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Spatiotemporal dynamics of urban health: Physiological data driven strategies for enhancing urban health and wellbeing

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Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

under the supervision of
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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Dimitra Dritsa declare that this thesis, is submitted in fulfilment of the requirements for the award of the degree of Doctor of Philosophy, in the Faculty of Architecture at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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THESIS FORMAT STATEMENT

This thesis is formatted following the requirements of a conventional thesis. Two papers submitted for publication are also presented in Appendix A and B. References to the two papers have been included in the main work whenever appropriate.

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ABSTRACT

The starting point for this research was the emergence of physiological data as a source of information that can help us understand how our interactions with the urban environment affect the human body. There is significant potential in extending existing methods for physiological data analysis in the urban domain in a way that maximises the benefits at the individual and the city scale. Physiological data could be used to identify the least stressful route, but there is currently a lack of research on their incorporation in pathfinding studies. The area of prediction of physiological responses during outdoor walking has also been understudied.

This study aims to address these issues by designing a methodology for collection and analysis of physiological data in the urban space. The methodology incorporates three components: (1) the collection and analysis of physiological data at an individual level, (2) the hotspot analysis of physiological responses at a city scale, and (3) the utilisation of the collected data in models for prediction of physiological responses, and pathfinding methods for the identification of the least stressful route. The methods and algorithms for each component of the methodology are calibrated using data collected in Sydney from experiments organised by the author, and publicly available data from a previous study conducted in Zürich.

The study acts as a pilot project that will pave the way towards large-scale experiments in this area. Its main contribution is that it supports the construction of tools for individuals who want to understand how different routes might affect their physiological responses, and have a calm experience while walking in the urban environment. It can also help researchers identify which parts of the city are associated with an increased intensity of physiological responses, possibly indicating increased stress levels. The construction of a theoretical and conceptual framework supporting the construction of the methodology also enriches current research on the links between urban environment, activity and physiological responses. Other methodological and practical contributions include the development of methods for analysing how movement may influence physiological responses as a physical stressor, and their incorporation in the designed methodology; also, the development of

methods for identifying physical and psychological stressors from contextual data, based on freely available OpenStreetMap and Point of Interest data, as an alternative to image-based analysis which was used in previous studies.

ABBREVIATIONS

ADAM	Adaptive Moment Estimation
AHR	Additional Heart Rate
ANS	Autonomic Nervous System
API	Application Programming Interface
CNN	Convolutional Neural Network
DBSCAN	Density-Based Spatial Clustering of Application with Noise
DNN	Deep Neural Network
DT	Decision Tree
ECG	Electrocardiogram
EDA	Electrodermal Activity
EDR	Electrodermal Response
EEG	Electroencephalography
FFT	Fast Fourier Transform
GIS	Geographic Information System
GPS	Global Positioning System
GSR	Galvanic Skin Response
HMM	Hidden Markov Model
HR	Heart Rate
HRV	Heart Rate Variability
KDE	Kernel Density Estimation
k-NN	k-Nearest Neighbors

LISA	Local Indicators of Spatial Association
LSTM	Long-Short Term Memory (Network)
MAE	Mean Absolute Error
ML	Machine Learning
MSE	Mean Squared Error
NS.SCR	Non-Specific Skin Conductance Response
OSM	OpenStreetMap
PANAS	Positive And Negative Affect Schedule
POI	Point Of Interest
STD	Standard Deviation
SVM	Support Vector Machine
RNN	Recurrent Neural Networks
RF	Random Forests
RMSE	Root Mean Square Error
PPG	Photoplethysmography
ST	Skin Temperature

PUBLICATIONS

Materials presented in chapter 1 have generated the following research output:

Dritsa, D. & Biloria, N. 2021, 'Mapping the urban environment using real-time physiological monitoring', *Archnet-IJAR*, Vol. ahead-of-print No. ahead-of-print, doi: https://doi.org/10.1108/ARCH-02-2021-0041.

Materials presented in Appendix A have generated the following research output:

Dritsa, D. & Biloria, N. 2021, 'Analysing the relationship between POI density and stimulus complexity in the urban environment', *Journal of Urban Design*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1080/13574809.2021.1903306.

Materials presented in chapter 1 are based on findings from the following research output:

Dritsa, D. & Biloria, N. 2018, 'Towards a Multi-Scalar Framework for Smart Healthcare', *Smart and Sustainable Built Environment,* vol.7, no.1, pp.33-52, doi: https://doi.org/10.1108/SASBE-10-2017-0057.

1
INTRODUCTION

1.1. CONTEXT

As a recent report by the United Nations shows, the world population might increase by 2 billion in 2050 (DESA/UN 2019), a growth which is expected to be absorbed by cities. There is thus increasing concern regarding the ability of urban areas to handle this challenge while retaining a healthy environment.

One research area related to this challenge is urban health, which has an explicit focus on the urban environment and its impact on population health (Galea & Vlahov 2005). The advancement of urban health requires knowledge of how different places perform in terms of the identified factors. This knowledge can be provided by traditional data collection sources, such as surveys, but these are usually conducted with low frequency and cannot capture the dynamic nature of urban phenomena. In the last decade, sensor-based networks and big data have brought a new perspective in the analysis of urban dynamics (Kitchin 2013). The availability of large-scale geo-tagged data sets, generated with high frequency, such as mobile phone data, has enabled new ways of analysing human activity patterns and their spatial output (Calabrese et al. 2013). Crowdsourced data which have relevance to health and physical activity have also evolved. Fitness applications such as Strava offer a vast collection of GPS tracks, which can provide us with a crowdsourced mapping of walking and cycling activity (Heesch & Langdon 2016). In the context of urban health, this information is largely assistive in the identification of places which attract physical activity.

Physiological data from consumer activity trackers is another example of such data, next to geotagged physical activity and environmental exposure data. As this study will show, these data sources have the potential to assist in the transition towards smarter and healthier cities. Current guidelines towards urban planning strategies for the enhancement of urban health include the mitigation of the following factors: air pollution, traffic, noise, social isolation, crime, prolonged sitting and unhealthy diet (Giles Corti et al. 2016). The promotion of walking through interventions in terms of accessibility, land use density and diversity and other parameters, is an essential component for mitigating many of these risk exposures. The enhancement of active transport, for instance, is essential for the reduction of traffic. Since traffic is a significant source of air pollution and noise, these two risk exposures would also be mitigated with the promotion of outdoor walking.

For these reasons, it is essential for urban planning authorities to collect information regarding current local trends in pedestrian activity, and identify potential clashes with traffic, environmental exposures and other factors that affect health. Smart technologies, such as GPS trackers, already play a significant role in this effort, according to a literature review conducted on this topic (Dritsa & Biloria 2018). As the review showed, the studies that address key risk exposures related to urban health, and harvested data at a population level, can be grouped in the following manner:

- studies which examine physical activity in relation to the urban environment
- studies which monitor environmental quality.

The first category includes studies which examine neighbourhood walkability (Rundle et al. 2016; Sallis et al. 2016), and the association of built environment characteristics with physical activity (Lachowycz et al. 2012; Wang et al. 2017). Studies which examine cycling route choice with the acquisition of GPS tracks can also be added here since they examine the same GIS data sets (e.g., Broach et al. 2012; Hood et al. 2011; Menghini et al. 2010).

The second category contains studies which map air pollution (Al-Ali et al. 2010; Dutta et al. 2009; Hasenfratz et al. 2015; Liu et al. 2011) and noise (Garcia Marti et al. 2012; Kanjo 2012; Maisonneuve et al. 2009; Rana et al. 2010).

The review indicated that the most commonly analysed data sets at the urban level, which also have an association with the guidelines for the advancement of urban health, are GPS tracks, air quality, weather and noise. The acquisition of GPS tracks has been largely helpful in studies which determine which features of the built environment enhance walkability, and is usually assessed in relation to data such as the presence of green, parameters related to land use, and street network data. Air quality data are usually acquired next to meteorological data, in order to extract their association for predictive models, apart from spatially mapping their concentration levels. Noise monitoring systems are usually participatory and are commonly derived for mapping purposes, without examining any interaction with other data sets.

Thus, movement mapping systems enhance our knowledge in terms of where people walk in a city and why they choose particular routes. Environmental sensing systems assist in mapping risk exposures in a city and identifying hotspots. What is currently lacking is information on user experience, and more specifically on the immediate effect that urban and environmental features such as traffic, air pollution and noise have on the human body, at a high spatiotemporal resolution. The investigation of this aspect is essential, as the user experience defines if an outdoor walk will be enjoyable or not.

The wide commercialisation of consumer activity trackers such as FitBit brings the emergence of physiological data as a new source of information that could potentially bridge this gap. Fitbit and other similar consumer activity trackers are examples of internet-connected devices that emerged in the past few years for applications such as building performance control, environmental quality assessment and personal health monitoring. The 'Internet of Things' (IoT) has become popular as a term that describes the larger ecosystem of such devices (Swan 2012); the term typically refers to everyday objects that commonly include sensing capabilities and can be connected to the Internet, while also communicating with other devices in some cases. Consumer activity trackers, also known as smartwatches (Swan 2012) include sensors for the measurement of movement and potentially also physiological data, such as heart rate. They are usually connected with a smartphone, and may include some functions such as notification of calls and messages. The term 'wearable technologies' or 'wearables' is commonly used as an umbrella term that describes such devices and technologies that can be worn (Gilmore 2016).

These devices collect a multitude of information related to the daily habits of the user, such as the step count and the duration and quality of sleep. This information is collected through self-tracking, which makes it distinct from covert monitoring or other types of collection of information where access is not given to the users that generate the data (Lupton 2016). The transformation of dimensions of everyday life to data acts as a prompt for the users of such devices to self-reflect on their habits, changing the way that they conduct their daily activities. This phenomenon emerged when the practice of self-tracking for self-knowledge and improvement started gaining traction, and led to the generation of the movement of the 'quantified self' (Lupton 2016). The increasing availability of information acquired through self-tracking also brought forth new research opportunities in several disciplines. The emergence of consumer activity trackers has revolutionised the measurement of physical activity and other aspects related to health. There is much interest in using this data as health records that can help in the development of clinical applications (Shull *et al.* 2014).

The increasing availability of physiological data from these devices has also brought forth new opportunities for researchers in the field of spatial sciences, as it is possible now to map bodily reactions while the user is moving in the urban space, with equipment that is wireless, widely available and relatively easy to use. As it will be shown in section 1.2, physiological responses are used as an indicator of stress and emotions. Physiological data from consumer activity trackers has thus the potential to add a new information layer that can enhance current research on urban health and wellbeing, by providing evidence in terms of how the body reacts during interaction with different urban and environmental parameters. In the context of urban health, the use of physiological data monitoring would be especially beneficial in the study of bodily experience during outdoor walks. As the promotion of walking is a significant component of strategies for the mitigation of risk exposures and the advancement of urban health, physiological data monitoring in the urban domain can assist in these efforts. Physiological data monitoring could be used by urban planning authorities to make informed decisions regarding what kind of changes in infrastructure or land use need to be undertaken to mitigate stress or negative emotions. The analysis of the variations of the perceived experience during an outdoor walk is also key for understanding why pedestrians choose particular routes and how the urban environment should be designed to provide a meaningful experience while mitigating exposure to stressors.

While there is large potential in this research area, this is still a relatively new field. More research is needed on methods for collecting and analysing physiological responses and understanding the parameters of the urban environment that may be linked to them. The review presented in section 1.2 will show that there are theoretical, methodological and technical issues in the previous studies in this area which need to be addressed.

In this context, this thesis focuses on the investigation of methods for the collection and analysis of physiological data in the urban space, aiming to enrich our knowledge on how our interactions with the urban environment affect the human body. The combination of these methods formulates a methodology for the analysis of physiological data, which can be used for the benefit of multiple stakeholders at the user and the city scale.

After presenting the broader research context, the rest of this chapter is devoted to the detailed presentation of the specific gaps that the designed methodology seeks to answer. A review of past studies on physiological data mapping in the urban environment is first presented; this review is the first in this area, as there has been no systematic mapping of the existing studies. The review leads to the research questions, aims and objectives (section 1.3) which drive the construction of the methodology.

1.2. MAPPING PHYSIOLOGICAL RESPONSES IN THE URBAN ENVIRONMENT USING CONTINUOUS MONITORING: OVERVIEW OF PAST STUDIES

The review presented in this section outlines the common themes that were discovered during the analysis of past studies on physiological data collection and analysis in the urban environment[1]. The review starts with outlining the general study characteristics, and progresses with the presentation of trends in the collection of physiological, movement and contextual data and methods of data analysis. Future prospects and current issues and challenges are then identified.

1.2.1. METHODS FOR STUDY SELECTION

Studies focusing on the following four criteria were identified via search in Google Scholar and Scopus:

(1) Usage of a portable monitoring system for physiological data monitoring

(2) Continuous monitoring of physiological data

(3) Focus on the outdoor environment

(4) Collection of contextual data related to spatial, urban or environmental parameters

43 studies which met these requirements were identified and were included in the review (Figure 1.1). While most of the reviewed studies include physiological data collected with wristbands, it was also decided to include a few studies where physiological data are collected with other portable recording devices, such as chest bands.

Studies which focus on stress or emotion detection without mentioning spatial or environmental contextual parameters were excluded, in order to focus on the unique challenges posed in the analysis of urban contextual data.

[1] The review presented in section 1.2 has been published in a slightly modified version in the journal Archnet-IJAR (Dritsa, D. & Biloria, N. 2021, 'Mapping the urban environment using real-time physiological monitoring', Archnet-IJAR, Vol. ahead-of-print No. ahead-of-print, https://doi.org/10.1108/ARCH-02-2021-0041).

AUTHOR	YEAR	CATEGORY	SAMPLE *	ACTIVITY **	PHYSIOLOGICAL DATA ***	TYPE OF ANALYSIS	ANALYSED PARAMETER
Hogertz	2010	Emotions	31	W, L	EDA, ST	Visual	Various urban settings
Massot et al.	2012	Stress	10 (blind adults)	W	EDA	Inferential	Various urban settings
Bergner et al.	2013	Emotions	7 (individuals with different cultural backgrounds)	W	EDA, ST	Visual	Various urban settings
Song et al.	2013	Physiological responses	13	W	HR, HRV	Inferential	Urban green vs other urban settings
Lee et al.	2014	Physiological responses	46 (young adults)	W	HR, HRV, BP	Inferential	Green (forest) vs urban setting
Song et al.	2014	Physiological responses	17	W	HR, HRV	Inferential	Urban green vs other urban settings
Song et al.	2015a	Physiological responses	19 (middle-aged hypertensive adults)	W	HR, HRV	Inferential	Green (forest vs urban)
Song et al.	2015b	Physiological responses	20	W	HR, HRV	Inferential	Urban green vs other urban settings
Nakayoshi et al.	2015	Comfort	26	W	ST, HR	Inferential	Thermal comfort
Aspinall et al.	2015	Emotions	12	W	EEG	Inferential	Urban green vs other urban settings
Zeile et al.	2016	Emotions	12	C	EDA, ST, HR	Visual	Various urban settings
Li et al.	2016	Emotions	30	W	EDA, ST	Inferential	Effect of isovist parameters
Hijazi et al.	2016	Emotions	13	W	EDA, ST	Inferential	Effect of isovist parameters
South et al.	2015	Stress	12	W	HR	Inferential	Effect of a greening treetment
De Silva et al.	2017	Safety	50	W	EDA	Inferential	Various urban settings
Yates et al.	2017	arousal	7	W	EDA, ST, HR	Predictive	Various urban settings
Tilley et al.	2017	Emotions	8 (older adults)	W	EEG	Visual	Urban green vs other urban setting
Neale et al.	2017	Emotions	95 (older adults)	W	EEG	Inferential	Urban green vs other urban settings
Osborne and Jones	2017	Emotions	30	W, L	EDA, ST, BVP	Visual	Various urban settings
Griego et al.	2017	Stress	37	W	EDA ,ST, HR, BVP	Inferential	Various urban settings
Komori et al.	2017	Physiological responses	10	W	HR, HRV	Inferential	Green (forest) vs urban setting
Chen et al.	2018	Emotions	4	W	EDA,ST,HR,EEG,RA	Visual	Various urban settings
Shoval et al.	2018	Emotions	68	W	EDA	Visual	Various urban settings
Kanjo et al.	2018 (a,b)	Emotions	34	W	EDA, ST, HR	Inferential + Predictive	Various urban settings
Chrisinger and King	2018	Stress	13	W	EDA	Inferential	Various urban settings
Fathullah and Willis	2018	Stress	9	W	EDA	Visual	Various urban settings
Nuñez et al.	2018	Stress		C	EDA, ST	Inferential	Various urban settings

Saitis and Kalimeri	2018	Stress	12 (visually impaired adults)	W	EDA, HR, BVP, EEG	Inferential + Predictive	Various urban settings
Caviedes and Figliozzi	2018	Stress	5	C	EDA	Inferential	Various urban settings
Engelniederhammer et al.	2019	Emotions	30	W, L	EDA, ST	Inferential	crowding density
Xiang and Papastefanou	2019	Emotions	30	W	EDA, ST	Inferential	Effect of isovist parameters
Paül i Agustí	2019	Emotions	28	W	HRV	Visual	Various urban settings
Flutura et al.	2019	Stress	7	W	EDA, ST, HR, HRV, BVP	Predictive	Various urban settings - focus on thermal comfort
Ojha et al.	2019	Stress	20	W	EDA	Inferential + Predictive	Various urban settings
Benita and Tunçer	2019	Stress	10	W	EDA, ST	Inferential	Various urban settings
Kyriakou et al.	2019	Stress	various (max=56)	W,C,L	EDA, ST	Predictive	Various urban settings
Birenboim et al.	2019	Stress	12	W	EDA, HR, HRV	Inferential	Various urban settings
Werner et al.	2019	Stress	17	C	EDA, ST	Visual/ descriptive	Various urban settings
Roe et al.	2019	Stress, restoration	21	W	HRV	Inferential	Effect of an urban intervention
Kim et al.	2020	Comfort	25	W	EDA, HR, BVP	Inferential	Various urban settings
Lee et al.	2020	Stress	16 (older adults)	W	EDA	Inferential	Various urban settings (focus on environmental barriers)
Rybarczyk et al.	2020	Comfort	28	C	HR	Inferential	Various urban settings
Fitch et al.	2020	Stress	20	C	HRV	Inferential	Various urban settings (focus on traffic conditions)

* The final sample size for each study, excluding participants who did not take part in continuous physiological data collection, or participants whose data were excluded due to artefacts and other errors.
** W=Walk, C=Cycling, L=Laboratory
*** Includes only the continuously measured physiological data

STUDY FOCUS

Green | Thermal comfort | Isovist parameters | Crowding density | Other

Figure 1.1. An overview of the reviewed studies

The analysis of the selected studies focused on the following points:

1. The general study characteristics (study objective, sample size, characteristics of the performed activities)

2. The data collection process for physiological, movement and contextual data; the instruments used for collection and the theoretical background which supported the contextual data selection
3. The data analysis process (data processing, data fusion, spatial aggregation and inferential or predictive analysis)

1.2.2. DESCRIPTION AND METHODOLOGICAL OVERVIEW OF REVIEWED STUDIES

1.2.2.1. GENERAL STUDY CHARACTERISTICS

The first study which involved continuous geotagged physiological data collection in the urban environment was the 'Bio Mapping' project (Nold 2009). Today this field is still in development, with most of the studies published in the past two years. The topic has attracted the interest of researchers in different fields, such as architecture, urban planning and design, urban health, geography, environmental psychology and affective computing. The study objective is most frequently to understand how the environment influences physiological responses, which are usually interpreted as stress (n=17) or emotions (n=15). Initially, most studies were connected to emotions, but in the recent two years, there has been a shift towards stress-related research (Figure 1.1, Figure 1.2). Some studies had a focus on a specific theme, such as thermal comfort and heat stress (Flutura et al. 2019; Nakayoshi et al. 2015), safety (De Silva et al. 2017), or the effect of crowding density (Engelniederhammer et al. 2019) and isovist properties (Hijazi et al. 2016; Xiang & Papastefanou 2019) on emotions. An isovist is the area which is visible from a given point in space. This factor is, thus, related to the visual field of the pedestrian. Other studies had a focus on a specific population, such as visually impaired adults (Massot et al. 2012; Saitis & Kalimeri 2018), middle-aged hypertensive adults (Song et al. 2015a) and older adults (Lee et al. 2020; Neale et al. 2017; Tilley et al. 2017).

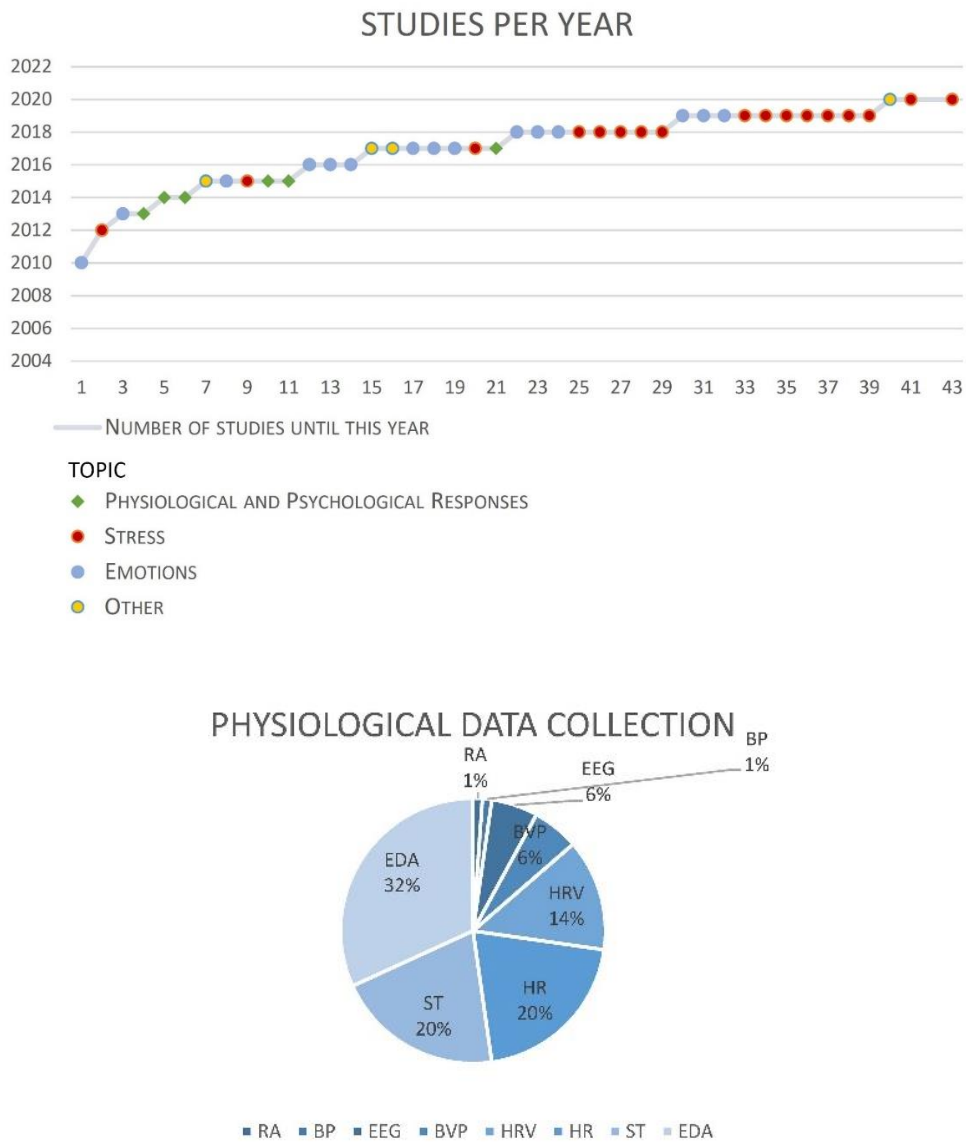


Figure 1.2. Upper: The increase in studies on physiological mapping in the urban space in the past years. Bottom: The frequency of appearance of different physiological data in studies.

It was observed that the number of participants was usually small (median=18). Most studies included measuring the participants' physiological responses while following a predefined path; very few studies have included free exploration (n=4). The data collection is almost always conducted for one day, with few exceptions (Komori et al. 2017; Lee et al. 2014; Lee et al. 2020; Roe et al. 2019; Song et al. 2015a; South et al. 2015). A group of researchers also repeated their experiment in different seasons (Song et al. 2013; Song et al. 2014; Song et al. 2015b). The application of the proposed methodologies under uncontrolled circumstances is thus usually not examined. The mode of exploration was most commonly walking (n=37) followed by cycling (n=7). Studies on cycling were mostly focused on stress (n=5), whereas studies on walking were more balanced in terms of theme. The outdoor walking activity lasted from 15 to 45 minutes, with few exceptions (Flutura et al. 2019; Komori et al. 2017). Only 4 studies complemented the outdoor data collection with a controlled experiment in the laboratory (Engelniederhammer et al. 2019; Hogertz et al. 2010; Kyriakou et al. 2019; Osborne & Jones 2017).

1.2.2.2. DATA COLLECTION

1.2.2.2.1. PHYSIOLOGICAL DATA

The most commonly tracked physiological measures were electrodermal activity (EDA) (n=28) and heart rate (HR; n=18). These measures are related to the activity of the autonomic nervous system, which regulates the bodily responses when the body is under stress, among other functions.

EDA (or galvanic skin response, GSR) refers to the changes in skin resistance which are caused by the sweat glands (Boucsein 2012). It is a typical physiological response to changes in psychological and emotional states, while it is also strongly involved in the thermoregulation of the body. It is one of the most widely used measures of sympathetic activation in response to external stimuli (Dawson et al. 2007).

In continuous HR monitoring, measurement is conducted with electrocardiogram (ECG) technology in the case of chest straps, and with photoplethysmography (PPG) in the case of wristbands. PPG utilises photodetectors for the identification of variations in light intensity due to changes in the blood volume (Allen 2007). PPG-based HR monitoring systems have been criticised, as they can exhibit inaccuracies due to movement. ECG is still considered as the most well-established and accurate method. Despite these issues, PPG has also become popular lately due to its simplicity and convenience, and it is the method that the consumer activity trackers use for tracking heart rate (Hwang et al. 2016).

Skin temperature (ST) is also measured in many studies (n=18), as an indicator of stress together with electrodermal activity. Other much less frequently used measures are blood volume pulse (BVP, heart rate variability (HRV), electroencephalography (EEG), respiration (RA) and blood pressure (BP) (Figure 1.2).

The most frequently used instruments for physiological data collection were the Empatica E4 (n=12) and the SmartBand by Bodymonitor (n=9), most commonly for EDA measurement. The sensors, in this case, are embedded in wristbands. As for HR and HRV measurement, the frequently used instruments include the Empatica E4 or the SmartBand (n=5), other portable data recording devices (n=7), other wristbands (n=4) and chest straps (n=2). The studies that mapped EEG used the Emotiv headset. A few studies also included custom made systems with sensors attached to fingers (De Silva et al. 2017; Massot et al. 2012)

1.2.2.2.2. LOCATION/MOVEMENT DATA:

More than half of the studies incorporated GPS tracking (n=33), with a separate GPS tracker, a smartphone or a GPS sensor built in the physiological data monitoring system. The collected data is used for the calculation of position. The properties of the movement of the participant are rarely considered, except for Benita and Tunçer (2019) and De Silva et al. (2017) who included speed in the physiological data analysis and Kim et al. (2020) who analysed gait patterns. Accelerometer data is rarely used in the analysis, except for Nuñez et al. (2018) who used it to collect vibration data while cycling and Lee et al. (2014) who used it for the assessment of energy expenditure while walking.

1.2.2.2.3. CONTEXTUAL DATA

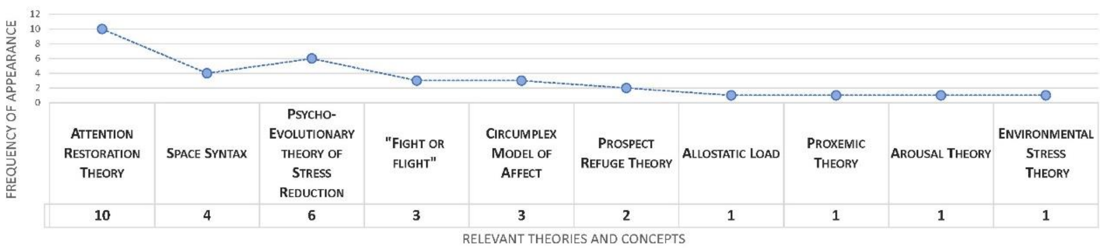


Figure 1.3. Frequency of appearance of concepts and theories related to stress and emotions in the studies.

The identification of contextual features is usually connected to theories and concepts related to stress, emotions and affect, as well as environmental and spatial psychology (Figure 1.3). In connection to the acute stress response, some researchers (Birenboim et al. 2019; Kyriakou et al. 2019) refer to the concept of 'fight or flight' (Cannon 1929), or the 'allostatic load'. These concepts will be analysed in detail in Chapter 3. Models of emotions, such as the circumplex model of affect (Russel 1980) were also used in some studies to categorise emotions in two dimensions, defined by the degree of valence and arousal (e.g., Li et al. 2016).

In terms of theories related to stress or emotions and space, the Attention Restoration Theory by Kaplan and Kaplan (1989) and the Psycho-Evolutionary Theory of Stress Reduction of Ulrich et al. (1991), were the most frequently mentioned. The prospect-refuge theory by Appleton (1975) was used in two studies, examining safety (De Silva et al. 2017) and the connection between isovist properties and emotional responses (Xiang & Papastefanou 2019). Space syntax (Hillier & Hanson 1984) was also used as a framework for studies that included isovist or accessibility analysis. Space syntax is a set of concepts and methods for the analysis of spatial properties and their effect on human behaviour; isovist and accessibility analysis are among the measures that are typically employed in space syntax analysis to understand properties of space, such as visibility and privacy, or investigate how the structure of the urban fabric affects pedestrian flow. The proxemic theory (Hall 1966) was also used in a study on the effect of crowding density on emotions (Engelniederhammer et al. 2019).

Almost all studies stressed the importance of collecting contextual data since only the acquisition of physiological data could not reveal what triggers each response. Urban features were measured or mentioned in most of the studies (n=37); the most commonly mentioned features were *green, isovist properties, traffic, road surface condition, intersection, bike lane,* and the *number of passing cars* (Figure 1.4). More than half of the studies (*n=23*) used video or photos collected by the participants or the researchers, for identification of relevant urban features; other data sources which were used in very few studies include satellite image data (n=1), OpenStreetMap data (n=3) or data from governmental sources (n=4). Some studies also examined zones rather than features; most commonly urban versus green zones (n=9). In this case, there was no fine-grained identification of more specific features. Some researchers also conducted an exploratory visual analysis of the maps after collecting the data, instead of systematic measurement of specific urban features.

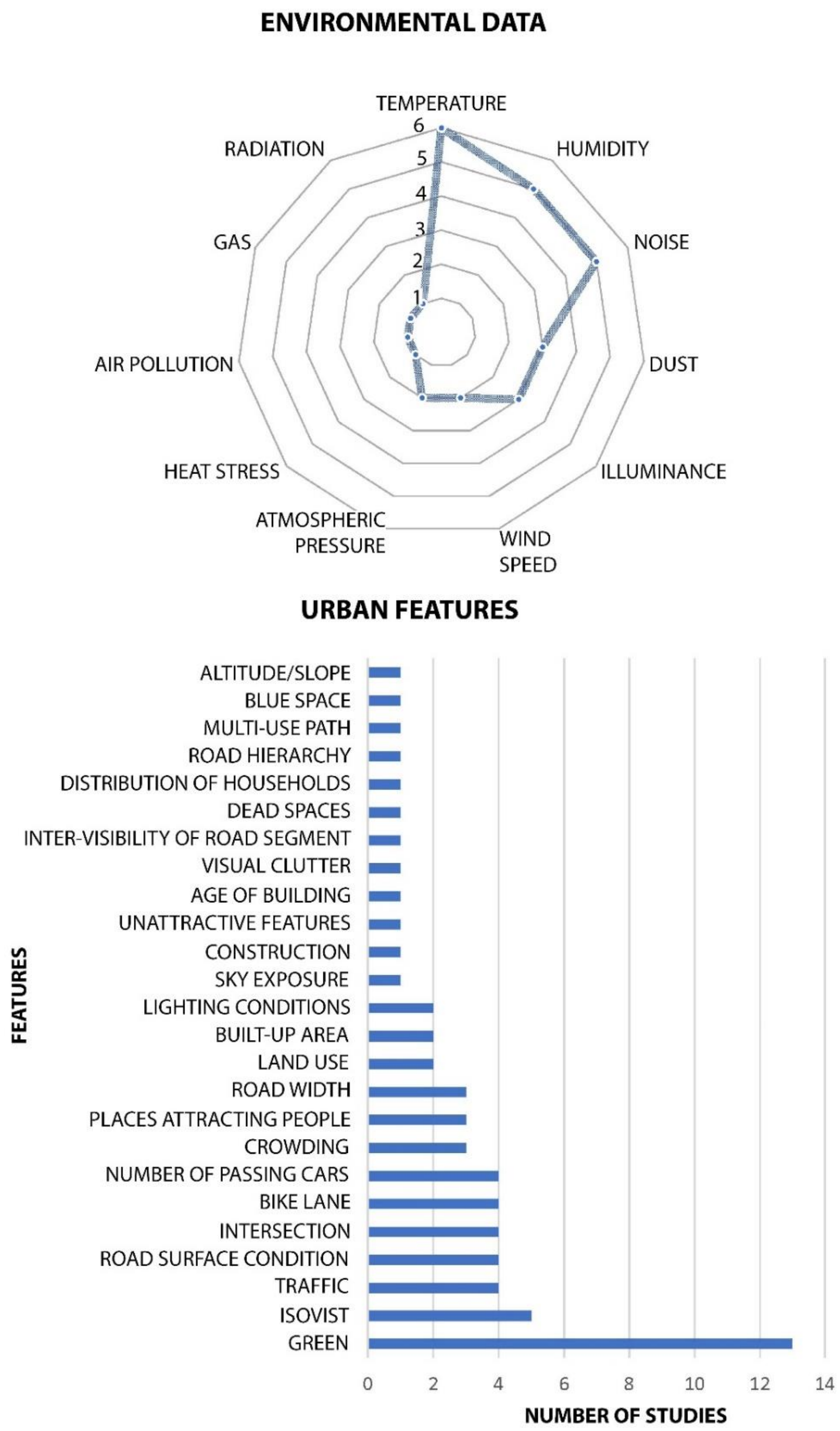


Figure 1.4. Frequency of appearance of different environmental data (left) and urban features (right) in the studies.

Environmental data were much less frequently included (n=8); the data collection was conducted by carrying a custom monitoring system in a box or a backpack. Noise data was sometimes monitored with a smartphone (Benita & Tunçer 2019; Kanjo et al. 2018b). The most frequently measured environmental data were temperature, humidity and noise (Figure 1.4).

The contextual data collection also included information regarding the perception of experience in selected locations. The studies utilised most commonly (n=30) a mixed-method approach to cover this gap, with a survey, questionnaire or interview with the participants. Shoval et al. (2018) and other researchers (n=8), for instance, used an app where the participants could rate in real-time the qualities of the built environment or specify their emotions concerning a particular location. Hogertz (2010) and Paül i Agustí et al. (2019) asked the participants to draw a map depicting their emotions during the walk. Other studies (n=18) used a questionnaire or an interview after the walk, where the participants could provide general feedback or rank their experience during different points or segments of the walk.

The subjective evaluation of the experience was then used in combination with the other contextual data. Zeile et al. (2016), for instance, used an app as a diary for self-reporting impressions and observations, asking the users to classify their feelings when a stress event was identified. The app complemented the analysis of video footage, which was studied in order to identify which features triggered emotional arousal. Osborne and Jones (2017) suggested a mixed-methods approach, which involved accompanying the mapping of the physiological data with material from qualitative personal interviews and video footage from a GoPro camera. This material was used then to examine the physical characteristics of the route and identify which features were related to moments of arousal. The video footage analysis, combined with the material from the personal interviews, enabled a rich contextualisation of the acquired physiological data.

1.2.2.3. DATA ANALYSIS

After data collection, the workflow usually incorporates one or more of the following steps (Figure 1.5):

(1) data processing and data fusion,

(2) geospatial mapping, sometimes including cluster or hotspot identification

(3) inferential analysis or prediction.

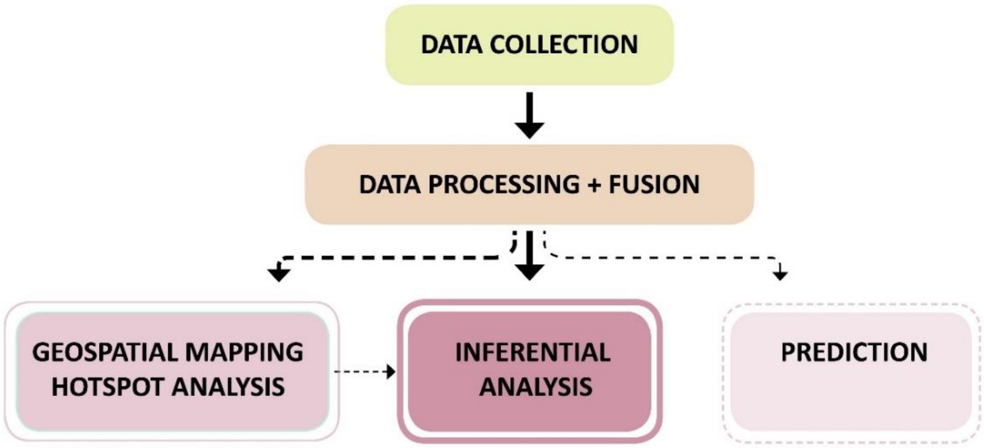


Figure 1.5. The steps of the workflow followed in the reviewed studies.

Step (1) involves processing the different data streams and combining all streams using a custom data fusion scheme, based on synchronisation of the timestamps. Step (2) involves methods for visualisation of the spatial distribution of the physiological responses, and in some cases, identification of areas which have statistically significant hotspots of responses. Some studies end at step (2), while other proceed to step (3) by using the collected data for inferential analysis. The goal here is usually to examine if the selected set of urban or environmental features influences physiological responses (or stress and emotions). Very few studies have also used physiological data in predictive analysis; an example here is the study of Kanjo et al. (2018b), who investigated the ability of different machine learning models to classify emotions based on collected physiological, movement and contextual data.

1.2.3. FINDINGS OF PAST STUDIES

This section builds on the descriptive analysis of section 1.2.2 and examines the findings of past studies. This examination aims to show the potential contribution of this strand of research to different areas.

1.2.3.1. UNDERSTANDING THE LINK BETWEEN URBAN ENVIRONMENT AND PHYSIOLOGICAL RESPONSES

The most significant contribution of this strand of research at the city scale is the identification of urban and environmental characteristics which have a negative effect on the organism by causing distress and negative emotions. Most of the reviewed studies focused on this problem, using regression models and tests that compare locations with different characteristics (t-test and ANOVA) for hypothesis testing.

One parameter that was included in many studies is the effect of green of physiological responses. These studies include mostly EEG and HR measurements. Aspinall et al. (2015) collected EEG data from 12 students during a walk in urban and green areas in Edinburgh and found that the green areas were associated with higher levels of meditation and less frustration, engagement and arousal. The study of Neale et al. (2017) had a similar setup but a much higher sample size (95 participants) and was focused on the experience of the elderly. This study showed that the 'engagement' levels were higher in the green areas when compared to quiet urban areas. Urban busy areas were associated with higher excitement in this study and were not connected to higher frustration levels. As for studies on the connection between HR and green, while walking, the analysis of Song et al. (2015a) showed that the average HR was lower when walking in an urban park, in comparison to walking in a city area. This analysis was based on data collected from young university students, and the experiment was conducted in Japan, in two environments with similar environmental conditions. Another study (Song et al. 2015b), which used data collected from middle-aged hypertensive individuals in central Japan, found that the HR of the participants was significantly lower when walking in the forest, in comparison to walking in the urban area. They noted that the two environments were significantly different in terms of environmental conditions such as temperature and humidity and that this may be one of the factors that influenced the result. The study of South et al. (2015) also suggested a connection between green spaces and HR. This study was conducted in spring and summer, in Philadelphia, Pennsylvania, and contained data from 12 participants. The findings showed that the exposure to green vacant lots during outdoor walking resulted in a lower HR compared to exposure to non-greened vacant lots.

While these findings suggest a connection between green and physiological responses, there are some concerns regarding the results of studies that include HR measurements. In these studies, the reported changes are sometimes in a range of 1 to 3 bpm. While the conducted tests show that the changes are statistically significant, their effect is very small, and since the experiments were in ambulatory conditions, there are many factors such as movement changes that may have influenced the results.

The effect of other features on physiological responses, such as land use and traffic-related parameters, is much less studied in comparison to the effect of green. Chrisinger and King (2018) examined the effect of various urban environment features on EDA during a 20-minute walk in California. The data collection was conducted in summer and autumn, and in some cases, the participants were walking in groups. There was a statistically significant increase in the EDA data in areas of mixed or residential land use, while the proximity to traffic, vacant lots and office buildings had the opposite effect. Saitis and Kalimeri (2018) collected data from 12 visually impaired pedestrians in Reykjavik and showed that the blind participants had significantly higher HR when crossing an intersection, in comparison to severely impaired individuals. The same finding was identified for walking in a shopping street. Birenboim et al. (2019) also conducted a study with 15 participants in Utrecht. They found that for most participants, crossing the main street without a traffic light was a significantly more stressful condition in terms of EDA responses, in comparison to a more neutral walking environment.

Finally, the few studies that focused on isovist parameters had conflicting results that could be attributed to differences in context. Hijazi et al. (2016) developed a regression model to determine the contribution of isovist properties in emotional responses. The study was conducted in Zürich, Switzerland, during autumn, with a sample size of 13 participants. While their results did not indicate a very strong relationship, it was noted that the studied spatial properties had a larger impact on negative emotions in comparison to the positive. The most critical isovist parameters in this model were occlusivity and perimeter. Occlusivity is connected to the degree of enclosure of space

(Xiang & Papastefanou 2019), and it has been connected to feelings of safety and security. The study of Li et al. (2016), which was conducted in the same city and during the same period, had similar findings. Xiang and Papastefanou (2019), who conducted a similar experiment in Hong Kong in springtime, noted that the results were different in their local context. The strong association between occlusivity and negative emotions, which was found in the studies of Hijazi et al. (2016) and Li et al. (2016), was not observed in the study of Xiang and Papastefanou (2019). The isovist area and maximum radial line were also significantly correlated with positive emotions in Hong Kong. An important finding of the study of Xiang and Papastefanou (2019) was that the transformation of isovist parameters might be a better predictor than the raw parameters.

As shown in this section, the broader research question which most studies have tried to answer up to now is related to the effect of different urban and environmental characteristics on physiological responses. This question is still far from being answered and requires research with a larger population sample. While some of the features used as inputs in the presented studies had good predictive power, it is difficult to identify if there is an agreement between the findings, due to the considerable variation in the feature set. More studies need to be conducted, considering differences in the local context. The influence of some features may vary across different cities and countries, due to differences in the climate and the urban fabric of the city, or cultural aspects. More research also needs to be conducted towards identifying the role of some understudied parameters, such as traffic and land use characteristics. It was also noted that some studies used models that were not appropriate for the statistical analysis of multiple data points generated from the same participants. They also did not mention any check for the effect of spatial autocorrelation, despite the fact that the presented maps of the spatial distribution of physiological responses sometimes suggested its presence. The analysis of spatial autocorrelation checks if the dataset has geographically close points with similar characteristics; if spatial autocorrelation is found, the results of inferential analysis may be skewed and the researchers have to choose statistical models which take this factor into account, such as spatial regression models (Anselin 2009).

