the network not to rely on these cues. Adding more variability in the training data could also be of a great help to create more ethical and trans-cultural emotional classifiers.

Finally, the last hypothesis is partially corroborated. In the first dataset, the ablated network (i.e., without the discriminant head) outperformed DeeREKt. In the second dataset, however, DeeREKt outperformed the ablated network. These results indicates that the benefit offered by the addition of the discriminant head might be situational. The explanation for this effect might be that, in the first dataset, the emotional information contained in the kinematics is sufficient in itself to achieve the classification task. Indeed, the data was recorded from actors given a complete liberty of movement. Their actions were exaggerated compared to those of the actors of the second dataset. In the second dataset, the actors had to portray the emotions but also to walk back and forth along a ten meter lane. This task imposed a restriction on the movements that actors could perform which in turn imposed a limitation on their emotional display. Consequently, in the first dataset, the emotional information contained within the kinematics was so present that any physical differences between the bodies of the actors would not improve the classification task. The use of the discriminant head may be only relevant if the training data contains task-irrelevant signals. Future studies should be designed to test such a possibility.

The use of the two datasets has demonstrated that DeeREKt can be trained to recognize emotions from different scenarios. However, the two datasets are quite different, both in terms of actions performed and data structure (e.g., 21 vs. 43 markers, different joints available). Future directions should focus on bridging the gap between different datasets and create a deep-learning model that would be transferable to behaviors of diverse nature. Such approach would offer the possibility to of achieving a dataset-agnostic model, for a better understanding of human emotions in laboratory and also in real-world situations.

Part IV

GENERAL DISCUSSION

7 DISCUSSION

This final chapter will shed light on the questions about how and why evolution has provided us with emotions. Then, I will describe a theoretical model that can account for the results available in the scientific literature. Finally, I will close this work by focusing on what data science can bring to a better understanding of the psychology of emotional body experience.

7.1 EMOTIONAL MODULATION OF HUMAN BEHAVIOR

Emotions are powerful modulator of human behavior. In Chapter 4, we saw that cadaverine (a molecule produced by the decomposition of dead tissues) elevates heart rate (HR), provokes strong unpleasant reactions, and makes participants want to move (i.e., go away). On the contrary, I highlighted that menthol reduces the HR elevation, provokes strong pleasant reactions, and makes participants want to stay in the room. Furthermore, the urge to move was triggered by the emotional perception of the participant and not the modulation of physiological parameters. In other words, it is not necessary that an odor elevates HR to trigger the urge to move.

The desire to move is not the only thing modulated by emotions. Indeed, in Chapter 6, we have replicated previous results of the literature and showed that emotions could be recognized and predicted simply from body kinematics. Our results highlighted that not all emotions are recognized with the same accuracy. Anger had the highest accuracy score. So high that the network did not make a single mistake in classifying this emotion. Furthermore, I showed that emotions are recognized and predicted without relying on physical characteristics of the participants. This finding would tend to suggest that humans may have developed a common mechanism to display their emotions to others. But how? Through which features?

In Chapter 5, I reported that emotions modulate the speed of walking, head angle, and motor coordination of participants. Anger increased the walking speed, lowered the angle of the head, and stiffened the body. On the contrary, joy elevated the angle of the head and relaxed the body, while also increasing the walking speed. Sadness was found to reduce walking speed and lower the angle of the head. Fear was found to also reduce walking speed, did not change the angle of the head, and greatly reduced the constraints imposed on the movement. Overall, from these results, we can motivate a distinction between the four dimensions of valence and arousal. Anger, fear, and sadness displayed different patterns of movements while being all negative emotions. However, they differed in terms of arousal. My kinematics data confirmed that anger is a high arousal emotion while fear and sadness are low arousal emotions. Joy displayed different patterns from the negative emotions. Joy is a positive emotions with high arousal. In future studies, it would be interesting to perform the same study with a positive emotion of low arousal to investigate how it would modulate the kinematics.

As showed in the present work and previous scientific literature, emotions are able to modulate all aspects of human behavior. Nevertheless, the question remains of understanding why emotions trigger these modulations. Why do humans seem to react strongly to an unpleasant odor? Is there a reason so important that all humans seem to display emotions through their kinematics following a similar pattern? I will try to offer possible explanations to these questions in the next section.

7.2 EVOLUTIONARY REASONS FOR EMOTIONAL MODULATION OF HUMAN BEHAVIOR

Humans and all living creatures have evolved to be adapted to their environment. This idea, now well recognized and accepted, stems from the seminal work of Charles Darwin, *On the Origin of Species* (Darwin, 1909). This theory of evolution has lead to major advances in the understanding of evolutionary trajectories of all species. It has also lead to major advances in the understanding of how the connections between our neurons developed (Whitacre & Bender, 2010). Most importantly for my PhD work, it has lead to major advances in the understanding of emotions are created (Barrett, 2017). Hence, during my PhD thesis, I thought about how and why evolution has provided us with emotions.

From an evolutionary perspective, the results presented in the previous sections are sensible. A dead and decomposing body on the ground is highly unlikely to be a good thing. It is even more unlikely that it will favor one's own survival. A dead body can be a signal of a killer lurking in the area. It can be a signal of the presence of a deadly airborne pathogen. Or it can mean that another human had a heart attack and died without anyone noticing, suggesting an asocial environment. Of these three cases, only one leads to survival. Hence, some people will walk away from the body and some will try to get close to it, eventually to find an identification and warn the authorities. If the first two scenarios were true, then only the individuals who stayed away survived and got the opportunity to pass their genes onto the next generation. Now, imagine being brought back 13,000 years ago. Agriculture just arrived. It is possible to imagine that a dead body back then was even more dangerous and detrimental for survival than it is now. Therefore, from an evolutionary perspective, it is understandable that only the individuals who managed to survive, passing their genes, education, and way of life to the next generation were the ones who tended to walk away from dead bodies.

Today, science does not know how cadaverine makes some people go away but not other. Maybe the individuals who tended to walk away had specific olfactory receptors to the molecule of cadaverine. Cadaverine is structurally similar to putrescine and probably stimulates one of our trigeminal receptors responsible for a sensation of tingling and burning (Frasnelli & Manescu, 2017; Wisman & Shrira, 2015). Perhaps these receptors were once the key that triggered spontaneous behaviors to walk away from dead bodies to spur survival. In Chapter 4, I showed that menthol triggered the desire to stay. It is probable that this effect is linked to the fact that menthol is fresh and found in food and dishes. Smelling good food is usually a worthy signal of survival. More generally, one can expect that evolutionary relevant negative odors will trigger the urge to move while evolutionary relevant positive odors will trigger the desire to stay.

Dead bodies lying on the ground are not the only danger that humans can face. Sometimes individuals are dangerous to each other. Therefore, knowing how others are feeling is vital to survive. If one sees an angry person walking towards them, one probably needs to avoid that individual. The advantage for the angry individual to display its anger is that it might help them to avoid danger and direct confrontation, for which a win is not certain. Our results showed that anger also seemed to tense the body. This could be seen as a protection of the body to withstand any incoming danger, a sort of evolutionary "brace for impact" maneuver. Indeed, the lowering of the head can protect the throat, one of the most vulnerable part of the body. The increased body tension can prevent a fall and damages to internal organs. Human societies have emerged because humans realized that social contacts are key to survival (Dunbar, 2003). Expressing emotions through micro variants of body kinematics may have emerged as a necessity to survive in dense populated areas.