1.2.3.2. SPATIAL ANALYSIS OF PHYSIOLOGICAL RESPONSES FOR UNDERSTANDING STRESS AND EMOTION PATTERNS IN THE URBAN FABRIC OF A CITY

The reviewed studies also showed that the collection and analysis of physiological responses in the urban space can be beneficial for understanding spatial patterns of stress and emotions in a local area. This analysis was conducted with methods for aggregation and clustering that allow the identification of hotspots.

The aggregation was most frequently conducted by averaging the responses over grid cells, points, zones or segments. Among the various methods, only the Getis Ord Gi* method allows identifying statistically significant clusters. The others are still useful, though, for visualising the variations in the spatial distribution of responses. These methods were commonly used for providing a visualisation of the responses in the studied area. The visual presentation of the hotspots was usually accompanied by a qualitative description of the contextual parameters of areas with intense stress or emotion responses. Many studies had as an objective the identification of features which influence physiological responses, and in those cases, the hotspot analysis was conducted for exploratory analysis and supported the hypothesis testing. For instance, Benita and Tunçer (2019) conducted hotspot analysis for the identification of stress hotspots. Then, they examined the distribution of the urban and environmental features in the hotspot and non-hotspot areas, to identify associations between features and stress responses. Shoval et al. (2018) constructed a map which was divided into grid cells, and each cell contained the average EDA data of all participants that walked through it. The researchers then conducted a qualitative analysis of the resulting visualisation by grouping the area in sites with different characteristics. Hijazi et al. (2016) used the Getis Ord Gi* method to identify hotspots of positive and negative emotional arousal. Then, they used photos describing the contextual characteristics of each cluster to understand which spatial conditions may be connected to positive or negative responses.

1.2.4. FUTURE PROSPECTS

As it was shown in sections 1.2.2 and 1.2.3, previous research on physiological responses in the urban space using continuous real-time monitoring has been primarily focused on testing theories of environmental psychology, or developing new theoretical models. The systematic analysis of the studies conducted in this area showed that for most of the reviewed studies, the broader research question was how the urban environment influences physiological responses. Further research in this area is undoubtedly significant, as it has the potential to bring considerable changes in the way that the urban environment is designed.

There are also some other potential contributions of this research field, which have not been investigated in previous studies, and can be identified at the local community level or the user scale. Given that there is a growing population with consumer activity trackers that sense physiological signals, we can imagine a future scenario where this data will be connected to a common platform for analysis, providing information to the local urban planning authorities in an anonymised manner. There is already a well-established presence of fitness tracking applications where users register their walking, running or cycling activity, using the GPS sensors of their smartphones or activity trackers. Endomondo, MapMyRide and Strava are among the most popular of such applications; the total number of uploaded activities in the case of Strava reached one billion in 2017, and two billion by the end of 2018 (Strava 2018). Strava has released Strava Metro as a service for urban planners and transportation analysts, offering anonymised, aggregated mobility data for a specified area in a bulk format. The utilisation of aggregated location data from fitness applications is already popular in a research context (Romanillos et al. 2015). Such data fall under the category of "user-generated health data", and their emergence has been discussed as a democratising force which challenges the traditional dynamics between health providers and citizens (Ostherr et al. 2017). Due to the rapidly increasing popularity of consumer activity trackers that enable physiological data tracking, this type of service could be offered in the future for physiological data as well. It could also be a part of local urban sensing initiatives, similar to crowdsourcing noise or air pollution data.

In this scenario, the analysis of physiological data at the urban scale would allow identifying local neighbourhood characteristics that have a positive effect on cardiovascular activity by encouraging activity and increasing aerobic exercise, or a negative effect by causing distress and anxiety. As mentioned in section 1.2.3.2, some of the studies which were included in the review included methods for the identification of hotspots of physiological responses; these methods can be used there to show which places are stressful or trigger negative emotional responses. In this way, the information derived from the analysis of physiological responses becomes actionable in the local context, as it allows the identification of local spots which need intervention.

At the same time, the localised analysis can still be used to enrich the findings presented in the reviewed studies, which are more related to broader research questions. One issue that was identified in the literature review is that most of the existing studies base their results on data gathered from a small population sample. The crowdsourcing scenario could assist in solving this issue by using data collected from a much larger and more diverse group, which can lead to more generalisable models.

The collection and analysis of physiological data in the urban space can also contribute to the advancement of health at a user level. Current methods for stress detection for individual use ignore the effect of urban space and have considerable difficulties in identifying the potential sources of stress when the user is moving outdoors. The methods used for the analysis of physiological data in the studies reviewed in this chapter are in the right direction towards covering this gap, as they consider the urban and environmental stimuli. A future prospect for this research strand at the user level could, therefore, be the implementation of the data analysis methods for creating a personalised tool for the participants. This tool could operate as an application that shows participants how different elements of their routes affect their personal stress levels. This task could be approached as a machine learning task for the prediction of physiological responses or stress from contextual data. As the literature review in this chapter shows (see also Figure 1.1), very few studies have worked towards this direction (Kanjo et al. 2018b; Ojha et al. 2019; Yates et al. 2017), since most studies focus on inferential and not predictive analysis.

Some studies have also referred to the potential of using the collected physiological responses to find the least stressful route for walking (Saitis & Kalimeri, 2018) or cycling (Werner et al. 2019), but this concept has not been further developed. The use of digital tools for pathfinding is well integrated into everyday life; the most popular route planning tools, though, take into account a very limited number of criteria, usually focusing on the shortest distance. The prospect of incorporating factors that can create a more pleasant and less stressful route is therefore very promising. It also provides a direct path for using the knowledge derived from the analysis of physiological data in a way that can have immediate benefits for the user. The redesign of urban spaces that are identified as potentially stressful is costly and requires considerable time and effort from the local authorities. The provision of route options that involve less exposure to urban stressors could, therefore, improve the experience of outdoor walking with minimal resources, in parallel to the long-term urban interventions.

The identified prospects for future research have the potential to act for the benefit of multiple stakeholders. The potential connections between the described steps and the different stakeholders are presented in Figure 1.6. The methods for identifying hotspots of stress or negative emotions will be most helpful at the city level, for the local urban planning committee. Methods for individual stress prediction and pathfinding for reduction of exposure to stressors will be most beneficial at a user level. The same data that is collected for these purposes can also be used to complement the broader research on the link between the urban environment and physiological responses.

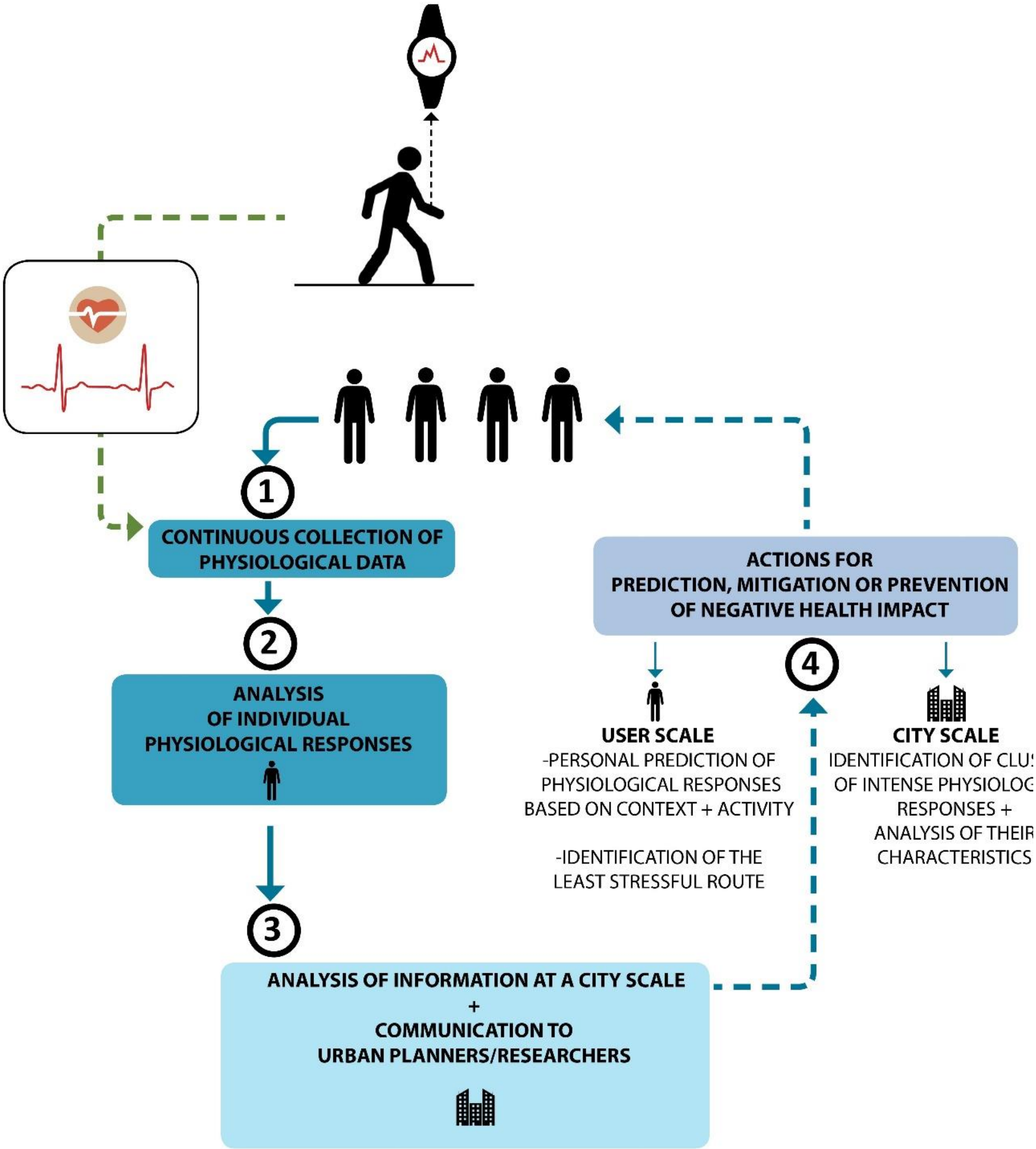


Figure 1.6. The connections between future applications and relevant stakeholders.

1.2.5. ISSUES AND CHALLENGES

A significant gap that was identified in terms of the overall approach in the past studies is the lack of progress in making the derived information more actionable for different stakeholders, at the city and the user scale. Section 1.2.4 outlined some scenarios for utilising and extending existing methods for physiological data analysis in the urban domain in a way that maximises the benefits at multiple scales.

There is currently lack of a methodology for collection and analysis of physiological data at the urban scale which combines all methods that will be useful at the city and individual level, in and out of a research context. The methodological analysis of previous studies in section 1.2.2 showed that some conceptual steps are generally followed in most studies. The stages of data collection, processing and fusion are necessary regardless of the goal of each study. There are some differences in the execution of these steps and the choice of relevant algorithms and tools, following the variation in the studied features. However, the most commonly followed steps do not cover the prospects that were identified in section 1.2.4. The area of prediction of physiological responses is especially understudied; the inclusion of both prediction and cluster identification was also very rare. The prospect of integrating this field of research with route optimisation studies for finding the least stressful or more comfortable route has also been identified but not further developed. A methodology for the collection and analysis of physiological responses in the urban environment, which maximises the impact of analysis by including all these aspects, is thus still needed.

Some other issues were also identified, related to several aspects of the study design and the methodology for data analysis followed in most studies. These issues can be grouped into two categories: issues related to the broader research question, and problems related to the scalability of the methods for data collection and analysis.

1.2.5.1. THEORETICAL, CONCEPTUAL AND METHODOLOGICAL ISSUES

1.2.5.1.1. LACK OF A CONCEPTUAL AND THEORETICAL FRAMEWORK DESCRIBING THE LINK BETWEEN URBAN ENVIRONMENT, ACTIVITY AND PHYSIOLOGICAL RESPONSES

Many different variables have been used as contextual data in the different studies, but there is still no consensus in terms of which of them influence physiological responses and how. Also, in some studies there is lack of a strong explanation regarding the selection of the studied features. Furthermore, the theories from the field of environmental psychology that were used have been almost exclusively supported until now by studies which examine physiological responses of participants that are sitting. It is uncertain if the urban and environmental features have the same effects during sitting and movement. These issues should be covered with a theoretical and conceptual framework, which would draw connections among the relevant theories, and situate within them the urban and environmental characteristics. The possible effects of movement should also be included there.

1.2.5.1.2. OVERLAP BETWEEN STRESS, EMOTIONS AND AROUSAL

Another issue is the overlap which exists between stress, emotions and arousal. Sometimes these terms are used interchangeably, especially when the grouping of negative and positive emotions is used instead of discrete emotions. Due to this issue, some of the reviewed studies may be measuring the same thing while giving it a different label. This issue is further complicated by the differences between reported and measured stress and emotions, which were found in several studies where the participants were asked to report their emotions or perceived stress levels for different locations (e.g., Shoval et al. 2018; Werner et al. 2019).

1.2.5.1.3. LACK OF ANALYSIS OF PHYSIOLOGICAL RESPONSES IN DIFFERENT CONTEXTS AND DURING FREE-LIVING ACTIVITIES

Another set of points which should be improved involves the study design that was used in most studies.

As shown in section 1.2.3, all the reviewed studies were focused on a specific context. It is difficult to say if the findings of each study are applicable in other environments, as there has not been any comparative study that would take the differences in contextual parameters into account. The only exception is the study of Xiang and Papastefanou (2019), who mentioned the possible cultural differences between the studied Asian and European environments in their analysis.

The vast majority of the reviewed studies also included data collected during a predefined walk. This study design creates an environment with similar circumstances for all participants; this choice is understandable, as the control of some variables is desirable in statistical analysis. At the same time, this setup cannot capture the wide range of contextual parameters within a city and the different activities that characterise the daily living. More research has to be conducted in this direction, using a study design that includes data collected during free-living activities. In this way, the collected data will capture a more accurate image of the contextual diversity found in daily outdoor walks.

1.2.5.1.4. LACK OF INCORPORATION OF THE EFFECT OF MOVEMENT

Another significant issue is the lack of inclusion of the effect of movement on physiological responses. The need to collect information regarding the activity has been mentioned in a few studies (Birenboim et al. 2019; Kyriakou et al. 2019; Werner et al. 2019). A recent study (Bielik et al. 2019), which compared physiological responses collected in the urban environment with responses collected during replications of the same walk in a controlled virtual reality setting, showed that the physiological arousal elicited from just viewing the urban form was lower than the same experience in the field. Some studies also reported a gradual increase of EDA along the route (Birenboim et al. 2019; Fathullah & Willis 2018, Griego et al. 2017; Osborne & Jones, 2017), and physical exertion might have played a role there. Up to now, this aspect has not been considered, and GPS data have been used mainly for geolocation of the responses. In parallel, movement analysis can be useful in the broader context of urban health, as it can be used to understand and promote physical activity in relation to the environment. There is thus another potential gain in the incorporation of movement analysis in the data fusion scheme, which should be considered in future studies. In this way, the collected data can be used simultaneously for stress mitigation and the promotion of physical activity.

1.2.5.1.5. LACK OF INCORPORATION OF NETWORK ANALYSIS DATA

There is also no integration of topological road network data (apart from Werner et al. 2019). The future inclusion of this data in the data fusion schemes will be essential for connection with route optimisation studies. It will also be useful for the identification of intersections. Many studies mentioned the observation of a possible link between physiological responses and intersections or traffic, in the context of walking (Bergner et al. 2013; Birenboim et al. 2019; Chen et al. 2018; Fathullah & Willis 2018; Hogertz 2010) and cycling (Caviedes & Figliozzi 2018; Nuñez et al. 2018; Zeile et al. 2016) but these were identified usually through video or visual examination of a map, apart from Chrisinger and King (2018) who used GIS. Topological road network data could be thus helpful for covering this gap.

1.2.5.2. ISSUES RELATED TO SCALABILITY

1.2.5.2.1. HEAVY RELIANCE ON PHOTOS AND VIDEOS AS SOURCES OF CONTEXTUAL DATA

Finally, there are some issues which affect the prospect of scaling up the study to include a large population sample, with data collected during unconstrained activities. One such issue is the heavy reliance on the use of video and photos as sources of contextual data. While the data collected from these sources is invaluable, the vast majority of studies that used these data sources examined the footage manually, which delays the process of analysis significantly. This issue can be handled in small scale studies, but it will become more amplified in the analysis of a large dataset, collected over many days and covering a large area. There are also questions regarding the ethical aspect of using this form of data collection.

1.2.5.2.2. AFFORDABILITY

While EDA data analysis has significant value for this research field, there is currently a lack of a low-cost consumer activity tracker that measures this signal. Affordability could, therefore, become an issue in a large-scale study. It would be of great value to explore more systematically what can be derived from affordable devices, which only track HR.

1.2.5.2.3. LACK OF A STREAMLINED, SCALABLE AND COMPUTATIONALLY EFFICIENT APPROACH THAT CAN BE APPLIED TO LARGE-SCALE STUDIES WITHOUT REQUIRING SIGNIFICANT MANUAL EFFORT

Another problem is the lack of a specialised platform or tool that can handle all the aspects of the collection and analysis of the different data streams. Most of the reviewed studies used at least two or more tools or platforms to cover all the required tasks. The overall process is still not fully streamlined and automated, as its nature is experimental in many studies.

The analysis of large sets of point data collected in an area with undefined boundaries will also have different computational challenges compared to the analysis of points of a predefined path. If we take spatial aggregation as an example, the area of grid cells or the length of the segment used for averaging the physiological responses are choices that affect the resolution of the analysis.

1.2.5.3. ACCURACY ISSUES

Another concern is the accuracy of the consumer activity trackers in comparison to clinical equipment. The Empatica E4 wristband, which was one of the most popular choices for EDA tracking, is considered as a device comparable to clinical equipment in terms of its power to identify stress-related events (Ollander et al. 2016). In terms of HR tracking equipment, some validation studies conducted in the past few years show the potential of using HR data from consumer wearable devices for research purposes (Lim et al. 2018; Shcherbina et al. 2017; Stahl et al. 2016; Xie et al. 2018). Shcherbina et al. (2017) compared HR data from Apple Watch, Basis Peak, Fitbit Surge, Microsoft Band, Mio Alpha 2, PulseOn, and Samsung Gear S2, with HR data from electrocardiographic monitoring, and found that most devices estimated HR within less than 10% error rate for all devices. Stahl et al. (2016) evaluated Scosche Rhythm, Mio Alpha, Fitbit Charge HR, TomTom Runner Cardio, Microsoft Band and Basis Peak. They reported that the correlation between the data from the consumer activity trackers and the criterion measure was high (0.87-0.96).

Other researchers though pose concerns (e.g., Wang et al. 2017b). At least two studies have shown that the measurement errors are higher during light exercise and minimised at high speeds (Dooley et al. 2017; Stahl et al. 2016). Apple Watch has lower error rates than other trackers (Dooley et al. 2017; Shcherbina et al. 2017; Wang et al. 2017b), but at least in one study, it produced significant errors during light and moderate activity (Dooley et al. 2017). Gorny et al. (2017) conducted a study for the validation of FitBit Charge HR which involved participant tracking for a month and found significant errors in HR reporting, which led to the misidentification of activity zones.

The study of Bent et al. (2020) also showed that the reporting of the HR data from the Empatica E4 can differ by approximately 12bpm from the actual HR during activity. The study of Benedetto et al. (2018), which involved a comparison of measurements from a FitBit Charge 2 and ECG data while the participants were cycling, suggested that there may be significant errors in individual measurements of the FitBit Charge 2. However, the mean error was small (-5.9 bpm). In another study, the accuracy of the FitBit Charge was higher during moderate activity and lower during light and vigorous activity (Dooley et al. 2017).

Gradl et al. (2019) provide a comprehensive review of fitness trackers and the signals they measure, as well as a rating of their potential ability to measure stress based on these signals.

While these studies point out that these devices cannot replace ECG technology at the moment, it is expected that at the accuracy issues will be eventually solved, on the basis that there is already a smartwatch in the market that has excellent results in terms of validity of heart rate variability during exercise at a very high intensity (Caminal et al. 2018).

1.2.5.4. ETHICAL CONSIDERATIONS

Finally, one issue that needs to be addressed is the disproportionate inclusion of population which is not disadvantaged from a socioeconomic or health perspective. Very few studies have focused on visually impaired people or elderly, and more research is needed on that front, also addressing the issues of people with other bodily or mental conditions. The inclusion of a qualitative data collection component along with the quantitative mapping is essential here, to gain a better understanding of spatial issues which may be more amplified in these cases.

A summary of the current challenges and future prospects is provided in Figure 1.7.

FUTURE PROSPECTS

A. CITY LEVEL

- **Inferential analysis:** Assistance in understanding the connection between the environment and physiological responses
- **Aggregation of physiological responses:** Assessment of the impact of local urban planning decisions on stress levels

B. INDIVIDUAL LEVEL

- **Stress/emotion detection with contextual analysis:** Personalized understanding of how different routes and outdoor environments affect stress/emotion levels
- **Predictive analysis:** Prediction of physiological states (i.e. stress) of a route based on contextual data
- **Route optimization:** Assistance in identification of the least stressful route

CURRENT CHALLENGES

A. METHODOLOGICAL ISSUES

- Lack of a methodology for collection and analysis of physiological data which can act for the benefit of multiple stakeholders (at the user and city level) and cover the identified future prospects

B. THEORETICAL/CONCEPTUAL ISSUES

- Lack of a theoretical and conceptual framework describing the links between urban environment, activity and physiological responses
- Overlap between the concepts of stress, emotions and arousal
- Lack of analysis of physiological responses in different contexts and during free living activities
- Lack of incorporation of the effect of movement in the analysis of physiological data in the outdoor space

C. ISSUES RELATED TO SCALABILITY

- Reliance on image-based methods for contextual data collection
- Affordability of data collection tools
- Lack of a streamlined, scalable and computationally efficient approach that can be applied to large-scale studies without requiring significant manual effort

D. ACCURACY

E. ETHICAL CONSIDERATIONS

- Lack of inclusion of population which is disadvantaged from a socioeconomic or health perspective

Figure 1.7. Current challenges and prospects.

1.3. RESEARCH AIMS AND OBJECTIVES

As shown in section 1.2, the collection and analysis of physiological data in the urban space can contribute significantly to the advancement of urban health. The review showed that future work in this area will be undoubtedly beneficial if conducted in a considerate manner. It will allow us to obtain a fine-grained understanding of how different environments generate different reactions at an individual or city level, because of urban stimuli or environmental factors. There is untapped potential in utilising physiological data collected in the urban space for the benefit of the local community and the users that generate the data.

The review also identified many issues in the existing methods for the analysis of physiological data, which hinder further research in this area. The lack of research into methods that could be used to extract useful information from the physiological data analysis and distribute it to different stakeholders, at the city and the user scale, is a significant gap in this research area. Other urban sensing initiatives related to urban health have managed to create much more direct links with the community; for instance, the visualisation of maps in a public dashboard, showing the hotspots of air pollution in a city (Badii et al. 2020), allows the city residents to plan their trips in a way that avoids exposure to pollutants. Urban sensing enriched with physiological data mapping has the potential to operate similarly and provide many benefits at the local community scale and the individual level. Currently, there is a lack of any effort towards this direction.

At the same time, research on the link between the urban environment and physiological responses is still in its early stages. There are still many issues hindering its progress; these are presented in detail in section 1.2.5. The research methods published to date for physiological data collection and analysis are designed primarily for use in a research context, in small areas and during predefined activities. These different domains can be bridged by creating methods for physiological data collection and analysis that address these issues and are scalable for future use beyond a research context.

Following the presented analysis, the research is linked to the following broader research question: *How does the urban environment affect physiological responses, and what is the role of different urban and environmental characteristics and activity in this process?*

Within this broader research question, which acts as the main driver for this study, the research will have a more specific focus on the generation of tools and methods that can assist in the provision of answers in the long term. Specifically, the research will explore the utilisation of computational methods, as these can be used in practical applications to link the physiological responses directly together with other relevant urban data and extract useful information, without requiring input from an expert. The research will thus investigate methods for the acquisition and analysis of physiological data in the urban space which can inform our understanding of the impact of the urban environment on health, and promote urban and individual health and wellbeing.

While the review in section 1.2 showed that some previous studies have also sought to answer the same broader research question, this study adopts a novel approach by attempting to cover the following gaps identified in section 1.2.5:

- *Lack of a methodology for collection and analysis of physiological data that can act for the benefit of multiple stakeholders at the user and city level*
- *Lack of research on methods for individual stress prediction during outdoor walking and pathfinding for reduction of exposure to stressors*
- *Lack of a theoretical and conceptual framework describing the possible links between urban environment, activity and physiological responses*
- *Lack of analysis of physiological responses in different contexts and during free-living activities*
- *Lack of incorporation of the effect of movement in the analysis of physiological data in the outdoor space*
- *Lack of efficient methods for the collection of contextual data*

The primary aim of this study is the construction of a methodology for the analysis of physiological responses in the urban space. The methodology seeks to inform and assist not only urban planners but also the citizens that generate the data. It should be applicable in a research context as well as a real-world setting and respond to different needs at the city and individual level. The focus will be on physiological data generated from wearables such as wristbands.

The study will attempt to address the following objectives to allow the synergy between the different stakeholders:

(1) To integrate the user-generated physiological data with other geotagged open data related to urban health, using scalable methods

(2) To establish methods for deriving patterns of physiological data responses and interpreting them at a user and a city level

(3) *To identify how the acquired information can be linked to computational models that can promote urban and individual health and wellbeing*

As defined in section 1.1, the study operates in the context of urban health. It attempts to enrich our understanding of the geospatial dimension of health by approaching it as a concept which should act simultaneously towards the benefit of both the user and the city. The primary focus will be on interpreting physiological responses in relation to stress, as this approach is more relevant in the urban health context. The research thus focuses on a specific area within the broader agenda of urban health; namely, the identification of methods for capturing and analysing physiological responses to urban stressors. The emotion-oriented approach will not be explored in this thesis, but this choice does not diminish its importance, as emotions encompass the subjective dimensions of experience, that are useful for understanding the interactions between people and space.

The computational methods that will be examined are relevant to the potential future applications presented in section 1.2.4. At the city scale, the aggregation of physiological responses can assist in identifying clusters of stress that may need intervention. At the individual level, physiological data collection and analysis can be used to provide a personalised analysis of the impact of context on stress and emotions, identify the least stressful route, and predict physiological responses based on spatial and environmental data. The computational methods that will be considered will be thus focused on hotspot and cluster analysis of physiological responses, individual stress analysis and prediction, and pathfinding for reduction of exposure to stressors, following the points discussed in section 1.2.4.

The study acts as a pilot project that will pave the way towards large-scale experiments in this area. It focuses on developing the conceptual and technical aspects of the components of the methodology and tests them in small-scale experiments.

Its main contribution is that it supports the construction of tools for individuals who want to understand how different routes might affect their physiological responses, and have a calm experience while walking in the urban environment. It can also help researchers identify which parts of the city are associated with an increased intensity of physiological responses, possibly indicating increased stress levels. The construction of a theoretical and conceptual framework supporting the construction of the methodology also enriches current research on the links between urban environment, activity and physiological responses. The research also involves the organisation of experiments for data collection (as it will be explained in detail in the next chapter, section 2.4) which generate new knowledge related to the broader research question. Other methodological and practical contributions include the development of methods for analysing how movement may influence physiological responses as a physical stressor, and their incorporation in the designed methodology; also, the development of methods for identifying physical and psychological stressors from contextual data, based on freely available OpenStreetMap and Point of Interest data, as an alternative to image-based analysis which was used in previous studies. A detailed presentation of the contributions is presented in Chapter 10 (section 10.3).

The design and testing of each component of the methodology also involved the development of scripts in Python. The scripts for each component can be found in the repository[2] created for this thesis in GitHub by the author.

1.4. THESIS STRUCTURE

The thesis is organised in two parts; The first part provides the necessary theoretical background and paves the way towards the construction of the methodology. The second part, starting from Chapter 5, presents the methods related to each component of the proposed methodology. More specifically, Chapter 5 outlines the methods for the analysis of physiological responses at an individual level. Chapter 6 moves the focus to the city scale, showing the results of the analysis of data collected in a series of outdoor experiments. The relationship between the contextual and activity data and physiological responses will be investigated in this chapter. Chapter 7 proposes methods for spatial analysis of physiological responses. Chapter 8 shifts the discussion back to the individual level, proposing methods for predicting physiological responses based on contextual and activity data. Chapter 9 proposes methods for route

[2] https://github.com/ddritsa/PhD-Thesis-repository

optimisation for minimisation of exposure to stressors. The presented models can embed physiological responses from one or more users, if available. Finally, Chapter 10 concludes the presented work by discussing the findings and suggesting further research directions.

A more detailed presentation of the content of each chapter follows below, starting from Chapter 2.

— Chapter 2 presents the proposed methodology for collection and analysis of physiological data based on urban and contextual data. The methodology incorporates three components: (1) the analysis of physiological data at an individual level, (2) the hotspot analysis of physiological responses at a city scale, and (3) the utilisation of the collected data in models for prediction of physiological responses, and pathfinding methods for the identification of the least stressful route. The research design is then outlined, presenting the steps taken to address the identified objectives and the experiments designed for data collection.

— Chapter 3 starts from a discussion of fundamental physiological functions related to daily activities, aiming to understand the connections between different concepts and functions such as information processing, stress, and physical activity. The physiological signals discussed in this study are also introduced here.
After that, the focus shifts from the body to the urban environment, to understand which urban characteristics may affect physiological responses by encouraging different kinds of physical activity or acting as psychological stressors. Urban theories on neighbourhood vitality, stimulation and restoration are discussed, showing how the urban domain becomes a vessel for the expression of the fundamental physiological concepts outlined at the beginning of the chapter. The chapter ends with the presentation of a theoretical and conceptual framework for the selection of contextual and activity-related features that may influence physiological responses. The features which are

identified here as significant in relation to physiological responses will be later used as input in the data analysis model.

- Chapter 4 outlines appropriate methods for the analysis of temporal and spatial data. The primary focus is on time-series and spatial data which are used in this research, such as speed, accelerometer, heart rate, electrodermal activity, street network and Point of Interest (POI) data. This chapter provides the necessary background in terms of algorithmic approaches related to the research and outlines a conceptual scheme for physiological, movement and spatial data fusion. This scheme is the basis for the methods presented in Chapter 5.

- Chapter 5 describes the methods related to the first component of the methodology presented in Chapter 2. The outlined methods involve the data collection, the analysis of movement, physiological and contextual data, and their fusion based on the literature reviewed in Chapter 4. An essential part of this process is the construction of the spatial database used for contextual data extraction, based on POI and OpenStreetMap (OSM) data. The features which were identified as relevant in the conceptual framework of Chapter 3 are extracted and incorporated in the analysis. A method is also proposed for the classification of physiological responses based on the underlying contextual and activity data. The method is based on classifying the underlying parameters as potential physical or psychological stressors.

  The method is, then, demonstrated using data collected during one of the experiments conducted in Sydney. Data from selected users are analysed, mapping the physiological responses occurring over a route and the built and environmental features which the user encountered. The physiological responses are matched to different contextual stimuli or changes in activity and other features and discussed accordingly. This part of the research will assist individuals in understanding how different parameters may affect their physiological responses. Researchers can also use the presented methods (particularly the data fusion model) to analyse physiological responses collected in the context of outdoor experiments.

— Chapter 6 extends the work presented in the previous chapter by using the data fusion model described in Chapter 5 for the analysis of the data collected during outdoor experiments in Sydney and Zürich. While the data fusion scheme also includes heart rate analysis methods, the focus will be on electrodermal activity data analysis from this chapter and onwards. The chapter first outlines the characteristics of the data collected in the different experiments. Then, it applies statistical analysis methods to investigate the relationship between the physiological responses and the movement-related and contextual features used in the data fusion scheme. This analysis enriches the presented methodology by providing evidence regarding the relationships between the different features and shows that the conceptual framework presented in Chapter 3 was in the right direction. The chapter also demonstrates that the data fusion scheme presented in Chapter 5 is applicable in different contexts.

— Chapter 7 presents the methods related to the second component of the proposed methodology. The presented work builds on previous studies that used hotspot analysis to identify clusters of physiological responses. It extends previous approaches by adding methods for separation of the derived hotspots of physiological responses into clusters. Methods for analysis of the importance of each cluster are also added, and for the extraction of its properties. This part of the research will help urban planners and researchers identify which parts of the city are associated with an increased intensity of physiological responses, possibly indicating increased stress levels.

— Chapter 8 presents methods related to the third component of the proposed methodology. This part of the work explores algorithms for predicting the physiological responses during a route based on the underlying contextual and activity-related parameters. Different machine learning models are tested against performance metrics related to the accuracy of the prediction. Data collected in Sydney and Zürich are used to train and test the models. The proposed methods can be used by individual users who want to understand how different routes might affect their physiological responses but do not have the required equipment.

— Chapter 9 presents methods for route optimisation towards finding the least stressful route. The conceptual framework proposed in Chapter 3 is used to select relevant features that may affect physiological responses. Network analysis is used for finding paths that satisfy the selected criteria. The spatial database described in Chapter 5 is used to extract the features and incorporate them into the network. Existing hotspots of physiological responses are also inserted in the network. Different options are explored for finding the optimal route and compared against the benchmark (the shortest route based on travel time) in terms of the exposure to stressors. Individuals can use these methods to minimise their encounters with potentially stressful urban features and have a calmer experience while walking in the urban environment.

— Chapter 10 discusses the overall work by revisiting the research question and evaluating how the findings of each chapter contributed to responding to the defined objectives. After elaborating on the research contributions and limitations, the thesis concludes with outlining future research directions.

2

RESEARCH DESIGN

2.1. INTRODUCTION

The previous chapter discussed the emergence of wireless activity trackers that collect physiological data as an example of smart technologies that can promote individual and urban health. The chapter showed that there is potential in extending existing methods for physiological data analysis in the urban domain in a way that maximises the benefits at the individual and the city scale. The review also identified several issues related to theoretical, methodological and practical aspects.

This chapter presents a methodology for collection and analysis of physiological data in the urban environment. The methodology is designed to address the aforementioned research objectives and the identified issues. The research design is subsequently described by outlining the experiments developed for data collection.

2.2. THE METHODOLOGY FOR COLLECTION AND ANALYSIS OF PHYSIOLOGICAL DATA IN THE URBAN SPACE

Following the research aims and objectives presented in section 1.3, a conceptual methodology is proposed for the collection and analysis of physiological data in the urban environment (Figure 2.1).

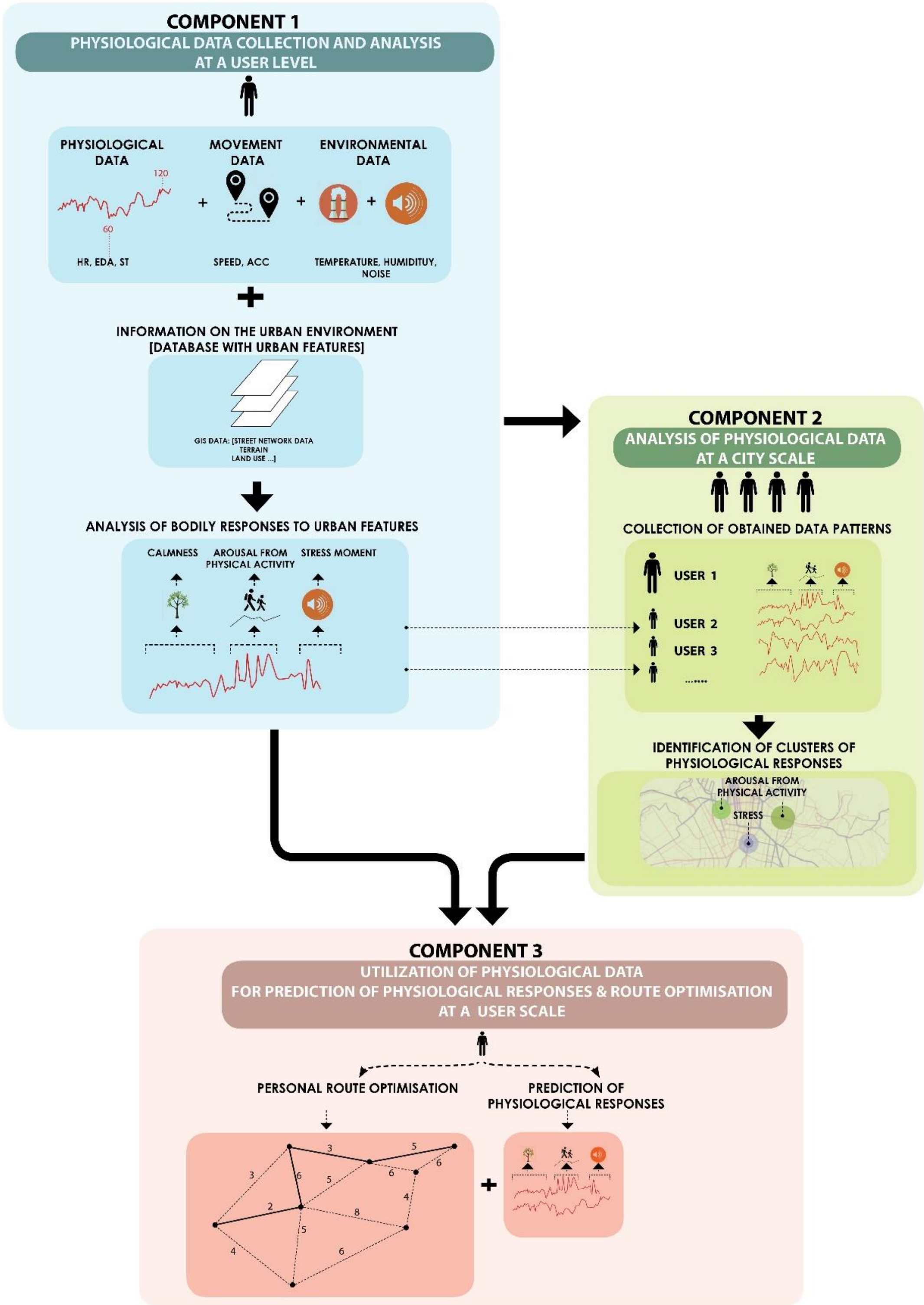


Figure 2.1. The components of the proposed methodology

The methodology is composed of the following three components:

(1) ***Collection and analysis of geotagged physiological data at a user level:***

   a. *Analysis and classification of acquired physiological responses, based on the extraction of movement patterns of individuals in the urban environment and analysis of urban and environmental features.*

(2) ***Analysis of geotagged physiological data at a city scale:*** *Identification of spatial clusters which generate similar physiological responses, indicating stressful areas where intervention is needed.*

(3) ***Utilisation of the collected data in route optimisation and predictive analysis at a user level:***

   a. *for individual route optimisation*
   b. *for prediction of physiological responses based on contextual characteristics*

Component 1 involves collecting individual physiological data, followed by their integration in a database composed of other geotagged data sets (movement, urban and environmental data), and analysis at an individual level. This stage includes a data fusion scheme for the different data sets and leads to a classification of physiological states (i.e., high/low physiological arousal or stress) accompanied by information on movement and the presence of different urban or environmental features at each state. Particular emphasis here is on identifying different movement phases which may be related to physiological responses and classifying them accordingly. This step will cover the gap identified in the previous chapter regarding the lack of incorporation of the effect of movement in the analysis of physiological responses.

Component 2 involves examining the routes at a city scale for the identification of clusters of intense physiological responses. The workflow shall involve hotspot analysis, cluster separation, identification of cluster significance and analysis of the properties of each cluster. This component will assist in understanding which clusters of the city are creating different physiological responses, and organising interventions based on that.

Component 3 involves utilising the analysed information at an individual level by identifying the least stressful route and predicting physiological responses based on spatial and environmental data.

In terms of the connections between components and different stakeholders, component 1 will be assistive at a city scale by being the primary input for component 2; at the same time, it can be used for individual analysis of physiological responses based on contextual data, assisting single users in understanding how their interaction with the urban environment affects their physiological responses. Component 2 is relevant for researchers and local planning authorities, while component 3 is beneficial for individual users.

2.3. LINKING THE PROPOSED METHODOLOGY WITH THE IDENTIFIED ISSUES

While the primary aim of this work is the design of the methodology for collection and analysis of physiological data in the urban environment, this research is still connected to the broader research question of *how does the urban environment affect physiological responses.* More specifically, the proposed methodology will incorporate solutions to some of the issues related to the broader research question, as identified in Chapter 1 (section 1.3). A summary of these issues is presented below:

(1) Lack of a theoretical and conceptual framework describing the possible links between urban environment, activity and physiological responses

(2) Lack of analysis of physiological responses in different contexts and during free-living activities

(3) Lack of incorporation of the effect of movement in the analysis

These points are relevant for the objective of this work and will inform the design of the methodology. The construction of the theoretical and conceptual framework is necessary for understanding which urban, environmental and movement-related features should be included as contextual parameters in the model. The organisation of experiments during free-living activities and in different contexts is also necessary for testing if these features have the same effect in different circumstances, and taking this into account in the designed methodology. The possible effects of movement also must be understood, before constructing a model for classification and interpretation of physiological responses according to their source. The investigation of these points is essential for ensuring that the designed methods are generalisable to a certain degree.

The design of all methods will be shaped having in mind the issues related to scalability that were identified in Chapter 1 (section 1.2.5.2). These issues are summarised below:

(1) *Heavy reliance on photos and videos as sources of contextual data*
(2) *Lack of a streamlined, scalable and computationally efficient approach that can be applied to large-scale studies without requiring significant manual effort*

This study will attempt to solve these issues by exploring the potential use of existing spatial databases such as OpenStreetMap (OSM) and Point of Interest (POI) data as an alternative to image-based analysis. The utilisation of POIs and OSM network data in the analysis of physiological data, without the inclusion of any other source for the provision of contextual data, is a novel approach. The choice of POI and OSM data for this purpose is based on their online availability and nearly global coverage. These characteristics will ensure the scalability and applicability of the methodology in different environments, in a way that would not be possible with image-based analysis. The inclusion of OSM data will involve the integration of topological street network data. This information will be essential for the construction of pathfinding models in component 3, and other parts of this research.

The conceptual design of the methodology will be followed by testing and refining the different methods with the help of practical experiments, which will be presented in the next section. A programming language (Python) will be used for the construction of all the methods, following a componential logic. This solution allows arranging the execution of all the necessary tasks as components of a streamlined process.