All humans have evolved to become part of a society because it made survival easier. Emotions could have also helped cement societies. Low-arousal negative emotions (e.g., fear, sadness) might have helped fostering social bonding by making people seek social contacts (Rimé, 2009). Social bonding is a vital aspect of survival and, in that sense, it is possible that negative emotions with low arousal have helped humans develop specific neurobiological circuits to facilitate such bonding (Carter & Keverne, 2002). The social advantage provided by positive emotions (regardless of arousal) might be seen as straightforward. I do believe that joy, for example, facilitates social bonding. However, I also believe that joy can provide many more benefits. As showed in Chapter 5, joy had the tendency to increase the walking speed, bring the head up, and release motor coordination. This pattern of emotional display could have fostered social bonding by optimizing eye contact probability. It could have also facilitated mate selection. Bringing the head up may make individuals appear taller and the increased walking speed may make them appear more vigorous. Furthermore, it has been shown that height is a defining factor when searching for a suitable mate (Brewer & Riley, 2009; Courtiol et al., 2010), which further support this hypothesis.

My studies were conducted on French participants, mostly well-educated. It would be of great interest to perform similar studies with participants from different cultures and backgrounds to understand the differences that may exist. Not all cultures have evolved the same way, simply because the adaptation required to survive in Australia 8,000 years ago was not the same than that in France (e.g., due to weather or local fauna). Therefore, differences are expected to be present if the same experiments are conducted within different cultures. Theses differences could be found in how individuals express their emotions. Nevertheless, social sharing of emotions would be universal across gender and culture, and I believe that the evolutionary advantages provided by emotions would also be universal (see Barrett, 2013; Rimé, 2009). Furthermore, it is not the emotions that are universals but rather the core mechanisms of emotional expression (Gendron et al., 2015, 2014). Studying and understanding this core mechanism requires a theoretical model, which will be described in the next section.

7.3 A THEORETICAL MODEL OF THE CORE MECHANISMS OF EMOTION

Emotion research, as psychology in general, has undergone many developments. Fifty years ago, Ekman and Friesen (1971) published their seminal article that lead many to believe that there were basic emotions universal across cultures. The scientific community now has enough evidence pointing to the fact that these results do not show that emotions are universal, but rather that humans construct their emotions (Gendron et al., 2015, 2014). As I have mentioned in the previous section, this explanation seems plausible from an evolutionary perspective. Why would Japanese individuals express their emotions the same way than Americans do, when their cultures, societies, and countries are so diametrically contrasted? The study of emotions is now transitioning from psychological science to societal questions. Such issues are constraining affective science to embrace new paradigms and innovating theoretical frameworks. The XXIst century is the century of affectivism. Many fields of research are trying to investigate how emotions impact their own fields (e.g., language, philosophy; Goldie, 2010; Pritzker et al., 2019). Major emotional theorists have even reflected on a possible transition for psychology from cognitivism to affectivism (Dukes et al., 2021). This is a golden opportunity for emotion researchers to study emotions with a societal context.

Combining knowledge from other domains of research with emotions will provide answers for many open questions (Barrett et al., 2007; Lindquist, 2021). For example, how do humans create emotional language? Does the fact of learning emotional words increase the emotional abilities of children? Only a solid theoretical framework will allow to foster answers to such questions. In Chapter 2, I described the major theoretical models of emotion. No theoretical model is perfect but the one I find most appealing is the Theory of Constructed Emotions (TCE) from Barrett (2017).

The TCE is based on the core idea that the only goal of the brain is making certain that the body functions correctly. A faster walk will require that more oxygen, blood, and nutrients are sent to the muscles. The brain will regulate this situation by drawing from its reserves to assert that the body will function correctly. This regulation mechanism is called *allostasis* (Sterling, 2012). However, the brain will try not to *react* to the demand. It will try to *predict* all changes that are going to happen and meet the needs before they arise (Barrett, 2017).

To predict, the brain needs the sensory inputs from the body and memory of all past experiences. Every time the brain makes a prediction (i.e., all the time), it compares its sensory inputs to past knowledge and computes a prediction error. By minimizing this error, the brain is able to effectively regulate body functioning. These sensory inputs are called *affect* (Barrett, 2017; Russell, 1980). Affective states are an evolutionary advantage designed to orient the organism towards positive outcomes (Batson et al., 1992). Emotions are born from a cognitive appraisal applied to affect (Ekkekakis, 2013). The TCE is able to account for most of the results available in the literature, including the ones defended in my PhD work.

Since all healthy humans have similar brains, all humans are able to express, perceive, and predict emotions. The cultural differences of emotions could then stem from different past experiences that construct different brain predictions. However, the TCE is not perfect. This theory is based on predictive coding (Friston, 2005). To make its predictions, the brain is hypothesized to use some kind of Bayesian inference. Nonetheless, it has been issued that the computational demands of a predictive brain would be too high for the capacities of the human brain (Kwisthout & van Rooij, 2020). Another limitation of the TCE and predictive coding principle is the difficulty to test it experimentally (Kogo & Trengove, 2015).

7.4 USING DATA SCIENCE TO UNRAVEL THE EMOTIONAL BODY EXPERIENCE

Experimentally testing predictive coding is difficult when applying classic psychological paradigms. Measuring a couple of responses (e.g., reaction times, eye movements) is not sufficient to model the affective experience of a person. Questionnaires alone can not objectify an emotional experience. Innovation is required. A paradigm shift that I propose is one offered by computer and cognitive sciences with clustering tools. For example, deep-learning models might provide one possible way to test predictive coding and the TCE. Deep-learning could afford the possibility to create lighter versions of a human brain to test some of its core functionalities. The Human Brain Project, for example, aims at recreating a network similar to the human brain. Initiatives such as the Human Brain Project are highly demanding and challenging but they might yield some long-awaited answers into the functioning of the human brain.

Future research to test the TCE could also draw from recent advances made in diffusion models, with networks such as DALL-e (Ramesh et al., 2022). DALL-e 2 is a deep-learning model that is able to generate realistic images, simply from a textual description of the image to generate. Perhaps such models could be developed to generate emotional body postures based on a given set of sensorial inputs (e.g., by providing values of blood pressure, BPM, glucose). Then it would be possible to test some of the TCE hypotheses. For example, based on a fixed set of sensory inputs, the TCE predicts that many different body postures could be generated. Indeed, there is no one-to-one relationship between sensory inputs and emotional body posture. Furthermore, it has been shown that emotions are able to create a motor signature in human movements (Lozano-Goupil et al., 2021). This emotional motor signature is not the same for everyone but the fear signature is always different from the joy signature. Therefore, it might be possible to extract these statistical regularities to create a prototypical emotional behavior (that would never exist in the real world) and understand its consequences.

Science is fundamentally transdisciplinary. Science is not conducted by lone, secluded scientists. Science is conducted by teams of researchers working together to unravel the mysteries of our world. Over the course of my PhD work, I worked in a multi-disciplinary team where each of us had our own area of expertise with some overlapping skills and a common theoretical framework. I also searched for collaborators outside the research team of my supervisor, to help find answers to our theoretical questions. This is why I worked with Doctor Thomas Peel (GSK, Belgium) in Chapter 6, in order to use new advances in computer science to answer psychological questions. This is also why my supervisors developed an I-Site project with the team of Professor Véronique Nardello-Rataj (UCCS, CNRS UMR 8181), in order to manipulate odor molecules, understand how an odor can modulate the emotional body experience, and ultimately trigger the urge to move (Chapter 4). This transdisciplinary approach stems from my data science background, where we search for experts in each domain to channel the knowledge into solving one problem. During my PhD work, I tried to apply this data science perspective to emotion research in order to study emotional processes in their context, not in isolated paradigms.

The fundamentally transdisciplinary aspect of data science is particularly relevant today, where the core of experimental psychology is in fact the data we gather. Managing digital environments is challenging. It is of vital importance to protect your data against loss, theft, or corruption. Then researchers need to analyze the data to be able to draw conclusions. The skills necessary to perform these steps are not taught during a classical psychology curriculum. Which is why researchers in psychology either need to enlist the help of data specialists or learn how to perform these steps. During my PhD, I implemented thorough procedures to safeguard against any kind of data loss, theft, or corruption. I set-up my computer so that every end of week, it would backup the content of my hard drive and take a snapshot of the current state of my operating system. At one time over those three years of PhD, I tried to reboot my computer but it refused to restart. I still do not know the reason behind that. Fortunately, it was a Monday morning and my backups are made on Fridays. It took me less than 10 minutes to revert to the previous state of the machine and everything went back to normal. Thus, one important aspect of my PhD work was to help the team of my supervisor to develop good practices in terms of data health and security.

This aspect of data health and security is even more relevant when the size of the gathered data increases or when data is collected remotely. Over the course of my PhD, I collected over 10 Tb of data. These 10 Tb can not fit in the storage of my computer and are split across three external hard drives. Fortunately, the procedures we had developed to store lightweight data sets were scalable. Therefore, the only thing we needed was bigger hard drives, which we bought. We are now in the process of rendering these large data sets available for other researchers, to foster open-science practices, and replicability. Furthermore, the methodology we developed, described in Chapter 3, section 3.4, and Appendix A allows to carry on with traditional experimental psychology outside the lab and with multiple participants at once.

How can you assert that the data are properly anonymized, protected while remaining accessible for analyses? All the computers were encrypted and the data were sent to a secured cloud storage, owned by the University and whose servers are located in France. Only the experimenters and the principal investigator had access to the data. Automated analyses scripts were triggered either automatically or by myself to process the data when we reached our desired number of participants. All the code produced to that end was saved to a Gitlab instance, also owned and managed by the University. I developed automated pipelines to assert that each modification in the code was not breaking everything or that the code was properly written and understandable by other humans. Finally, we are now entering discussions with relevant organs of the University to assess the patentability of our work, so that other researchers or companies may benefit from it.

Working with specialists from different fields of research allowed me to help change the perception that I had and that some have of psychology. For some researchers or students, psychology is seen as an old and very conservative field of research. This could not be farther away from reality. Psychology as a discipline has drawn from biology, neuroscience, computer science, and mathematics to be where it is now. Psychology is constantly evolving. However, this is not always reflected in the education provided to students. During my PhD, I had the opportunity to teach for around 64 h, to cognitive science and psychology students (undergraduate and masters). I mostly taught courses about data analysis, managing big data sets, and data science in general. I tried to change the perception of psychology to include the need of transdisciplinary work and management of digital environment. I made this effort because I strongly believe that education is the key to help psychology continue its evolution towards affectivism.

7.5 Conclusion

The growing interest in emotions is visible within society. Every startup and personal coach are now aiming at selling emotional training, development, and books to help their clients "harness the power of their emotions". An internet query on "harness the power of you emotions" yielded nearly 4,000,000 results in only 0.61 s. Of all these results, surely there are some good resources backed-up by the latest findings in emotion research. However, the positive outcome that I am seeing is that people are getting interested in emotions and they want to know more about and understand their own emotions. This is an golden opportunity for emotion researchers to share their knowledge and disseminate what science currently knows about emotions. Lisa Feldman Barrett is trying to change how we all understand emotions. She has published books for researchers, the general population, and presented her findings during TED talks (Barrett, 2018a; Barrett, 2018b). Changing the mind of the general population and researchers takes time. We are only at the first quarter of the XXIst century. Who knows what the future holds for emotion. I look forward to seeing the next theoretical advances and I hope to see the day where science will have found the answers to how, why, and what are human emotions.

Part V

APPENDIX

A APPENDIX

This article has been submitted for publication to *IEEE Transactions on Affective Computing*.

A.1 INTRODUCTION

The cardiac activity is one of the most vital organism in the human living being. Therefore, understanding its functioning and being able to measure its activity is crucial. However, the mechanism by which the heart sends blood throughout the organism is complex and adapts as a function of the ongoing behavior. Hence, a good methodology is key to modeling the human physiological system especially in remote psychological testing.

The heart generates an electrical signal, which has been described since the early 1900's (Bowen, 1904). Multiple methods have been developed to measure such activity, in particular for medical reasons (Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996). However, academic work has also developed the need to measure physiological responses during experimental manipulations. More specifically, HR and HRV are used to demonstrate the influence of external stimulations on the brain and body. Human studies in cognitive neurosciences have reported possible functional associations between emotion and HR (Appelhans & Luecken, 2006). In pathological cases, depression, anxiety, and stress impact more specifically the adaptive properties of HR and perturb the patterns of HRV. In the fields of human psychology, studies have reported how both HR and HRV are sensitive to sensorial modalities such as odors (Alaoui-Ismaili et al., 1997; He et al., 2014), music (Karageorghis et al., 2006), and touch (Manzotti et al., 2020). Finally, in the new tech age, HR is being used to verify the quality of a signal. This is the case of studies using functional near-infrared spectroscopy to measure changes in cerebral hemodynamics during physical activity (Guérin et al., 2021b). But the question remains how to select the best method for a given use of HR and HRV, as physiological indicators of adaptive human behavior.

The present contribution aims to offer a step-by-step guidance to collect good physiological measures in active individuals using a remote setting. It is aimed at engineers and researchers who are in need to optimize the selection, analysis, and interpretation of physiological heart measurements in adult individuals who are engaged in a behavioral short-lasting task (a few minutes) without the presence of the data analyst. A point-to-point guide is presented with available Python code to perform the data processing for optimal computation of HR and HRV.

A.1.1 *Heart functions in context*

The cardiovascular system is responsible for transporting nutrients and removing gaseous waste from the body. This system is comprised of the heart and the circulatory system. Hence, HR and HRV are the physiological indicators that can be used to describe how the cardiovascular system is regulated over time. HR, usually measured as the number of heart beats per minute (BPM), reflects how the heart is responding to the current demand in blood and oxygen of the body. When exercising, for example, the muscles are in need of more energy and oxygen to accommodate the demand. Therefore, the heart beats faster to increase the amount of oxygen sent via the blood vessels to the muscles. This would be visible as an increase in the number of BPM within a couple of seconds after the occurrence of an event. HRV is more subtle as it reflects the changes in the interval of time between successive heartbeats (Shaffer & Ginsberg, 2017). HRV is influenced by many core mechanisms of the human function (e.g., respiratory system, circadian rhythms) and most notably by the ANS. Broadly speaking, HRV is a measure of how good the heart is at adapting its functioning to match bodily requirements.

It might seem like a daunting task to find its way through the vast amount of existing literature on HR and HRV (a PubMed query on "heart rate OR heart rate variability" returns over 380,000 articles). Adding the wealth of technologies available to measure cardiac activity, the task is even harder. Every smartwatch now has a way of recording either HR, HRV, or both, giving the impression that their measurements are straight forward, and that their physiological correlates are easy to understand. Designing a correct experiment is essential in order to record, compute, and interpret valid complex physiological data. First, one needs to define the conditions in which HR and HRV will be recorded especially in remote testing protocols (will the participants be performing a seated reaction-time task or will they be walking around a city?). Then, one needs to select the appropriate measurement to answer the research question. If the question concerns the level of arousal or physical effort, HR may be sufficient; if it is a question of regulation abilities (which is often the case), then HRV will be needed. Knowing the experimental settings and which measurements will be used will, in turn, guide the selection of the recording device and the length of trials needed to perform the computations. Only then will one be able to actually record, pre-process, and analyze the data to obtain usable information.

This report aims to provide the necessary methodological tools to start choosing a measurement, recording, pre-processing, and computing HR and HRV across different use cases.