2.4. RESEARCH DESIGN

2.4.1. OVERVIEW OF RESEARCH STRATEGY

The research strategy for addressing the research aims and objectives involves tackling different components of the methodology. The strategy is organised in three main steps (points 1-3 in the scheme presented below): (1) *literature review*, (2) *experiment design and analysis of the collected data*, and (3) *construction of the components of the methodology*. As the research is primarily focused on constructing a new methodology, the main objective of the designed experiments is to test and refine the methodology by collecting data from multiple users. The second aim is the investigation of some parameters linked to the construction of the methodology. The scheme presented below outlines the actions related to each step of the research strategy:

1) Literature review
   a) The first part of the literature review (Chapter 3) will be dedicated to identifying possible links between urban environment, activity and physiological responses. The product of this phase will be a theoretical and conceptual framework that will act as the backbone of this research.
   b) The second part of the literature review (Chapter 4) will lead to the identification of appropriate methods for the analysis of the multiple data streams. The product of this phase will be the creation of the data fusion scheme.
2) **Experiment design and analysis of data collected during different activities for the following purposes:**
   a) Primary goal: To build the designed methodology
   The research will utilise the data collected during the different experiments to support the design and calibration of algorithms for different steps of the methodology. Most of the tasks of this step require the construction of a ground-truth dataset for the application of supervised machine learning algorithms. The required tasks are the following:
      i) Construct the activity and EDA artefact classification algorithms that will be used in the data fusion model
         (1) Collect labelled activity data for training the activity classification model
         (2) Collect EDA data and use them for training an EDA artefact classification model
      ii) Collect data for the development of the cluster identification algorithm
      iii) Collect data for training the machine learning model for prediction of physiological data
   b) Secondary goal: To test the assumptions of the conceptual framework:

This part of the research will involve inferential analysis (Chapter 6) for the investigation of the relationship between features of the urban environment, activity and physiological responses, based on the conceptual framework presented in Chapter 3.

Chapter 3 will show that there is strong evidence to support the presented links. However, some effects may manifest differently during unrestricted outdoor movement and under specific circumstances, or have a different magnitude based on the context. The inferential analysis in this step will, therefore, assist in obtaining a better understanding of these relationships in real-world circumstances. This analysis will also be highly significant in the context of the broader research question. It will be used to build and refine the model for classification of physiological responses in component 1 and the pathfinding model of component 3.

This phase also involves testing the assumption that POI data can be used as an indicator of the stimulus-related complexity of an environment. Chapter 3 will provide the necessary theoretical background for this argument. This analysis is presented in Appendix A, and it acts as a supportive step for this research.

3) **Construction of the components of the methodology**

This is the final step of the research, where the developed theoretical and conceptual framework and the collected data will be used for the following tasks:

a) *Construction of the data fusion model and the scheme for classification of physiological responses according to different stressors (component 1 of the methodology)*
b) *Construction of a workflow for cluster analysis of physiological responses (component 2 of the methodology)*
c) *Construction of a machine learning model for prediction of physiological responses based on contextual and movement data (component 3 of the methodology)*
d) *Construction of a pathfinding model, for finding a route that minimises exposure to stressors (component 3 of the methodology)*

e) Demonstration of the applicability of the designed methods in different contexts

The overall research strategy is presented in Figure 2.2.

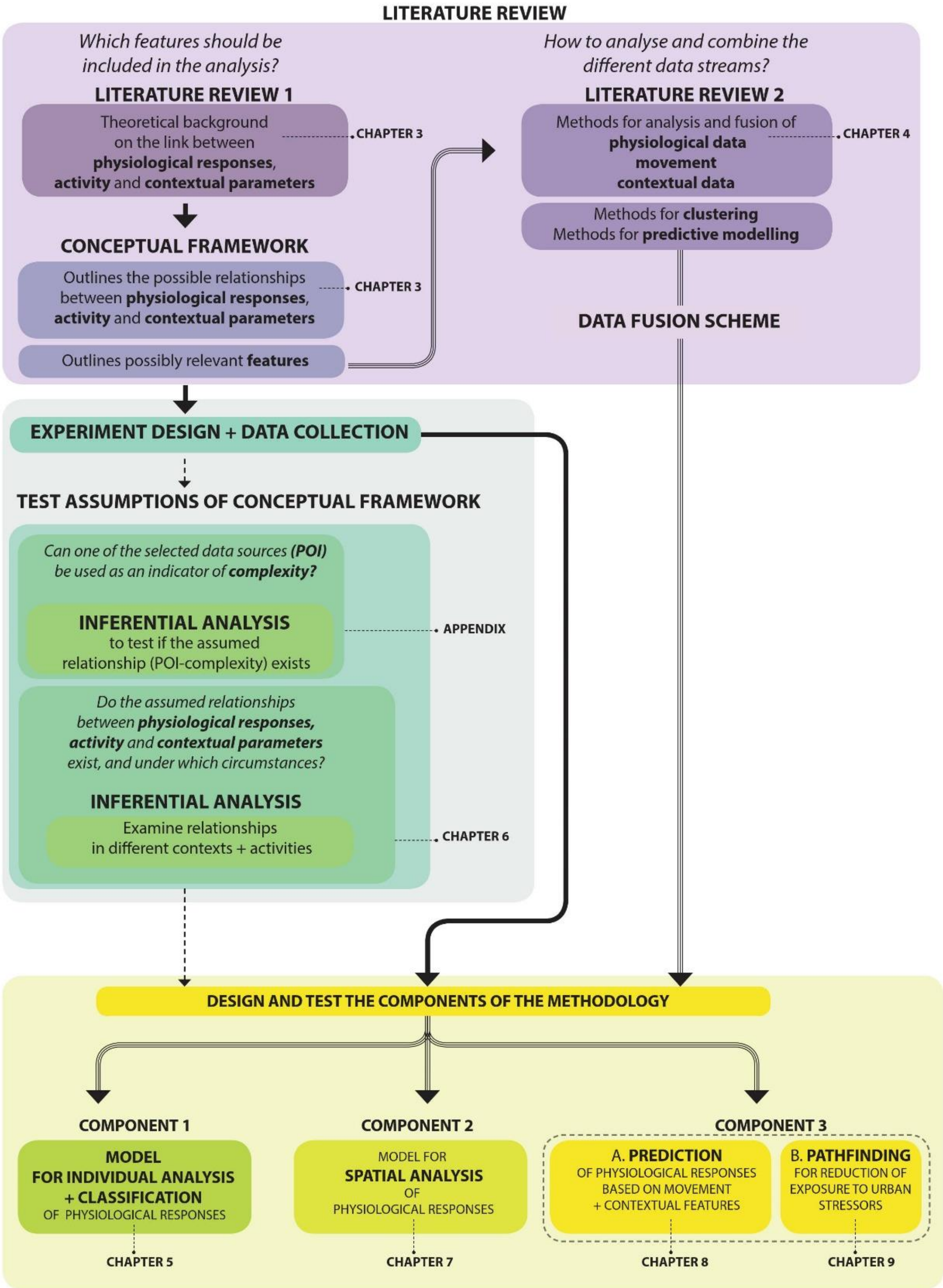


Figure 2.2. The research strategy

The following section will elaborate on the experiments that were designed to support the outlined research strategy.

2.4.2. EXPERIMENT DESIGN

The research involved a combination of controlled, semi-controlled and uncontrolled experiments for data collection. This definition is based on the degree of control over the parameters that can affect the studied variable (Kircher et al. 2017). The semi-controlled experiment is a hybrid between the two other setups; in this study, it involved asking the participants to walk on a predefined outdoor route.

The inclusion of the three different setups was necessary due to the different requirements of each task in the research strategy. A set of experiments was organised accordingly. These experiments were conducted in Sydney after obtaining ethics approval (UTS HREC REF NO. ETH19-3752). Secondary data were also used from an existing database with publicly available data. This database included data collected in Zürich in the context of a similar project (ESUM 2018). The dataset was used after obtaining ethics approval (UTS HREC REF NO. ETH20-5253). The letters of approval for the two ethics applications are provided in Appendix D (section D.1 and D.2). Figure 2.3 presents the different datasets, classifying them according to the setup and demonstrating the relationships between the studied populations. The same data were used for different purposes, such as inferential analysis, prediction of physiological responses, hotspot analysis and other tasks, as it will be explained in Chapters 5 to 9.

The experiments conducted in Sydney involved two phases (A and B). Phase A involved a controlled and a semi-controlled experiment, and Phase B involved an uncontrolled experiment. All participants in Sydney completed Phase A; most of them also completed Phase B. The primary targets for recruitment were people affiliated with UTS (research/master students, working staff, and their family members and friends).

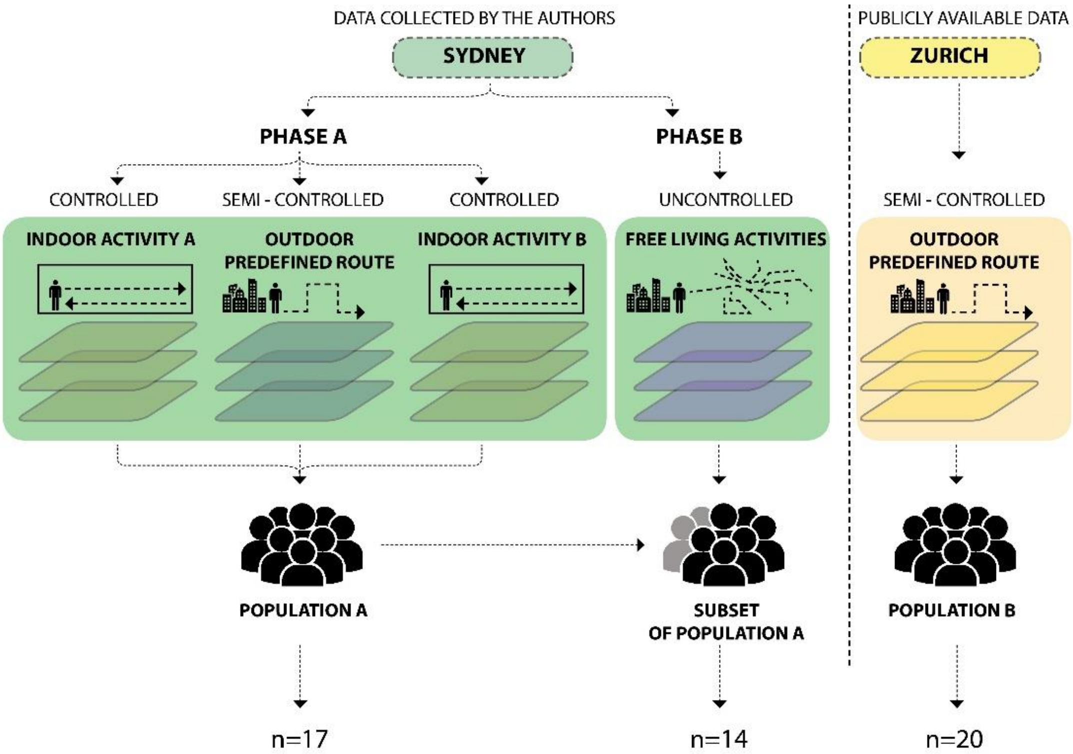


Figure 2.3. Presentation of the datasets used in this study.

A brief description of the conducted experiments follows below.

- Phase A involved indoor and outdoor tests. This phase started with an indoor experiment where all participants were given two wristbands (FitBit Charge 2, Empatica E4) and were asked to perform the same set of activities (moving, sitting, standing, talking) for a specific time. The indoor test was followed by an outdoor experiment where all participants walked on a predefined route around UTS, for approximately 40 minutes. A map of the route is presented in Figure 2.4. After that, the indoor test was repeated. The data collection was organised separately for each participant at their convenience. After each test, the users were asked to complete a questionnaire regarding their perceived experience during the test, using the PANAS scale to measure the affect (Watson et al. 1988). The questionnaire is presented in Appendix D (section D.4). The total time needed to complete all the activities of Phase A (controlled indoor and semi-controlled outdoor activities) was approximately 1.5 hrs.

— Phase B involved uncontrolled data collection during the participants' daily routine. The participants were asked to use the two wristbands and their smartphone for data collection while walking outside. This phase lasted seven days. A questionnaire and a note-taking component in the form of a journal was also used for qualitative data collection.

As for the data collected in Zürich (Ojha et al. 2019), the setup was very similar to the outdoor test of Phase A in Sydney. The participants were again following a predefined route in a local neighbourhood.

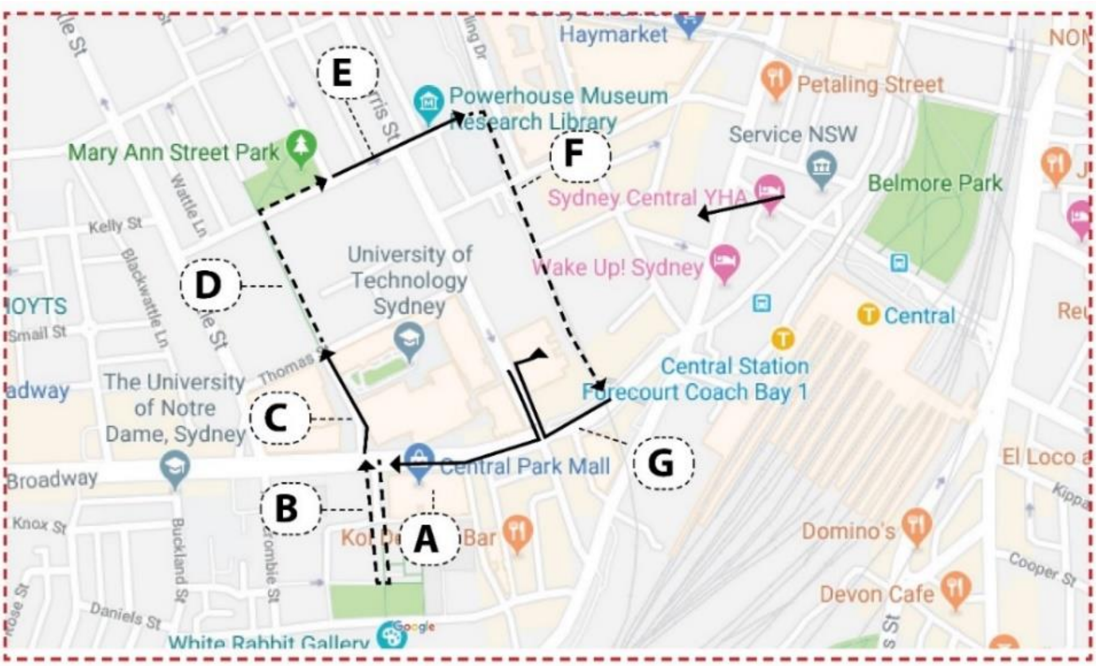


Figure 2.4. The predefined route for the outdoor test in Phase A of data collection

A more detailed description of Phase A (focused on the outdoor route) and B of the experiments in Sydney will be provided in Chapter 6. The protocol followed in the indoor tests in Phase A is outlined in detail in Appendix C (section C.1.1). The participant information sheet, which was used to explain the procedure to the prospective participants, is provided in Appendix D (section D.3).

The note-taking component in Phase B was used as a form of self-reporting during the free-living activities. The participants were asked to keep short notes at the end of each day regarding the places that they encounter during their routes. The inclusion of these observations and notes was primarily designed for identifying any unexpected incidents that might influence the results. The notes were also inspected for the identification of any useful information regarding the user experience. The guide given to the participants for using the equipment and keeping notes during the free-living activities is presented in Appendix D (section D.5).

The two wristbands (FitBit Charge 2, Empatica E4) which were used in the experiments conducted in Sydney can be viewed in Figure 2.5. They were chosen based on the following parameters: the data that they capture, the cost, the ease of measurement and use by the participants, and the ease of accessing the captured data. The FitBit Charge 2 was chosen as an example of an affordable consumer activity tracker which captures HR data. It can also be connected to Strava, which is a third-party application that captures the movement of its users using GPS data, and allows the integration of different consumer activity trackers. The fact that this device can be connected to Strava eases the process of collecting the captured data automatically, using only the user credentials (email and password), as explained in Chapter 5 (section 5.2.2). However, the FitBit Charge 2 does not capture EDA data, which can offer more information regarding the changes in stress levels compared to having only the HR data. The Empatica E4 was chosen as a device offering the measurement of EDA and accelerometer data with high accuracy (see section 1.2.5.3) while also capturing heart rate data. However, its cost is much higher, thus lowering its market reach. The two devices do not capture GPS data, but this step can be easily covered in both cases by using the smartphone of the participant.

Figure 2.5. The wristbands used in the study (left: FitBit Charge 2; right: Empatica E4)

Due to these reasons, it was initially decided to use both wristbands in order to capture all the desired parameters (HR, EDA, GPS, accelerometer data) and test the capacity of the algorithms to be used by devices of different degrees of affordability. The participants were asked to wear the two wristbands simultaneously, one on each hand.

As for the role of each experiment in the overall research plan, the indoor tests in Phase A were primarily designed to support the construction of the EDA artefact recognition and activity classification algorithms in step 2a of the research strategy presented in section 2.4.1. These required the collection of data during a designed sequence of activities, to act as ground truth data. A controlled experiment was the most appropriate design for this case, as the performed activities had to be timed and labelled.

All the outdoor data from Sydney and Zürich were used for the calibration of the cluster analysis methods. Semi-controlled and uncontrolled experiments were the most suitable for this purpose, as the designed methods had to be constructed based on data collected in the urban space. They also had to be applicable in real-life circumstances. The same applies to the collection of data for the prediction of physiological responses.

The inferential analysis related to the conceptual framework (step 2b of the research strategy) included the analysis of all the available data, to study the effect of different features on physiological responses under diverse circumstances. The primary focus was on the data collected in the urban space, but the data from the indoor experiments were analysed as well, with the results presented in Appendix C. The inclusion of data from two different contexts was invaluable for the inferential analysis, but also for ensuring that the designed methodology is not only applicable in a specific setting.

The data collection for the experiment in Sydney was conducted between July and November 2019. 18 participants completed the indoor and outdoor controlled and semi-controlled activities. From this group, 15 also participated in the uncontrolled data collection during free-living activities. One participant was excluded from the data analysis, as they exhibited very low activity in terms of EDA responses, producing very few responses above the 0.05μS threshold during several hours of data collection. The final sample size for the data collected in Sydney was thus 17 for the controlled and semi-controlled activities and 14 for the uncontrolled activities (Figure 2.3). The dataset collected in Zürich contained data from 30 participants; among those, 20 generated usable data without artefacts (Figure 2.3). Figure 2.6 displays the demographic characteristics (age and gender) for the data collected in Sydney. The figure does not include the same information for the data collected in Zürich, as there was no available gender data. The table with the age data for Zürich (named 'Pre_Post Survey' in the ESUM repository; ESUM 2018) also had some errors (two participants had the same ID but different demographic information and one participant ID was missing). Therefore, it was decided not to report detailed information for the age data for the Zürich dataset. However, all the participants in the Zürich dataset were between 20 and 51 years old, according to the table mentioned above, with most of them aged 20 to 39 years. The selected participants in the Zürich dataset are a subset of this age group.

Demographic characteristics		Sydney		
		Phase A		Phase B
		Controlled (Indoor activity)	*Semi-controlled (Outdoor activity)*	*Uncontrolled (Free living activities)*
Number of participants *(including participants who were later excluded due to artefacts in the data)*		18	18	15
Final sample size *(number of participants after excluding some participants due to artefacts in the data)*		17	17	14
Gender *(for final sample size)*	Female	9	9	8
	Male	8	8	6
Age *(for final sample size)*	20-29	7	7	5
	30-39	8	8	8
	40-49	2	2	1

Figure 2.6. Demographic characteristics for the data collected in Sydney

While the sample size is small in each of the analysed datasets, the previous chapter showed that studies that measure physiological responses in the urban environment usually have a small number of participants (median=18). From those studies, those that included inferential analysis had a similar sample size (median=20). Only four studies had more than forty participants.

The sample size of this study is, therefore, similar to other studies related to physiological responses in the urban environment. The scope is limited to studying a relatively small number of participants, and the results will reflect the characteristics of the studied population. The inferential analysis presented in Chapter 6 may be vulnerable to the type II error, and the collected data cannot cover all the possible situations in terms of context and diversity in the participants. The limitations regarding the external validity of the study will be considered in the interpretation of the results. However, the primary focus of the study was on the construction of the methodology, and not on the inferential analysis. The results will still be helpful despite the known limitations and reflective of similar contexts. They will also be very assistive towards the future organisation of collaborative studies among different countries. The study will act as a pilot project that provides a proof of concept and showcases its potential. The scope of the project is limited to testing the viability of the developed methods and solving the existing challenges. These steps are essential for confirming that the overall concept is sound before moving to experiments on a larger scale.

Another issue which should be discussed here concerns the difficulty to collect data with the FitBit Charge 2. After the experiment commenced, it was discovered that the smartphones of some participants could not connect to the FitBit Charge 2 wristband. This was due to a recent upgrade in the smartphones' Android software. Due to this issue, the HR data from the FitBit devices of approximately half of the participants could not be accessed. The connectivity issues of the FitBit Charge 2 wristband, and the choice of using data from two wristbands, have some repercussions. First, some components of the designed algorithms are more useful for users of the Empatica E4, as the FitBit Charge 2 lacks some data layers (specifically EDA data). However, most FitBit devices also collect accelerometer data, which can be accessed using the FitBit API, and then used to predict the EDA data (which is currently unavailable in FitBit devices and some other commercial activity trackers). Chapter 8 is devoted to the presentation of methods for this type of predictive analysis in detail. Second, the algorithms for HR analysis were tested using the HR data from the Empatica E4 and any available data from the FitBit devices. The methods involving HR analysis need more calibration, as explained in Chapter 5 and 10. The inferential analysis was also conducted using only

EDA data from the Empatica E4 wristband, as explained in Chapter 6. These issues are discussed in detail in the next chapters and in section 10.4, which presents the research limitations.

2.5. CONCLUSION

This chapter presented a methodology for collection and analysis of physiological data in the urban environment. The methodology was designed as a response to the main challenges and prospects identified in Chapter 1, and it was presented at a conceptual level.

The research design was then described, consisting of literature review on topics relevant to the construction of the methodology, analysis of data collected during experiments, and construction of the methods related to each component of the methodology. A series of experiments in Sydney were designed to support the research. The experiments involved data collection during a controlled indoor setup, a semi-controlled setup (walking on a predefined route) and an uncontrolled setup (data collection during free-living activities). Publicly available data collected in Zürich were also acquired.

The next chapters (Chapter 3 and 4) will present the results of the specialised literature review, paving the way for the detailed presentation of each component of the methodology from Chapter 5 and onwards.

3

UNDERSTANDING THE CONNECTION BETWEEN URBAN FEATURES AND PHYSIOLOGICAL RESPONSES: A REVIEW

3.1. INTRODUCTION

As shown in Chapter 2, the links between urban environment, movement and physiological responses are not well understood. Most studies up to now analysed the effect of green on physiological responses. For this research, it is essential to identify contextual features which may affect physiological responses, and map them.

Furthermore, existing theories from the field of environmental psychology, which connect environmental parameters to stress and emotions (Kaplan & Kaplan 1989; Ulrich et al. 1991) are mostly focused on the analysis of the restorative capabilities of the environment while sitting. Since this research is focused on the measurement of physiological responses during outdoor walking, it is essential to understand the potential effects of movement on physiological responses, and include them in the analysis.

This chapter aims to cover these gaps by providing a theoretical background on the process of generation of physiological responses. As explained in the previous chapter, this chapter outlines the theoretical background which supports the design of the proposed methodology. This work primarily supports component 1 (Figure 3.1).

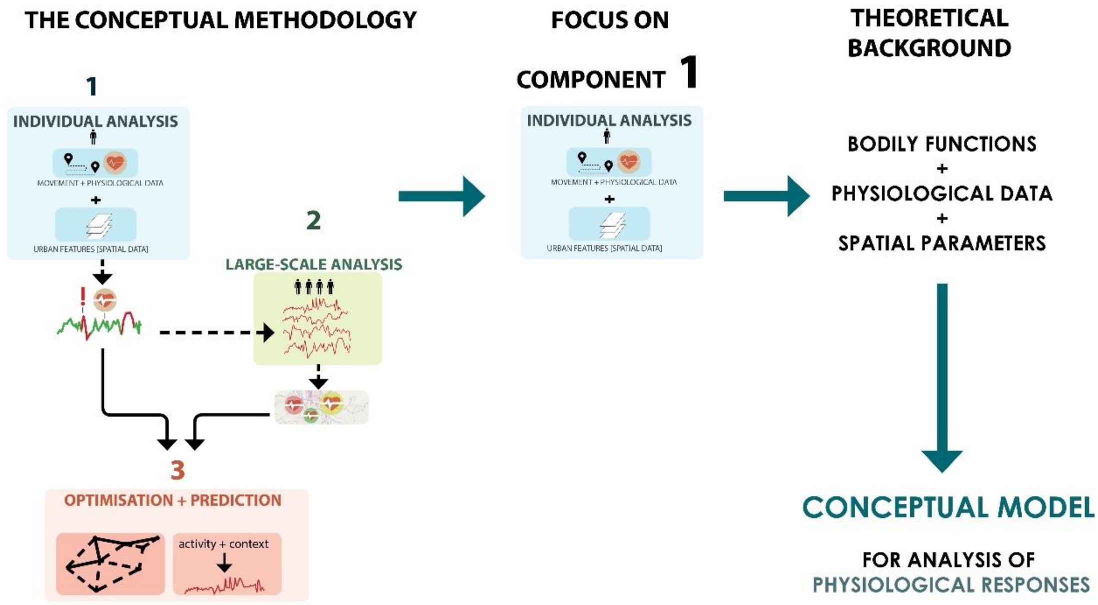


Figure 3.1. The aim of the chapter and the connection with the conceptual methodology.

The chapter is organised as follows: section 3.2 situates physiological responses within broad concepts related to health. This part of the review examines the underlying bodily mechanisms related to physiological arousal, stress and physical activity. Section 3.3. describes the impact of stress, physical activity and other factors on the examined physiological signals (HR and EDA). The focus then shifts to the study of the urban environment (section 3.4) and its role in modulating physiological responses.

After outlining relevant theories from studies on physiological arousal, stress research and environmental psychology, a theoretical framework is presented in section 3.5. The theoretical framework assists in categorising features of the urban environment in terms of their potential effect on physiological responses. A conceptual framework is then presented, outlining the specific urban and movement-related features that this work will examine, and the possible links between these features and physiological responses. The chapter ends with a discussion of the presented work and the future steps in section 3.6.

3.2. INFORMATION PROCESSING, STRESS AND PHYSICAL ACTIVITY

This section commences with a brief review of fundamental bodily processes associated with physiological responses (Figure 3.2). The concepts which will be examined involve information processing, stress and physical activity.

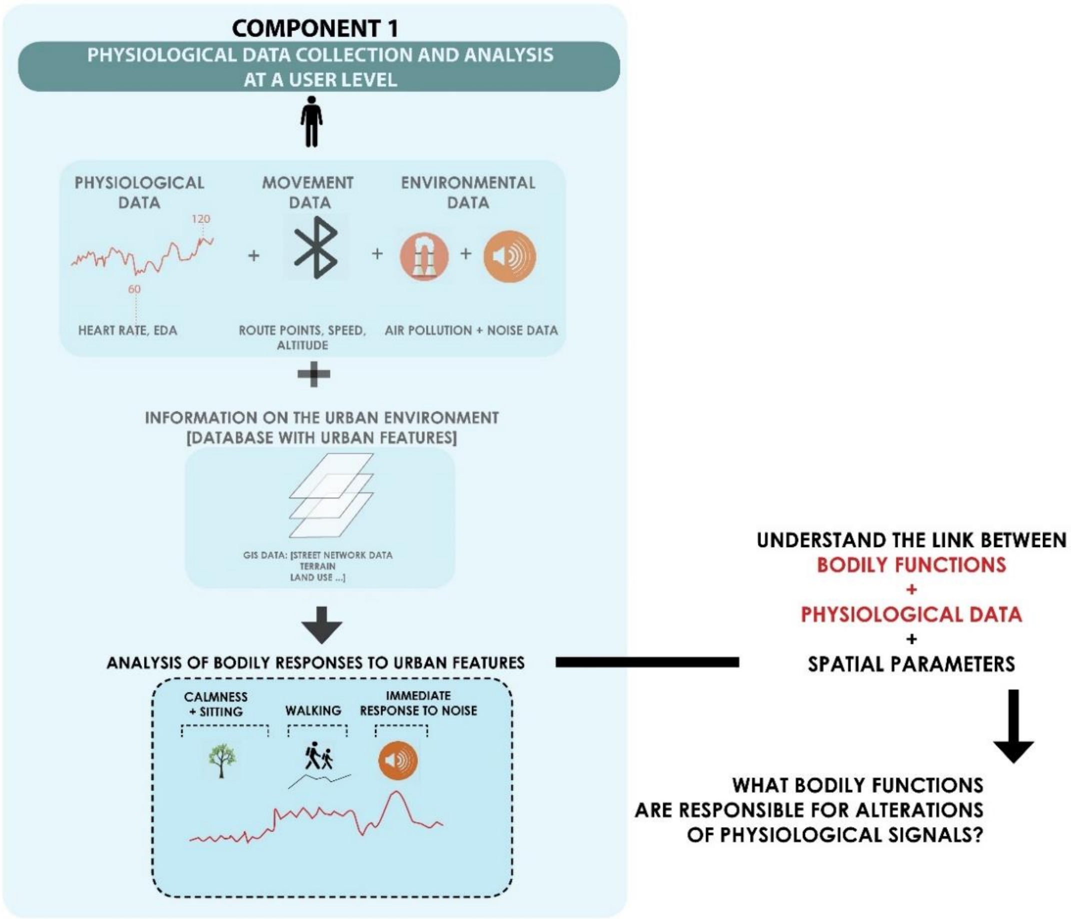


Figure 3.2. Schematic diagram situating the topics explored in section 3.2 in relation to the proposed methodology

3.2.1. SENSORY PROCESSING, PHYSIOLOGICAL AROUSAL AND THE AUTONOMIC NERVOUS SYSTEM

The autonomic nervous system (ANS) plays a significant part in the regulation of various bodily functions. The ANS consists of the sympathetic and the parasympathetic system. The sympathetic system mobilises the system to prepare it before action, while the parasympathetic system assists in restoration from stressful activity (Ulrich et al. 1991), among other functions. To decide which system should dominate, the body analyses endogenous and exogenous information received in the form of sensory input. When humans interact with the environment, they receive such information from various sources of stimulation, such as light, sound or tactile vibration. These are perceived by the organism through systems which process sensory information, such as vision and proprioception (Kleckner et al. 2017).

The functions of the autonomic nervous system are intertwined with daily activities. A route to a nearby park, for instance, involves walking, looking at street signs and shop windows and noticing attractive or aversive smells, while paying attention to cars, pedestrians passing by and traffic lights. During this experience, the brain tries to allocate resources optimally, responding to the various occurring changes in bodily and environmental state. This process includes various steps, such as perception, information processing, and the behavioural outcome. This experience is accompanied by changes in various physiological signals, such as HR and EDA.

The sympathetic nervous system plays a significant role in modulating these changes, responding with short-term, reflex-like responses, or long-lasting variations. The excitation of the central nervous system facilitates these operations, from perception to behavioural outcome (Boucsein & Backs 2009). Studies refer to this phenomenon as arousal. This term has been used to describe experiences which might be perceived in a positive, neutral or negative way. Such experiences involve situations that create excitement, activation, enhanced attention, threat and stress, or 'freezing' when facing unexpected circumstances.

Early approaches to this topic approached arousal as a unidimensional phenomenon, where similar situations are expected to elicit similar changes in the physiological markers associated with it. According to Duffy (1951), for instance, physiological arousal is the mobilisation of energy which is stored in the tissues to be used in cognitive processes and movement. Duffy theorized that this energy is related to the perceived effort required to prepare and complete a task; also, that it affects the reaction to stimulation in terms of time and sensitivity. The concept of a unitary (or unidimensional) arousal though elicited doubts (Boucsein 2012), because measures of physiological arousal (such as EDA and HR) seemed to have different behaviour in different circumstances of activation, and low correlation, changing in different directions (Taylor & Epstein 1967). Following these concerns, more complex theories replaced the concept of a unitary arousal model. These have been analysed in detail in a recent review of unidimensional and multidimensional arousal theories (Boucsein 2012). Boucsein proposed a model which builds on previous approaches and suggests the existence of the following four arousal systems: The *affect arousal* system, which is activated when there is a change in stimulation, or if a stressful or emotionally significant situation occurs, and triggers orienting and defensive responses; The *preparatory activation* system, which prepares the body for intended movement; The *effort* system, which can be activated in situations requiring increased attention or cognitive load; and the *general arousal* system, which reflects the generalised state of activation and is associated with mostly physical strain.

The ability to understand physiological changes is known as *interoception*. The physiological changes related to arousal may be associated with positive or negative emotional states, or may not be perceived by an individual. Self-reports of experiences of arousal do not always coincide with physiological markers of arousal, and a measure of interoceptive ability is the correspondence between objective physiological changes and subjective self-reports of experiences of arousal (Kleckner et al. 2017). The link between physiological measures and behavioural, cognitive and emotional changes is the subject of the domain of psychophysiology (Boucsein & Backs 2009). In this domain, physiological responses are grouped under two categories: responses to stimulus-related events, and indicators of a change in the general state of the organism (Boucsein 2012). Examples of stimulus-related events are the concepts of orienting, habituation and conditioning, while the generalised states involve states of general arousal, emotion and stress.

The following sections will provide a brief description of concepts and states related to physiological arousal, starting from the response of the organism to stimulus-related events (the orienting response). The discussion will then move to stress theory; physical activity will also be discussed in the end in relation to the other concepts.

3.2.2. THE ORIENTING AND DEFENSIVE RESPONSE

The immediate response of the organism to changes of stimuli is known as the 'orienting response' (Boucsein 2012). Humans find themselves in this situation in many circumstances; for instance, the perception of a sudden noise coming from a bus is an event that can capture the attention of a pedestrian and cause an orienting response.

The investigations of Sokolov (1963) have been influential in studies on the orienting response. According to the comparator theory of Sokolov, information from the stimuli is processed and compared with stimulus patterns that are already known to the organism. Novel information elicits an orienting response, which is diminished as this stimulation pattern is repeated; an effect which is known as habituation.

The orienting response is a part of the complex mechanisms involved in information processing, and it is associated with an attentional shift which may be voluntary or reflexive (Huertas et al. 2011). The attentional system evaluates environmental stimuli in order to determine if they have a positive or negative value. When a situation is evaluated as threatening, attention is shifted towards important stimuli, and irrelevant features are filtered out. This process is known as selective attention (Pilgrim et al. 2010). Orienting responses can appear when the organism perceives any change in the environment. When the presented information is perceived as threatening, this generates a physiological reaction known as the defensive response. Defensive responses are associated with an observed increase in response measures after repeated stimulation, known as sensitisation instead of habituation.

After habituation, an individual may experience an orienting response again, if there is any change in various factors related to the stimulus, such as novelty, intensity, modality, sequence, frequency or complexity (Boucsein 2012).

3.2.3. STRESS

3.2.3.1. DEFINING STRESS

The concept of 'fight or flight' has been used to describe stress since it was popularised by Cannon (1929, 1939). The evolution of theoretical models of stress began with Cannon's concept of 'homeostasis'. This term was used to describe the idea that the body has a set of acceptable values for physiological variables such as core temperature. In this model, deviations from the acceptable values are viewed as a threat to bodily stability (homeostasis). This concept later evolved, leading to the generation of the currently well-established 'allostatic load' model, proposed by McEwen and Stellar (1993). The model is based on the concept of 'allostasis'. This term was proposed by Sterling and Eyer (1988) instead of 'homeostasis', to describe that rather than one set of physiological variables associated with a stable state, there are many 'steady states' associated with different functions, such as movement or digestion. A change from one state to another means an alteration in the expected set of physiological variables. Stress-related mechanisms anticipate and respond to the demands generated by a change in state.

Acute stress generates a complex chain of responses, which happen in the brain and the sympathoadrenal and hypothalamic-pituitary-adrenal axes, as well as the autonomic nervous system. The activation of these systems regulates the release of hormones (epinephrine, nonepinephrine, cortisol). Cardiovascular activity is also increased through the activation of the sympathetic nervous system in order to prepare the organism to face the challenging situation.

Stress has been frequently described as 'high general arousal with a negative emotional tone' (Boucsein & Backs 2009). While the term stress is most usually associated with distress, the concept of positive stress for the organism also exists, and it has been conceptualised as 'eustress'. Another issue here related to inconsistencies in the terminology is that stress has been used as a term that describes the overall experience, the physiological reactions, the psychological interpretations of the bodily reactions, the behavioural outcomes, or different combinations of these aspects (Le Fevre et al. 2003).

The theme of eustress has been largely overlooked (Kupriyanov & Zhdanov 2014), which leads to an incomplete view regarding the positive contribution of stress mechanisms to health. The different approaches towards the definition of eustress can be separated in two streams: one which defines eustress as a physiological response, and one which states that the distinction between eustress and distress relies on the cognitive perception of the physiological functions, which is evaluated as positive or negative (Kupriyanov & Zhdanov 2014).

3.2.3.2. TYPES OF STRESSORS, INTERACTIONS BETWEEN STRESSORS AND FACTORS WHICH AFFECT STRESS RESPONSE

A stressor can be any activity or situation that generates stress (Hackney 2006). There have been indications that the brain recognises at least two different types of stressors: physical or physiological, and psychological or emotional (Dayas et al. 2001). Physiological stress is associated with conditions which are perceived as a bodily threat, such as extreme heat, pain and physical trauma, infection, sleep deprivation or exposure to cold. Psychological stress is generated by experiencing or anticipating a threat, including social conflicts and environmental stressors such as noise. This categorisation is focused on the pathways of neural activation associated with each stressor. Other approaches, such as that of Ulrich et al. (1991) identify three types of stressors: bodily reactions, elicited emotions, and behavioural responses.

Positive or neutral experiences, such as physical activity, or listening to loud music in a pleasant setting with friends, can also act as stressors, generating physiological responses related to stress without being perceived negatively, or having a necessarily negative impact on the body. The increase in intensity or duration (or their combination) of the stressor appears to play a role in determining the switch from eustress to distress (Kupriyanov & Zhdanov 2014). Le Fevre et al. (2003) also state that the impact of the stressor is determined by the timing, the source, the perceived control over the stressor and the perceived desirability of the stressor. This view demonstrates that a stressor can have a different impact on different individuals, resulting in a positive or negative perception of the experience.

Overstimulation and understimulation have also been studied as psychological stressors, and it has been found that both conditions can induce the release of stress hormones (Frankenhaeuser et al. 1971). The first situation refers to exposure to intense sensorial input, while the second condition refers to its reduction.

There has also been evidence that multiple stressors can act synergistically and generate a greater response than the response to each stressor. Some researchers have tested this hypothesis with the combination of physical and mental stressors (Webb et al. 2017; Rousselle et al. 1995). Other studies though, do not find this synergistic effect (Wasmund et al. 2002).

The magnitudes of response also vary among individuals in the case of exposure to psychological stressors. There are medical conditions that can lead to a reduced reactivity to stress, such as the denervation of the heart which occurs in heart transplant patients (Gorman & Sloan 2000). Differences also occur in the absence of medical conditions. (Gliner et al. 1982; Manuck and Schaefer 1978; Manuck and Garland 1980).

One question that has not yet received a clear answer is when stress responses become harmful for the organism. According to McEwen (1998), the acute effects of stress responses result from the adaptation of the organism to the presented challenge, and are reversible. However, prolonged stress and the chronic repetition of stress responses can have an effect of 'wear and tear', leading to ill effects on the body. The anticipation of stressful events is also likely to add to this effect. McEwen (1998) identifies three types of responses related to 'allostatic load'. Type 1 includes the accumulation of responses, whose effect is related to their frequency and magnitude. Type 2 includes sustained responses which fail to shut down, and type 3 includes the failure of the organism to respond to a challenging situation. One hypothesis presented in that paper was that the repetition of stress responses (related to Type 1) leads to the other two types of allostatic load, where there is a failure to respond or shut off the response.

Brosschot et al. (2005) also proposed a prolonged activation model, where the accumulation of physiological responses to stressors over time is regarded as the primary factor that leads to a pathogenic state in the long term. The inclusion of stress responses that might occur while anticipating a stressor, or after its disappearance, is a key element in this model.

Another view on this topic was proposed by Ursin and Eriksen (2010), who disagreed with the link between repeated acute stress responses and ill effects on the organism, as presented by McEwen's allostatic load model (1998). According to the cognitive activation theory of stress (CATS) (Ursin & Eriksen 2004; Ursin & Eriksen 2010), the adverse effects arise in cases of a sustained state of high physiological arousal, related to a challenge that cannot be resolved by the individual. This theory thus relates negative effects to the concept of 'coping'.

Despite their differences, the presented theories generally agree that the chronic repetition of stressful responses, especially of sustained duration, can become harmful for the organism. Studies have shown that chronic exposure to stressors increases the ratio of sympathetic versus parasympathetic activity in the autonomic nervous system, which leads to a higher risk of cardiovascular morbidity and mortality (Gorman & Sloan 2000).

3.2.4. PHYSICAL ACTIVITY AND EXERCISE

Physical activity, and particularly exercise (a purposeful, structured activity; WHO 2020) is considered a physical stressor (Hackney 2006; Rousselle et al. 1995), as it is a condition where the sympathetic nervous system takes control. There has been plenty of evidence showing that exercise is a state which is accompanied by high physiological arousal (e.g., Lambourne & Tomporowski 2010). Exercise has been used extensively as a physical stress trigger, with several variations in duration and intensity (e.g., Wasmund et al. 2002; Webb et al. 2017). Intense exercise to the point of exhaustion triggers the release of the same hormones (catecholamines) as a stressful interview (Oleshansky & Mayerhoff 1992).

There is though plenty of evidence that exercise alone does not have adverse health effects, apart from situations of overtraining or high-intensity training for individuals that cannot cope with it. On the contrary, catecholamines enhance physical performance during exercise, as they participate in the transportation of oxygen to active muscles (Zouhal et al. 2008). Studies have shown that exercise is a physical stressor to which the body can adapt over time (Huang et al. 2013b; Sanchis-Gomar et al. 2012), as it is resolved through coping mechanisms. There have been several suggestions that chronic exercise improves coping with stress (e.g., Puterman et al. 2010). Exercise, therefore, appears to be a physical stressor that causes high general arousal associated with positive emotion, or in other words, a kind of 'eustress' (e.g., Sanchis-Gomar et al. 2012).

Walking and cycling are examples of dynamic exercise (Laughlin 1999). In dynamic exercise, there is an increase in oxygen uptake at the beginning of the exercise, and then the oxygen uptake stabilizes at each intensity (Fletcher et al. 1995). If the intensity of physical activity does not increase, the individual that performs the exercise reaches a state defined as the 'steady state'. In the context of walking, this is a state where the individual keeps walking at the same pace until stopping the exercise.

Duration and intensity are factors which affect the experience of exercise as a stressor. Physical activity which lasts longer than 60 minutes or is at great intensity triggers the release of stress-related hormones, as the organism tries to adapt to the increased physiological demands of the stressor (Acevedo et al. 2007). This experience might be perceived initially as an emotional state of a high degree of activation or engagement, shifting closer to the negative affect when the activity becomes laborious. The physical effort related to exercise intensity is also dependent on the physical fitness of the individual. Sedentary people or elderly might find moderate exercise more challenging in terms of energetic demands (Lee et al. 2003).