A.1.2 *Selecting an indicator of physiological regulation*

HRV notably reflects the amount of regulation exerted by the ANS. Many different types of approaches have been reported in the literature in studies aiming to measure HRV (for a review, see Shaffer & Ginsberg, 2017). The approaches can be divided in two categories: frequency- and time-domain measurements.

In the frequency-domain, the measurements are divided into four frequency bands, each reflecting a particular physiological response These frequency bands have been defined by an international task force working on HRV (Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996). The high-frequency band (0.15-0.4 Hz) reflects the influence of the respiratory system on HRV. The low-frequency band (0.04-0.15 Hz) reflects the influence of the brain on HRV, via the vagus nerve and baroreceptors. The very-low-frequency band (0.033-0.04 Hz) reflects the intrinsic activity of the heart. Finally, the ultra-low-frequency band (< 0.033 Hz) reflects the influence of longer physiological regulation mechanisms, such as body temperature and circadian rhythms (Shaffer et al., 2014). These measurements must be computed on long cardiac recordings, that is, at least three minutes to extract high and low frequencies, and 24 h to obtain ultra-low-frequencies.

Time-domain measurements reflect the variance in the amount of time between successive heartbeats. These measurements are easier to compute than frequency-domain measurements as they can be calculated on shorter trials. However, they do not provide a complete description of the underlying physiological mechanisms. Time-domain measurements include, but are not limited to, the SDSD and RMSSD. The RMSSD is one of the most reported metric in scientific literature and is used to estimate the vagally mediated changes reflected in HRV (Shaffer & Ginsberg, 2017). In the following case studies, we were limited to trials of maximum 4-min length, in individuals that were not immobilized (possible occurrence of motion artifacts). Hence, we focused on the development of a rigorous method to pre-process the data collected remotely before computing the RMSSD metric that are expressed in milliseconds. Our approach can be applied to recordings ranging from 30-60 s (referred to as ultra-short recordings; Munoz et al., 2015) to five minutes.

A.1.3 *Selecting a recording device*

When selecting a recording device, it is of critical importance to verify the sampling frequency of the device. The sampling frequency is the number of recordings per seconds that a device can make. The higher the frequency, the more precise the analysis can be. The Nyquist–Shannon theorem states that the sampling frequency must be at least two times superior to the frequency of what is measured. A healthy human has a HR between 42 and 210 BPM (0.7–3.5 Hz; Opthof, 2000). Thus, to record accurately the HR of a healthy human, it is necessary to have a sampling frequency of at least 7 Hz. But to measure time differences in heartbeats of the order of 10 ms (100 Hz), one must use a sampling frequency of at least 200 Hz. This is why prior studies on HRV have shown that the minimum sampling frequency of an HRV recording device should be > 200 Hz especially if coupled with sub-efficient pre-processing. Nevertheless, in recent times, it has been shown that this limit can be tuned down to below 100 Hz if a strong pre-processing approach is adopted to offer the means to mathematically enhance the R-peak detection prior to HRV computation (Laborde et al., 2017).

A wide range of sensors are available to record cardiac activity. The most used and most reliable of all is the ECG. With a high sampling frequency of typically 1000 Hz, the ECG is the optimal indicator from which to extract both time- and frequency-domain measurements of HRV. The ECG measures the electrical activity of the heart via electrodes positioned on the skin. It is a non-invasive method to record cardiac activity but requires the electrodes to be positioned correctly and connected to an ECG machine. Therefore, this measure is mainly used in hospitals for clinical reading, and in laboratories collecting physiological data during seated activities. Interpretation of ECG can be done by trained investigators only. The gold standard in ECG research is the Biopac wireless system (Biopac Systems, Inc., Goleta, CA, USA).

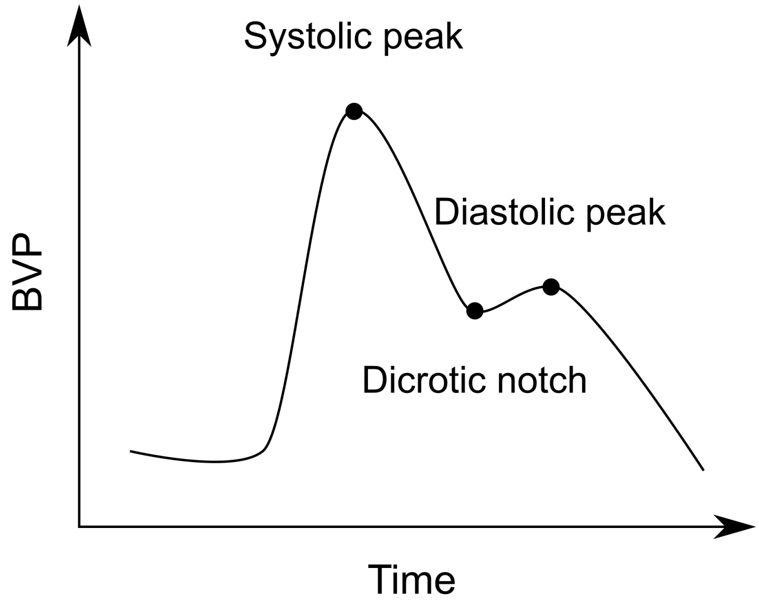
PPG sensors have been developed to measure cardiac activity quickly, easily and in virtually any setting. PPG sensors work on the principle of reflective pulse oxymetry (Sinex, 1999). These sensors have a built-in light emitter and receiver. The emitter sends light through the skin and the receiver measures the amount of light returned. The basic principle is that oxygenated blood absorbs more light than non-oxygenated blood. Therefore, when a heartbeat sends oxygenated blood through the body, the PPG sensor measures a change in the light absorbed and detects the presence of a heartbeat. PPG sensors are now widely used in medical and in laboratory settings, as well as in commercial applications (most smartwatch now include some form of a PPG sensor). However, the difficulty is to chose a sensor that is accurate, reliable, and resistant to environmental artifacts. The data presented in this report have been collected using the available PPG sensor included in the Empatica E4 wristband.

The Empatica E4 wristband (Empatica S.r.l, Milano, Italy) is a medical device that can record PPG data, electrodermal activity, and skin temperature. The E4 is a lightweight wristband that can record data for up to 32 h and can be used in buildings but also outside, which affords more ecological opportunities. Its PPG sensor records data at a sampling frequency of 64 Hz using two light sources, green and red, and one light receiver. The green light is used to detect the heartbeats, while the red light is used to measure the amount of light present. This reference amount of light provides the mean to remove motion artifacts. The E4 has a low sampling frequency compared to the Biopac for example. Therefore, it is important to acknowledge this and apply an efficient pre-processing step to remove small motion artifacts, noise, and enhance the validity of the cardiac peak signals before computing HRV.

A.1.4 *Data pre-processing*

All signals contain noise, which can take on many forms and can originate from many sources. Movement can provoke displacements of the wristband; the skin tissues might move slightly and induce noise as motion artifacts in the measurement. PPG sensors are highly sensitive to motion-induced noise. Separating the signal from the noise is the goal of the data pre-processing step. The theoretical and ideal waveform of the blood volume pulse (BVP) signal consists of three parts: a systolic peak, sometimes followed by a dicrotic notch, and finally the diastolic peak (see Figure 29). This waveform is the signal one should seek in a BVP recording. Note that only small motion artifacts are easily removable. In case of a large motion artifacts, the best method is to remove the concerned part of the signal from further analyses (Laborde et al., 2018).

Figure 29
Schematic of the Waveform of the BVP Signal



Note. Characteristics of the waveform are highlighted with black dots (systolic peak, dicrotic notch, and diastolic peak).