3.2.5. SUMMARY AND CONCLUSIONS

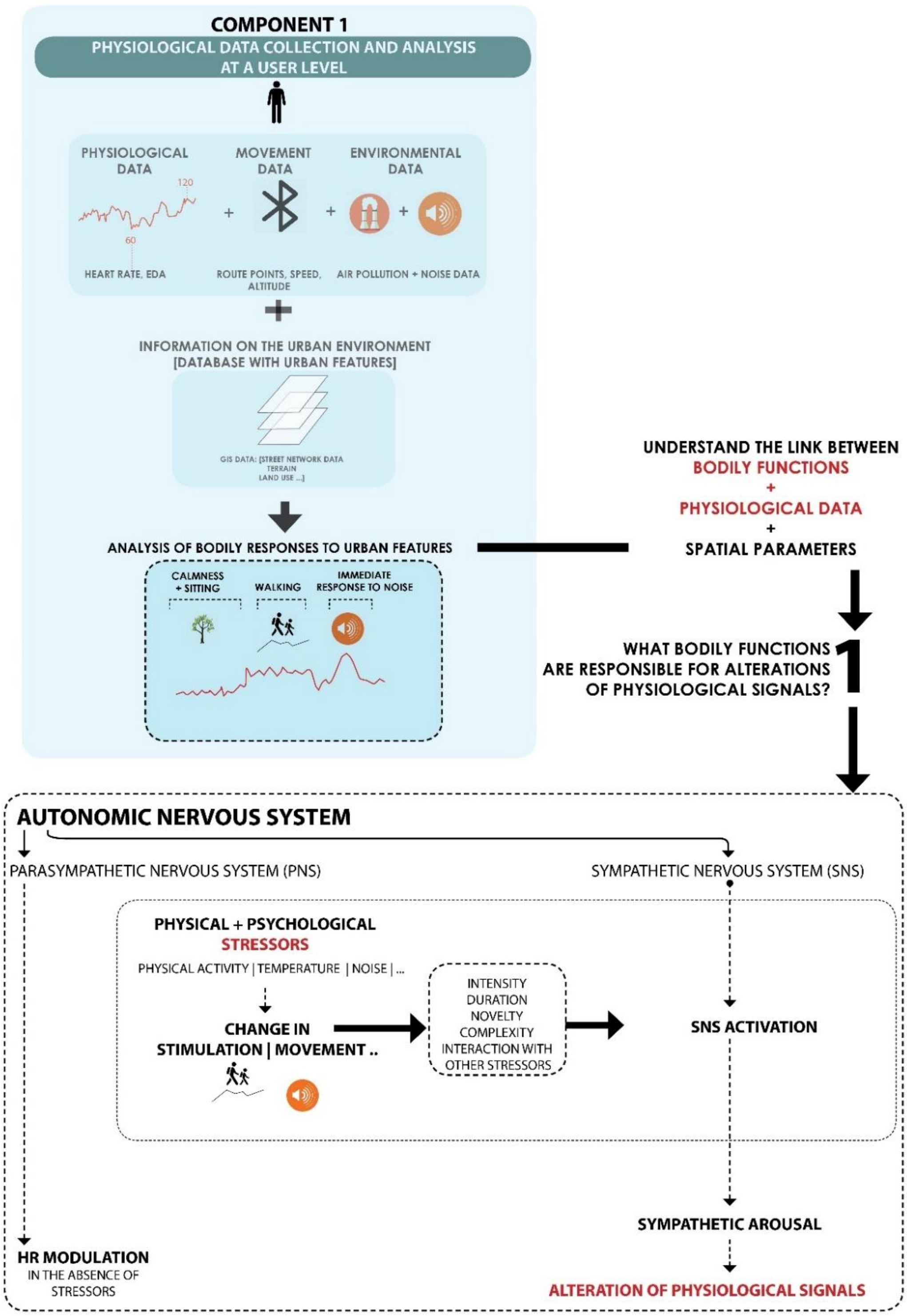


Figure 3.3. The relationship between the autonomic nervous system, stressors and sympathetic arousal

The reviewed literature showed that understanding the functions of the sympathetic nervous system is critical for understanding many of the physiological changes experienced in the various facets of daily life. The activation of the sympathetic nervous system is connected with responses to stimulation, physical activity and other kinds of physical and psychological stress, and may manifest as a physiological response in measures such as HR and EDA. The parasympathetic nervous system also modulates physiological responses and in particular HR, but this happens mostly during the 'rest and digest' state; this is why the emphasis has been given on the 'fight or flight' activities which are modulated by the sympathetic nervous system. A summary of these phenomena is presented in Figure 3.3.

As it was shown in the short review presented in sections 3.2.1. to 3.2.4, there are links between the different concepts and states that were discussed. Stress could be seen as a broader category, which can include physical or psychological stressors related to changes in the state of the organism or the surroundings. Defensive responses could be situated in this broader category as examples of stimulus-related events related to an unexpected change in the surroundings. This change acts as a psychological stressor and creates an alarming state for the organism. Defensive responses typically have a very short duration. The excessive presence of stimuli, or their absence, can also act as a psychological stressor, causing overstimulation.

Stress can also be linked to physical stressors. Environmental parameters, such as temperature, belong to this category and can affect physiological responses. Physical activity is also considered a physical stressor and affects physiological responses. Changes in posture and spontaneous movements may cause a physiological response with a short duration, due to the change in state; physical activity for an extended duration can also affect physiological responses, as it can cause a sustained increase in sympathetic arousal. A significant difference between physical activity and the other stressors is that this stressor is not perceived negatively, and it has been linked with positive health outcomes in the long term.

Following the reviewed literature, this work will refer to stress as a concept related to an increase in physiological arousal, associated with a change in the state of the organism, or an unexpected change in the surroundings. The definition of stress that will be adopted here follows the allostatic load model and shall include changes in movement, changes in the stimulation levels in the surroundings, and other environmental stressors such as heat. The physiological responses that can be classified as stress under this definition may be accompanied by negative or positive feelings, according to each individual's capability to cope with each stressor. Physical activity will also be incorporated into the adopted approach as a stressor, but it will be given a different label and separated from stimulus-related responses.

Based on the presented review, we could group the contextual and movement-related features of the urban environment to physical and psychological stressors which can affect sympathetic arousal and elicit physiological responses. Psychological stressors primarily include auditory and visual stimulation, which can be linked to orienting and defensive responses or overstimulation. Physical stressors include temperature and physical activity. This categorisation is based on the reviewed definitions of stress as a state that is not necessarily perceived negatively, especially in the case of physical activity.

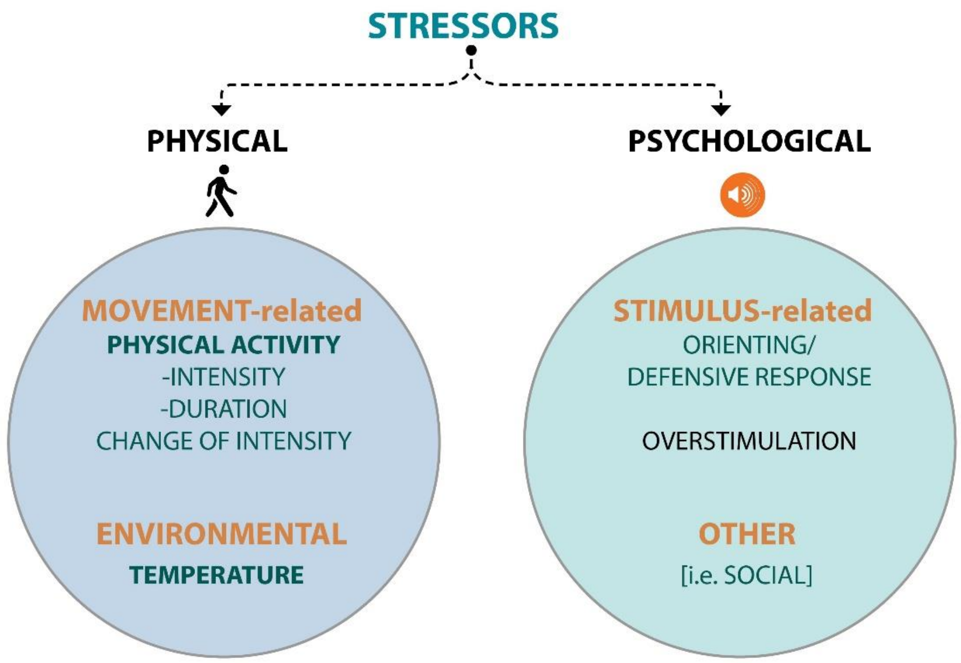


Figure 3.4. A categorisation of stressors related to physiological responses based on the factors that initiate the arousal.

These two categories (Figure 3.4) are conceptual and focus on factors that have importance in urban design and planning. The two categories describe the potential of the activity or a contextual factor leading to a physiological response. This conceptualisation aims to highlight that both activity and contextual factors affect sympathetic arousal, and thus physiological responses. At the same time, the source of physiological responses is different in each of the two categories. The subcategory of movement-related events was created to emphasise the strong links between activity and physiological responses, while recognising that its effect may be positive, in contrast to the other stressors.

3.3. THE EFFECT OF DIFFERENT PARAMETERS ON MEASURES OF PHYSIOLOGICAL RESPONSES

After identifying some states and conditions associated with alterations of physiological data, this section introduces the physiological signals that will be analysed in this research. The possible effects of stress (focused on stimulation and movement-related effects) will be outlined for each signal.

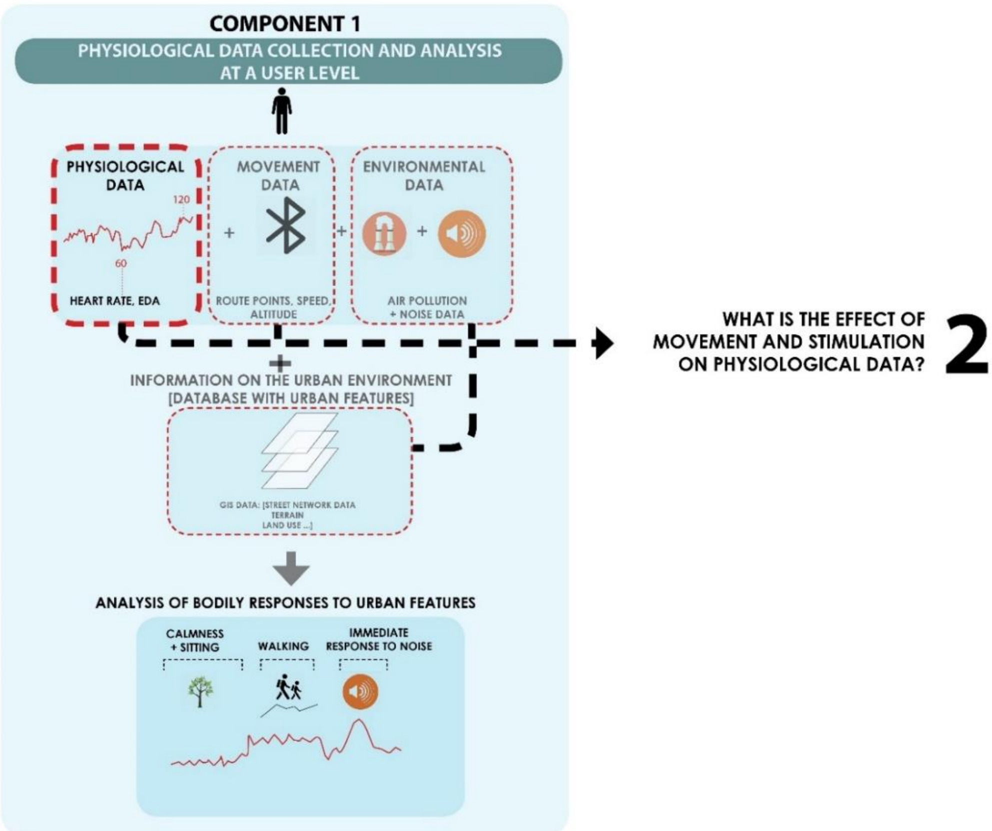


Figure 3.5. Schematic diagram situating the topics explored in section 3.3 in relation to the proposed methodology

The aim is to identify how other studies have used the analysis of these signals to measure physiological arousal in different conditions. The review will refer to parameters such as the expected time of appearance of a physiological response after the presentation of a stimulus. These parameters will be necessary for the construction of the algorithms for analysis of physiological responses. This part of the review will, therefore, assist in designing the methods for the physiological data analysis in component 1 of the designed methodology, as shown in Figure 3.5.

HR is affected by both systems of the autonomic nervous system and reflects their activity (Shaffer et al. 2014). The sympathetic system increases HR, while the parasympathetic system brings it down (Ulrich et al. 1991).

EDA, on the other hand, is not influenced by the parasympathetic system, and it is frequently used as a marker of sympathetic activity (Visnovcova et al. 2013).

The EDA signal is composed of two components: the tonic and the phasic component (Figure 3.6). The tonic component (tonic EDA) is a smooth curve representing the slow changes in electrodermal activity over time. The phasic component (phasic EDA, or electrodermal response, EDR) is connected to the immediate reaction to external stimuli, as reflected in the EDA signal.

These reactions have the shape of a peak and are superposed on the slowly changing component (tonic EDA). Peaks can also occur without a stimulus; such a peak is called a 'Nonspecific skin conductance response' (NS.SCR) (Boucsein 2012). EDRs are generated 1-2 seconds after the stimulus, and typically have a steep rise and a longer decay (Sibley et al. 2008). An example of stimulus-related EDRs and NS.SCRs can be seen in Figure 3.6. Figure 3.7 displays the measures typically used to evaluate an EDR (amplitude, recovery time/2, rise time, latency).

While HR, EDA and their measures exhibit fluctuations that can correlate, this relationship varies and is dependent on the exact circumstances. Early studies have warned against trying to find strong correlations between the two signals as time series, and suggest that correlations may be found potentially in fragments, but they should be seen as different physiological measures that cannot be used interchangeably (Taylor & Epstein 1967).

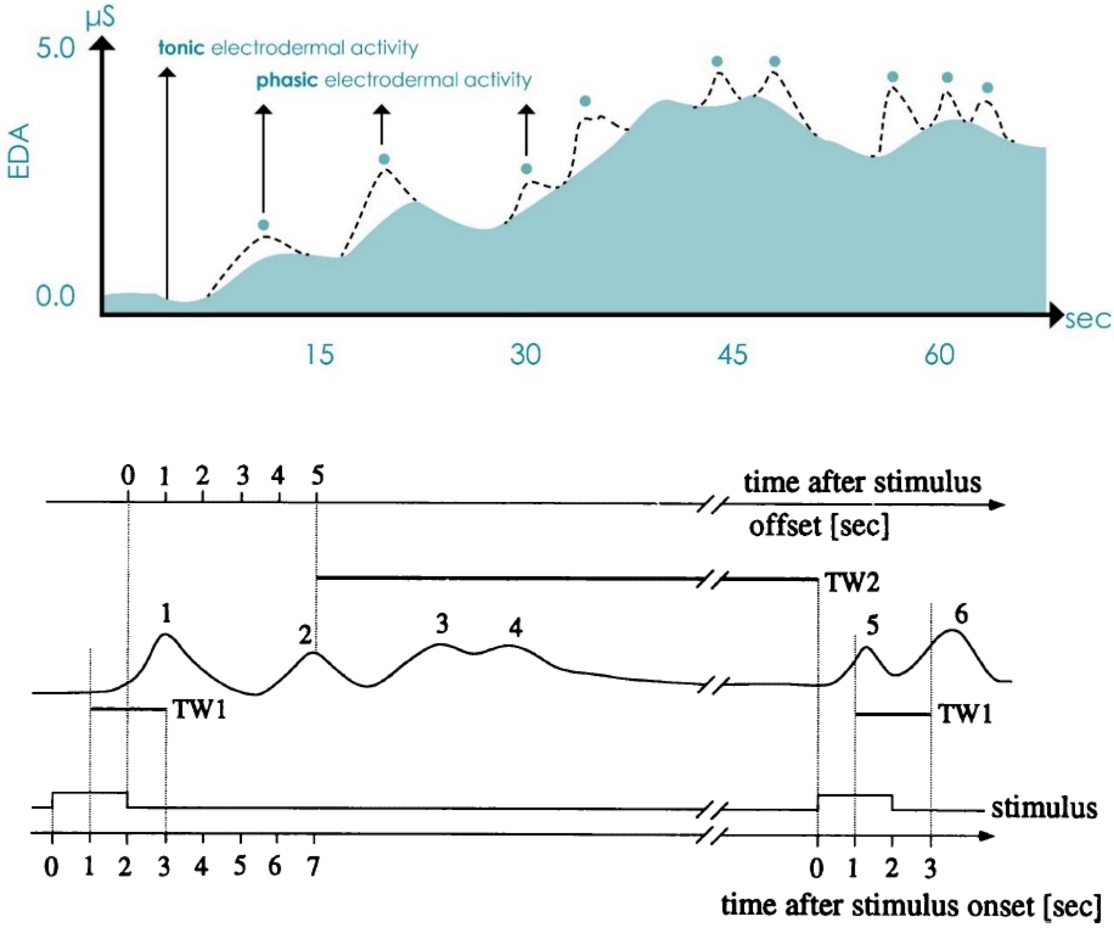


Figure 3.6. Upper: The tonic and the phasic components of EDA. Bottom: EDRs and NS.SCRs elicited after stimulation (acquired from Boucsein 2012).

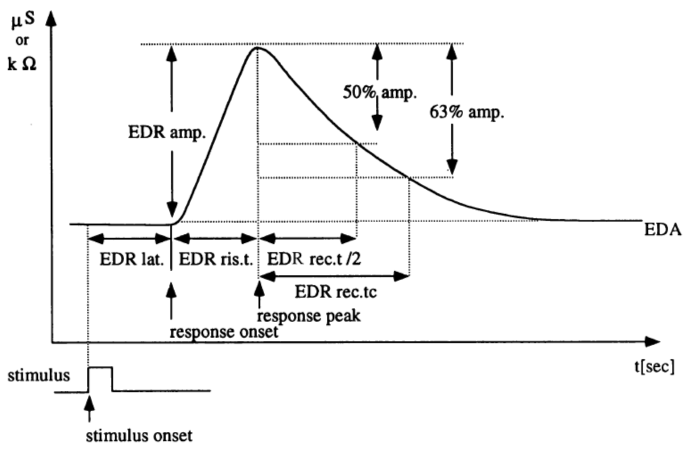


Figure 3.7. A typical EDR and its measures (acquired from Boucsein 2012)

The rest of this section discusses how the physiological signals which will be analysed in this research are usually affected by different parameters.

3.3.1. STRESS AND PHYSIOLOGICAL RESPONSES

EDA measurement is a well-established method in stress research. Both tonic and phasic EDA measures have been used in this context (Boucsein 2012). In the case of tonic EDA, a rise in the EDA levels indicates a rise in stress levels. The frequency of NS.SCRs has also been used as a measure of tonic EDA activity (Boucsein 2012). Various researchers have used this as the primary measure of assessing stress arousal. Tulen et al. (1989), for instance, measured changes in tonic EDA during the Stroop Color Word Test, which has been extensively used as a method for inducing conditions of stress and anxiety in laboratory conditions. They found a significant increase in tonic EDA levels, while also noting that a high EDA level before the stimulation resulted in a smaller increase. Wang et al. (2016) used the changes in tonic EDA to measure the ability of urban park scenes to lower stress. They found that viewing scenes with green brought the highest reduction of tonic EDA, while the lowest reduction was during viewing urban roadway scenes. Zeile et al. (2016), in their study on mapping urban emotions with wearable sensors, also used the increase in tonic EDA as a stress identifier, combined with a decrease in skin temperature.

This method, though, does not capture the instantaneous stress response to a stimulus and depicts the slower changes over time. Phasic EDA measures, on the other hand, can be used to study the immediate stress reaction. These include the number of EDRs in a specified time window, as well as their amplitude, latency and area under the EDA curve. The EDR amplitude is the most frequently used measure (Boucsein 2012). The experience of stress elicits the generation of a higher number of EDRs compared to a relaxed state, and with a higher amplitude.

Both phasic and tonic measures of EDA can be used in ambulatory conditions, depending on the phenomenon that is studied. Several researchers have combined tonic and phasic measures; a classic example in ambulatory stress measurement is that of Healey and Picard (2005) who used tonic and phasic measures (tonic level, number of

EDRs, the sum of EDR amplitudes, the sum of EDR durations and sum of EDR areas in a segment) as a part of a model for stress assessment during driving. The only difficulty lies in the measurement of latency, as it is necessary to know the exact second when a stimulus occurs, in order to measure the response time.

3.3.2. STIMULATION AND PHYSIOLOGICAL RESPONSES

For a more detailed analysis of the acute physiological effects of stimulation, the relevant literature on orienting and defensive responses can be consulted. Tests for the analysis of physiological measures during the orienting response typically involve the presentation of a series of stimuli that have a short duration (i.e., 1-5 seconds) and are repeated for some times (e.g., 10-20) with a short interval (Boucsein 2012). EDRs are the most typically studied measure, as they are connected to the stimulus and reflect a short-term change in the sensitivity of systems used to analyse the stimulus properties. The changes in EDR amplitude can be used for measuring habituation to a stimulus (Boucsein & Backs 2009). Tonic responses can also be attributed to the appearance of a stimulus, and they reflect slower changes in the sensitivity of the receptor systems. The change in tonic EDA may be retained after the end of habituation to the stimulus, while initially it may also be influenced by the level of general arousal (Boucsein 2012). The response may also contain an increase in both tonic and phasic measures. Phasic EDA measures (and particularly the EDR amplitude) exhibit a clearer relation to stimulus intensity. If the stimulus signifies a start of a cognitive or motor action, the impact in the strength of the orienting response may be more significant. This phenomenon is described as the effect of 'significance' (Boucsein 2012); it could occur, for instance, if the users know that they must move immediately after a sound is heard.

Regarding differences between orienting and defensive responses, it is difficult to distinguish the two only by the EDA measures, though the amplitude of EDRs in defensive responses may increase compared to orienting. The observation of phasic HR changes may provide clarification, as the orienting response tends to cause a deceleration of HR, while the defensive response causes its increase, preparing the body to move in order to face the 'fight or flight' situation (Boucsein 2012).

3.3.3. MOVEMENT AND PHYSIOLOGICAL RESPONSES

HR rises at the beginning of any muscular activity in order to adapt to the new physiological state of the organism. This increase can be attributed to the concept of 'allostasis' which was introduced before. The HR continues rising as the intensity of exercise increases (Dourado et al. 2010) or does not fluctuate much if the intensity is steady. The ability of HR to decrease after exercise and return to its normal rates within a specific time is a signifier of a healthy cardiovascular system. This phase is known as HR recovery. The phases of increase at the start and decrease at the end of the exercise last one minute or less (Cole et al. 1999; Whipp et al. 1982).

As for changes in EDA in relation to exercise, there have been studies that suggest an incremental increase of EDA with the increase in exercise intensity (Boettger et al. 2010; Turaçlar et al. 1999). In the studies of Posada-Quintero (2018) and Schumm et al. (2008), it was shown than when the walking speed increased, it was accompanied by an increase in the phasic EDA, even without the existence of a startling event. These peaks were, therefore, NS.SCRs. Schumm et al. (2008) observed that at the fastest walking speed (6 km/h), the NS.SCRs tended to have a uniform distribution; the peaks generated after startling events were still detectable.

This effect has been observed since early studies on EDA in ambulatory conditions (e.g., Blank 1946). However, a consistent relationship between physical activity and electrodermal measures has not been established yet. In cases where it has been observed, it has been attributed to the gradual increase of the functioning of the sweat glands during exercise or the emotional arousal as an outcome of the activity (Doberenz et al. 2011).

Apart from the effects related to the activity of an extended duration, spontaneous movements can also affect physiological responses. The transition from one posture to another, as well as handgrips and head-tilts, can cause an acute HR increase which can have significant magnitude and is attributed to a brief contraction of muscles. (Borst et al. 1982).

The transition from a posture to another may also be responsible for a change in EDA. This change may be more significant when the individual perceives this as a situation where they have to maintain their balance. Potential postural instability can be perceived as a threat, related to fear of fall, and generates a response in the autonomic nervous system (Sibley et al. 2008). Situations such as floor perturbations can have this effect, even if they are predictable, as Sibley et al. (2008) showed.

Finally, small movements of the skin under the electrodes used for measurement may cause artefacts in the EDA signal (Boucsein 2012). These artefacts can usually be identified by the irregular shape of the resulting signal.

3.3.4. PERSONAL FACTORS, CONTEXT AND INTERACTION BETWEEN STRESSORS

The effects outlined in sections 3.3.1 to 3.3.3 can be influenced by personal factors and each experiment's specific circumstances.

In terms of personal factors, many studies have mentioned that the outlined effects of exercise on HR can be affected from interpersonal differences, such as hereditary factors, environment and sex (Sato et al. 2000). Age and fitness level may also play a role; for instance, the HR increase at the onset of exercise is still observed but at a slower rate in the case of elderly (Ishida et al. 2000) and trained individuals (Sato et al. 2004). Some studies have also identified a HR increase at a slower rate (Sato et al. 2004) and a less intense reaction to psychological stressors (Acevedo et al. 2006) in trained individuals.

A significant factor that should be considered is the existing sympathetic arousal at the beginning of a measurement. In terms of external circumstances, environmental variables, such as heat or cold and humidity, can also act as independent stressors which cause physical stress on the organism. When this happens during exercise, it triggers an increase in HR, which is not accompanied by increased energy expenditure (Freedson & Miller 2000). The sequence of stressors also appears to play a role in the case of interaction between exercise and temperature as physical stressors. When there is already a stressor before the exercise, the HR may have already been affected by that. In this case, the exercise might not elicit the increase in HR that would happen otherwise. In the experiments of Craig and Cummings (1963), for instance, the increase was observed when the subjects were in a cool environment (18 °C). In higher temperatures (21 °C and 38 °C) there was already an accelerated standing HR, and the increase in walking HR was not observed. A psychological stressor that appears during exercise may also cause an additional increase in HR that is not due to metabolic demands; Szabo et al. (1994), for instance, showed that a mental arithmetic stressor applied during cycling at low and moderate intensities elicited a change in HR that was larger than 10bpm. Other researchers also have similar findings (e.g., Rousselle et al. 1995);

Finally, some additional factors which may affect physiological responses are speech and breathing patterns. Speech can affect physiological responses due to the high variation that it creates in the respiratory patterns (Schubert et al. 2009). In the recent study of Mackersie et al. (2016), it was shown that both normal and fast speech brought a significant rise in tonic EDA, in comparison to baseline levels.

3.3.5. SUMMARY AND CONCLUSIONS

As shown in this section, there are many similarities between the physiological responses to different conditions. For instance, the acute HR increase is a typical response to a sudden movement, as well as to the presentation of a threatening stimulus. These similarities are related to the overlapping between the concepts of stress, and responses to movement and stimulation changes. While the literature was reviewed and presented separately for each condition, the links between the different conditions or concepts are evident.

Figure 3.8 presents a summary of the described movement-related and stimulus-related effects on physiological responses. Apart from the orienting response, the other states described in the figure can be considered stress responses (or stress-related states) under the reviewed definitions of stress.

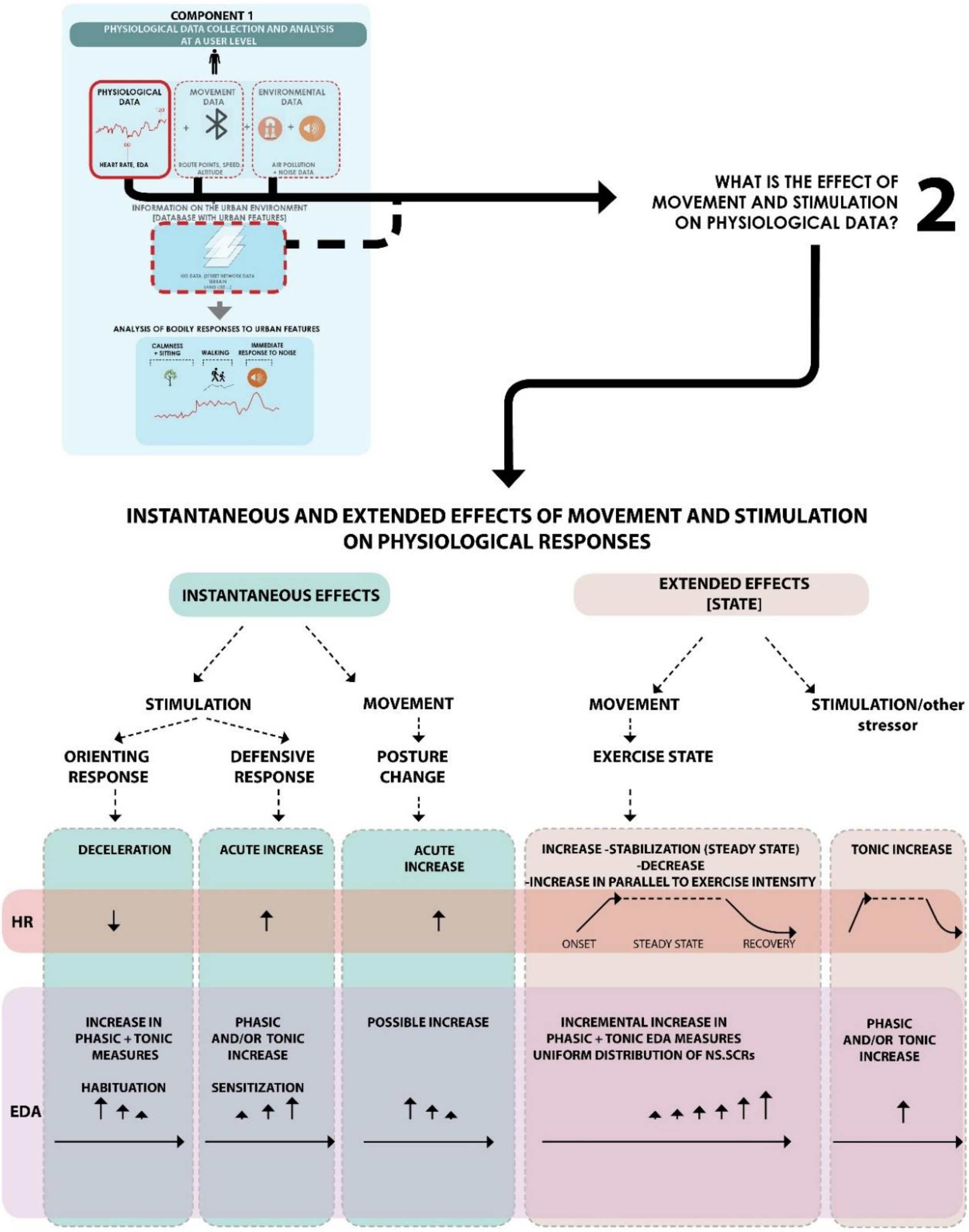


Figure 3.8: A summary of typical physiological (EDA and HR) responses to stimulation and movement

3.4. PHYSIOLOGICAL RESPONSES DURING INTERACTIONS WITH THE URBAN ENVIRONMENT

There has been much theoretical debate on which characteristics are necessary for the achievement of high-quality urban life. Qualities such as neighbourhood vibrancy became the focal point of urban design and planning after the criticism of Jacobs (1961) regarding the lack of vitality in communities designed following the modernist dogma. One of the most influential theorists in this domain after Jacobs, Montgomery (1998), identifies the following as the "physical conditions for making a city": development intensity, mixed-use, fine grain (number and proportion of small enterprises), adaptability, human scale, city blocks and permeability, contact and visibility, public realm, movement, green space and water space, landmarks, visual stimulation and attention to detail, and architectural style as image.

Some of those characteristics also play an essential role in creating urban environments that promote urban health. Mixed-use and high density, for instance, have been identified as necessary ingredients for the creation of walkable environments, while green spaces encourage physical activity, and have benefits for mental health (Giles Corti et al. 2016).

While these effects are well known, they are usually described in the discourse on urban health from a policy-oriented perspective, and the emphasis is on long-term effects on health and quality of life. As the focus of this research is on the instantaneous physiological effects that occur through interaction with different places and spaces, the following section examines spatial qualities from this aspect, reviewing relevant theories from the domain of environmental psychology.

This part of the chapter is organised following the identification of movement and stimulation as significant parameters that affect physiological responses. These factors will be now examined in connection to urban space. The review will commence with discussing which urban environment features may influence movement patterns. The focus will then shift to urban features can act as psychological stressors or generate a stimulating or restorative experience.

The relationship between this part of the research and the proposed methodology is described in Figure 3.9. The following review shall inform the design of component 1 by providing the theoretical background for selecting urban features that can act as physical or psychological stressors. These features will be later used as contextual parameters that may influence physiological responses, in the methods for analysis of physiological data.

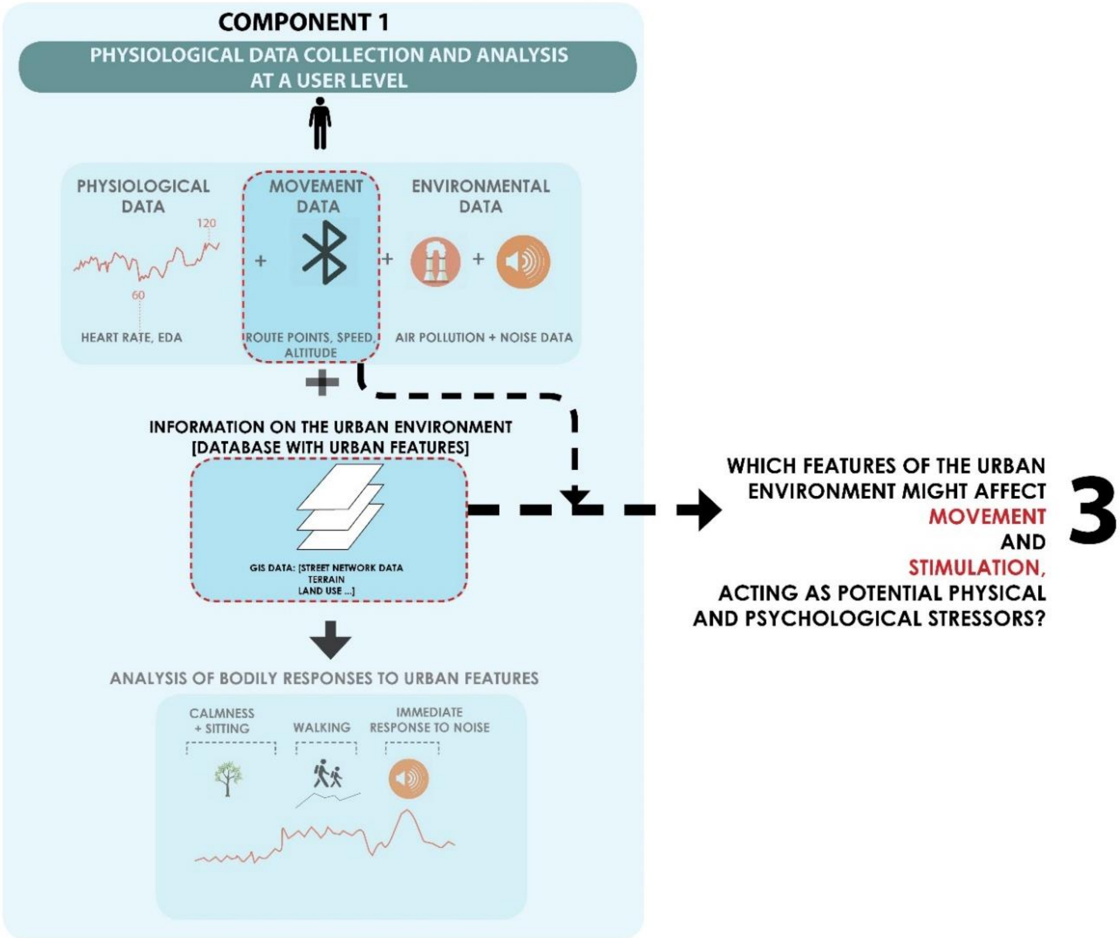


Figure 3.9. The topics explored in this section in relation to component 1 of the proposed methodology

3.4.1. PARAMETERS THAT AFFECT THE EXPERIENCE OF WALKING IN THE URBAN ENVIRONMENT

Walking as a form of physical activity has been studied extensively from a medical and biomechanical perspective, regarding various parameters such as gait patterns and cardiovascular activity. The experience of walking during various daily activities is much less studied, due to the difficulty in controlling the various encountered conditions. While walking in the gym or the park is often at a steady pace, walking in the urban environment for leisure, commuting or any other purpose is an activity which is intermittent and affected by various factors at different scales. Such factors are the shape and dimensions of the urban network, the land-use patterns which determine the distance from work and other destinations, the environmental parameters such as weather, and the static and moving obstacles which impose frequent slow-downs, stops and turns.

To study movement in the urban space, it is necessary to first understand movement as a natural act of the body in an abstract space, without a particular purpose or context. Some studies have investigated the natural, unconstrained movement of humans, in situations where nothing is dictating or imposing a pace. These studies show that the pace which is adopted naturally by the body is that which minimises the physical effort required for the movement (Selinger et al. 2015). Some studies have suggested that the perception of distance affects speed, resulting in the adoption of a slower pace in the case of covering very short distances (Seethapathi & Srinivasan 2015). Individual factors, such as the age and the stride length, can also affect speed; the stride length is a factor that can explain some differences identified in the walking speeds among males and females (Blessey et al. 1976), while age can affect speed due to reduced functioning in terms of vision, reaction time and musculoskeletal activity (Iosa et al. 2014).

Apart from these individual factors which affect the characteristics of walking, the urban environment also influences the walking pattern. A significant parameter which influences movement is the presence of obstacles. Non-flat surfaces such as stairs and slopes create physical challenges and reduce the walking pace because they require more effort for their traversal (McIntosh et al. 2006). Apart from the gradient, the terrain surface and vegetation can also reduce the speed and affect the intensity of the exercise. Running through deep vegetation, for instance, elicits an increase in magnitude and variability in the energetic demands, as it involves the activation of many more muscles in comparison to running on flat terrain (Creagh et al. 1998). Obstacles are also any objects or places which cause an unintended stop or slowed pace; such cases are places with increased pedestrian density.

Some obstacles are more challenging for people with difficulties in moving, such as crossings. There, they must synchronise their gait speed with the traffic lights, and this requires the adoption of a speed which may exceed their capabilities. This situation leads to an increased risk of falling (Iosa et al. 2014; Duim et al. 2017), as well as more significant physical effort, due to the constant accelerations and decelerations. The study of Sellers et al. (2012) was one of the first to address the issue of obstacles as factors which limit the quantity and quality of physical activity within the urban environment; their study measured the effects of a park and urban environment on a 30-minute brisk walk, finding that due to the lack of interruptions, the participants were able to achieve higher activity intensity in the park than in the urban environment.

From the literature reviewed in the former sections, we can make the following assumptions regarding the relation between urban characteristics and associated changes in speed and activity intensity (summarised in Figure 3.10): Environments without obstacles make it easier to retain a steady walking speed, and therefore a steady activity intensity (Case A in Figure 3.10), or a 'steady state' for the organism, following the allostatic model of stress which was explained in section 3.2.3. Physiological responses may appear (or increase in intensity) in this case when there is a change from a steady state to another, or when the duration of the activity is high.

On the other hand, environments which contain many obstacles may be related to many changes in activity intensity due to the many accelerations and decelerations caused during the interactions with the obstacles (Cases C and D in Figure 3.10). The activity intensity also increases during walking uphill on a non-flat surface (see Cases B and D in Figure 3.10). Non-flat surfaces also cause a high fall risk, as they cause a significantly different walking pattern than that of walking on a level surface, with a more significant variation in speed, step length and step width, parameters which have been associated with greater instability (Sheehan & Gottschall, 2012). More physiological responses may be observed in this case (and especially in Case D), due to the high presence of factors which change the activity intensity and increase the physical effort.

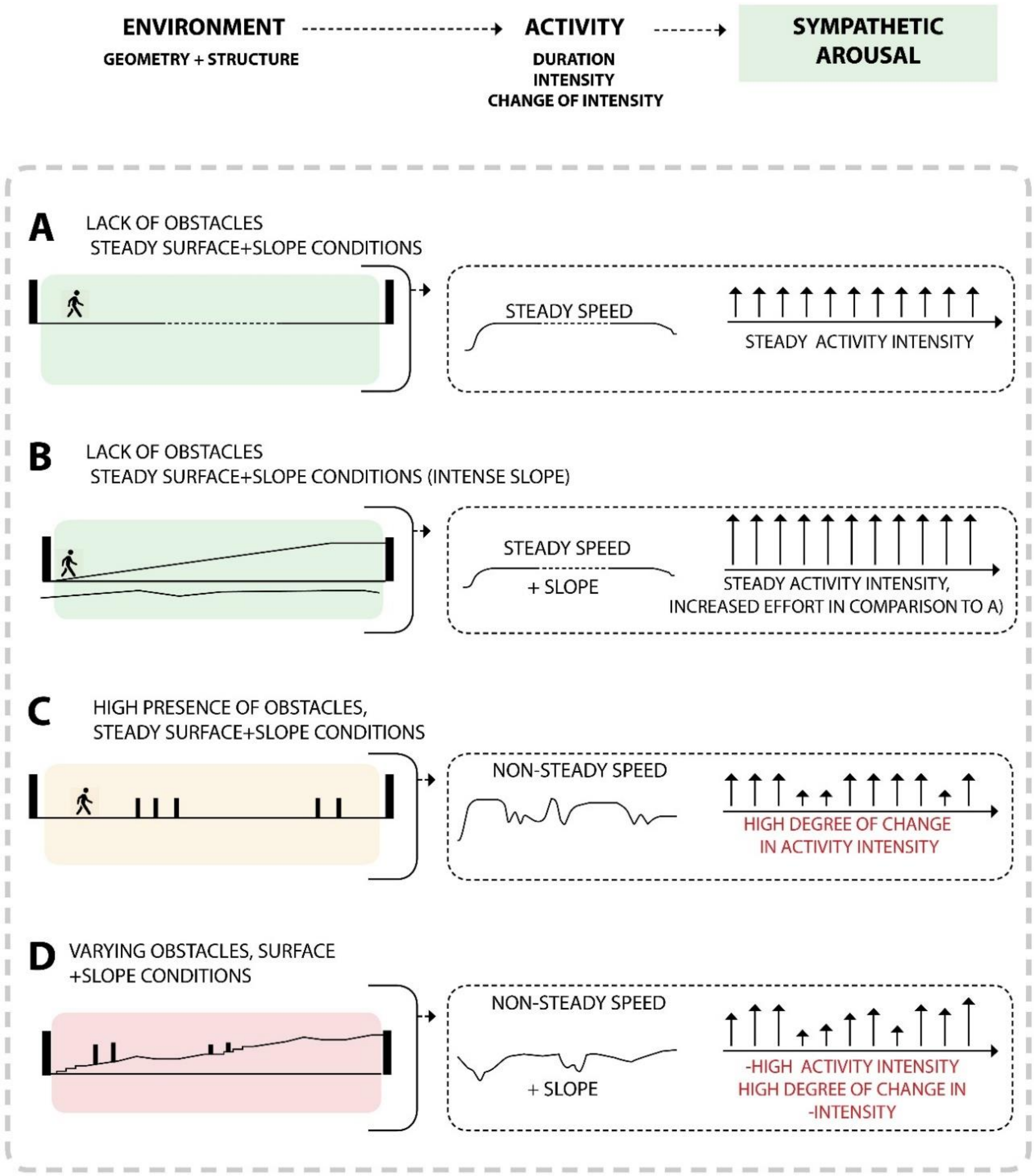


Figure 3.10: Urban characteristics and associated changes in speed and activity intensity

Obstacles, slope and surface conditions are, therefore, parameters which might affect the movement pattern. Due to the links between movement and physiological responses, these parameters also have the potential to influence physiological responses. Other spatial parameters, such as road length and surface area, can also be included here. Steps can also be considered as a condition with an effect similar to that of a slope.

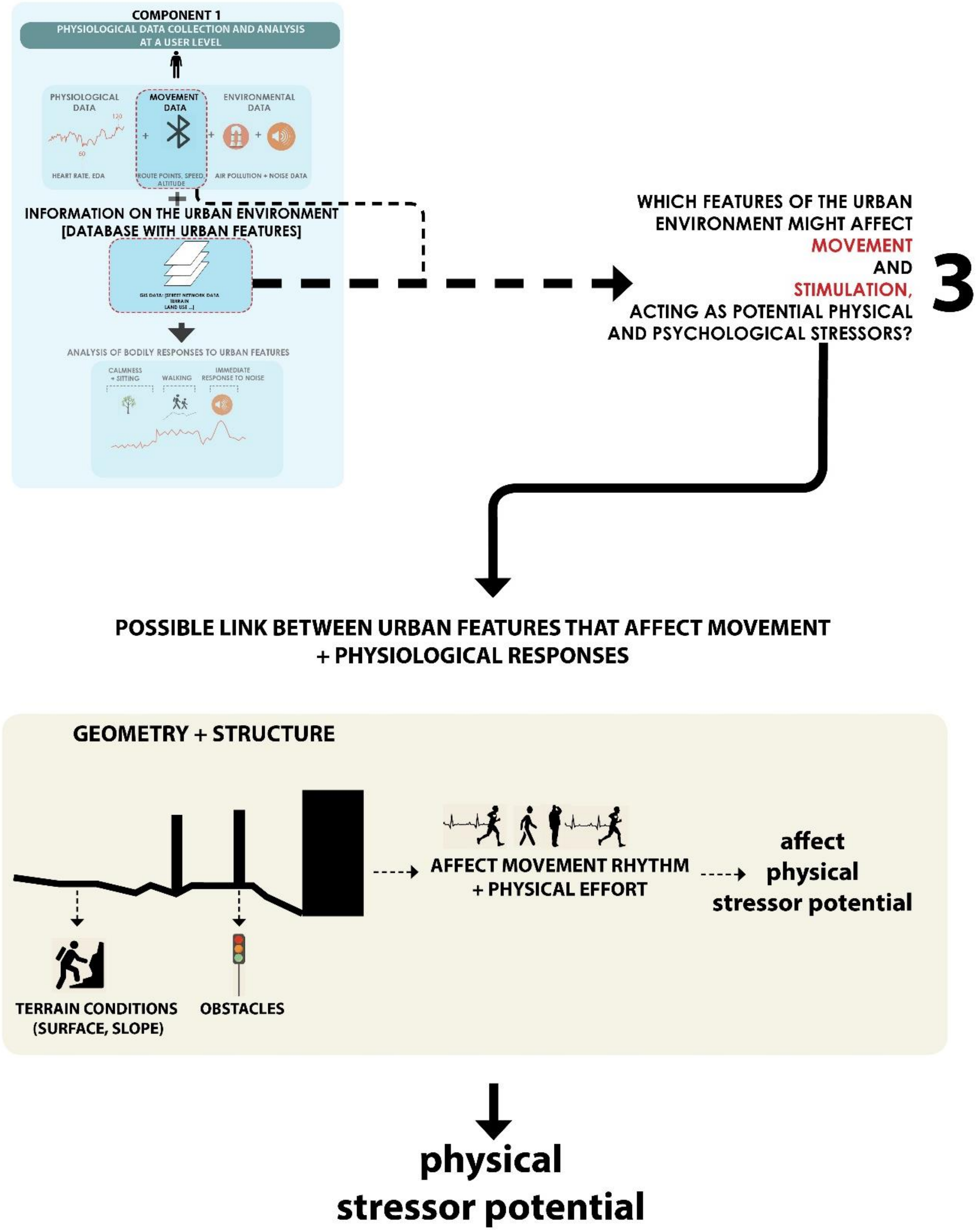


Figure 3.11: Spatial parameters which have the potential to act as physical stressors

Following the categorisation presented in section 3.2.5 (Figure 3.4), the study suggests the grouping of spatial characteristics that influence movement under the name 'Physical stressors'. This conceptual grouping is presented in Figure 3.11. While this section has focused more on the relationship between movement, physical activity and space, the temperature is also a physical stressor. It can thus be included in the category of physical stressors, along with the spatial characteristics which affect it (e.g., presence of green canopy). The term ‘physical stressor potential’ is used to highlight that the presence of these urban features does not automatically mean that physiological responses will be elicited whenever a pedestrian encounters them; this potential may be actualised or not, and the resulting experience may vary between individuals or at different times of the day.

3.4.2. SENSORY STIMULATION, PSYCHOLOGICAL STRESSORS AND RESTORATION IN THE URBAN SPACE

Urban space is composed of elements which emit many sensory cues, such as visual, auditory and olfactory stimuli. These cues are processed by humans during their interaction with the environment, shaping their experience. This experience can be perceived as a combination of states that fall in the two dimensions of activation and affect. The encounter of an architecturally interesting church, for instance, can elicit excitement for a tourist that sees it for the first time; this can be described as a state of high activation and positive affect. In emotion theory, the dimensions of activation and affect are used to depict the intensity of the emotion and the degree of pleasantness, respectively (Boucsein 2012). In the example stated above, the encounter of the new stimulus could be accompanied by physiological changes, such as small changes in the HR and EDA. The perception of this experience could be described as a state of engagement or excitement.

The sensory experience is significantly affected by the complexity and novelty of the stimuli surrounding an individual (Geller 1980). Urban stimuli operate as any other stimulus which can induce orienting and defensive responses, depending on factors such as complexity and novelty (Berlyne 1960) among others, as it was explained in section 3.2.2. and 3.2.3. These parameters induce curiosity, create motivation towards exploration in the urban environment, and affect a subject's emotion or arousal as it interacts with a stimulus over time. Complexity is defined as the degree of diversity and variety in the stimulus. As for the novelty factor, this is unique for each individual (Geller 1980).

The presence of stimuli, though, does not necessarily lead to a pleasant experience. Noise, for instance, is a stimulus which might be perceived negatively by the human body, acting as a psychological stressor. The number and complexity of stimuli which shape the experience are important factors, as excessive sensory input can lead to overstimulation. The experience of this effect in the urban space gained significant interest after Milgram conceptualised it as the theory of sensory overload (Milgram 1970) in the context of urban life. Milgram based this theory on the capability of humans to perceive information. When the amount of information presented to an individual becomes too high, it may be difficult to process it. The perception of experience also changes over time, and during repeated interactions with the same stimulus. Berlyne (1960) argues that stimuli with high complexity might seem overwhelming and initially induce a negative response in terms of affect, especially when many complex stimuli are encountered together. With repeated exposure, the arousal is increased, as the information is processed, until the novelty effect wears off and the positive affect decreases. According to Berlyne, simple stimuli with a low degree of complexity are more appreciated in the first interactions. After that, the positive affect is reduced.

Urban space also contains elements which can lower stress. This ability in connection to the natural and urban environment is commonly discussed as restoration. Two major theories have dominated this discussion: the Psycho-Evolutionary Theory of Stress Reduction of Ulrich et al. (1991) and the Attention Restoration Theory by Kaplan and Kaplan (1989). Ulrich et al. (1991) also outline other theories that have been influential in the shaping of the two aforementioned; for instance, the theory that restoration from stress is easier in environments of low intensity and arousal, and the overload perspective that excessive external stimulation requires larger processing time and therefore slows down restoration. Attention Restoration Theory views restoration as the process of recovering from cognitive fatigue, generated by information processing, while the Psycho-Evolutionary Theory of Stress Reduction focuses on the emotional rather than mental state as the source of fatigue.

These theoretical concepts will be further discussed in the following sections, in connection to specific urban and natural elements which are related to stimulation and may trigger or lower physiological responses.

3.4.2.1. URBAN CHARACTERISTICS THAT CAN ACT AS PSYCHOLOGICAL STRESSORS

3.4.2.1.1. NOISE

One of the most commonly studied psychological stressors is noise. The primary source of noise for the general population is traffic; a significant factor that determines noise exposure is, therefore, proximity to traffic nodes and arteries (Babisch 2011). Several studies have confirmed that exposure to noise generates acute physiological effects which are not associated to the possible damage of the hearing organ but are more related to the activation of stress mechanisms through the autonomic nervous system (Babisch 2011; Basner et al. 2014; Lusk et al. 2004; Stansfeld & Matheson 2003). Most commonly, the studied subjects have increased blood pressure, while HR is also affected (Babisch 2011; Basner et al. 2014; Lusk et al. 2004; Stansfeld & Matheson 2003). Stress hormones can also be elevated (Babisch 2011; Basner et al. 2014).

The field studies which investigate immediate cardiovascular effects of noise during everyday activities are few (e.g., Huang et al. 2013a; Kraus et al. 2013) and commonly measure one or more of the following parameters: blood pressure, HR and heart rate variability. Blood pressure and HR responses might be mediated by different mechanisms. Blood pressure is affected by overall noise exposure, and HR immediately increases in elevated noise exposure (Kraus et al. 2013) and especially sudden noise peaks (Lusk et al. 2004). Mahmood et al. (2006) also studied the effect of noise on HR, but in laboratory conditions, and with noise levels of 90 dB, much higher than the two studies mentioned above (Huang et al. 2013a; Kraus et al. 2013). They found that HR was elevated in most subjects, taking from 2 to 5 minutes to return to normal levels for most subjects. Regarding short-term effects of noise exposure during commuting, one study found that cycling was associated with more exposure to higher noise levels than other commuting modes, as there is no protective structure around cyclists for noise mitigation. Finally, recent studies have also included EDA measurement to assess the sympathetic stress reaction to noise. In the study of Notbohm et al. (2013), who measured the EDA of subjects exposed to traffic noise in a laboratory setting, EDA increased in all subjects.

A significant factor which determines the magnitude of disturbance is the time of the day and activity conducted during the exposure. The activity that is disturbed because of noise exposure is significant for the estimation of the impact. The acute physiological effects are most intense during activities that require concentration and attention (Babisch 2011).

In line with other studies on combinations of stressors that were discussed in section 3.3.4, there has also been evidence that noise acts synergistically when it interacts with other stressors, and the overall effect of the stressors on the organism is increased (Stansfeld & Matheson 2003; Huang et al. 2013a).

3.4.2.1.2. MIXED-USE, DENSITY AND SENSORY STIMULATION

As it has been suggested by Jacobs (1961) and Montgomery (1998) among others, mixed-use is a necessary ingredient for the creation of vibrant urban environments. Many theorists have, though, pointed out that the implementation of mixed-use is necessary but not enough (e.g., Montgomery 1998; Yue et al. 2016). The definition of mixed-use is complicated, according to Grant (2002), as the term can be used for very different conditions, such as mixing the intensity of different land uses, increasing the diversity of uses, but also integrating currently segregated uses. The latter case shows us that mixing uses is not good by definition, as, for instance, industrial use is separated from other uses for good reason, due to environmental concerns. How much integration and diversity of land use is needed to fuel the creation of a vibrant neighbourhood remains, therefore a question. Density has also been discussed in the urban planning discourse as a necessary ingredient for enhancing physical activity (Giles Corti et al. 2016), and an essential condition for neighbourhood vitality (Montgomery 1998).

There has not been any research connecting explicitly mixed-use with stress levels or physiological responses. However, mixed-use development is connected with some factors which are related to increased levels of information input and psychological stress. Mixed-use and commercial development may be connected to an increased presence of signs, diverse colours and sounds, in comparison to residential land use. For instance, King et al. (2012) found that the noise levels were much higher in a mixed-use area than a residential area. While these factors are affected by traffic, architectural style and other features, one factor that is generally associated with commercial and mixed-use regardless of other parameters is the increased presence of human activity (McConville et al. 2011; Moreno & Fernandes 2011; Rodríguez et al. 2009). The feeling of crowding, which has also been associated with high-density development apart from mixed- and commercial use, may act as a psychological stressor (Chu et al. 2004). This effect might be caused by other additional factors apart from overstimulation, such as the perception of control over personal space (Stokols 1976). Engelniederhammer et al. (2019) tested the effect of crowding on physiological responses using sensors capturing EDA and the presence of other humans, among others. They found alterations in aversion and excitement indicators associated with the number of intrusions of personal space, though more research is needed in order to extract more concrete results.

The increased presence of stimuli may also lead to increased activity in terms of information processing, without necessarily leading to a negative experience. The study of Neale et al. (2017), which used EEG monitoring to compare the effect of urban areas with different qualities on older adults, showed that urban busy areas were associated with higher excitement in comparison to urban green areas. Stimulation is necessary for generating feelings such as excitement, and its lack may create negative perceptions for the urban web. Places which may be of historical or cultural importance, for instance, are significant elements of the urban web from a psychophysiological point of view, as they can act as sources of sensory stimulation (Brebner et al. 1976). There is a considerable body of literature on landmarks and their role in terms of visual stimulation (e.g., Montgomery 1998) and their capability to act as reference points that allow an individual to create a city's mental map (Lynch 1960). According to Kevin Lynch (1960), the presence of many landmarks joined by known streets is a factor which signifies a good city, as it is “imageable”, in contrast to a dull city, where the residents are not able to recognise a large proportion of its urban web and associate it with a familiar symbol. The experience of a stimulus also depends on the rate at which information is perceived; therefore, pedestrians can process the sensorial characteristics of their surroundings at their own pace, while drivers or cyclists are engaged at another cognitively complex task at the same time, which limits their capabilities (Geller 1980). There is thus no recipe for deciding how much complexity (in terms of the available stimuli) is good, as personal experiences differ and change over time.

3.4.2.1.3. NATURAL ENVIRONMENTS AND URBAN SPACES AS RESTORATIVE PLACES

The two dominating theories in the field of stress restoration have generated a set of guidelines in terms of spatial qualities which determine the restorative capabilities of a place. In the Attention Restoration Theory, these characteristics are the feeling of "being away" (the psychological distance from activities of daily life), the extent or richness and organisation of surroundings, the fascination or presence of aesthetic and captivating qualities which can capture the involuntary attention of the individual, and the compatibility between the environment and the individual's needs and intentions. In the Psycho-Evolutionary Theory of Stress Reduction, the defining characteristics are the openness and depth of the place, the presence of a medium degree of complexity in terms of stimuli, the high presence of natural elements (water, trees) and the absence of threatening circumstances.

In terms of which spaces have these characteristics, there has been plenty of evidence that exposure to parks and forests elicit feelings of stress reduction and lower related physiological markers. Recent studies highlight the positive psychological responses to interaction with green environments as compared to urban environments, while also suggesting that they do not need a long time to take effect. Park et al. (2011) show that even a short exposure to natural environments (15 minutes) yielded much less tension, anxiety, confusion and fatigue than the same acts in urban areas.

There has also been evidence that even viewing a natural environment can assist in stress restoration. Lee et al. (2009) found an improvement in several physiological markers related to stress. In the study of Ulrich et al. (1991), all subjects reported much higher levels of positive affect and lower rates of anger and fear when viewing a video of natural environment after exposure to a stressful movie, as opposed to when viewing sounds and imagery of an urban environment after being exposed to the same stressor. Their evaluation included continuous monitoring of HR, muscle tension and EDA levels during the experiment. The physiological indicators suggested a more significant decrease of autonomic arousal and faster return to baseline conditions in the case of exposure to a natural environment, compared to the exposure to an urban environment.

Recent studies, though, have identified potential bias in the overpromotion of natural environments (Weber & Trojan 2018). This view is supported by arguments such as the fact that the urban environments which usually feature in the studies that promote the healing effects of natural environments are urban streets with transportation as their primary activity, while the chosen natural environments are always those of recreational character (Staats et al. 2016). Since this criticism first emerged, there have been studies which show that urban settings might also have restorative capabilities; for instance, San Juan et al. (2017) found that sitting and walking in two urban squares for 30 minutes had a restorative effect and a decrease in negative affect. The selected squares also fulfilled the criteria in terms of spatial qualities necessary for restoration, according to the Attention Restoration Theory and the Psycho-Evolutionary Theory of Stress Reduction.

In a literature review on the restorative capabilities of urban environments, Weber and Trojan (2018) showed that the restorative capabilities of everyday urban environments are understudied. The few existing studies demonstrate that the perception that urban environment is in principle, not restorative is wrong. The presence or proximity to natural elements (including vegetation such as trees in urban streets) was associated with positive results. This finding was in line with the suggestion of Psycho-Evolutionary Theory of Stress Reduction that a high number of natural elements is a good predictor of high restorative capabilities of a place. Weber and Trojan (2018) also found that cultural-historical places, art galleries, museums and churches had a positive restorative effect, while residential areas were identified as the least restorative when compared with recreational and cultural-historical areas. It was also shown that apart from the place itself, the activity that the place hosts is of equal importance; for instance, shopping in a mall, visiting a park and sitting in a café were all rated positively as restorative activities, while walking was the least restorative in comparison to the other three. Architectural features also raised the fascination of subjects, as it was found in another study, increasing the restorative effect, while building height had a negative effect, possibly due to an increased feeling of enclosure. The low level of social stimuli was also evaluated positively in the context of restoration in some studies. Finally, it was found that intercultural and age differences also play a role; for instance, it was found in two studies that adolescents preferred coffee shops and video arcades for their restorative potential, while elderly rated higher a café targeted to seniors.

One common theme that emerged was that two of the criteria set in the Attention Restoration Theory had particular importance: the ability of space to fascinate the subjects and generate an effect of “being away”. One other point which emerged from recent studies is the difference between physiological measurements of stress relief and reported psychological benefits. For instance, Tyrväinen et al. (2014) showed that while a visit to an urban park and urban woodland had more positive effects in perceived stress relief in comparison to a visit to the urban centre, physiological measurements (salivary cortisol concentration) suggested similar bodily reaction to stress in all three environments.

Another point which has to be considered is that the therapeutic effects of a place are not related only to its visual properties and that the full sensory experience has to be considered. In the case of green, for instance, recent studies (e.g., Wooller et al. 2015) have suggested that multiple sensory inputs, including sounds and smell, contribute to its potential therapeutic effects of green. Weber and Trojan (2018) also stressed the need to consider this aspect in future research on the restorative capabilities of urban spaces.

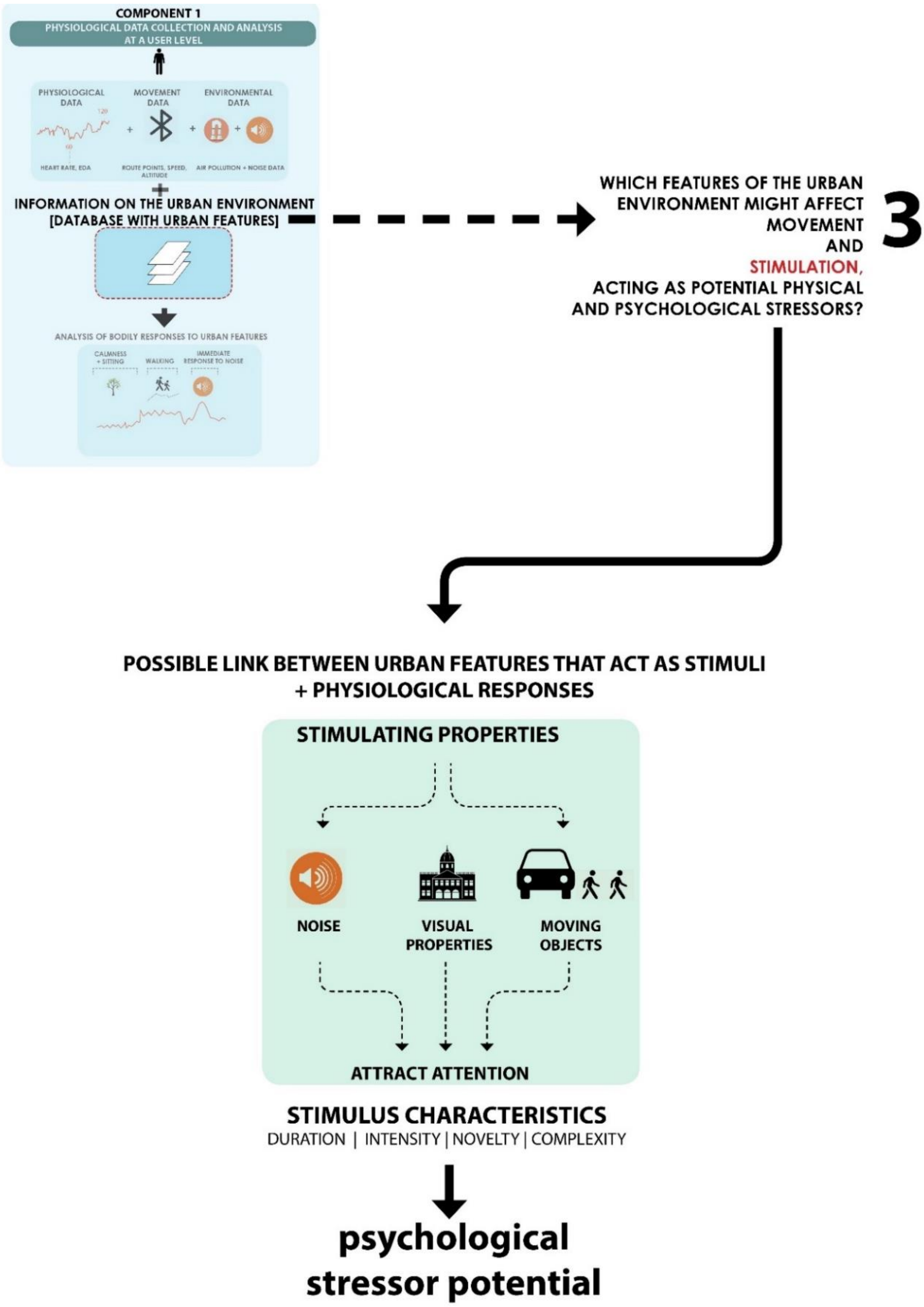


Figure 3.12. The relationship between urban stimulus characteristics and physiological effects in the urban environment.

The literature presented in section 3.4.2 is summarised in the conceptual scheme presented in Figure 3.12. The figure demonstrates that the relationship between stimulus characteristics and physiological effects, which was described in detail in section 3.2 and 3.3, is also applicable in the urban space. It seems thus appropriate to select and organise urban features for the construction of the spatial database based on stimulation properties (intensity, duration, novelty, complexity), while also considering the interaction between stimuli. Novelty is not a relevant factor in traffic and land use density, but intensity plays a large role. Novelty and complexity are significant parameters in the case of landmarks, cultural spaces and architectural features. Additionally, intensity and complexity may be assessed by evaluating the patterns of spatial concentration of many stimuli together and how these patterns change in space. The duration of stressor will be later assessed by examining the pattern of interaction of the user with space.

Finally, similar to the identification of urban features which can act as physical stressors, the study proposes here the stimulation-based categorisation of urban features and their grouping under the name 'Psychological stressors', following the categorisation proposed in section 3.2.5.

3.5. PRESENTATION OF THE THEORETICAL AND CONCEPTUAL FRAMEWORK

As this review showed, the study of fundamental bodily processes is essential for understanding the psychophysiological experience in the urban environment. This experience is affected by physical and psychological factors. Based on the reviewed literature, stress is the physiological response of the organism to a change in state or the surroundings. Stimulation is connected with the concept of stress; the appearance of a stimulus or a change in the stimulation pattern may capture the attention of the individual, who then processes this information to decide if it is threatening or not. These concepts are at the centre of urban theories related to psychophysiological experience, such as Milgram's theory of sensory overload, as well as the Attention Restoration Theory and the Psycho-Evolutionary Theory of Stress Reduction. The way that the urban and physical environment is structured around us plays a significant role in shaping our daily experiences. Urban stimuli operate as any kind of stimulus, which can attract our attention or even lead to overstimulation when the intensity or complexity of the stimuli is high. Noise also acts as a potential psychological stressor, with different effects depending on the duration and intensity of the stimulus.

Movement is also an integral part of our interactions with the urban environment. Physical activity is related to the concept of stress and may generate sympathetic arousal comparable to the exposure to a psychological stressor. It is, though, mediated through different pathways than sympathetic arousal elicited from immediate changes in stimulation, and usually it does not initiate negative emotions unless the intensity and duration lead to high physical strain. Its effect is also beneficial for the organism. The movement pattern, and thus the physiological effects associated with it, is influenced by the structure of our environment. At a small scale, anything that causes muscular movement is related to physiological bodily effects. A change in posture, for instance, causes a change from a steady state to another, and this can generate a physiological response. Parameters related to the structure of the surroundings, such as the presence of obstacles, can affect physiological responses as they generate different movement patterns. The terrain condition is also a significant factor, increasing the activity intensity in cases of slope or irregular surfaces.

There is also a complex interplay between space, movement, social interaction and psychophysiological experience; apart from the changes in sympathetic arousal which may occur during due to changes in excitation or stress levels, talking also changes the breathing pattern, which may cause artefacts in electrodermal activity recordings. Furthermore, social interaction during walking might affect the movement pattern, as it can become challenging to keep a steady rhythm during a conversation.

Our experience during interactions with the urban environment can thus be seen as a sequence of physiological events, which affect our perception of this experience and are dependent on the following factors: intention (which affects the rhythm of movement and the psychological state), personal factors (age, level of physical training, medical history, and past experiences which shape our perception of stimuli as threatening or exciting) and interaction with physical and psychological stressors. The reviewed studies in Chapter 1 showed that there has been some progress in mapping the perception of experience, but these efforts have suffered from possible misinterpretations of sympathetic arousal as stress which is necessarily negative. The health benefits from physical activity have also been overlooked in these studies. In order to assist future research in analysing urban experience through physiological data from a health-oriented perspective, we need to understand the interactions between activity and context and analyse changes in sympathetic arousal from this perspective. The urban experience is, in this context, the effect of interaction between changing levels of stressors, with changing levels of intensity, duration, novelty and complexity.

The analysis of urban parameters which affect physiological responses led to the identification of 'physical stressors' as a category of urban features which affect movement (see section 3.4.1), and 'psychological stressors' as features related to visual and auditory stimulation (see section 3.4.2). The temperature could also be included in the category of physical stressors, but it should be separated from movement-related effects for better conceptual categorisation. As shown in Figure 3.13, these features suggest an increased potential for eliciting physiological changes associated to each category. The personal factors, as well as the characteristics of interaction with space, are the parameters that determine the chances of activating the 'stressor potential', as it is called here. The scheme presented in Figure 3.13 summarises these points and will act as the theoretical framework of this study.

Figure 3.14 provides a more dynamic representation of the framework, illustrating the main ideas from the perspective of a user moving in space. As shown in the figure, each instance of interaction with space is affected by the characteristics of stimulation. The urban stimuli may have a different significance for each user according to their traits and their history of encounters with this place. Additionally, the user activity before visiting this space creates a state of high sympathetic arousal, which may affect the responses.

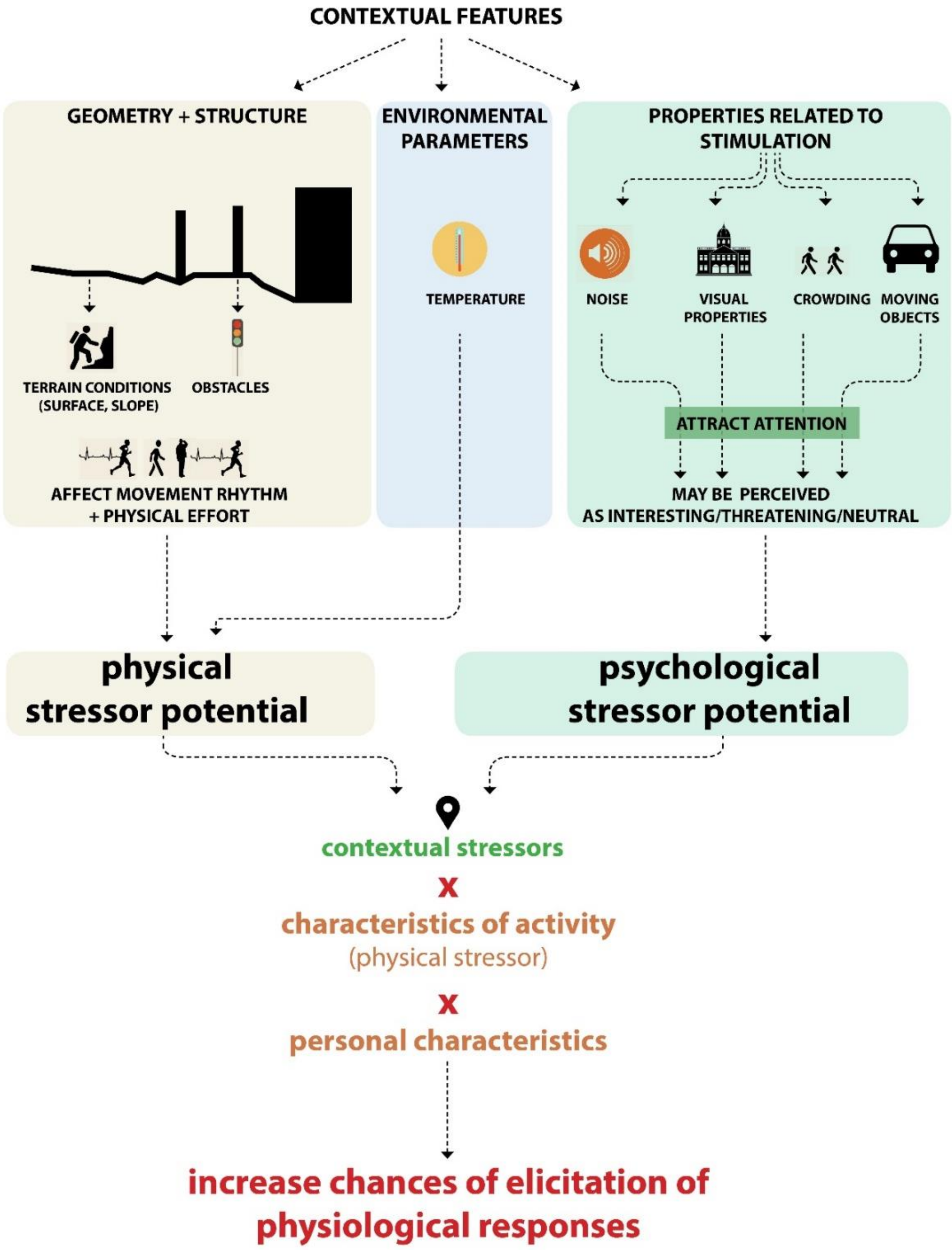


Figure 3.13. The theoretical framework

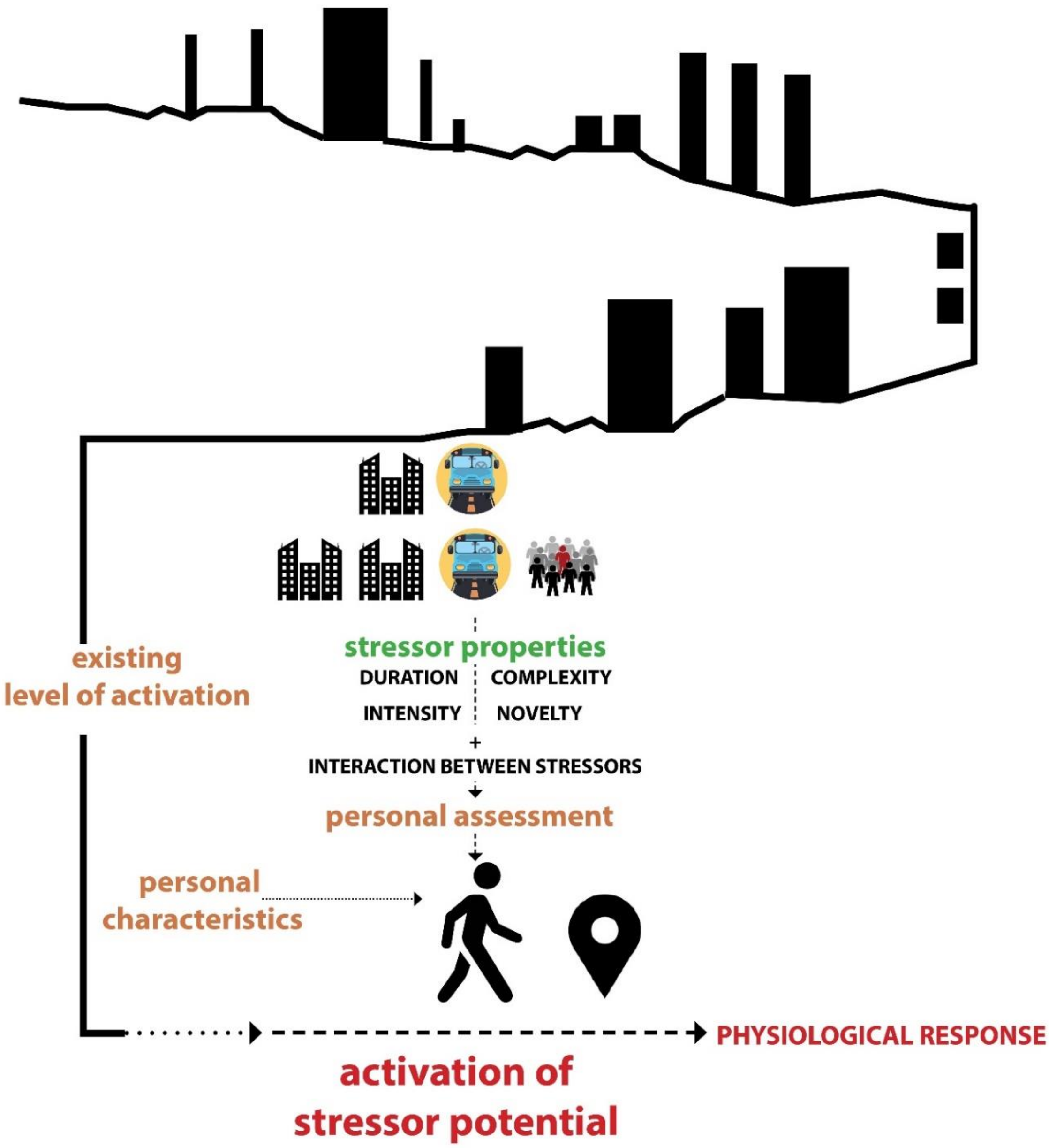


Figure 3.14. A presentation of the theoretical framework from the perspective of a user moving in the urban space

The theoretical framework, which was designed based on the reviewed literature, led to the identification of specific features or the urban environment that could be related to physiological responses. Traffic and the presence of mixed-use were selected as significant features which are connected to stimulation levels and can potentially act as psychological stressors when their presence is intense. Traffic was selected due to its link to noise, which is a psychological stressor. The inclusion of the density of mixed-use was based on the logic that higher levels of this feature would be connected to higher stimulus intensity and complexity, due to a higher presence of signs and other diverse visual elements. Additionally, this feature can act as an indicator of the levels of crowding, which is linked to an increased presence of moving stimuli which a person has to avoid while walking, and has been associated with psychological stress. It was also decided to focus on features associated with a high intensity of physiological responses. From this perspective, the inclusion of the presence of green would not be necessary. The inclusion of traffic and mixed-use is enough to separate places of high levels of stimulus complexity from less complex environments for the scope of this research. Future work could involve a reconsideration of this point and include green as a significant feature if needed.

In terms of physical stressors, terrain conditions and slope may increase the intensity of physical activity, while temperature also plays an important role, especially when there are intense temperature changes. Traffic lights were also included as features that may affect movement, while also being possibly connected with increased stimulation levels due to the high concentration of people and cars that they can create. For this reason, it was decided to include traffic lights as a feature that may act as a possible physical and psychological stressor.

As for movement-related features, it was decided to include the activity intensity, the duration of the activity, the change in activity and the presence of steady-state activity as features that represent different aspects of activity related to physical stress.

It should also be noted that the features which were identified as potential psychological stressors could, sometimes, act as physical stressors as well, affecting movement. For instance, crowding may lead to deviations from following a straight walking path, causing small accelerations or decelerations when encountering others in the street. The same applies to interactions with traffic and traffic lights, as these parameters may alter the speed of walking in order to avoid any accidents. These features will be kept in the category of psychological stressors due to their links with stimulation levels, but their capacity to act as physical stressors should be kept in mind as a possibility.

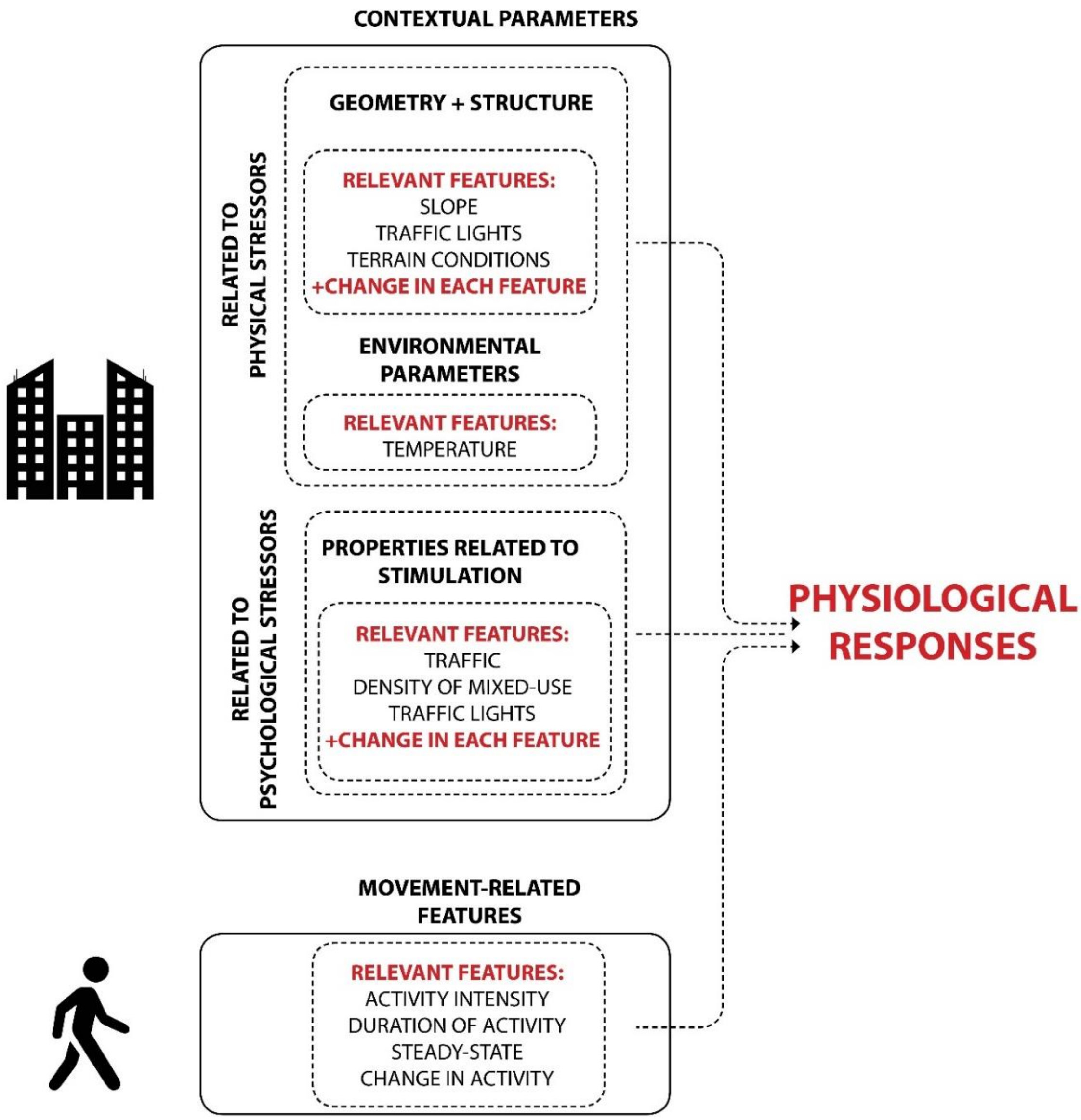


Figure 3.15. The conceptual framework linking urban and movement-related features to physiological responses.

Figure 3.15 illustrates the possible links between the selected features and physiological responses. This scheme was derived from the reviewed literature and the designed theoretical framework and shall act as the conceptual framework of this research. All the spatial features will be derived from the analysis of OpenStreetMap (OSM) and Point of Interest (POI) data, and they will act as representations of the estimated potential of a space to elicit physiological responses. OSM data will be used for the extraction of variables related to traffic and other physical stressors. POI data will be used for the representation of mixed-use. The movement-related features will be unique for each individual, and they will be derived from the analysis of time-series movement data (speed and accelerometer).

To confirm that the use of POIs for the representation of mixed-use is justified in the context of this research, an analysis was conducted using POI data and exploring its relationship with stimulus complexity. The only studied context for this analysis was Sydney; however, its urban fabric has enough diversity to cover various levels of POI density and complexity.

The analysis showed that POI density has a moderate but significant association with the complexity of the environment and its predictors as identified by Ewing and Clemente (2013). These predictors included different variables that are related to stimulation levels, such as the number of buildings, the number of dominant building colours, the number of accent colours (colours of other objects or surfaces which have a significant presence in the view), the number of pedestrians, the presence of outdoor dining and the presence of public art. The associations between these predictors and POI density were also analysed, finding a strong and significant relationship between POI density and two predictors (pedestrian activity and outdoor dining). The overall findings show that POI density can be used as an indicator of stimulus complexity in lack of more accurate image-based data sources. Its capability to capture the differences in the degree of pedestrian activity is highly significant in the context of this study, as crowding is a significant factor that can act as a stressor and affect physiological responses. The analysis is presented in detail in Appendix A.

It was decided not to include a separate indicator for the parameter visual properties in the conceptual framework, as this parameter is connected to the other parameters related to stimulation. It is assumed that a higher presence of mixed-use and traffic is connected to a higher presence of variations in colour, form and movement in the visual field of the pedestrian. Apart from the previously discussed link between POI density and pedestrian activity (which is related to movement in terms of visual properties), the analysis presented in Appendix A showed that POI density was also related to the number of buildings and the number of accent colours in some of the tested models. It was thus decided that the other parameters related to stimulation can also act as a representation of the differences in visual properties for the scope of this research.

The final step of this phase was the construction of a conceptual scheme for the analysis of physiological responses, based on the reviewed literature. Considering that movement and contextual factors act as the two groups of stressors based on the presented framework, we need to identify changes in states in these stressors and analyse physiological responses from this perspective. The review also showed that while exercise is a stressor, its effect in the long term is positive for the organism. In the context of this research, this suggests that it would be of use to identify and study separately physical stressors (and especially the effects of movement) from stimulus-related events.