A.2 VISUAL INSPECTION

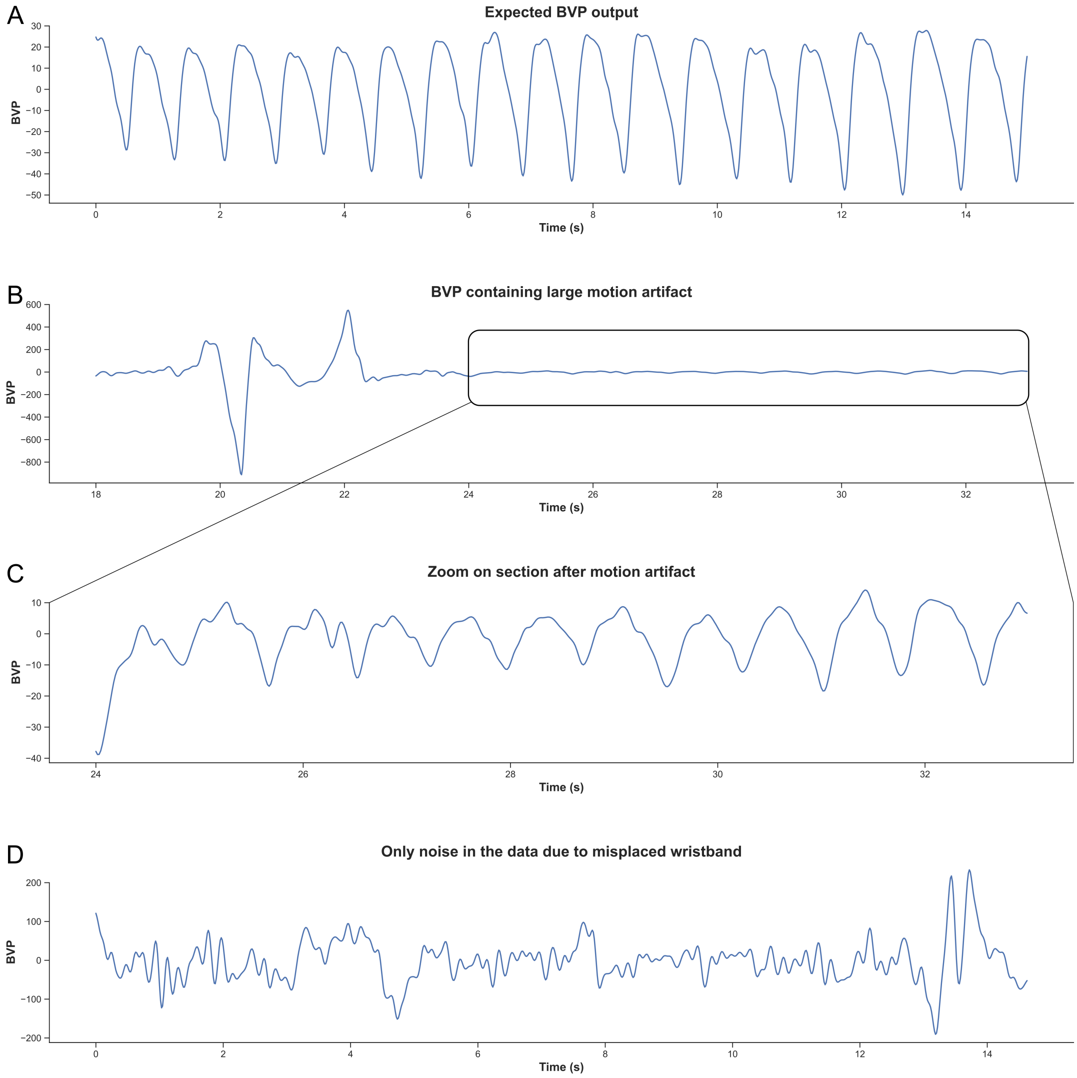
Before attempting to compute either HR or HRV, it is necessary to inspect the raw signal and identify which parts are noise and which parts are meaningful data. Figure 30, Panel A shows an expected blood volume pulse (BVP) signal recorded from a BVP wristband. In this example, the presence of noise is very limited and the systolic peak can be clearly identified. Figure 30, Panel B shows a BVP signal with a large and long motion artifact that would be difficult to remove. Hence, this section of the trial would probably need to be removed from further analysis.

A.2.1 *Filtering*

A filter is only a tool that must be guided by reason. First, one should keep in mind what is considered noise and what is considered data. Several methods exist but one possible approach is to define a range of acceptable BPM (e.g., 42–210) and consider that everything outside this range is noise. This method can be considered valid, as the normal range of BPM found in humans is between 42 and 210 BPM (Opthof, 2000). Then, one can convert these values to Hz (0.7–3.5) and design a bandpass filter that will remove values outside this range only. The range of BPM can be narrowed, depending on the task performed by the participants. For an endurance runner, studies have found that HR can rise up to 184 BPM while during walking HR only rises up to around 159 BPM (Karvonen & Vuorimaa, 1988). For a seated participant, as is the case for many psycho-physiological experiments, one could consider a range of 54–150 BPM. Indeed, for a healthy adult at rest, having a heart rate below 54 BPM or

Figure 30

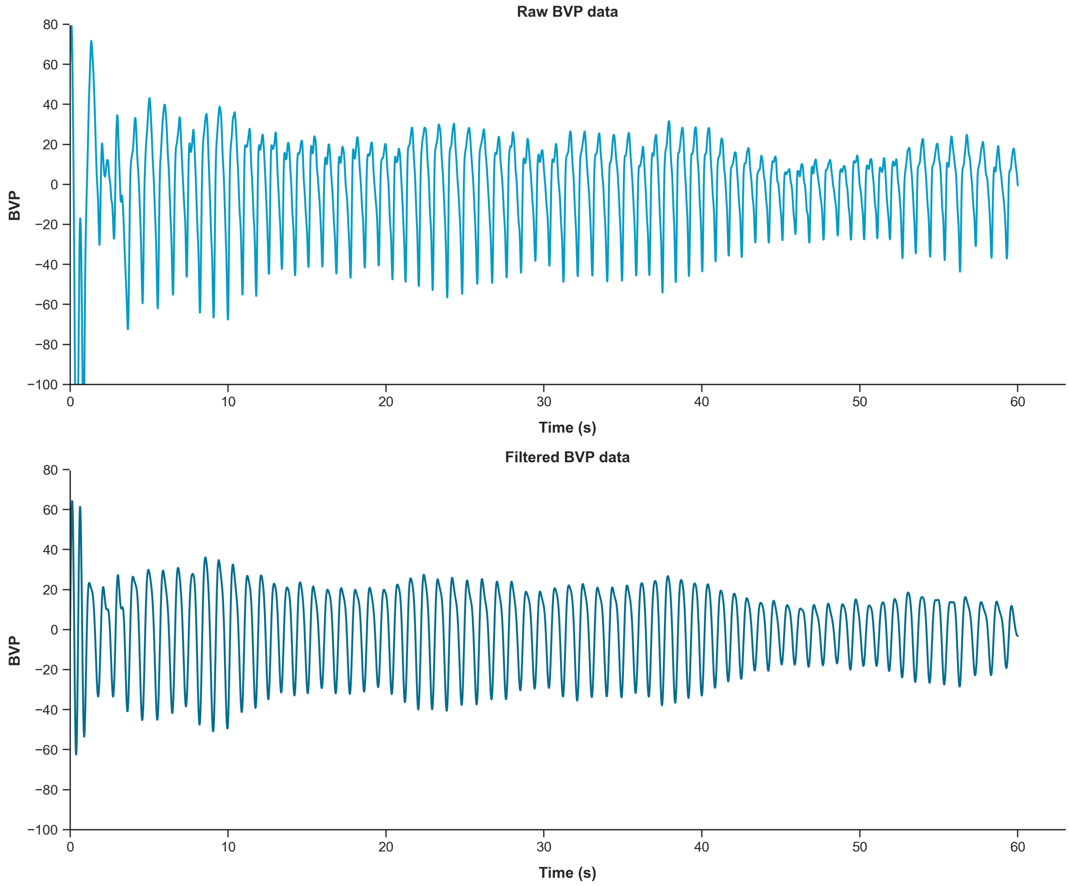
Example of Different Artifacts in a BVP Signal



Note. Examples of different raw signals. Panel A shows the expected BVP output when the wristband is correctly positioned and without motion artifact. Panel B shows a BVP signal with a big and long motion artifact (~3 s). Panel C shows a zoom on the BVP section of Panel B, without the motion artifact. Panel D shows a BVP signal that contains only noise, usually happening when the wristband is loosely positioned on the wrist of the participant.

above 150 BPM is unusual (Bernstein, 2011; Levine, 1997). An example of such filtering can be found in Figure 31. However, using this type of filters can result in small disturbances in the signal, which could potentially influence the computation of the measures. Therefore, a filter is to be used only when the signal is very noisy.