A conceptual scheme (Figure 3.16) was thus designed for the analysis of physiological responses from this perspective, including the following steps:

1. Movement analysis for identification of:
    a. Phases of similar activity intensity, duration of each phase, and overall duration of the activity
    b. Changes between steady states or phases of similar activity intensity
2. Physiological data analysis for identification of tonic and phasic physiological states and responses
3. Contextual analysis for identification of:
    a. Parameters related to stimulation: stimulus type, intensity, duration and frequency of appearance, stimulus novelty and complexity
    b. Changes in the stimulus (or the overall stimulation levels)
4. Synthesis of movement, physiological and contextual analysis, for:
    a. Classification of physiological responses based on their possible sources (physical, psychological or both types of stressors)

These steps, which are depicted in Figure 3.16, will drive the construction of the data fusion model for the analysis of the different data sources related to this research.

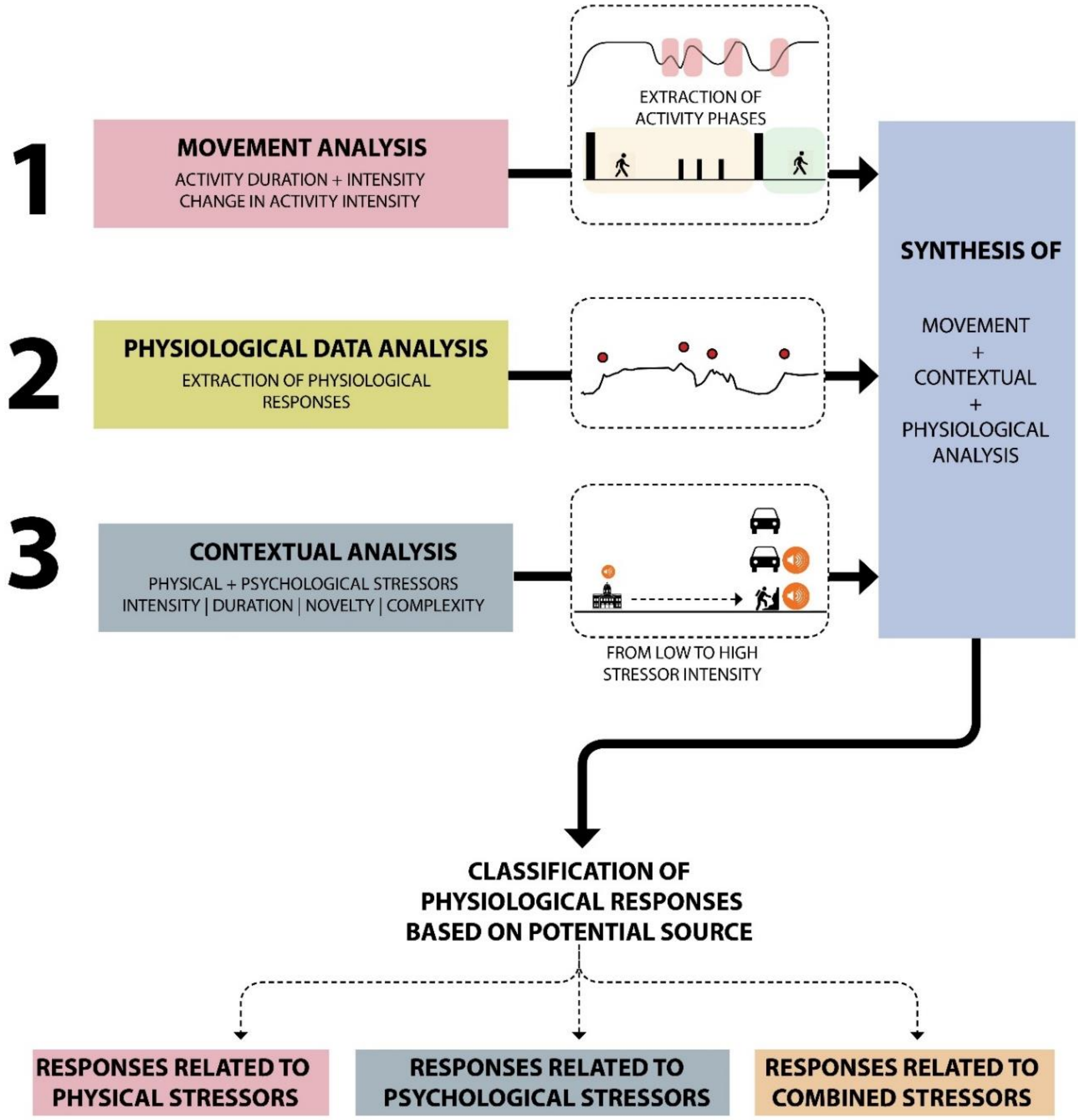


Figure 3.16. A conceptual scheme for analysis and interpretation of physiological data in the urban domain, based on analysis of movement and context

Finally, Figure 3.17 shows that each part of component 1 of the proposed methodology is connected with one step of the designed scheme for analysing physiological responses in the urban environment.

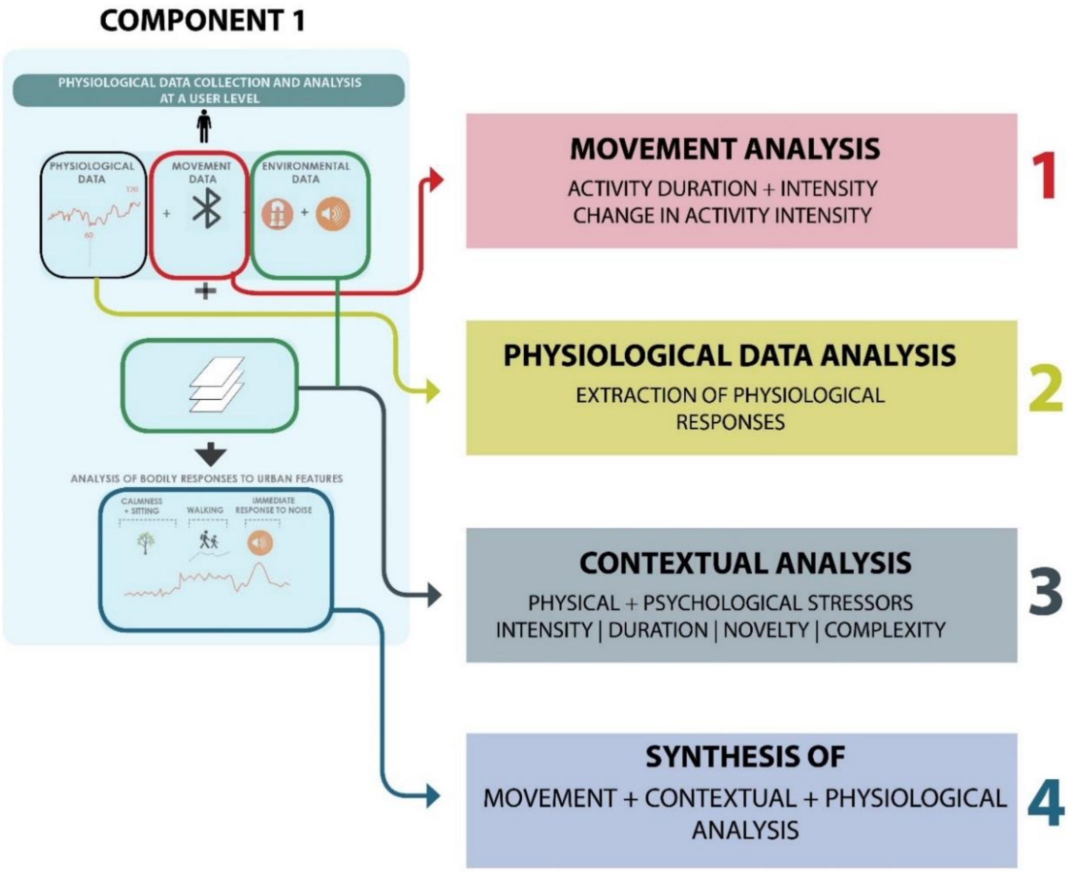


Figure 3.17. Connection of the designed scheme for the analysis of different data with component 1 of the methodology

3.6. DISCUSSION

The literature which was reviewed in this chapter started from a thorough analysis of different concepts related to physiological responses. The impact of different parameters, such as physical activity or changes in stimulation, were also discussed in relation to the physiological signals which will be analysed in this research (HR and EDA). Then, the discussion shifted to the urban environment. Theories from environmental psychology were reviewed in order to position this research in the context of relevant theoretical discourse focused on the urban space. The combination of relevant theories from different domains led to the identification of movement and stimulation as two significant sources of physiological responses in the urban space. These two factors are related to physical and psychological stress, respectively, following relevant literature from stress theory. Based on this categorisation, it was decided to group the urban and movement-related features in two categories (physical and psychological stressors) based on their capacity to affect movement or auditory and visual stimulation levels and thus elicit physiological responses. Environmental factors (mainly temperature) also fit in this categorisation, being classified as a physical stressor. The review of relevant literature from stress theory also showed that different stressors can interact with each other. This finding included the interactions between exercise and other psychological stressors.

Based on these findings from the literature review and their translation in urban space, a theoretical framework was designed. The theoretical framework adopts existing theories related to stress and physiological arousal and describes how different elements of the urban environment may act as physical or psychological stressors while also considering the presence of activity as a physical stressor. It contributes to current research on the links between urban environment and physiological responses by situating movement in the context of stress theory and thus covering a gap that was identified in Chapter 1. It is also a useful tool for analysing the properties of different urban features concerning the impact that they can have on information processing and movement. The grouping of different features in two categories helps understand the combined effect that these features can have on physiological responses.

After constructing the theoretical framework, a conceptual framework was created (Figure 3.15). This framework was designed after considering which urban features should be the focus of this research. The feature selection was based on assessing each feature's possible impact on physiological responses based on existing literature; there is already evidence linking, for instance, noise and physiological responses, and the same applies to crowding. Traffic and density of mixed-use were thus selected as representations of these factors (and indicators of differences in stimulation levels) in urban space. The next step of this work (Chapter 4) shall focus on methods for analysing these features from a data-driven perspective.

The next step was the presentation of a scheme for the analysis of physiological responses was presented (Figure 3.16) based on the presence of physical or psychological stressors, or both. This scheme will be the ending point of the data fusion model presented in Chapter 5. The responses which are analysed in this way could be interpreted as indicators of acute stress, based on the reviewed literature. This interpretation includes changes in movement and other cases that are recognised as a change in state from the organism, but they may not be perceived as a negative experience from the individual. This research shall refer to the adopted scheme as a ‘model for the analysis of physiological responses’, to avoid any confusion with other studies which consider stress as a state with a negative emotional tone. Based on the reviewed literature, responses related to physical activity and movement changes are expected to be perceived as a neutral or positive experience (‘eustress’), unless the duration or intensity of activity becomes too high. Responses during stimulation from auditory or visual sources could be associated with a shift of attention or excitement in the case of the orienting response, or distress in the case of repeated responses that do not habituate soon. The different types of responses are most likely attributed to different arousal systems, following the multidimensional model of arousal proposed by Boucsein (2012) that was presented in section 3.2.1. This scheme was devised for analysis of responses in the urban space and is thus more focused on physiological responses that can be attributed to movement or spatial and environmental factors encountered during outdoor walking. Other psychological stressors, such as work or family-related factors, are not included in this scheme, as it focuses on the effects of urban space.

Future work could involve an extension of the conceptual framework towards the inclusion of more features. Another factor that may be included in a future extension of this research is the link between physiological responses, space and emotions. A brief theoretical background on mood and emotion assessment in relation to the bodily responses that are examined in this research is provided in Appendix F. It was decided to stop at this brief review and narrow down the scope of this research by focusing on the physiological responses and not on their perception for the time being. The future identification of the emotions that a place or a set of circumstances can elicit could still be of value. The acquired knowledge would add information regarding how an individual evaluates and perceives the changes in bodily functions elicited by a place. This information is significant, as a negative emotional state in connection to a place might cause the individual to avoid revisiting this place, while positive emotional states may attract more people. At the same time, it is uncertain whether one place will elicit the same emotion in different people. Studies that investigate the connections between autonomic responses and emotions rely on an individual's ability to perceive changes in bodily functions and connect them to an emotional state. This ability is related to the individual's cognitive complexity and emotional awareness, which develop through a person’s interactions with the external world and evolve through life. The same bodily reaction to an external stimulus might be perceived differently in different individuals. All these factors shall be considered in the possibility of extending this work in the future.

4

DATA MINING METHODS FOR MOVEMENT-RELATED, CONTEXTUAL AND PHYSIOLOGICAL DATA: A REVIEW

4.1. INTRODUCTION

The literature review presented in the previous chapter led to the design of a theoretical framework describing the links between activity, urban environment and physiological responses. A conceptual framework was also designed, identifying contextual and movement-related features which might be related to physiological responses. This chapter extends this work by providing sufficient background on data analysis methods which can be used to materialise this framework. As explained in Chapter 2, the work presented in this chapter is a preparatory step for the design of the methodology for the collection and analysis of physiological data in the urban space.

The chapter is organised as follows: section 4.2 discusses concepts related to the data mining methods which are going to be used in this research. General data mining methods and techniques are first introduced, and then the discussion shifts to methods relevant for time series and spatial data. Section 4.3 goes a step further by discussing data analysis methods related to the specific data that will be used in this research. This review will involve methods related to processing speed and accelerometer data for the analysis of activity (section 4.3.1), HR and EDA data processing (section 4.3.2) and POI and OSM data processing (section 4.3.3). Section 4.4 presents a scheme for fusion of the examined data. The data fusion model will be the backbone of component 1 of the methodology presented in Chapter 2, and it will be used as the first step for analysis leading to the other two components. Finally, section 4.5 concludes the chapter by reflecting on the examined methods and describing the next steps.

4.2. DATA MINING METHODS AND TECHNIQUES

4.2.1. DATA PREPARATION

General-purpose data mining tasks commonly include data preparation or pre-processing (such as data cleaning, data transformation, feature selection and extraction) and data analysis (such as clustering, classification and prediction).

Data preparation or pre-processing includes handling of missing data, correction of errors and noise reduction in the data. Data transformation includes preparatory steps that give an appropriate form or scale to the data before the analysis. Such a step is normalisation, which is the process of scaling the data to a specified range.

Data reduction is necessary when the data set has a large size, thus requiring a long time for the computations. Segmentation may also be performed using binning or histograms for data reduction (Han & Kamber 2006). Feature extraction is also frequently applied at the pre-processing stage, towards the creation of new variables that reveal different trends in the data. Measures such as the mean, variance and standard deviation (STD) are usually calculated; the mean represents the average or centre of a set of values, while the variance and STD show the dispersion of the data (Han & Kamber 2006).

4.2.2. MACHINE LEARNING

Machine learning (ML) was first introduced as a term in 1959, referring to a computer program that can learn from existing data a pattern of behaviour that may be unknown or unpredictable by its programmer (Joshi 2020).

There are different types of machine learning methods, based on how the pattern of behaviour is inferred from the existing data. These methods are typically classified into three groups: supervised learning, unsupervised learning and reinforcement learning.

The methods which will be used in some parts of this research involve supervised and unsupervised learning; hence, these two methods will be briefly introduced here.

Supervised learning involves the extraction of a pattern based on a feedback mechanism that uses existing labelled data or continuous values as the ground truth data, and aims at minimising the error of the prediction based on different performance metrics. Unsupervised learning is used when there are no available ground truth data that can guide the process of knowledge extraction, and the behaviour or pattern in the data is inferred in other ways, such as separating the data in groups based on their similarity.

4.2.2.1. UNSUPERVISED MACHINE LEARNING: CLUSTERING

Clustering is a method frequently deployed for exploratory data grouping when there is no prior knowledge of the possible classes where a data object might belong (Han & Kamber 2006). Grouping is a task which can be employed for various purposes in the context of data analysis, including data segmentation and identification of hidden relationships (Myatt 2007). The decision is based on the similarity between the different data points, which can be evaluated using measures such as the Euclidean distance (Myatt 2007).

Grouping, in its simplest form, may be performed by identifying all objects that share the same class or value or fall within a range of values (Myatt 2007). While this method is the most straightforward and does not require advanced computational techniques, it requires a level of prior knowledge or instinct about possible existing groups within the dataset. Its application also requires an approach of trial and error in terms of different combinations of values. This approach may lead to an exhaustive search until an appropriate recipe is found.

Clustering is considered an unsupervised machine learning task and is defined as the identification of similar objects and their subsequent grouping in clusters (Zolhavarieh et al. 2014). Popular methods for data clustering include partitioning, hierarchical, density-based, grid-based and model-based (Han & Kamber 2006).

Hierarchical clustering starts with examining all the data points as potential clusters. At each step, the clusters are examined to decide if they can be merged. The number of clusters is reduced at each step, and the merging continues, forming a tree-like cluster structure, called a dendrogram, until a criterion is met. This approach is computationally expensive compared to others, but it has the advantage that the number of clusters does not have to be known in advance (Keogh & Kasetty 2003).

An example of clustering by partitioning is the K-means clustering algorithm. In this approach, the centres of the clusters are first randomly chosen. Then, after evaluating similarity, each data point is assigned a class based on its nearest centre. After that, the clusters' centres are re-estimated, by finding the average centre in each of the clusters. This step is repeated until the centres of the clusters do not need to change. This approach is widely used due to its simplicity and the small processing speed. However, the number of clusters must be known beforehand. The choice of the initial centres can also affect the result significantly (Han & Kamber 2006).

Density-based clustering is based on growing a neighbourhood around data points by evaluating if the density in the distribution of the points is above a set threshold. A popular density-based clustering algorithm is DBSCAN (Ester et al. 1996).

Clustering is frequently used in the context of exploratory analysis, to discover classes or categories in a data set, and can lead to interesting discoveries and trends. The main problem concerning the larger group of unsupervised methods is the evaluation of the result, which often relies on the subjective opinion of the analyst. As a general rule, clustering is considered successful when the resulting data groups have high homogeneity and a large separation from each other. Several measures have been proposed for this evaluation, such as calculating the distance between cluster centres.

The proposed methodology will involve clustering methods for the identification of hotspots of physiological responses and their separation in distinct groups of points (clusters). These methods will be described in detail in Chapter 7.

4.2.2.2. SUPERVISED MACHINE LEARNING: CLASSIFICATION AND PREDICTION

In data mining, classification and prediction describe the process of predicting the values or the class of an object, based on a model or function derived from an existing dataset. Classification and prediction tasks are usually based on pattern identification using existing ground truth values. They are thus considered as supervised machine learning tasks. The existing dataset is used as training data in order to identify the underlying structure behind objects and classes or values. This approach can be used to predict discrete classes or labels, as well as values, as happens in predicting daily fluctuations in the stock market (Han & Kamber 2006). The prediction of classes or labels is known as classification, and regression refers to predicting continuous values.

This section will present different machine learning algorithms commonly used for regression and classification. These algorithms are going to be used in two parts of the research: in Chapter 5 and Appendix E, for activity classification during the processing of the movement data and artefact identification during the processing of the EDA data, and in Chapter 8, for prediction of physiological responses based on movement and contextual characteristics. The different approaches and methods are only described here briefly, to provide background knowledge regarding models and terms which shall be used later on.

One of the simplest and most commonly used models for the prediction of continuous values is linear regression. This model is usually based on minimising the mean square error between the actual and the predicted values. While it has broad applicability, it has the drawback that it is suitable for linear relationships between the input and output features, and is not applicable for relationships of higher complexity.

Another relatively simple algorithm used for both classification and regression is the 'k-nearest neighbors' (k-NN) algorithm. When the objective is to identify the most appropriate value or label of a test point, the k-NN algorithm analyses the points contained in the training set, finds the *k* most similar data points and averages the value of those points. The algorithm does not assume any specific relationship between the data points and can be used to approximate linear or more complex functions (Faul 2019; Joshi 2020).

The decision tree (DT) algorithm is based on constructing a tree-like structure of nodes, branches and leaves, where the nodes represent rules used to separate the input data in different branches according to their properties or attributes, and eventually determine the most appropriate labels or values. One advantage of the DT algorithm is that it is interpretable. It is thus frequently used when there is interest in understanding the underlying mechanism behind the data generation (Joshi 2020).

The support vector machine (SVM) algorithm is also suitable for linear and non-linear models and involves creating a 'hyperplane' for the separation of the data points in categories with clear boundaries (in the classification task). The SVM algorithm was initially created for classification problems, but its use was later extended to regression tasks (Joshi 2020).

Another approach involves the construction of ensemble algorithms based on the combination of many weak learners. Ensemble algorithms include bagging and boosting techniques, based on the way that the models are trained. Bagging involves splitting the dataset into several sets and training different decision trees in a setup where each tree uses data from a different set; then, the output is determined by methods such as voting in classification tasks and averaging for regression tasks. Random forests (RF) is a popular ensemble algorithm based on creating multiple decision trees, using a method similar to the bagging technique. The RF algorithm also uses a subset of the features for each training set, apart from splitting the overall dataset into smaller sets. This method creates more variation in the decision trees used for the ensemble, and reduces overfitting, resulting in better handling of noise in the data (Joshi 2020). In boosting techniques, the weak learners are trained sequentially and not in parallel, as in bagging. A popular ensemble algorithm based on boosting is the XGBoost algorithm (Chen & Guestrin 2016).

Another family of models includes neural networks and deep learning methods. Neural networks were conceptually inspired by the structure of the brain, and are composed of neurons or nodes, and connections between nodes, or *synapses*. There are three types of nodes; the *input* nodes (referring to input features), the *hidden* nodes, which contain the functions that build the predictor, and the *output* nodes, that contain the predicted outcome. The connections between the nodes contain weights, which are generated randomly or sampled from a predefined distribution in the beginning, and updated as the algorithm progresses. The training of the network involves updating the weights by calculating the error between the actual and the predicted values in each round, and 'backpropagating' the errors in order to change the weights in a direction that minimises the error.

Deep learning refers to neural networks which have more hidden layers. Some subclasses of deep learning models have become popular lately in association with specific problems, such as speech recognition, object detection and time series analysis. These models are the convolutional neural networks (CNN), the recurrent neural networks (RNN) and the long-short term memory networks (LSTM).

CNN models incorporate convolution functions that run through the dataset and are applied on small sections of the data, creating new features that help highlight some properties of the original data. The convolutional layer can be more than one, and is commonly followed by pooling layers for dimensionality reduction, and then by one or more fully connected hidden layers. CNN models have been very successful in image analysis for object recognition; one of the most famous examples is the work of Krizhevsky et al. (2012), who used a CNN model for the classification of a dataset containing more than 15 million images in 22000 categories.

RNN models were primarily created for time series data modelling but suffered from the vanishing gradient problem. LSTM models were developed later and overcame the limitations of the RNN models (Hochreiter & Schmidhuber 1997). The LSTM model contains a series of blocks that operate as gates and decide which information of the network's previous state should be kept or forgotten. Due to this feature, they can retain past information from the model wherever appropriate, and use it to determine the output of the prediction. LSTM models have been used successfully in problems which involve complex sequences, such as natural language processing tasks (Cheng et al. 2016). A recent development involves the combination of CNN and LSTM models (e.g., Karim et al. 2018), an approach can be used for harvesting the advantages of both models. This combination has been popular in complex tasks that have a temporal structure, such as emotion classification in outdoor routes (Kanjo et al. 2018b), or video classification based on identifying human actions (Wu et al. 2015).

Usually, the experimentation for a regression or classification task involves testing multiple different models, tuning the hyperparameters using techniques such as grid search, and determining the most appropriate for the given task based on performance metrics such as the mean squared error (MSE) and the mean absolute error (MAE) for regression problems, and the accuracy score, or other metrics (precision, recall and F1 score) for classification problems. The method of cross-validation is commonly used for understanding how the model performs in different variations of the training and testing dataset. One of the most commonly used cross-validation methods is k-fold cross-validation, where the dataset is split into *k* sets, and *k* versions of training and testing datasets are created. Each set is used only once as the testing dataset, and the rest of the data form the training dataset each time. The process is repeated *k* times, and the performance metrics from the *k* folds are averaged to determine the final score (Faul 2019).

4.2.3. DATA MINING METHODS FOR SPATIAL AND TEMPORAL DATA

While the methods described above are generally applicable and can serve as a guideline in terms of possible steps suitable for different tasks, their implementation in a real-world task requires some modifications and considerations, especially when the data is multidimensional and heterogeneous.

The data sets which will be analysed in this project (GPS, accelerometer, HR, EDA, skin temperature, OpenStreetMap (OSM) data, Point of Interest (POI) data) have very different properties as they belong in different categories. They can be separated in temporal data, which have the form of time series (accelerometer, HR, speed, EDA, skin temperature) and spatial, static data (OSM, POI data), while the OSM data also have a graph structure. Some datasets also have both temporal and spatial dimensions (GPS data). As these data sets are heterogeneous, data cleaning and indexing require a combination of approaches to enable smooth access and data query during the analysis (Zheng et al. 2014). Additionally, some common data mining techniques have to be explored in connection with domain-specific knowledge; such a case is the estimation of physical activity intensity. Furthermore, POI and OSM data contain semantic information apart from latitude and longitude data. This information has to be retrieved and organised in ways that are useful in the context of this research.

The following sections will provide a background on data analysis methods for each data type and domain of research and then propose a method for data fusion to support the specific objectives as stated in the framework.

4.2.3.1. DATA TYPES: TIME SERIES

Accelerometer data, speed, and the physiological signals examined here (HR, EDA, skin temperature) are composed of numerical values which are collected over time and form a continuous set of observations. This data type is known as time-series data (Fu 2011).

Before proceeding with data analysis, it should be examined whether the data is stationary or not. Time series data is stationary when the behaviour of its statistical properties is not significantly affected by the change of time. Many types of time series data exhibit non-stationary behaviour, including physiological data (Fukuda et al. 2004). In such cases, it should be considered if non-stationarity must be removed by removing the slow changes in the mean, with methods such as differencing.

A common pre-processing step in time series data is the reduction of data points by techniques such as sampling, or segmenting the time series and interpolating the mean value of each segment (Fu 2011). A time-series object can also be segmented in smaller objects, with a window with fixed or varying length, thus allowing the detection of patterns and periodic trends (Fu 2011). Several features are then extracted from each window in the time or frequency domain (e.g., mean, STD) for its representation.

4.2.3.2. DATA TYPES: SPATIAL DATA

Spatial data can include raster and vector data and can contain spatial and non-spatial attributes. Spatial attributes may include latitude, longitude and other properties related to geographical location, such as elevation, while non-spatial attributes contain information such as the name of an area and population (Shekhar et al. 2011). Spatial data mining is a field with unique challenges and processes in terms of both management and analysis, compared to traditional data mining techniques. One of the most frequently mentioned properties of spatial data is spatial autocorrelation: while traditional data mining techniques may assume an independent identical distribution of values, in spatial datasets, geographically close points often have similar characteristics, and this has to be taken into account in the analysis (Shekhar et al. 2011).

Spatial relationships between data points can be represented in various ways, including set-based, topological, directional or metric representations. In set-based representation, data points are analysed as members of sets which have properties such as union and intersection. A form of topological representation is the exploration of space as a network where edges form relationships of connectivity between nodes. Other models of analysis of spatial relationships explore relationships of coordinates in terms of properties such as distance (Shekhar et al. 2011).

These relationships are also often depicted in choices regarding the indexing and structure of spatial data in the formulation of spatial databases. In the case of temporal data, time-series data points can be ordered by sorting the timestamps. If we want to find a neighbourhood of data points that are temporally close to a specified point, these points' indices will be within close range of the index of the specified point and thus easily accessible. An example would be to make a query for the segment surrounding an intense peak in one hour of HR measurements. This type of sorting and indexing is not so explicit in spatial datasets. However, allowing easy retrieval of neighbourhoods of data points is still very important, as this type of query is very frequent in tasks such as looking for the nearest neighbours of a point in terms of spatial proximity. Popular solutions for this problem involve spatial partitioning and data partitioning techniques, such as k-d trees, quadtrees, R-trees and their variations, and grid-based spatial division (Eldawy et al. 2015).

Spatial clustering is a popular procedure in spatial data mining, as it can be used to detect areas where a phenomenon has a more intense appearance. Hierarchical and partitioning clustering algorithms have been used for this purpose. A widely used density-based algorithm is the density-based spatial clustering of application with noise

(DBSCAN) proposed by Ester et al. (1996). The algorithm offers a good alternative to the K-means algorithm for spatial applications, as it focuses on the discovery of areas which have points above a specified density threshold. It is thus a very popular algorithm in the context of analysing spatial datasets which might include areas with very few, scattered points, with low densities, which do not belong to any cluster (Ester et al. 1996). Hotspot analysis is a special category of spatial clustering. It is based on the evaluation of similarity between neighbouring data points, and it is commonly used in crime mapping, analysis of the spread of diseases and other fields. Common methods here include the application of local indicators of spatial association (LISA), among others (Shekhar et al. 2011).

4.3. MINING MOVEMENT, PHYSIOLOGICAL AND SPATIAL URBAN DATA: TRENDS AND CHALLENGES

4.3.1. MOVEMENT DATA

4.3.1.1. SPEED AND GPS DATA

GPS data analysis has emerged as an alternative to traditional travel survey methods in transport research (Schuessler & Axhausen, 2009). Methods for GPS data post-processing have been used for different facets of travel behaviour analysis, such as travel mode identification (Schuessler & Axhausen, 2009) and trajectory analysis. Data pre-processing commonly includes speed calculation and typical data cleaning procedures, while data analysis usually employs data grouping methods towards the detection of trips and stops.

The data pre-processing step mostly involves data cleaning. The obtained GPS tracks might contain errors due to poor indoor signal reception, signal reflection by building surfaces and roads, and distortions during travelling by public transport (Schuessler & Axhausen, 2009). Sometimes there are also strong positional jumps which are realistically not possible. Therefore, data cleaning commonly includes identifying points with unrealistic values, and deletion or another manipulation of points following a large temporal or spatial gap, to handle cases of signal loss (Hwang et al. 2013). Smoothing might also be applied for the reduction of errors. After that, the speed can be calculated as the first-order derivative of the GPS points in relation to time, while the acceleration is the second derivative (Schuessler & Axhausen, 2009).

Data grouping methods may be applied for activity detection or separation of data to different sessions. This task can be conducted by analysing if the gap between subsequent timestamps exceeds a threshold (e.g., 45s to 900s in Schuessler & Axhausen, 2009).

After that, data partitioning is again applied for each session, for the detection of stops and periods of movement. Filters based on speed values can be used for this purpose. Papandrea et al. (2013), for instance, use a speed threshold of 1.3m/s for the detection of stops.

Another way to identify possible stop points is by spatial clustering. Hwang et al. (2013) have implemented this step in their method for extraction of mobility measures; first, they identify possible stop points by a kernel density estimation (KDE) analysis of point density. These points are then used as seeds for a DBSCAN algorithm, which identifies points which cluster around stop locations. Temporal filtering is applied after that, to identify if the points which belong to a spatial cluster are also continuous. A majority filter is also applied to take care of misclassified points. This filter is based on calculating the most common value among temporal neighbours. At the final step, different attributes are assigned to trips and stops, based on parameters such as time of arrival, speed and trip duration.

After separating trips from stops, some studies extract information regarding the purpose or mode of the trip. Schuessler and Axhausen (2009) for instance, propose a fuzzy logic approach which takes as input the speed and acceleration during the extracted activities and calculates the maximum likelihood of mode. They also use the assumption that the transition to a new travel mode is preceded and followed by a short phase of walking; therefore, if these phases are not detected, the activity in question can be joined with its neighbouring activities.

This research area has also benefited from the emergence of POI data, which allow the semantic analysis of GPS trajectories, towards the extraction of information regarding the context of movement and personal preferences in terms of visiting places. An example here is the study of Yan et al. (2011) who propose a framework for the semantic analysis of GPS trajectories, which analyses the characteristics of the movement of users and uses the POI data to estimate the context of their movements and stops. Papandrea et al. (2013) also use a combination of POI and GPS trajectory analysis to analyse POIs that humans visit in their daily routes. In this case, the research aims to identify the places where users spend a considerable amount of time. To identify the "stay-locations", they apply a DBSCAN clustering algorithm to identify possible regions of interest. They also extract semantic information from the tag labels to categorise the stop and also use as a POI measure the 'relevance', which refers to the history of visits that the user has paid to this particular POI.

GPS data can also be used to predict metabolic energy cost (and thus physical activity intensity) in the context of walking, after the extraction of speed. The most widely used formula is that of Pandolf et al. (1977), which relates the metabolic energy cost to the weight of the individual, the carried load, the speed and the terrain slope. New, more accurate alternatives to this formula have been established in recent years, such as the model of Ludlow and Weyand (2016).

Figure 5.1. provides a summary of the outlined methods, while situating them within component 1 of the conceptual methodology.

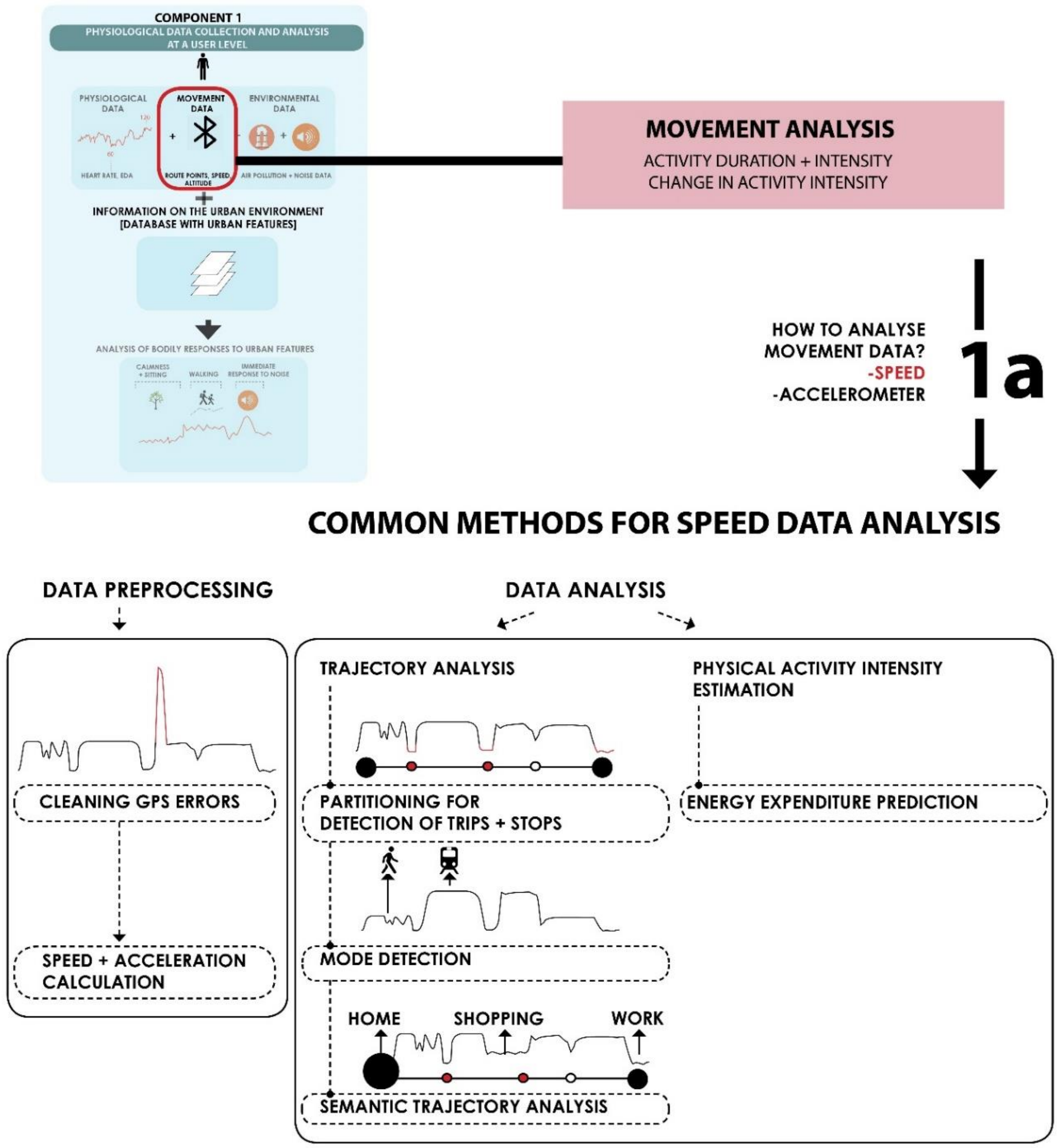


Figure 4.1. Common approaches to the analysis of speed data

4.3.1.2. ACCELEROMETER DATA

Acceleration refers to the change of speed in relation to time, and its unit is the gravitational acceleration g (1 g = 9.8m·s^{2}) (Chen & Basset 2005). The acceleration values recorded with an accelerometer contain information regarding the acceleration generated by bodily motion and gravitational acceleration. Other factors also can contribute to the accelerometer output, such as external movements from vehicles or other machinery which produces vibration, or accidental movements of the sensor (Bouten et al. 1997). A triaxial accelerometer contains information regarding the movement in the vertical axis (z) and the horizontal axes (x,y). During human locomotion, the most significant increase in magnitude is found in the vertical axis (z), and the increase in movement is reflected as an increase in magnitude and frequency (Bouten et al. 1997). Accelerometer data acquired from smartphones may differ from data from wristbands, as wristbands capture hand movements under all circumstances, while smartphones might be held in a pocket instead of the hand in some cases (Dobbins & Rawassizadeh 2018).

The usage of accelerometer data can assist in two areas: in physical activity intensity estimation, and activity classification. The two tasks are related, as activity classification may involve the separation of phases of sitting, walking, running, and other states with different activity intensity. A difference here is that activity intensity estimation returns an assessment in the form of a numerical scale, while activity classification partitions the data in discrete classes, which are then used to infer the context during some user actions.

Regarding intensity estimation, triaxial accelerometers can estimate the energy expenditure of a subject reasonably. Uniaxial accelerometers do not provide such an accurate estimation but can demonstrate well the differences in physical activity among different subjects (Levine 2005). Activity intensity estimation models are based on the principle that the energy expenditure is significantly related to the accelerometer signal (Bouten et al. 1997), and especially to the integral of the modulus of the accelerometer values.

There have been some concerns regarding the loss of accuracy during graded walking (Terrier et al. 2001). For outdoor movement, GPS analysis and open amplitude API can compensate here by providing information regarding the altitude change. Moreover, different individuals might respond differently to the same task, and such variations cannot be captured by the sole usage of accelerometers (Yang et al. 2019).

The data pre-processing stage may include a low-pass or high-pass (Chen & Basset 2005) filtering. Feature extraction depends on the context of the study. The estimation of activity intensity usually involves the extraction of accelerometer counts, a procedure which includes converting the negative values to positive ones with full-wave or halfwave rectification, and integration with a specified time window, such as 1-minute (Chen and Basset, 2005). The integration of the signal has the disadvantage that it might average activities with two different intensities if both of them fall in the same time window.

Feature extraction for activity classification commonly involves the calculation of mean, median, STD, root mean square and variance values from the time domain, and energy, or entropy and mean frequency from the frequency domain (Dobbins & Rawassizadeh 2018). These features are calculated in a sliding window. Some studies also recommend a combination of data from all channels in one vector (e.g., Kanjo et al. 2018a).

The data analysis step here involves using the extracted features to estimate activity intensity or activity classification. For the estimation of activity intensity, studies frequently use cut points (thresholds) in the accelerometer counts for the separation of sedentary, moderate and vigorous activity, and then measure the time that the user spent in each category (Troiano et al. 2014). Some studies have also explored the combination of HR monitoring with kinematic measurements (accelerometry and occasionally GPS monitoring) for the assessment of activity intensity. The obtained data are used for various purposes. Costa et al. (2015), for instance, used GPS together with accelerometers and HR monitoring in order to determine stops during the participants' journey and exclude them from the data processing. The energy expenditure was calculated from HR combined with accelerometer data, following the branched equation model of Brage et al. (2004). De Müllenheim et al. (2018) also used GPS, accelerometers and HR monitoring to determine which combination is best for physical activity assessment. GPS was used for the calculation of speed, from which the activity intensity was estimated. In that study, the combination of methods did not yield better results than physical activity estimation through GPS monitoring alone. They suggest, though that in the absence of GPS monitoring, the combination of accelerometry and HR monitoring produced better estimations than accelerometry alone. Another example is that of Romero-Ugalde et al. (2017), who propose a piecewise model which simplifies the model of Brage et al. (2004) by using a linear combination of HR and accelerometer counts for energy measurement when the subject is conducting a light activity, and HR for moderate and vigorous activity. Dowd et al. (2018) show that the number of such studies is still small and does not allow comparison of results between studies. There is currently no consensus in terms of which method is better for the measurement of activity intensity.

As for data analysis methods for activity classification, Godfrey et al. (2008) provide a comprehensive review of techniques applied for this purpose, using data from accelerometer signals. The earliest techniques for accelerometer signal analysis involved the separation of static from dynamic activity with the application of thresholds. Veltink et al. (1996), for instance, used first a threshold for separation of static and dynamic activities, and then the mean and STD values for distinguishing different kinds of dynamic activities (walking, climbing stairs, cycling). Lyons et al. (2005) also used a similar approach utilising thresholds, with a 1-second moving window, and added a posture detection method for further separation of static activities to sitting, standing, and lying. Mathie et al. (2002) also proposed a model for separating sedentary from active behaviour, which computes the integral of the raw accelerometer data in segments using a non-overlapping moving window (essentially extracting the 'accelerometer counts' which were mentioned above) and uses a threshold for separating dynamic from static activity. Figo et al. (2010) provide an extensive review of features from both time and frequency domains, evaluating their performance as metrics in simple classification tasks with 2 or 3 activity classes. Their experiment suggested that the metrics which were the most powerful predictors in the time domain were the difference between consecutive values and the minimum values, leading to very high accuracy, while the tested frequency domain measures also had a very good performance.

Supervised and unsupervised machine learning methods have also been explored for activity classification from accelerometer data. Kwon et al. (2014) provide sufficient background regarding studies that have used supervised learning. Several classifiers have been used, such as RF, Naïve Bayes, SVM and K-NN (Erdaş et al. 2016) This method though requires the generation of a training data set of adequate size, which is a time-consuming task (Kwon et al. 2014). Furthermore, the data labelling process suffers from problems related to inaccuracies in the reports, such as overestimating time spent during different activities or underestimating momentary activities (Dobbins & Rawassizadeh 2018). Some recent studies attempted to tackle this problem by approaching activity classification as an unsupervised learning task, where there is no labelled dataset for training the algorithm.

As an alternative, unsupervised partitioning methods have also been explored with success in activity classification. As Kwon et al. (2014) state, the basic set of activities used in classification tasks (walking, running, sitting, standing, lying down) have significantly different profiles in terms of accelerometer data: the energetic activities (walking, running) exhibit significant variations at all channels (x,y,z), with this effect more prominent in the case of running. Sitting, standing and lying down have much lower variations at all channels, close to constant, while when the subject is sitting or lying, the z values are also higher than the others. In terms of appropriate statistical measures, these differences can be captured by extracting the mean and STD values from windows with a small length and a 50% overlap. Their experiments showed that the Gaussian method was the most successful, while hierarchical clustering and DBSCAN also performed well. Dobbins and Rawassizadeh (2018) compared the performance of different clustering algorithms after feature selection, and hierarchical clustering produced the most well-separated clusters, while in that case, DBSCAN had the worst performance.

The approaches to accelerometer data processing which were outlined here have been summarised in Figure 4.2.

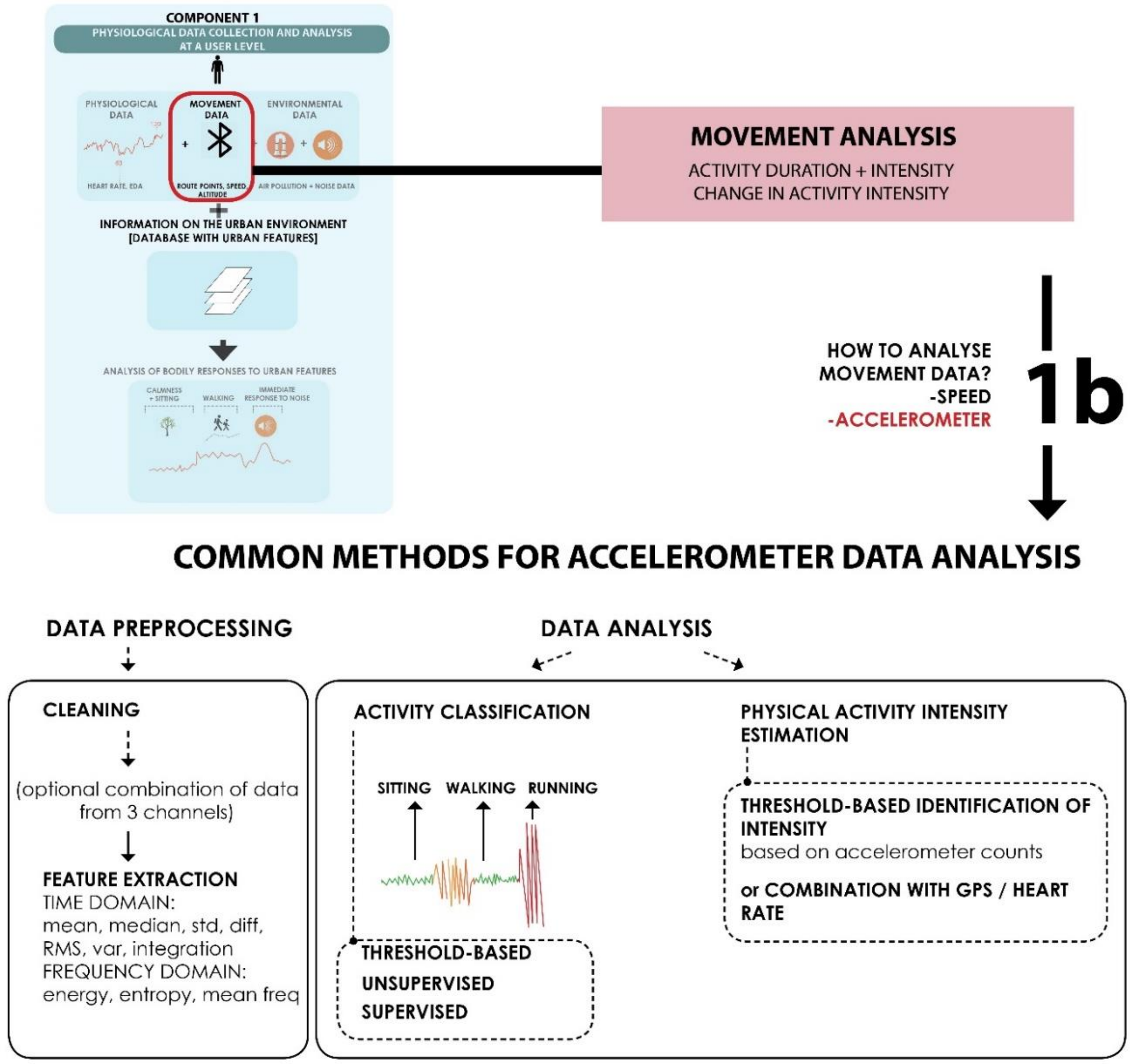


Figure 4.2. Common steps in the analysis of accelerometer data

4.3.2. PHYSIOLOGICAL DATA

4.3.2.1. HR DATA ANALYSIS

Jennings et al. (1981) define three classes of variables related to HR analysis: sustained HR, heart rate variability (HRV) and event-related HR. Sustained changes reflect the tonic response of the HR to an ongoing situation, and last more than 30 seconds, while event-related responses are the immediate responses to changes in stimulation and typically last less than 30 seconds. The sustained HR response can be measured by extraction of the mean and variance.

A category of studies examines HR as a measure of activity intensity due to its significant relationship with oxygen consumption during exercise (Colberg et al. 2003; Strath et al. 2000). For the assessment of physical activity intensity, some features that have been used as measures are the mean HR, the difference between HR during rest and activity (activity HR -resting HR) and the number of minutes above a certain per cent of maximal HR. Other frequently used procedures for the estimation of the activity intensity involve the comparison of HR at peak exercise to the estimated maximal HR (HR_{max}) (Levine 2005), the calculation of the estimated per cent HR reserve (Strath et al. 2000) or the summated-heart-rate-zones method (Edwards 1993). The relationship between HR and energy expenditure is, though, not linear, and has large inter-individual variations (Levine 2005). Romero-Ugalde et al. (2017) suggest that this relationship is weaker during lower intensity exercise. Chapter 3 also showed that HR is not only activated during physical activity but also in other circumstances which cause psychological or physical stress and increased need for information processing.

HRV has also been used extensively for the assessment of autonomic activity. The input here is RR-intervals (R corresponds to the peak of a beat, and RR-intervals are the intervals between consecutive beats in the electrocardiogram). This signal depicts, therefore, the variations in RR intervals (Figure 4.3). In terms of HRV features, the following are standard measures of autonomic activity in the time domain: RMSSD, the root mean square of the successive differences, is considered a measure of parasympathetic nervous activity. The natural log of RMSSD is also frequently calculated. SDNN is the standard deviation of RR intervals. NN50 is the number of pairs of consecutive RR intervals with a difference larger than 50 ms, and PNN50 is the NN50 divided by the total number of RR intervals.

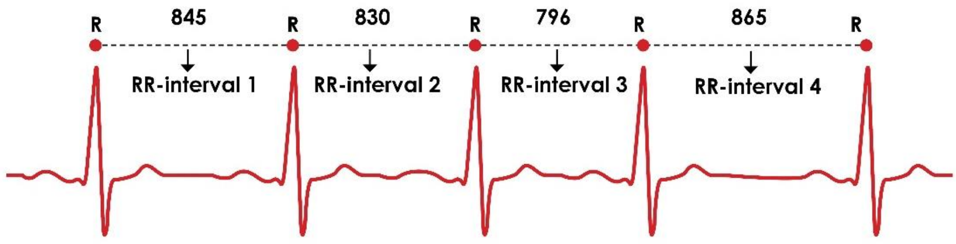


Figure 4.3. Heart rate variability (HRV): The variation in successive RR-intervals

In the frequency domain, spectral analysis can be conducted for HRV analysis, by methods such as the fast Fourier transform (FFT), producing components in three different bands. The low-frequency component has been connected with sympathetic stimulation, while the high-frequency component shows the influence of respiration. The ratio of low frequency to high frequency (LF/HF) has also been used as an indicator of sympathetic modulation (Acharya et al. 2004). This analysis should though be conducted in periods where the signal is stationary, excluding posture changes (Jorna 1992). This measurement becomes difficult during exercise, as then the data becomes non-stationary (Tulppo et al. 1996).

Data partitioning may be applied for separating phases where there is a change in environmental conditions and removing the non-stationarity of the HR data. Bernaola-Galván et al. (2001) proposed a method for HR data partitioning for this purpose, which divides a dataset recursively by evaluating the similarity between each point and its neighbouring subsets based on extracted statistical features. Clustering methods have also used for partitioning HR data; Yun et al. (2018), for instance, used spectral clustering and Gaussian mixture for dividing HR datasets into clusters.

A task which is essential for this research is the analysis of HR changes in a way that separates changes due to movement from event-based fluctuations, caused by emotional events or changes in the environmental stimuli. A popular approach here is that of Myrtek (2004), who proposed an algorithm for detecting HR changes due to emotion in conditions when the subject is moving. The algorithm, called Additional Heart Rate (AHR), involves monitoring the subject's movement with an accelerometer, to distinguish emotional from physical activity. The algorithm computes the mean HR in segments of 60 seconds and compares it to the average HR of the previous 3 minutes. If there is a change in HR larger than 3bpm, and there is no intense activity detected in the accelerometer data, the segment is classified as an instance of emotional activation.

Kusserow et al. (2013) noted that Myrtek’s algorithm is based only on activity intensity and does not consider postural changes, which can affect HR, as shown in Chapter 3. They proposed thus a refined version which includes the detection of primitive activity classes (‘sit’, ‘stand’, ‘walk’) and the transition between activities. Then they segmented the data in order to extract the duration and intensity of the stress activation phases.

A summary of the outlined methods is shown in Figure 4.4.

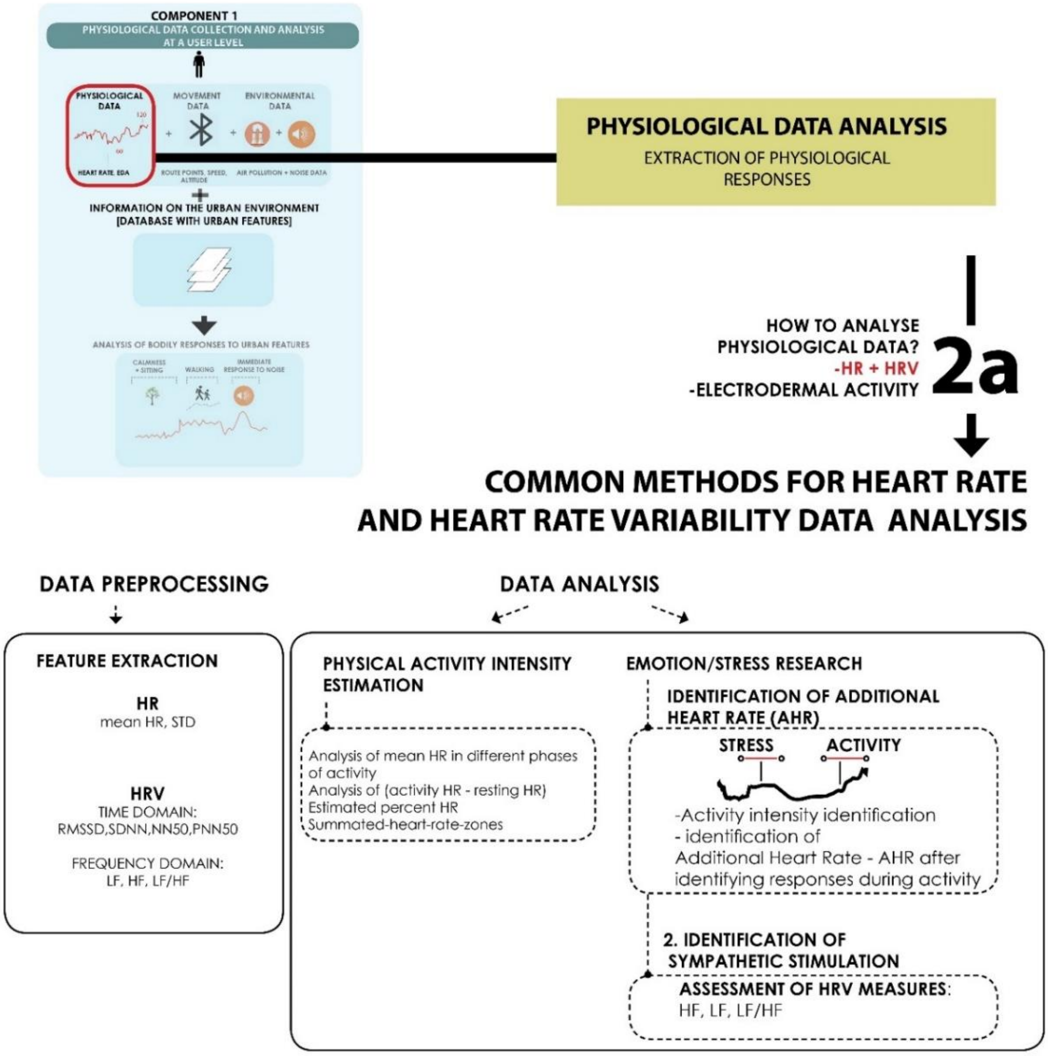


Figure 4.4. Common approaches to HR and HRV data analysis

4.3.2.2. EDA DATA ANALYSIS

As discussed in the previous chapter, the EDA signal can be described as the outcome of the convolution of two signals: the tonic EDA, which contains information regarding the slow changes in the signal, and the phasic EDA, which contains the peaks (EDRs).

In terms of data cleaning procedures, smoothing can be applied to eliminate noise, in a frequency that does not affect the EDR shape; Alexander et al. (2005), for instance, smooth the signal over a 300ms window.

For the identification of EDRs, a peak recognition algorithm is usually employed, by finding local minima and maxima around points that have a zero derivative or excluding curves that cannot be fitted to a modelled response, such as a polynomial function (Alexander et al. 2005; Healey & Picard, 2005; Storm et al. 2000). The tonic signal is then extracted by removing the peak points, sampling them at a lower frequency and interpolating them. A phenomenon which requires special attention for peak identification is the fact that EDRs can overlap (Alexander et al. 2005; Boucsein 2012). Some examples of overlapping EDRs can be seen in Figure 4.5. In that case, there might not be a point where the derivative is zero, which reduces the accuracy of derivative-based approaches to peak identification. As an alternative to former models based on signal deconvolution, Green et al. (2014) propose a model for EDR identification that labels data segments according to the positive or negative tendencies in the second-order derivative and identifies an EDR positively if the segments form an acceptable pattern.

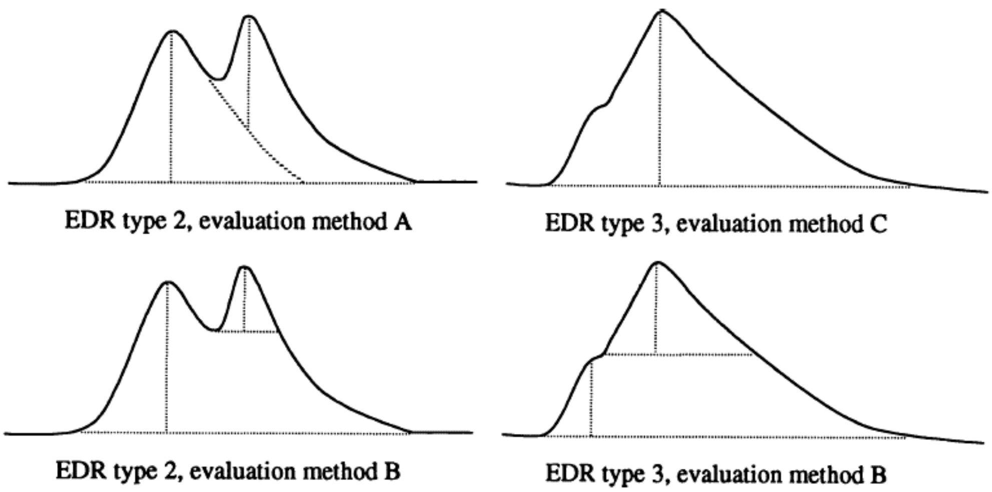


Figure 4.5. Types of overlapping EDR responses (figure acquired from Boucsein 2012)

The algorithms designed for EDR recognition also implement filters to detect if the identified peak conforms to the typical characteristics of an EDR. A threshold of 0.02-

0.05µS is usually defined before the extraction of the phasic responses. Only the responses which exceed this threshold are considered as valid (Valenza & Scilingo 2014). The time between EDR onset and peak is also expected to be between 0.5 and 5s (Green et al. 2014).

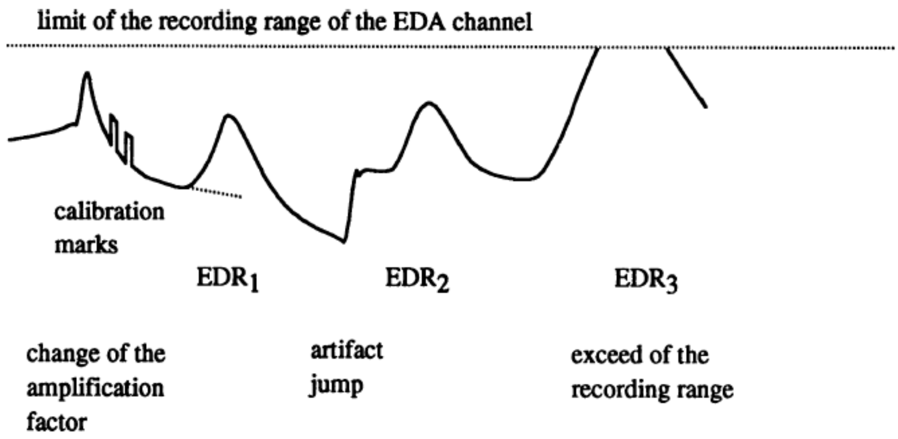


Figure 4.6. Types of artefacts in EDA measurement (figure acquired from Boucsein 2012)

EDA fluctuations which do not conform to these expectations may be artefacts and noise due to excessive hand movements and loss of contact between the electrode and the skin. A steep increase or decrease of the signal is also a typical characteristic of an EDA artefact (Figure 4.6).

Cleaning the signal from artefacts is a crucial part of the EDA data processing, as they might be wrongly interpreted as EDRs if this step is omitted. Ojha et al. (2019) applied a one-level Haar wavelet transformation (WT) for artefact removal. The guide of Braithwaite et al. (2013) proposed down-sampling the signal; some studies also apply a low-pass filter for smoothing. Taylor et al. (2015) provide a review of some techniques which have been applied for artefact removal, such as the application of a low-pass filter or exponential smoothing, the definition of thresholds for minimum and maximum EDA (Kleckner et al. 2018), and thresholds for slope, amplitude and width of the phasic response. They have also proposed a method for automatic classification of errors, using a supervised machine learning model.

After separating the tonic and the phasic EDRs, their characteristics are analysed in a chosen time window, and the following features may be extracted: Number and mean amplitude of EDRs, number of NS.SCRs, mean levels of tonic EDA and sum of EDR amplitudes (Boucsein 2012). If there is a timestamp for the origin of a stimulus, the latency from stimulus onset to the appearance of the EDR can also be calculated.

In terms of data transformations, a log transformation may be applied to improve the distribution of the EDA tonic levels and EDR amplitudes. Zero responses must be corrected before the transformation in this case. Square root transformation may also be applied. Data normalisation is also necessary, to take account of the interindividual variations in the minimum and maximum values of the EDA signal. EDA measurement is more accurate when the EDA recordings can capture the minimum and maximum arousal levels of the individual (Boucsein 2012).

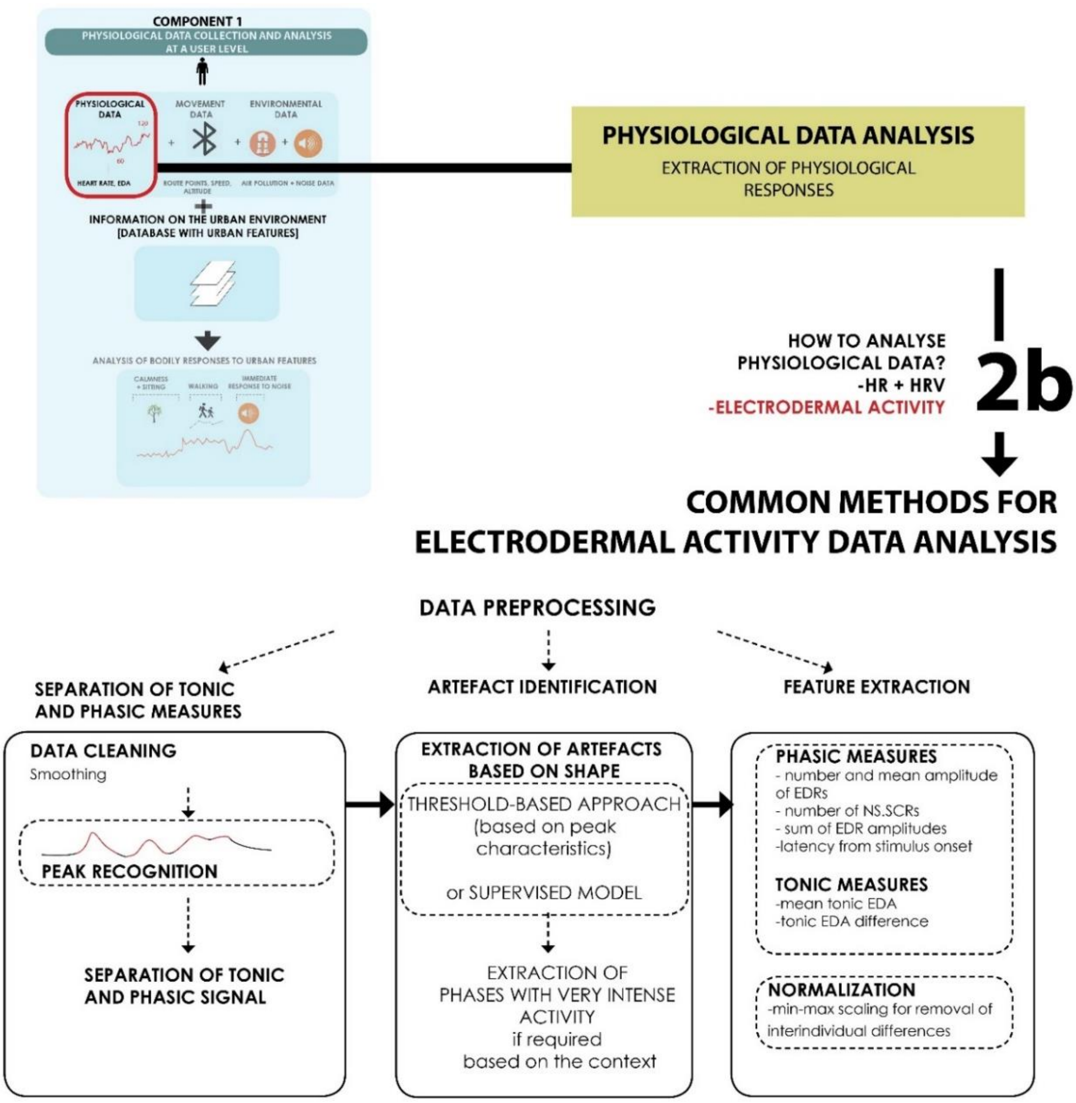


Figure 4.7. Common methods implemented in the analysis of EDA data

A summary of the reviewed methods for EDA data analysis is provided in Figure 4.7.

4.3.2.3. EDA AND HR DATA FUSION

After data pre-processing, the extracted features from HR and EDA are frequently combined to be used as input for classification tasks such as analysis and prediction of stress and emotion or mood.

These two areas overlap in terms of the usage of physiological data but differ in the states which are predicted. In the prediction of emotions, the subjects report their subjective emotions as discrete entities or describe them in a two-dimensional space by reporting the valence and arousal levels. The participants may be asked to report their emotions while being exposed to situations known for eliciting specific emotions, such as viewing slides with emotionally heavy content. Other studies which focus on emotion recognition in outdoor circumstances instruct the participants to walk on a route (Kanjo et al. 2018a) or report their mood and emotions for a week or longer, while they follow their daily activities. In stress recognition, the subjects usually perform a set of stress-inducing tasks, such as mental arithmetic or a public speaking test, followed by a relaxation period (e.g., Sun et al. 2012). The objective is, then, to analyse the data and determine if the extracted features correspond to a stressful situation or not.

As for the models used for analysis, moods and emotions are considered a sequence of events and the chosen models for analysis reflect that. Earlier approaches suggested the Hidden Markov Model (HMM) as a suitable approach. Recent studies used the LSTM neural network (LSTM), often combined with a CNN, to model more accurately the dependence on previous emotional states (Huu Son 2017; Kanjo et al. 2018b; Ringeval et al. 2015). Such an example is the study of Kanjo et al. (2018a) on predicting emotions based on environmental, physiological and activity data.

For stress analysis, proposed approaches include different classifiers such as decision trees, Naïve Bayesian classifiers (Zhai & Barreto 2006), linear discriminant analysis (Minguillon et al. 2018) and SVM (Sun et al. 2012). HMM have also been used when speech data act as the input (e.g., Zhou et al. 2002). Some researchers have also proposed Artificial Neural Networks (ANN) as a suitable model (e.g., Sharma & Gedeon 2011; Alić et al. 2016).

In the studies on physiological data mapping in the urban environment that were reviewed in Chapter 1, it was observed that there is still a lack of consensus regarding an appropriate method for stress detection in outdoor studies. Some studies (Benita & Tunçer 2019; Kyriakou et al. 2019; Nuñez et al. 2018; Werner et al. 2019; Zeile et al. 2016) use the combination of EDA and skin temperature for the identification of stress. A time window is classified as a stress moment when an increase of EDA coexists with a decrease with skin temperature within a very short time window. This approach has been one of the most popular in outdoor stress mapping using continuous physiological data. More rules may be added, considering the slope of increase of EDA, the moment when the skin temperature starts decreasing, and the number of responses in a 10-second window.

Other studies have used different approaches; Kim et al. (2020), for instance, propose the segmentation of physiological and movement data in portions which are significantly different from their neighbouring segments. This method is based on the identification of change points. Lee et al. (2020) use the STD of EDR as the measure of individual stress. They separate the study area using a 10x10m grid and then extract the intensity and the frequency of this metric in each grid cell. The samples are divided into high-stress and low-stress indicators by setting a threshold based on the distribution of the number and intensity of responses.

One issue that appeared in most studies on automatic stress recognition is the acquisition of ground truth data. This process commonly involves exposing the subjects to a series of situations known for inducing stress, usually in a controlled, indoor setup, and it is automatically assumed that the subjects are in a physiological state of stress during these situations. All kinds of sympathetic arousal are grouped under the label of stress, interpreted as distress. Some studies also include a phase where the subjects report their perceived stress levels (e.g., Choi et al. 2012). Perceived stress levels, though, only report the perception of phenomena related to sympathetic arousal, and may differ from the actual change in physiological markers, as the correspondence between physiological changes and self-reported stress depends on the interoceptive ability of the individual to understand such changes (Kleckner et al. 2017). This phenomenon has to be considered in the design of stress recognition algorithms, as it may distort the classification accuracy. Gjoreski et al. (2017) describe this problem in detail and address the difficulty of determining the starting and ending time of a perceived stressful situation and the issues that this causes in stress classification tasks.

Furthermore, studies often focus on mental stress detection and do not include other stressors which occur in typical daily conditions, such as physical activity. This problem is a source of concern (e.g., Sun et al. 2012; Wijsman et al. 2011) also for general stress detection models apart from the studies focused on stress responses in the urban space, which were reviewed in Chapter 1. More research is required towards a model which takes into account multiple stressors. Sun et al. (2012) have attempted to incorporate physical activity in a stress detection model, by including accelerometer data. The duration and intensity of activity though may not be enough to elicit stress responses which might mask the responses to psychological stressors. Can et al. (2019) also identify this problem, but they chose to discard the portions of data where the participant was conducting an intense activity. This choice depends on the context of the study. It is also affected by the theoretical definition of stress that the researchers choose. Accelerometer data are helpful here as they provide more information and allow the detection of artefacts caused by a high degree of movement. If the context of the study does not involve intense movements, then the portions of intense movement can be automatically discarded. However, there are cases where intense movement is the reason for the increased EDA or a significant symptom related to a specific situation (Boucsein 2012; Taylor et al. 2015). If this information is valuable in the context of the research, the portions of intense movement should be kept for analysis, though artefacts should still be detected.

Another issue is the period of exposure to the stressor, and the choice of window size for data analysis. Some researchers have suggested that a window length between 10 and 17.5-minutes yields better classification results (Can et al. 2019). This approach seems appropriate for recognition of fluctuation of general stress levels during the day, but in some cases, it may cause information loss regarding events which elicit instantaneous responses that last less than a minute. When the focus is on examining the effect of the urban environment on physiological experience, it might be more appropriate to think what is the rate of change in the surrounding circumstances and choose a window length that reflects the time of transitioning from a set of contextual variables to another (for instance, the time needed to walk on a street segment).

4.3.3. POI AND OSM DATA

4.3.3.1. POI DATA

Points of Interest (POIs) have been utilised in urban computing as proxies of land use data, as they contain spatiotemporal information regarding the usage of space. Land use data from official sources, such as governmental institutions, are often outdated and have a low spatial resolution (Liu & Long 2015). Remote sensing has been largely assistive for the extraction of land use patterns, using image analysis (Liu & Long 2015; Yao et al. 2016) but the extracted land cover data have low-level semantic features (Yao et al. 2016); it is also difficult to maintain an updated database which keeps up with rapidly changing urban environments. POIs have emerged in the past ten years as an alternative data source that can cover these knowledge gaps and provide new insights into land use analysis. Apart from the high spatiotemporal resolution, they have the advantage of online availability and nearly global coverage (Liu & Long 2015), characteristics which explain their increasing popularity, as they allow the creation of data acquisition and utilisation models which can be used potentially anywhere.

POI data are a form of spatial data and include both spatial and non-spatial attributes. The spatial attributes are geographical coordinates (latitude, longitude), while the non-spatial attributes are the several tags (e.g., 'park') which accompany them.

A POI is created when people identify a location as interesting or useful and post this information online. POIs are, therefore, classified as volunteered geographic information, or VGI (Goodchild 2007). As Jiang et al. (2015) point out, anybody can create a POI, and this information is not checked by any authority; therefore, inaccuracies are possible. There is also no compulsory structure in terms of the data provided for each POI. Most commonly the information entered includes name, geolocation (in the form of coordinates or address) and a set of categories or tags which give descriptive information regarding the POI (e.g., 'Chinese restaurant', 'children-friendly'). Areas of Interest (AOI) have also emerged as an extension of the concept of Points of Interest and refer to areas with a large density of POIs and are therefore considered attractive and recommended for tourists (Laptev et al. 2014). Skoutas et al. (2016) have also proposed the term Streets of Interest (SOI), suggesting that there is need to identify spatial aggregations of POIs in a way that relates them more explicitly to the street network.

The incorporation of POI analysis in urban studies has been rapidly growing in the past ten years. POIs have been used in spatial analysis with the following goals: Fine-grained and disaggregated analysis of land use or employment characteristics (Jiang et al. 2015; Liu & Long 2015; Wang et al. 2018; Zeng & Lin 2016), identification of regions or areas with similar functions, assessment of point or area attractiveness (Laptev et al. 2014) in the context of recommendations for tourists, assessment of neighbourhood vibrancy and vitality (Humphrey et al. 2019; Wu et al. 2018; Yue et al. 2016; Yue et al. 2019; Zeng et al. 2018), and trajectory analysis (Yan et al. 2011).

There have been concerns regarding potential gaps between the POI information available online and the actual situation (Jiang et al. 2015). However, the rapid development of user-content platforms that allow POI publishing is expected to minimise this problem. Another issue is the difficulty to estimate the size of each POI; this can also be tackled if the analysis is accompanied by the analysis of POI-related content from social media or other online information.

To analyse the non-spatial attributes, data pre-processing here may include string manipulation for extracting the information contained in the tags. This process is commonly followed by grouping the tags using a scheme of common land use categories. The scheme could be a hierarchical structure constructed by the authors or following an existing taxonomy. Some studies have one subclass of 15-20 categories connected with a higher level of 3-5 categories (Wang et al. 2018); other studies have only one level with less than ten categories (Liu & Long 2015). The choice of this scheme is crucial as it affects the extracted measures of POI diversity. The algorithmic approach used for this classification is unclear in the majority of studies. Jiang et al. (2015) proposed a model for automatic classification of POIs in different categories, following the NAICS (North American Industry Classification System) taxonomy. In that case, there was an existing database of POIs with assigned labels, which was used for training the model.

In terms of feature extraction, POI information can contribute in data analysis in two ways: the spatial attributes give information regarding the density of POIs in an area, and the non-spatial attributes reveal differences in the patterns of use (e.g., diversity in land use and expected time of use). This analysis scheme is supported by the features extracted during data pre-processing, which include spatial density estimation (Wang et al. 2019), and diversity estimation (Yue et al. 2016).

For the calculation of POI density, a simple approach is to measure the number of POIs per area, (Zeng & Lin 2016) or per population number (Yue et al. 2019). A limitation of this approach is that it cannot be directly applied when the analysed region is one area, without any indication of the existence of subregions within this area. In this case, one approach is to segregate the space in order to measure the ratio of POIs per area. Some well-established methods to do this include quadrat analysis and Voronoi-based analysis, where space is divided into equal-sized quadrat and Voronoi cells, respectively. The density is, then, calculated as the number of points which fall into each cell (Yu et al. 2015). The main limitation of these methods is that they do not reflect well the density variations at a neighbourhood of each point, and there is a larger probability for false estimation for points that are close to the boundaries of the cells. For this reason, Kernel density estimation (KDE) is preferred over quadrat and Voronoi-based analysis, as it takes into consideration the cell neighbours. KDE though requires the computation of distances for all pairs of the point grid, which results in increased computational cost (Laptev et al. 2014).

KDE for networks also needs a different treatment than that simple 2-dimensional KDE, as Okabe et al. (2009) explain; this is particularly important for the case of urban networks, where the distribution of functions and the effect of their intensity is closely related to the topological layout of the streets (Yu et al. 2015). Okabe et al. (2009) and Yu et al. (2015) thus propose an alternative method for KDE for networks. In that case, each point is projected on the nearest network segment, and the search space is defined by evaluating the distances on network terms. This calculation is based on finding the neighbouring network segments within the specified distance, which is calculated as shortest-path distance. Yu et al. (2015) have also proposed an alternative way of finding network segments within the search radius that do not require computation of the shortest path, to make the process less computationally intensive.

Apart from spatial density, the distribution of POIs can be assessed from the perspective of diversity, using information extracted from the POI tags. A widely used way to calculate the degree of diversity is by using the Shannon entropy formula (Yue et al. 2016), a measure which has also been adopted for POI analysis and has become popular recently as an indicator of the level of mixed-use (Yue et al. 2019; Zeng et al. 2018). Most frequently, this feature is used in the context of assessing neighbourhood vibrancy and vitality.

After data pre-processing, the features extracted from the POI data (density, diversity) are used as representations of land-use types, land use density or degree of mixed-use, and they are analysed next to other data sets for different purposes.

One category of studies compares POI density and diversity in different areas by using descriptive statistics to study how land-use patterns change in different zones, or if they are related to other measures. Zeng and Lin (2016), for instance, used POI density, degree of POI concentration (POIs within 500m/POIs within 2000m) and entropy as measures of land use characteristics around an urban rail transit zone. Wang et al. (2018) also used POIs as proxies of land use for the examination of the relationship between land use intensities and the structure of the urban network; by examining the centrality indicators of the urban street network, they found a significant correlation between the two, especially regarding the closeness and straightness centralities. Wang et al. (2019) also used POI density as a measure of spatial distribution patterns of ‘commerce-tourism’ and studied its relationship with crowd clustering characteristics extracted from Baidu heatmaps.

Other studies use features extracted from POIs for the automatic classification of the land use type. An example is the study of Liu and Long (2015), who used a combination of POIs and street network data for this purpose; the street network data was used for the extraction of land parcels, and the POI density (the density of POIs within each parcel) was used to determine for each parcel the possibility of being urban, using a cellular automata model. After that, the POI entropy was used to determine the degree of mixed-use, and the dominant POI type was extracted to identify each parcel's use function.

Other studies use POI density and especially diversity to assess neighbourhood vibrancy and vitality, as mentioned above. In this case, the features extracted from POIs are combined with other indicators of vitality; Zeng et al. (2018), for instance, combined population density, accessibility (the distance of POIs from hospitals, shops and tourist attractions), livelihood (number of banks, food services, leisure and recreation and other services) and POI diversity, in order to extract the degree of vitality in different areas. Humphrey et al. (2019) also measured vibrancy in the context of street safety, by calculating the number of POIs for each POI category, and the number of extra hours each POI is open in relation to the opening hours of its category. As Yue et al. (2016) point out, there is still lack of consensus in terms of appropriate measures for mixed-use and vitality; there have been though recent efforts towards a framework for the measurement of vitality, such as the one proposed by Yue et al. (2019).

POIs have also been used as proxies of land use in studies where the goal is to discover geographic boundaries of areas with similar characteristics. There is often a need to segregate space in ways that do not necessarily conform with the administrative boundaries; such an example is the identification of hotspots of human activity, which are not spread uniformly across areas prescribed in administrative boundaries. Spatial clustering may be performed for this purpose, with algorithms such as DBSCAN (Vu & Shin 2015).

As an alternative to DBSCAN, Laptev et al. (2014) suggest an algorithm for discovering 'Areas of interest (AOI)' which returns clustered areas based on local point density ranking. The algorithm pays special attention to the identification of small, walkable clusters, as it is created in the context of Areas of Interest which should be walkable by tourists within a reasonable time. Skoutas et al. (2016) also proposed a method for identifying Streets of Interest, which also implements street network data and is based on ranking streets according to the number of POIs that are close to them. A notable approach is that of Yuan et al. (2015), who proposed a framework called Discover Regions of different Functions. Their proposed method combines semantic analysis of POI tags with region clustering based on raster analysis of road network and human mobility data based on GPS trajectories from taxicabs.

In the past ten years, POI analysis has also been explored at a user level, in the context of analysing GPS trajectories and finding users with similar location history. An example here is the study of Xiao et al. (2010) who propose a method for semantic analysis of location history. The users' trajectories are first analysed for the extraction of stops, and the closest POI is found for each stay point. Hierarchical clustering is then applied for the identification of POI groups, to build a tree structure which represents categories of locations with different levels of similarity. After that, the user’s GPS trajectory is abstracted by replacing the stay points with semantic locations corresponding to the tree levels. The travels become then sequences of semantic locations, which can be assessed in terms of similarity by finding subsets which match in terms of visited locations and travel time and then calculating a similarity score based on factors such as the hierarchical level at which the locations are similar, and the number and length of matches. The identification of patterns in user activities is part and parcel of applications which incorporate any sort of recommendations.

Finally, Figure 4.8 summarises the POI analysis methods outlined in this section, connecting them to the conceptual methodology.

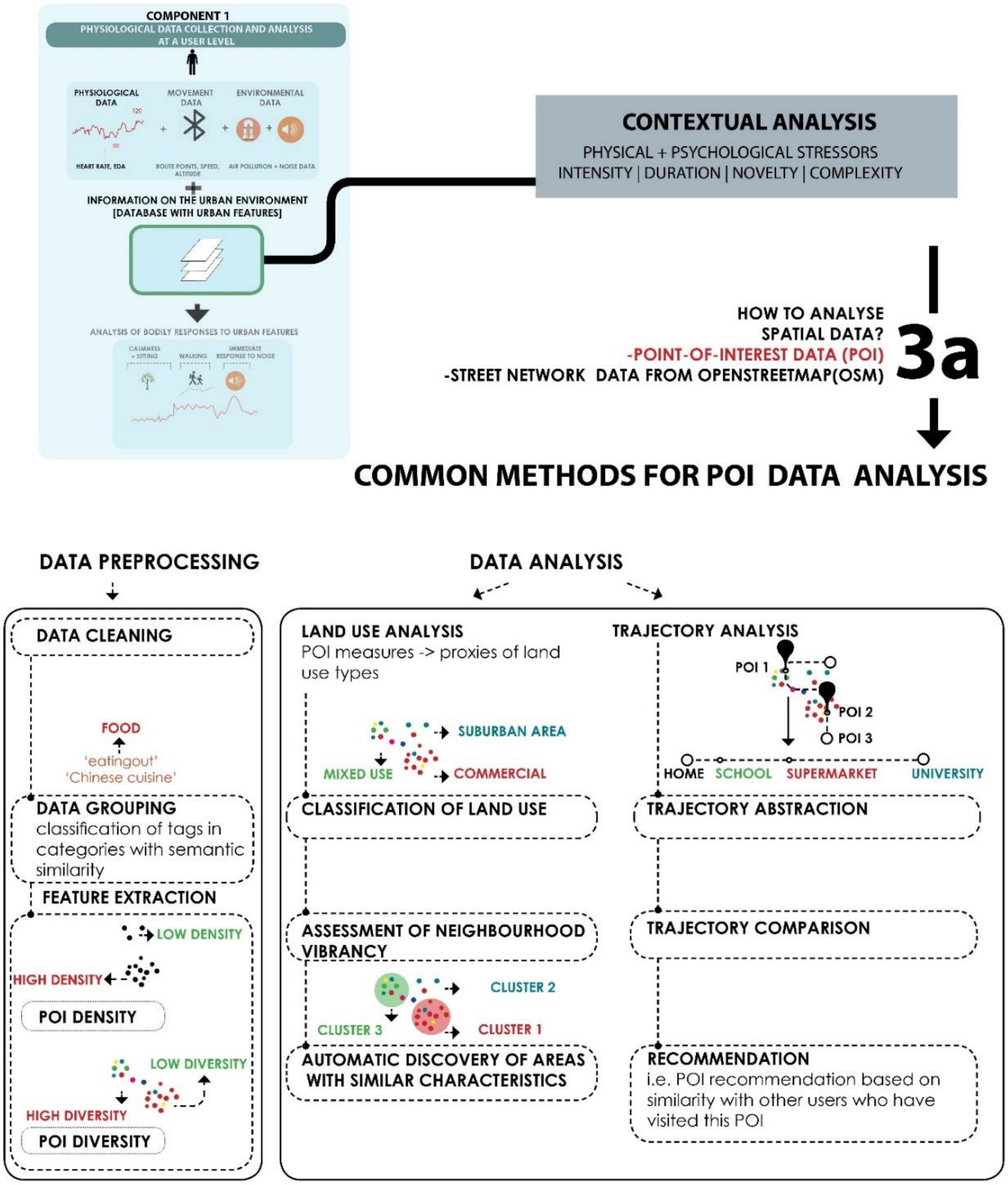


Figure 4.8. A summary of methods commonly used in POI data analysis.

4.3.3.2. OSM DATA

OpenStreetMap (OSM) is an open database created from volunteered information and data from trusted official sources (Jilani et al. 2014). OSM data is a form of spatial data, with street network data as its main feature. Geographical information is stored in the form of nodes, which have coordinates in terms of spatial attributes. The database also contains information regarding the topological connectivity between nodes (Haklay & Weber 2008). Each street segment is stored as a link which connects a pair of nodes. In terms of non-spatial attributes, the database contains semantic information regarding the characteristics of each link and node, which is usually stored following a tagging schema. The schema includes classes for frequently used features (Haklay & Weber 2008), stored as key-value pairs. There is no restriction regarding the use of tags, and the tagging schema operates more as a guide.

Street and node data can be analysed in terms of geometrical, topological and semantic properties. Each category involves the extraction of different features, which can be used to infer the role of a street segment in the overall network and the spatial qualities associated with this role. The computed features are often combined with POI data (Liu & Long 2015; Skoutas et al. 2016; Wang et al. 2018) for spatial analysis.

Geometrical properties involve characteristics such as the road length, width and number of lanes; these features can be easily extracted at a segment level. Data pre-processing steps here may include string processing for extraction of useful features in a consistent format. It may also be of use to extract features at a street level, by joining continuous street segments. A street is cognitively recognised by humans as a unique entity with its own name and has properties such as straightness and number of intersections, which affect mobility patterns according to the space syntax theory (Hillier & Hanson, 1984). Street straightness can be computed by measures that assess a curve's linearity, such as those described in Žunić and Rosin (2011).