Figure 31
Example of a Raw and Filtered BVP Signal



Note. The filter used here is a 3rd order Butterworth bandpass filter, with cut-off frequencies set between [0.9, 2.5] Hz (54–150 BPM). The participant was presented with a pleasant odor while being seated. BVP: blood volume pulse.

A.3 DATA PROCESSING

After selecting an HRV measurement and cleaning the signal, it is now time to compute both HR and HRV. Many scientific analysis toolboxes have been developed to compute time-domain measures of HRV, mostly relying on MATLAB, R, or Python. This guide will only focus on one of them, HeartPy, an open-source Python toolbox developed to be a noise-resistant algorithm that handles PPG data well (van Gent et al., 2019, p. 1). The computation of the RMSSD (and generally of all time-domain measurements of HRV) relies on the accurate calculation of the time interval between two heartbeats. Missing or time-tampered beats can lead to dramatic increases in the computed values. Therefore, it is vital to perform a correct detection of cardiac beats to confirm the validity of the BVP signal.

A.3.1 *Peak detection*

The goal of the peak detection process in HeartPy is to detect the systolic peak in the BVP waveform (see Figure 29). HeartPy detects cardiac peaks in the signal in a three step process. First of all, a moving average is computed with a window of 0.75 s. Then, the regions of interest are highlighted where (a) the amplitude of the signal is higher than the moving average and (b) between two points of intersection. Finally, the peaks are selected at the maximum value within the region of interest (van Gent et al., 2019). The moving average can be scaled to refine the peak detection, and in such case, the best scaling factor is determined by minimizing the SDSD and computing a likely BPM value. For example, if the SDSD is minimal but the BPM is 210, then the peaks would not be correctly identified.

After these processing steps, the R–R intervals between time series of peaks are computed. However, not all detected peaks represent cardiac pulses accurately. Therefore, it is necessary to run an outlier rejection pass to refine the peak selection and to be able to compute a valid RMSSD value. HeartPy implements a technique called quotient filtering (Piskorski & Guzik, 2005). The idea behind this filter is that if a RR–interval is too short (e.g., < 300 ms) or too long (e.g., > 2,000 ms) then it might be an artifact or an incorrectly identified peak. These thresholds can be adapted; 300 and 2,000 ms are values based well above physiological time between heart beats observed in healthy individuals (de la Cruz Torres et al., 2008; Piskorski & Guzik, 2005). A visualization of the result of such peak detection algorithm, and selection procedure is presented in Figure 32.

A.3.2 *Computing HR and HRV*

Once the peaks are correctly labeled, the RR–intervals can be recomputed. These intervals are the basis of the computation of HR and of all time-domain measurements of HRV.

The BPM are calculated as:

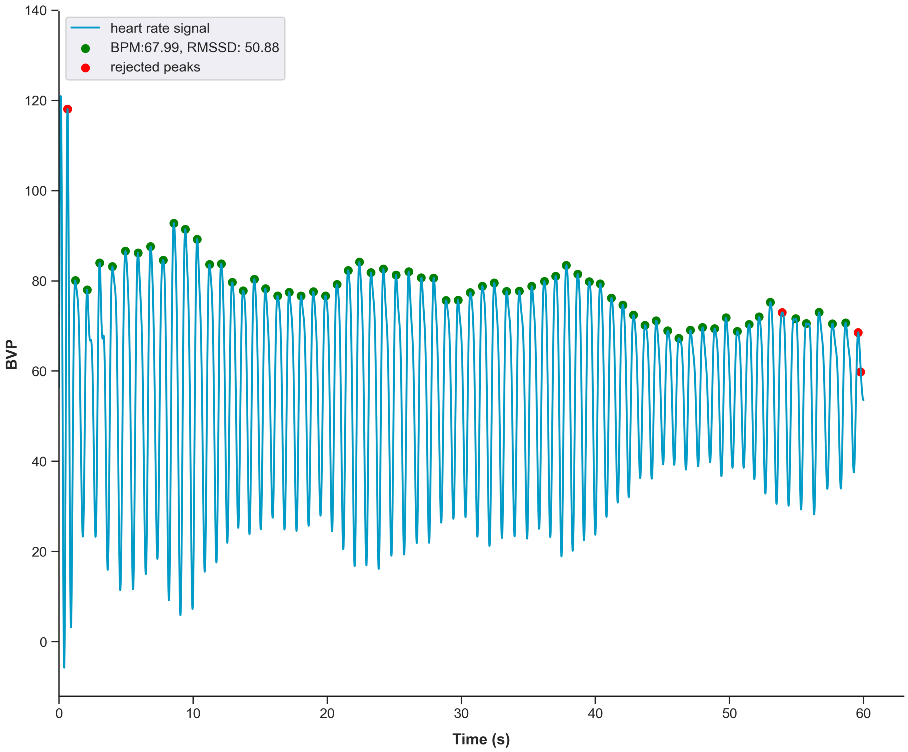
$$BPM = \frac{60000}{\frac{1}{n}\sum_{i=1}^{n} RR_i} \tag{8}$$

The RMSSD is calculated as follows:

$$RMSSD = \sqrt{\frac{1}{N-1}(\sum_{i=1}^{N-1}(RR)_{i+1} - (RR)_i)^2)} \tag{9}$$

In the following section, we report a case study for which our method was used to collect data remotely. Individuals were invited to wear the Empatica E4 wristband and were instructed to smell a series of odors. In addition to their subjective self-rating responses, physiological reactions to the odorant stimuli were recorded, uploaded through a secured cloud storage before the automatic computing of HR and HRV was completed.

Figure 32
Example of Peak Detection and Fitting



Note. Data used come from the same seated trial as Figure 31. Green dots represent peaks classified as correct while red dots represent incorrect peaks. During this 60 s trial, the HR and RMSSD of the participant were 67.99 BPM and 50.88 ms, respectively.

A.4 CASE STUDY: EVALUATING THE IMPACT OF ODORS ON PHYSIOLOGICAL RESPONSES

The COVID-19 pandemic caught everyone by surprise. From one day to the next, the world stopped. The collection of experimental data was halted and when the world activities started up again, restrictions were maintained for individual protection. For some fields of researcher, safety measures were only a minor setback. For those working in human sciences, data collection became difficult. To be able to conduct our ongoing work on olfaction, we developed an experimental protocol to benchmark odors that required no human–human contact. The odor vials were placed on a rack in a disinfected and ventilated room. Each participant entered the room and followed the on-screen and audio instructions.

A.4.1 *Innovative methodology*

The setup was made of a recording computer, a wristband to measure cardiac activity (i.e., Empatica E4), a chin rest, and closed vials containing the odor molecules. Participants were instructed to place the wristband on the non-dominant hand to reduce motion artifacts. A short video illustrated the steps to follow. All instructions were audio recorded with a male neutral voice tone at a moderate slow speed of speech (120 words per minute).

The wristband was connected to the computer and the instructions were programmed via PyschoPy (Peirce et al., 2019). All instruments were synchronized using the software LSL, that acts as a lightweight interface between the computer that sends the instructions and triggers the stimuli onsets, and that receives the inputs from the participant (questionnaire responses, signals from wireless equipment). When an event is sent to LSL (e.g., stimulus on-set, cardiac input), a timestamp is associated to the event based on the computer clock. When the experiment is completed, LSL saves the data to a single file that contains data points from all recording devices on a unified time series.

At the beginning of each trial, participants were asked to place the odor vial number X (i.e., ranging from 1 to 10) on a holder in front of them. They were told that during this period they could move freely. The odor vials were marked with numbers on top of them so that the participant knew which one to place in front of them. The chin-rest and vial holder were provided to ensure that the distance between the vial and the nose of the participant was always the same. Each participant was only free to change the height of the chair for optimal comfort. Once the vial was positioned, the participants were asked to avoid moving their non-dominant hand (on which was placed the wristband).

All the answers were directly recorded and synchronized with the wristband data. The different psychological scales collecting the self-evaluation of affective changes during each trial were implemented directly on the computer. The participant was invited to respond using the mouse key with their dominant hand. At the end of the session, data files were automatically uploaded to a NextCloud server owned by the University of Lille to safeguard against data loss and to follow the European rules set by the National Data Protection Commission (CNIL).

Then, the Python codes were applied to the Empatica E4 data to process and analyze the relevant dependent variables that included BPM and RMSSD. Raw and processed data were finally logged to the NextCloud server, to safeguard against possible data loss. In the initial study, the Empatica E4 wristband only was used. Nevertheless, the setup enables today the use of additional quantification tools (e.g., eye tracking, EMG band strips) to characterize remotely the human experience of multi-sensory environments that include odors and sounds.

A.4.2 *Experimental proof-of-concept*

Our innovative methodology was used to investigate how odors would modulate both the HR and HRV of a total of 45 participants (27 female participants). Their sense of smell was assessed using the Sniffin' Sticks Screening 12 Test (Burghart;

Wedel, Germany; Hummel et al., 1997). Threshold was set as a score below 10 for men and below 11 for women. This led to the rejection of 10 participants. Two odor molecules were used: eucalyptol (1,8-cineole 99%, CAS number 470-82-6) and camphor ([1R]-[+]-camphor 98%, CAS number 464-49-3). Both were single molecules and concentrated at 10% in ethanol.

These two molecules were selected as they both hold an evolutionary value (i.e., easily found in nature) and are pleasant (eucalyptol; Frasnelli et al., 2011; Müschenich et al., 2020) and somewhat unpleasant (camphor; Alaoui-Ismaili et al., 1997; Vernet-Maury et al., 1999). Positive odors have been found to decrease HR and increase HRV, while the opposite was observed for negative odors (He et al., 2014). Therefore, in this proof-of-concept we expect HR to be lower when smelling eucalyptol than camphor. Conversely, we expect HRV to be higher when smelling eucalyptol than camphor.

BVP data from the wristband was filtered with a 3^{rd} order bandpass Butterworth filter between [0.9, 2.5] Hz after the removal of discrete motion artifacts. No trials were excluded for large time intervals of motion artifacts. Two dependent variables were computed: BPM to characterize physiological arousal and RMSSD as an indicator of the effects of odors on vagal tone. Both were computed as a difference between the baseline (i.e., 30 s before each odor) and 60 s after odor presentation. These differences were computed to offer a more accurate index of the influence of each molecule on the reactivity of HRV (Laborde et al., 2018). In the following, we conducted a one-way RM ANOVA (Odor [eucalyptol, camphor]) on each dependent variable (Δ BPM and Δ RMSSD) to demonstrate the effect of odor on HR functioning in a remote physiological experiment.

The RM ANOVA on Δ BPM showed a significant main effect of odor, $F(1, 27) = 8.44, p = .007, \eta_p^2 = .24$, with higher BPM differences for camphor (M = 5.56, SD = 3.20) than for eucalyptol (M = 2.45, SD = 1.42, $p = .007$, $d = 1.26$). The RM ANOVA on RMSSD differences showed a significant main effect of odor, $F(1, 32) = 4.44, p = .043, \eta_p^2 = .12$, with lower RMSSD differences for camphor (M = -6.37, SD = 19.51) than for eucalyptol (M = 6.47, SD = 12.73, $p = .043$, $d = 0.78$).

This study served as a proof-of-concept to illustrate the possibility of bench marking odor stimuli through physiological remote data collection. Our work also demonstrates that the physiological responses can be measured and analyzed with a wristband PPG sensor. Future work can include other quantification devices to characterize the user experience in remote real, virtual, and augmented virtual reality experiments.

A.5 CONCLUSION

With the technological offer available today, it is possible to record good quality heart signal outside the laboratory. This wealth of techniques offer researchers unique opportunities to study psycho-physiological processes in active moving individuals. However, the technique must be guided with theory and methodological rigor. Researchers should keep in mind why the measurement of HR or HRV is needed. When coming back to the research question and constraints, it will then be possible to design a good experiment to collect meaningful data. With the correct recording time, the optimal choice in recording tool, the corresponding HRV will be computed, with a proper pipeline process for data analyzes. Only then will experimental science be able to offer valid data to gain a better understanding of the influence of environmental, physiological, and psychological factors on HR and HRV in active men and women. The innovative methodology presented in this work will allow researchers to use lightweight PPG sensors to efficiently record HR and HRV measurements in remote settings. The Python codes are made available to foster better transparency and repeatability of physiological data reported in a wide range of psychological sciences.

ACKNOWLEDGMENTS

J'aimerais commencer par remercier la Professeure Yvonne N. Delevoye-Turrell, ma directrice de thèse et première mentor. Lorsque j'ai décidé de faire un stage avec vous, en Licence 2, jamais je n'aurais pu imaginer que nous travaillerions ensemble pendant presque 8 ans. Je n'ai jamais eu de regrets et ce n'est certainement pas maintenant que cela va commencer. J'ai toujours dit que vos doctorants avaient la meilleure directrice de thèse et je le pensais. Maintenant, je le sais. J'ai beaucoup d'admiration pour vous et votre parcours. Vous avez une carrière aboutie et une belle famille, ce qui représente pour moi le meilleur des accomplissements. Votre capacité d'adaptation, votre *résilience* est incroyable. Vous avez des doctorants qui sont tous différents et qui vont tous dans des directions différentes. Cela dit, vous êtes capable de vous adapter à chacun d'eux, de leur faire apprendre ce dont ils ont besoin pour réaliser ce qu'ils veulent faire (qu'ils en soit conscients ou non). Il a fallu attendre cette dernière ligne droite dans ma thèse pour que je me rende compte de tout ce que vous m'avez appris. Merci de toujours m'avoir invité à participer aux rendez-vous avec vos partenaires privés. Merci de m'avoir appris à gérer un budget et des contrats. Merci d'avoir eu confiance en moi et en mes capacités le temps que j'acquiers cette confiance. Ce ne sont pas que vos qualités d'enseignement et d'accompagnement qui font de vous une belle personne, un mentor. Ce sont aussi vos qualités humaines. Merci, donc, de toujours avoir été là pour moi. J'ai traversé quelques périodes difficiles personnellement et vous avez toujours été disponible pour m'écouter, me conseiller, m'aider à trouver les réponse tout en me laissant résoudre mes propres problèmes moi-même. Je ne dis jamais les choses à la légère et même si les choses semblent évidentes, je préfère les dire clairement. Alors, pour tout ces choses et pour toutes celles que je n'ai pas mentionnées ici, je vous remercie.

J'aimerais remercier la Pr. Clarisse Dhaenens-Flio, la Pr. Sylvie Droit-Volet, le Pr. Ludovic Marin, la Pr. Véronique Nardello-Rataj, la Dr. Magalie Ochs et le Dr. Thomas Peel, pour avoir accepté de participer à mon jury de thèse. C'est un privilège que de pouvoir échanger avec vous sur mes travaux de thèse.

Je tiens à remercier plus particulièrement Thomas Peel. Merci d'avoir pris de ton temps personnel pour m'accompagner, toutes les deux semaines, sur la partie deep-learning de ma thèse. J'ai toujours beaucoup apprécié nos rendez-vous. Il m'est arrivé de penser que je n'avais pas assez avancé et que j'allais te faire perdre ton temps. À chaque fois, j'avais tort. À chaque fin de rendez-vous, j'étais reparti, j'avais récupéré de l'énergie et je savais dans quelle direction aller. Rien n'a jamais été un vrai problème, nous avons toujours réussi à trouver une solution pour faire fonctionner notre réseau. Enfin, merci de m'avoir donné ma chance à Marseille, c'est une expérience qui a beaucoup compté pour moi.

J'aimerais remercier Marion et Ségolène pour tous les moments que nous avons passés tous les trois pendant nos thèses respectives, à Ségolène et à moi. Tous ces moments passés nous ont permis de nouer des liens et une amitié que, je l'espère, nous ferons durer encore longtemps !

Je remercie chaleureusement la Team FATAAL. Cette belle équipe que nous avons créée et que nous avons fait vivre pendant près de 4 ans. Merci donc au noyau dur de cette équipe, Yvonne, Adamantia et Ségolène. Cette Team FATAAL nous a tous aidé à avancer, à travailler et à passer le confinement et le COVID beaucoup plus facilement. De nombreux étudiants sont passés par notre Team FATAAL et chacun d'eux a fait grandir notre équipe. Une personne m'a tout particulièrement marqué. Merci Roxane d'être venu passer du temps dans notre équipe à Lille pour ton indoc. Tous ensemble, nous avons su brillamment mener notre petite barque FATAAL au travers de tous les dangers ! P.S.: même si le temps de notre belle équipe s'achève au même moment que ma thèse, j'espère que notre chère directrice de thèse se souviendra de son nom complet.

Merci à Guillaume Stempfel et Laurent Madelain d'avoir accepté de participer à mon Comité de suivi de thèse. Il m'est arrivé d'entendre des doctorants stresser à l'approche d'un comité de suivi de thèse, par peur de ne pas avoir assez accompli de choses. Je n'ai jamais eu ce sentiment. J'ai toujours beaucoup apprécié vous présenter ce que j'avais fait et écouter vos conseils pour la suite.

Merci à Laurent Ott, pour ton soutien technique et logique. J'admire ta faculté à décomposer ce que l'on te dit et voir où il manque quelque chose et comment on pourrait résoudre ça. Merci aussi pour nos discussions sur /e/ OS et l'open-source, j'étais content d'avoir quelqu'un avec qui en parler. Les chercheurs et doctorants de SCALab ont beaucoup de chance de t'avoir à leurs côtés, merci !

Comment ne pas remercier Emmanuelle Fournier et Sabine Pierzchala. Tout le monde le dit et c'est vrai, vous êtes les Wonder Women du labo ! Merci de m'avoir facilité la vie en m'aidant pour toutes les parties administratives de la recherche. Rien n'a jamais été compliqué et je n'ai jamais, à aucun moment, ressenti l'angoisse administrative parce que je savais que vous étiez là.

Merci à toute l'équipe de la plateforme IrDive et de la Fédération de Recherche Sciences et Cultures du Visuel où j'ai passé la majorité de mon temps. J'aimerais remercier particulièrement Diane Togbe, Laurence Delbarre, Nathalie Castelein et Mohamed Ladrouz pour leur soutien logistique et technique.

Merci à mes amis Bretons, Anna, Gwenn et Aymeric et mes amis Nordistes, Quentin et Romain. Merci pour les moments que nous avons partagés et tout ce que vous m'apportez. Même si je le dis pas souvent et que je ne donne pas beaucoup de nouvelles, je vous aime.

Merci à ma famille, une des choses les plus importantes que j'ai dans ma vie. Merci à mes grands-parents, Monique et Michel, de toujours être présents dans les bons et les mauvais moments. Je vous admire énormément et je vous aime d'autant plus. Merci à mes oncles et tantes, Jean-Jacques, Véronique, Jean-François, Anne et Juliette, pour votre soutien, votre joie de vivre et tous les moments passés ensemble. Merci à mes cousins, Alexandre, Marion, Noémie, Valentine, William, Adrien, Pauline et Hélène, pour tous les fous rires, les films à Port-de-Couze, les sessions de surfs, les parties de 2K et tous les souvenirs que nous partageons. Merci Valentine, Guillaume, Pandora et Thaïs de m'avoir accueilli les weekends quand j'étais à Marseille. J'ai adoré venir vous voir et partager du temps avec vous !

J'aimerais aussi remercier la famille Guérin – Patte pour leur accueil plus que chaleureux. Merci Monique, Jean, Gauthier, Delphine, Renaud, Agnès, Jean-Dominique, Matthieu, Marianne, Armand et Énola. Rien n'est encore signé et comme dit Renaud, la garantie décennale n'est pas encore passée, mais merci de me faire me sentir à ma place dans votre famille.

Merci à ma Maman, merci à mon Papa. Merci d'avoir tout fait pour que je sois heureux aujourd'hui. On m'a raconté que la vie n'a pas toujours été simple pendant que je grandissais mais je ne m'en suis jamais rendu compte. J'ai grandis et évolué dans un environnement incroyablement aimant et protecteur. Vous m'avez permis de faire mes propres choix et de tracer mon chemin comme je l'entends. Je vous en suis éternellement reconnaissant. Papa, tu m'as dit un jour qu'une façon de savoir si l'on avait fait les bons choix dans la vie était de regarder où nous en étions maintenant et si l'on était heureux. Je vous l'ai déjà dit mais j'aime bien répéter les choses : je suis heureux d'être où je suis et d'être qui je suis. Merci d'être vous.

J'aimerais conclure cette section en remerciant la femme que j'aime. Merci Ségolène d'être aussi parfaite pour moi. Je suis conscient de la chance que j'ai d'avancer à tes côtés. Nous avons vécu beaucoup de choses tous les deux. Nous avons eu la chance de faire nos thèses au même moment et au même endroit. Quelle chance d'avoir pu partager les hauts et les bas ensemble ! Nous avons vécu notre meilleur confinement ensemble, dans mon appartement de 28 m^2. Et maintenant nous entamons un nouveau chapitre de notre vie ensemble. Pendant tous ces moments, tu as été là pour me voir danser de joie en écoutant Magic System et pour m'aider à comprendre comment surmonter les difficultés de la vie. Comme le dis si bien ton chanteur préféré, grâce à toi, des flots de couleurs éclatent et le monde semble bien plus beau. Je ne peux pas imaginer un futur sans toi, sans nous. Je t'aime.

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Ce travail a bénéficié du soutien de la Fédération de Recherche Sciences et Cultures du Visuel (FR CNRS 2052 SCV).

This document was typeset using the typographical look-and-feel `classicthesis` developed by André Miede. The style was inspired by Robert Bringhurst's seminal book on typography *"The Elements of Typographic Style"*. `classicthesis` is available for both LaTeX and LyX:

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