The analysis of topological features is mainly used for predicting pedestrian or traffic flow based on the structure of the street network. Topological properties include the extraction of features used in network analysis, such as node centrality measures (node degree, closeness and betweenness). As above, it is important to decide if the analysis should be conducted by considering street segments alone or joined. The space syntax theorists suggested using axial lines, which are street segments alone or joined based on their straightness so that they form ‘the longest visibility line’. Some researchers have also proposed street-based topological representations, where street segments are joined when they have the same name, or on the basis that they form good continuity (Jiang & Liu 2009).

If a semantic analysis is included, data pre-processing may include a method for sorting and filtering the tags. The analysis of the keys and tags depends on the nature of the project; for instance, the key 'highway' contains the primary descriptors of a road, and has a wide range of possible values (e.g., 'motorway', 'residential' [3]). The analysis of these tags allows the extraction of information related to traffic volume. A scheme is usually employed at this stage in order to determine the relationships between the tags. For instance, the Open Transport Map project (Open Transport Map 2020) utilises a scheme for the analysis of traffic volume, which identifies 6 levels of traffic intensity based on the values of the 'highway' key.

Sometimes the subset of the OSM dataset used for analysis contains so many tags that it becomes difficult to inspect them manually. Some researchers have proposed methods for solving these issues with an automatic assessment of semantic similarity between tags; Ballatore et al. (2013), for instance, set up a web crawler for extracting keys, tags and their relationship from the OSM website, in the form of a graph. Then they computed a similarity score based on their topological relationship in the graph.

One issue that should be considered before using OSM data is the assessment of the data quality. Studies have shown that the levels of accuracy and completeness vary, with improvements needed in the poorer and less populated areas (Pullar & Hayes 2017). Ground truth datasets from trusted sources can be used for this purpose, but these are usually difficult to obtain and not freely available to the public (Barron et al. 2014). Barron et al. (2014) have provided a framework for quality assessment based on parameters such as the evolution of OSM features over time, the number of contributors in the area, the mapping activity of different contributors, the 'currentness' of data, the logical consistency of the road network in terms of topological connectivity, and the quantity and number of POI tags. Other methods for automatic quality assessment have also been explored, focusing on specific classes of the OSM data; Jilani et al. (2014), for example, devised a supervised learning method for measuring the accuracy of the 'highway' key, based on geographical and topological

[3] https://wiki.openstreetmap.org/wiki/Key:highway

road characteristics associated with different semantic subclasses belonging to the ‘highway’ class (e.g., ‘footway’, ‘residential’, ‘pedestrian’).

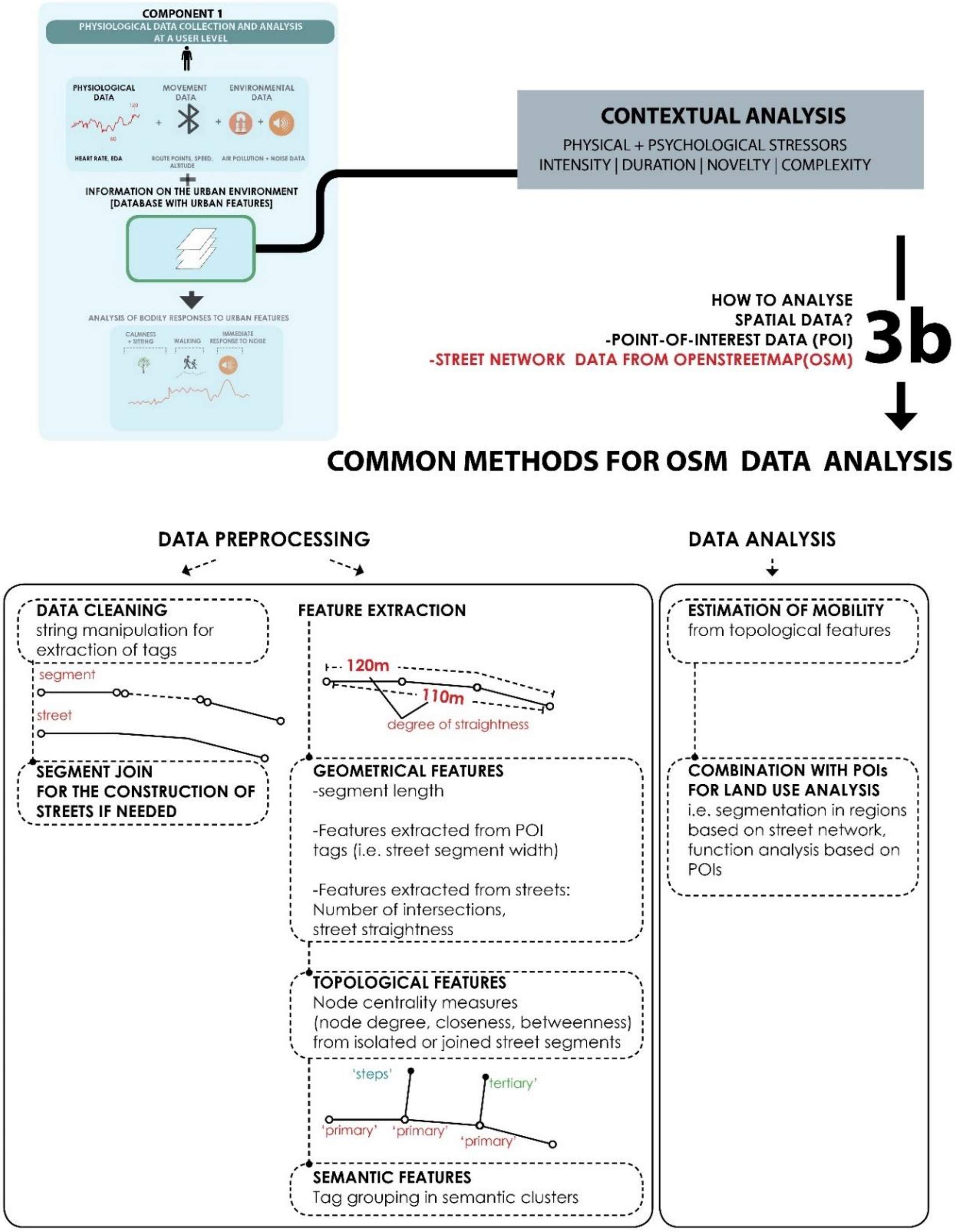


Figure 4.9. A summary of methods commonly used in OSM data analysis.

The methods outlined in this section are summarised in Figure 4.9.

4.4. THE PROPOSED SCHEME FOR DATA ANALYSIS

Based on the reviewed methods of data analysis, the following scheme has been devised for the analysis of movement, physiological and spatial data for the purposes of this project (Figure 4.10):

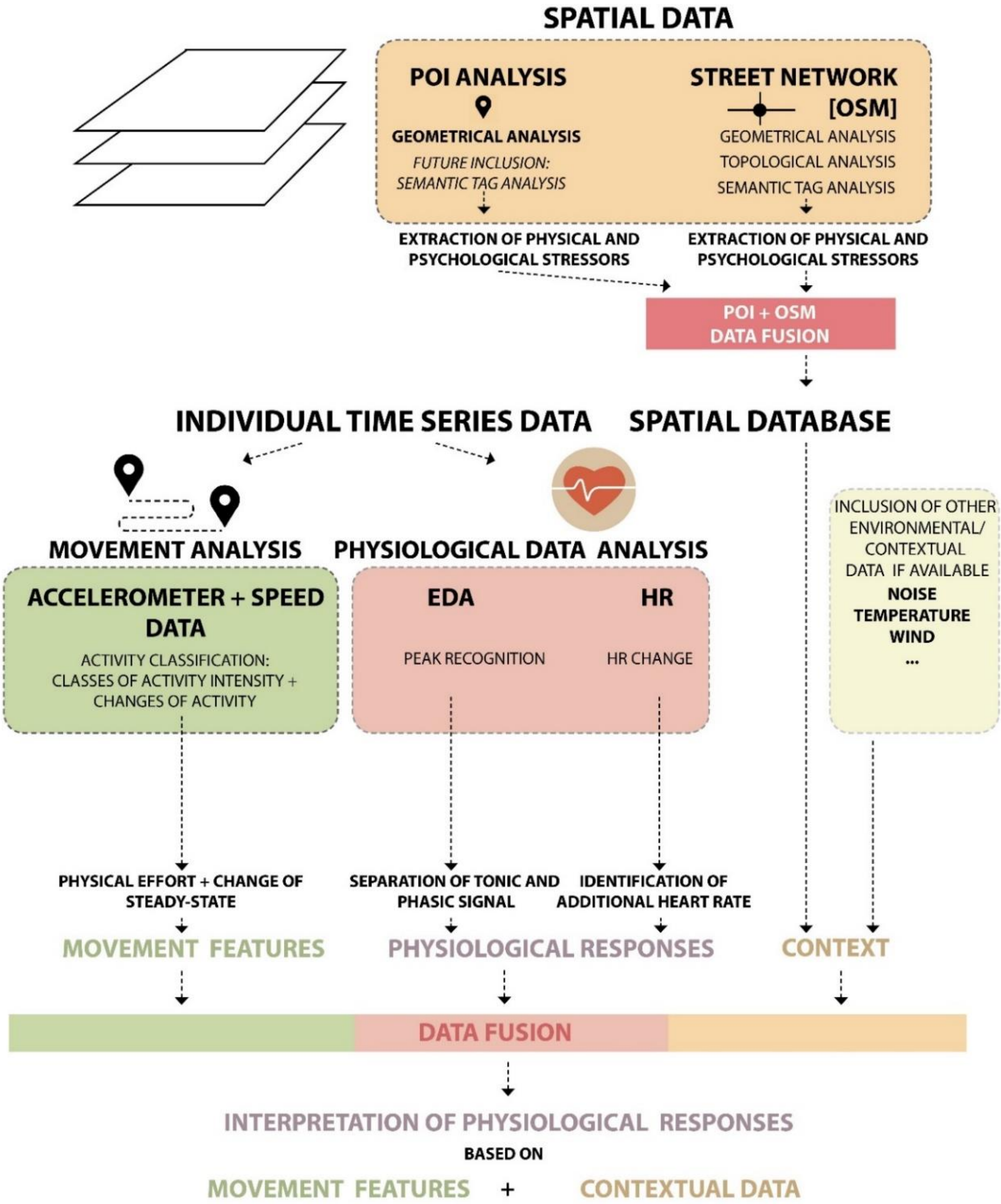


Figure 4.10. A schematic depiction of the proposed data fusion model for the analysis of physiological responses

A. Construction of a spatial database, with feature extraction from POI and OSM (street network) data. This stage shall involve the following components for the identification of contextual physical and psychological stressors:
   - POI analysis: extraction of POI density as a measure of complexity and intensity of stimulation
   - OSM (street network) analysis: extraction of geometrical and topological features, and semantic analysis for the extraction of physical stressors (surface conditions, slope) and psychological stressors (traffic levels, feeling of safety)
   - Fusion of POI and OSM data: transference of POI features to their closest street nodes
B. Movement data processing for the identification of movement changes:
   - Accelerometer data analysis for activity classification (threshold-based, supervised or unsupervised data partition task) and identification of changes in activity intensity
   - Speed analysis for the extraction of additional data related to activity intensity
C. Physiological data processing for the identification of changes in sympathetic arousal:
   - EDA processing: separation of tonic and phasic signal (with a peak detection algorithm)
   - HR processing: Identification of changes in HR (using a peak recognition algorithm, or the AHR method)
   - Fusion of the processed activity data and the EDA and HR data for the identification of possible movement artefacts (physiological responses during short-lasting changes in movement)
D. Spatial, movement and physiological data fusion
   - Extraction of relevant spatial characteristics for each GPS point of the movement and physiological data
   - Extraction of physiological responses by extracting the EDA peaks (and other relevant features) and the changes in HR

- Classification of physiological responses based on the underlying contextual circumstances during the physiological responses. This step will be based on extracting the activity class or the activity change, and the level of physical and psychological stressors from spatial data.

As shown in Figure 4.10, the scheme also contains a placeholder for the possibility of adding other data related to this research.

4.5. DISCUSSION

This chapter reviewed typical methods and procedures related to the data that will be analysed as a part of this work. This review was primarily conducted for the identification of data analysis methods which are relevant for this work. Different approaches for each task were outlined, and the benefits and limitations of each method were discussed.

The review led to the construction of a data fusion model (presented in section 4.4) which will be the basis for building the methods for component 1. The next chapter (Chapter 5) shall outline these methods in detail. All the steps of the data fusion model were designed based on the literature review presented here. For instance, the data fusion model includes the task of activity classification. Experiments were conducted to assess the performance of the different approaches that were outlined here for this task, including supervised and threshold-based approaches, and the best-performing method was selected. The methods which will be used for EDA analysis, including peak recognition and identification of artefacts, were also designed based on the literature reviewed in this section.

The other two components will also utilise some of the methods which were outlined in this chapter. The methods for analysis at the city scale (component 2 of the methodology), presented in Chapter 7, will utilise the spatial clustering and hotspot analysis methods. The analysis of topological features retrieved from the OSM data will also be included in the workflow of cluster analysis, for the prediction of pedestrian flow and its analysis in relation to the clusters.

The methods presented in Chapter 8 for prediction of physiological responses will also involve testing the machine learning models presented in section 4.2 of this chapter, in relation to component 3 of the methodology. The history of physiological responses for each user will be used together with a vector composed of the analysed activity classes and the spatial information (physical and psychological stressors) to investigate if it is possible to predict physiological responses based on a sequence of points for visitation and knowledge of their spatial characteristics. Some of the models which were tested in the context of similar tasks (predicting emotions in the urban space), based on the literature reviewed in this chapter, will be compared to other models presented in this chapter.

The second reason for conducting this review was to identify possibilities for improving this work in the future, based on the identified methods. For instance, the work which will be presented in the next chapters shall involve only the analysis of POI density, in terms of POI data processing. It was decided to focus on this feature due to time constraints. However, a future version might benefit from involving semantic POI analysis to identify POI categories that may act restoratively (green, water) or act as landmarks, capturing the attention of the pedestrian. This task could be conducted as a simple data grouping task for a small sample of POIs; otherwise, it can be investigated as a supervised machine learning task for the assessment of semantic similarity.

Another step that could be added in the future involves analysing past trajectories for route comparison and identification of novelty of the stimuli which the user encounters. This step could be conducted using methods for the semantic abstraction of trajectory and identification of the degree of similarity, such as those described in Xiao et al. (2010).

This chapter was the last preparatory step that paved the way towards constructing the methodology proposed in Chapter 2. From the next chapter and onwards, the methods related to each component of the methodology will be presented and discussed in detail.

5

METHODS FOR ANALYSIS AND CLASSIFICATION OF PHYSIOLOGICAL RESPONSES BASED ON MOVEMENT ANALYSIS AND CONTEXTUAL FEATURES

5.1. INTRODUCTION

After presenting the theoretical and conceptual framework in Chapter 3, the previous chapter discussed methods for analysing the different data sources related to this work. A scheme for data fusion was outlined, focused on the extraction of the variables included in the conceptual framework.

This chapter builds on the presented literature and shows how it is utilised to construct the main product of this research, the methodology for the collection and analysis of the physiological data. The chapter presents component 1 of the proposed methodology (Figure 5.1). This component involves the data fusion scheme and the proposed model for classification of physiological responses based on movement and contextual data. The main novelties of the method are the incorporation of movement analysis and the incorporation of spatial data for inferring the contextual circumstances during each response without image-based methods.

The data fusion model is based on the scheme presented in the previous chapter. Each step is analysed in depth in section 5.2. The methods for classification of physiological responses based on movement and contextual data are also presented there. Section 5.3 demonstrates the use of the methods related to component 1 with the help of data collected from two participants during free-living activities. Finally, section 5.4 reflects on the presented examples and discusses limitations and future directions. The code related to this component can be found in the repository created for this thesis in GitHub[4].

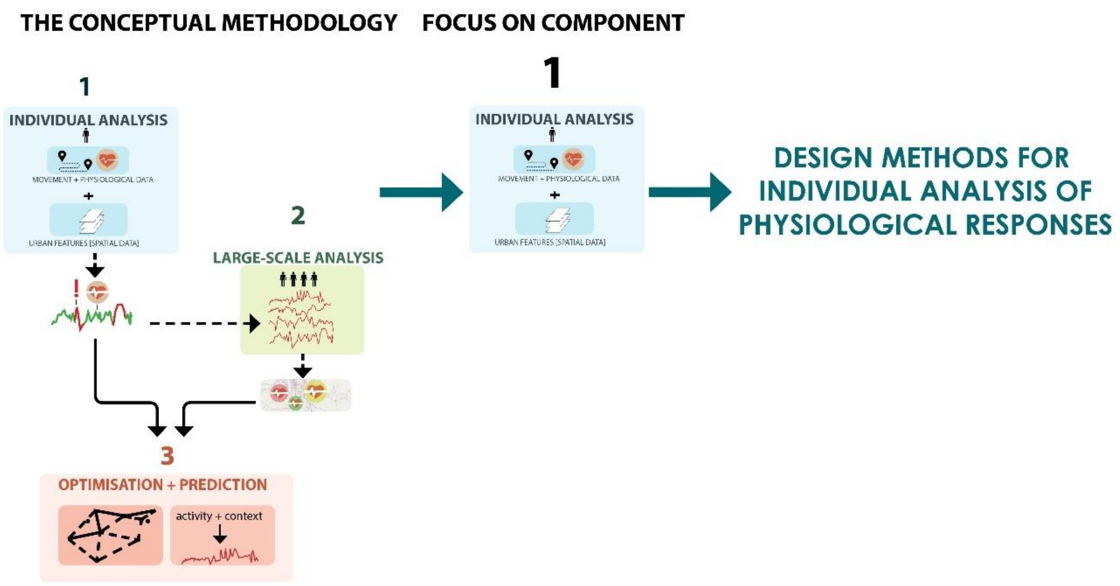


Figure 5.1. The aim of the chapter and the connection with the conceptual methodology.

5.2. THE PROPOSED METHOD FOR DATA COLLECTION AND ANALYSIS

This section presents the methods used for data collection, analysis and fusion, leading to the scheme used to classify physiological responses.

5.2.1. SETTING UP THE SPATIAL DATABASE: PREPARATION OF POI AND OSM DATA

5.2.1.1. POI DATA ACQUISITION:

The construction of the spatial database starts with the acquisition of POI data. The *osmnx* Python library (Boeing 2017a) was used to acquire POI data. The POI database for Sydney was constructed using the coordinates of the Central Station in Sydney as the central point for the query, and as parameters a 25km radius. This procedure led to

[4] https://github.com/ddritsa/PhD-Thesis-repository/tree/main/1st%20component

the construction of a dataframe which contains POI names, coordinates, and any other available tags.

5.2.1.2. STREET NETWORK DATA ACQUISITION

The second step for the construction of the spatial database involves the acquisition of street network data. This step should be conducted in a preparatory stage, and the database should be updated frequently in the case of long-lasting projects, to keep up with changes. Platforms such as Google Maps and OSM can be considered potential data providers; the choice depends on budgetary constraints (as the APIs of Google Maps are not available for free), spatial coverage, and quality. For the purposes of this project, the OSM platform was chosen, on the basis that there is already a significantly high number of contributors and edits in Sydney (Pullar & Hayes 2017).

The Python library *osmnx* was used for OSM data acquisition, defining a bounding box with Central Station as its centre. The request for OSM data returns a dataframe with two branches; one for the nodes and one for the ‘ways’ (links between nodes).

5.2.1.3. URBAN AND POI DATA PRE-PROCESSING

After collecting the spatial data, the POI and OSM data must be indexed based on their spatial proximity, allowing fast nearest neighbour queries. The chosen approach among the methods presented in section 4.2.3.2 was to construct a k-d tree. Euclidean distance was chosen as a metric for the k-d tree as it led to significantly faster calculations, but for larger areas, the Haversine distance should be preferred. Two separate k-d trees are constructed: one for the POI data (which will be referred to as the ’POI k-d tree’) and one for the OSM nodes (‘OSM k-d tree’). The overall process is depicted in Figure 5.2.

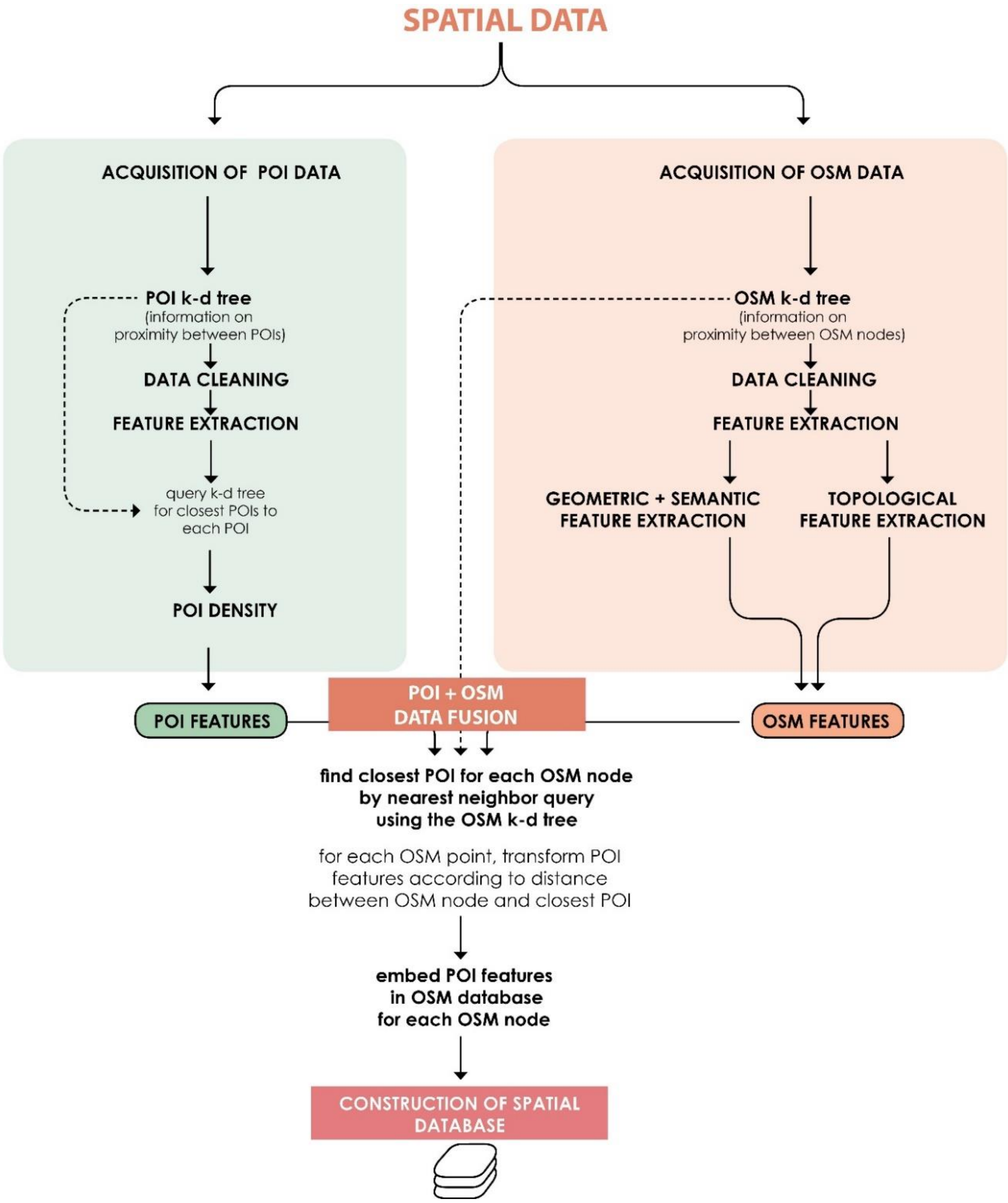


Figure 5.2. OSM and POI data acquisition, analysis and fusion

5.2.1.3.1. EXTRACTION OF TRAFFIC INTENSITY LEVELS AND TRAFFIC LIGHTS FROM OSM DATA

A particularly important component in the OSM data pre-processing is the semantic analysis of the tags. The tags associated with each geometrical entity (node or link) are grouped in categories reflecting different classes and levels of physical and psychological stressors. For each node or link, a script is applied for tag processing to extract the dominant categories. These categories are stored in a different column as properties.

The main psychological stressors that can be assessed here are associated with traffic. The increase in road traffic intensity elicits higher levels of noise intensity, which is a psychological stressor, as shown in the literature review. While navigating in this environment, the user might also be more alert than usual, due to the high number of moving objects which act as auditory and visual stimuli and may cause an increased load in terms of information processing. In the OSM database, traffic intensity can be inferred from the semantic analysis of the 'highway' tags, as mentioned in Chapter 4 (section 4.3.3.2). The adopted approach here is to extract information relevant to traffic and create a ranking system that reflects the increase in intensity. The scheme for the assessment of traffic intensity is devised as follows.

Level 0 includes tags associated with very low traffic, including tags related to pedestrian activity. The tags 'tertiary', 'secondary' and 'primary', included in levels 1 to 3, represent a hierarchy from lower to heavier traffic. According to the OSM tagging guidelines for Australia (OpenStreetMap: Australian Tagging Guidelines 2020), the 'tertiary' tag corresponds to 'minor through roads within a local area'. The 'secondary' tag refers to 'major through roads within a local area', while the 'primary' tag refers to arterial routes.

Level 4 contains roads with the highest traffic intensity and includes the tags 'motorway[5]' and 'trunk[6]'. The tag 'motorway' is used for roads with high performance, according to the OSM tagging scheme, including national highways and expressways. In Australia, this tag is used for the metropolitan motorway network, for 'M' classified roads, while the 'trunk' tag is used for 'A' classified roads (OpenStreetMap: Australian Tagging Guidelines 2020), The tags which have the notation '_link' next to a road type (e.g., 'motorway_link') indicate the presence of a road that leads to this road type. This scheme is very similar to that used in the Open Transport Map site (Open Transport

[5] https://wiki.openstreetmap.org/wiki/Tag:highway%3Dmotorway
[6] https://wiki.openstreetmap.org/wiki/Tag:highway%3Dtrunk_link

Map 2020), which was previously mentioned in Chapter 4. The only difference is that the two lowest levels of traffic volume are merged in one here.

The study of Novack et al. (2018) also shows that the adopted hierarchy reflects a gradual increase in noise levels, as the traffic levels increase from 0 to 4. Their study assessed the noise levels found in streets with different OSM 'highway' tags. They found that most of the streets with the 'residential' tag (positioned in level 0 in the hierarchy adopted here) were associated with the lowest noise levels (50 dB). Streets with the 'tertiary', 'secondary' and 'primary' tag generated higher noise levels (60, 65 and 70 dB, respectively). The streets with the 'motorway' tag had the highest noise levels (75 dB). The adopted hierarchy thus reflects the differences in the noise levels based on the street type, as intended.

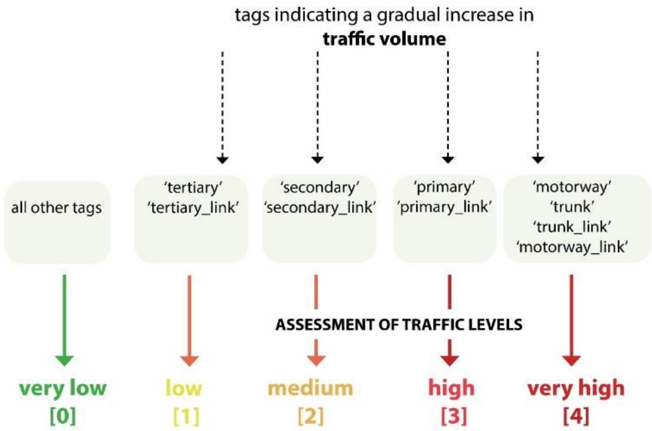


Figure 5.3. The scheme used for the analysis of OSM tags

This hierarchy has been constructed manually for this project, by extracting and cleaning the tags, building a tree with lists of tags contained at each class, and then querying each OSM node and link in terms of the class membership of each tag. The scheme is depicted in Figure 5.3. Figure 5.4 presents an example of the assessment of traffic intensity (volume) in Sydney CBD, using the scheme.

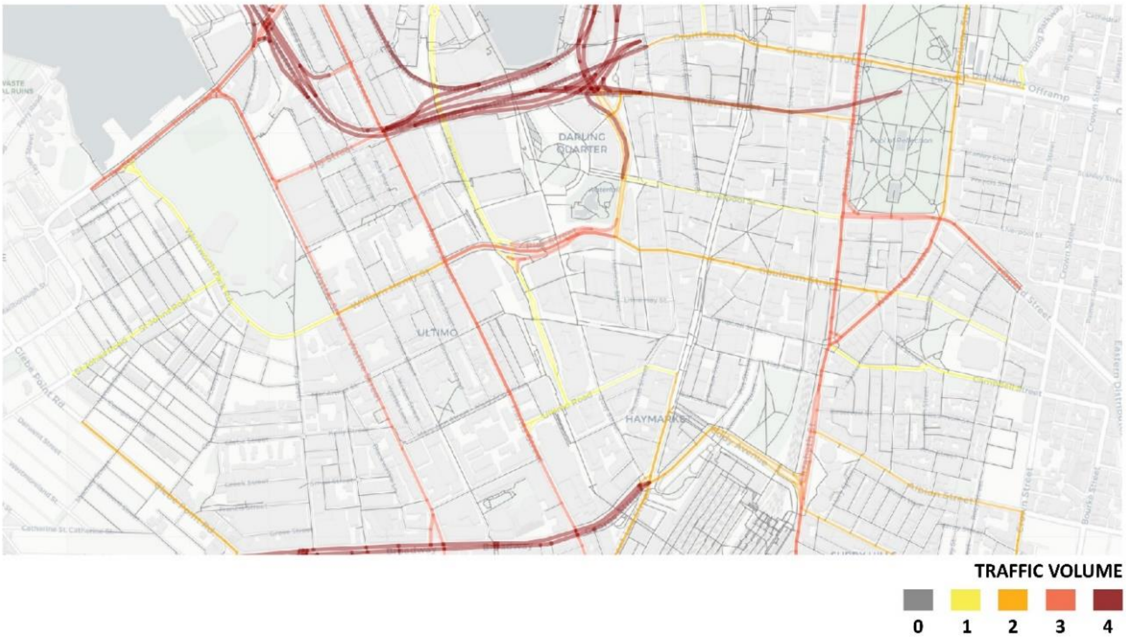


Figure 5.4. Application of the scheme for assessment of traffic intensity in Sydney

The ‘traffic_signals’ tag is also used to identify the presence of traffic lights. The nodes associated with traffic lights are added to the categories of both physical and psychological stressors, following the conceptual framework created in Chapter 3.

In terms of topological features, node centrality measures are extracted and stored for each OSM node. This data will be later used in Chapter 7 for the estimation of pedestrian activity, as a part of the method for analysing the significance of clusters of physiological responses.

Information regarding possible psychological stressors is also extracted from the POI data. As discussed in Chapter 3, POI density is used as an indicator of factors related to stimulus intensity and the complexity of the environment. The logic behind this choice was that a densely built environment with many shops, businesses and cafes has a larger possibility of containing more auditory and visual information than a residential environment, while also attracting more people. The process of decoding all this information and navigating in the crowd may require the allocation of more mental resources, and it is hypothesised that this might affect differently physiological responses in comparison to an area with low POI density. The expected direction of the effect is an increase of physiological responses in number, intensity or both, in areas with high POI density.

5.2.1.3.2. CALCULATION OF POI DENSITY

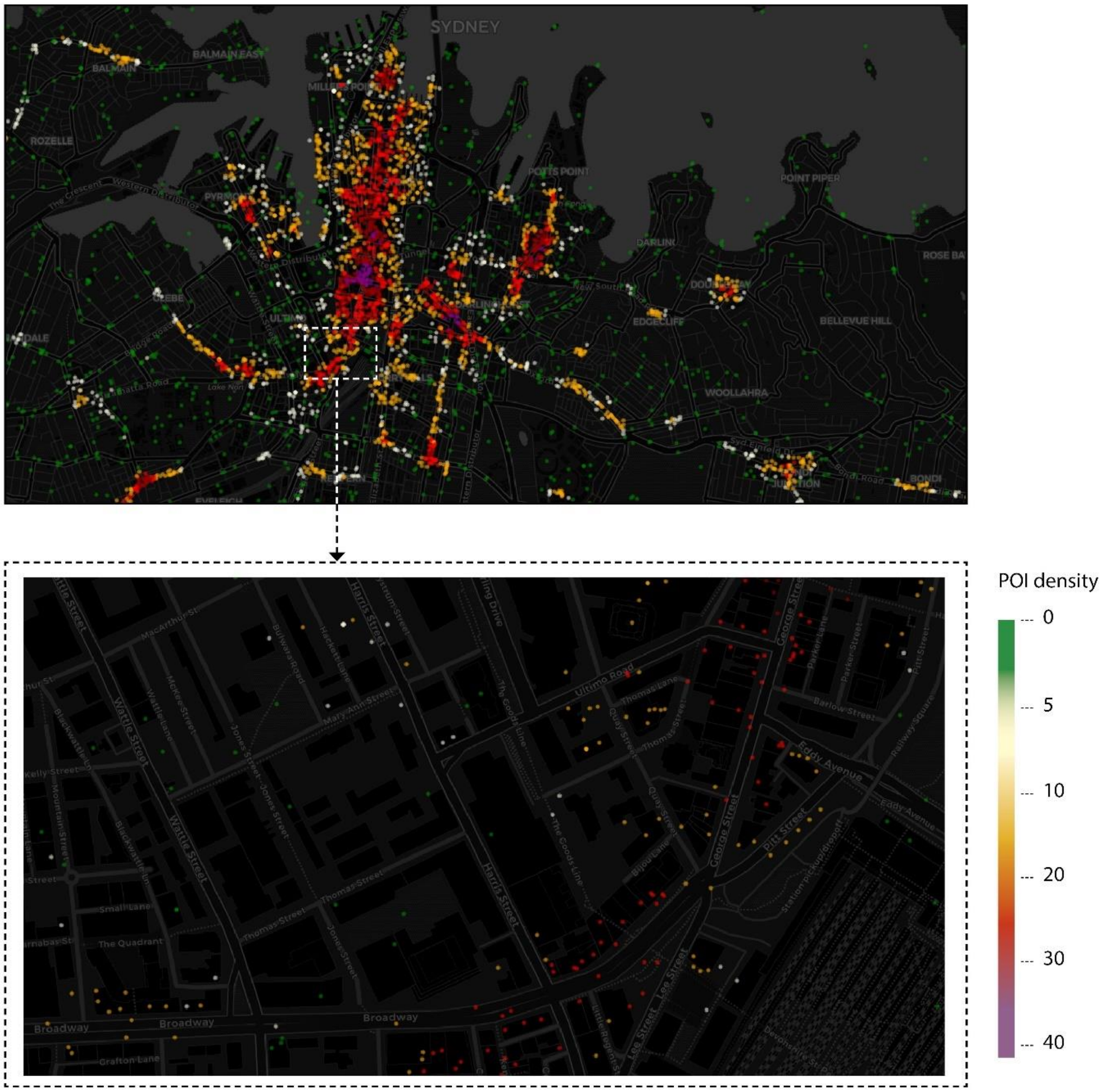


Figure 5.5. The spatial distribution of POI density at different scales.

POI density is calculated by querying the k-d tree for the number of POIs within 100m of each POI. The k-d tree allows very fast access to the closest points in terms of proximity. This method allows identifying differences in density at a very fine scale, and avoids the smoothing effect that would occur if alternative methods were to be used (see section 4.3.3.1), while still displaying large-scale trends (see Figure 5.5).

5.2.1.3.3. POI AND OSM DATA FUSION

After calculating POI density, the closest POI is identified for each node from the OSM database, using the k-d tree. The following features are extracted from this operation: *closest POI density* and *closest POI distance.* This allows us to combine information from the POI and OSM databases and project information of mixed-use density on the street network data. In areas with a low overall POI density though, the closest POI from a street network node may be located far away, while having a high POI density. In this case, it would be misleading to infer that this node has a high POI density. Instead of directly using the closest POI density as a density metric for the node, the following metric is used:

$$\textit{Node POI density} = \textit{closest POI density} / [\ln(\textit{closest POI distance} + 1)]^2$$

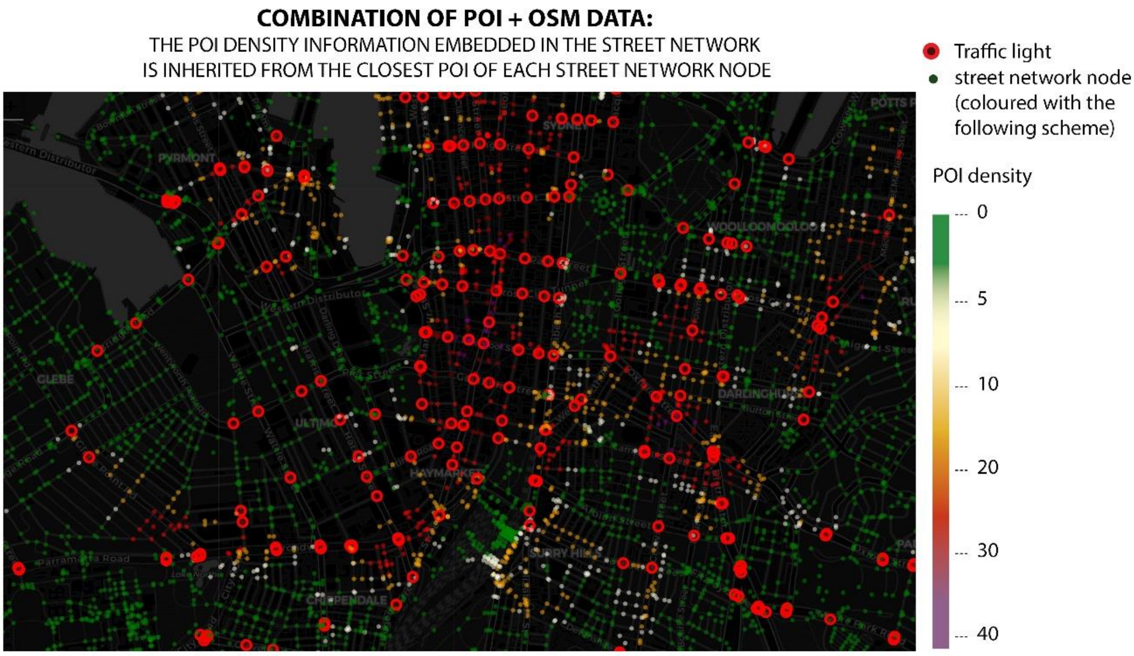


Figure 5.6. The outcome of combining POI density data with OSM nodes.

With the application of this equation, the POI density metric is exponentially decreased in relation to the distance between the node and the POI, providing a more accurate representation of the actual conditions. The category of the closest POI is stored only if the POI is within 50 m of the node. The index of the closest POI is also stored in the

OSM database for future use. The outcome of this phase is shown in Figure 5.6. Figure 5.7 outlines the contents of the spatial database.

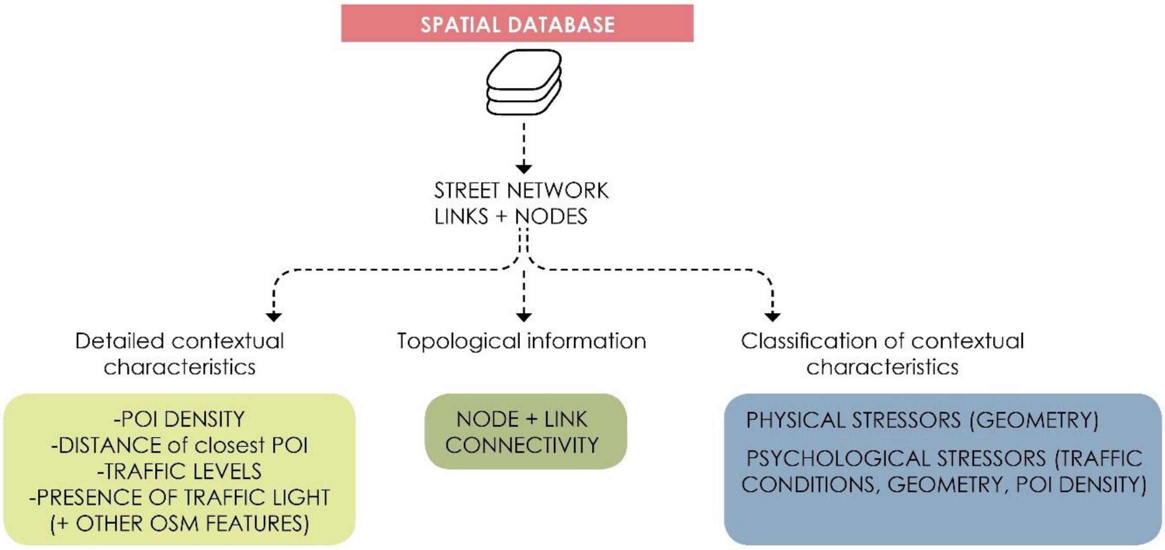


Figure 5.7. The contents of the spatial database

5.2.2. MOVEMENT AND PHYSIOLOGICAL DATA COLLECTION

The main goal for this phase was to reduce the workload involved in collecting and pre-processing the data. It was also important to ensure that the devised methods are flexible and allow integrating different devices.

For this reason, it was decided to connect the different activity trackers with a third-party application (Strava) that allows the integration of different brands. This approach covers many popular activity trackers (e.g., FitBit, Garmin, Apple Watch). It does not work for the Empatica E4 tracker, though, as the Empatica E4 only allows downloading manually the data from a web interface.

Two components were thus designed, to ensure flexibility and cover all these cases: one for collecting data from consumer activity trackers that can be connected to Strava, and one for the Empatica E4 tracker.

The component designed for automatic extraction of the data from Strava uses a web crawler designed using the Python library *Beautiful Soup* (Beautiful Soup documentation 2020). The web crawler goes through the HTML tags of each user's webpage and extracts their activities by fetching a series of download links. The activity files are then extracted from the download links (without actually downloading the files). The information is returned in the form of a dataframe, containing the following data columns: timestamp, latitude, longitude, altitude, HR. The sampling rate is 1 sample per second.

The second component includes a set of scripts designed for dealing with the collection and pre-processing of data derived from the Empatica E4 wristband. The accelerometer, EDA and skin temperature data collected with the Empatica E4 wristband are initially sampled at different rates (32 samples/sec for the accelerometer data, and 15 samples/sec for the EDA and skin temperature data). Each session is downloaded as a zipped folder, which contains a separate CSV file for each dataset.

Pre-processing steps here involve automatic processing of the CSV files and synchronisation of all the datasets in one dataframe.

After that, the dataframe containing all the activities is separated in activity sessions, by calculating the time difference between the last timestamp of each activity and the first timestamp of the next activity. If this difference exceeds a threshold (here defined as 15 minutes), the two activities are considered as separate; otherwise, they are merged. This step is necessary for separating different trips of the same user. It also assists in merging sessions which are part of the same trip (this happens when the users accidentally start and stop the activity tracking many times during one session)

The designed algorithms for this part were focused on the tested devices (FitBit and Empatica E4), but can be easily modified to include data from other devices, as long as they lead to a common structure in the end. The overall process of data collection is depicted in Figure 5.8.

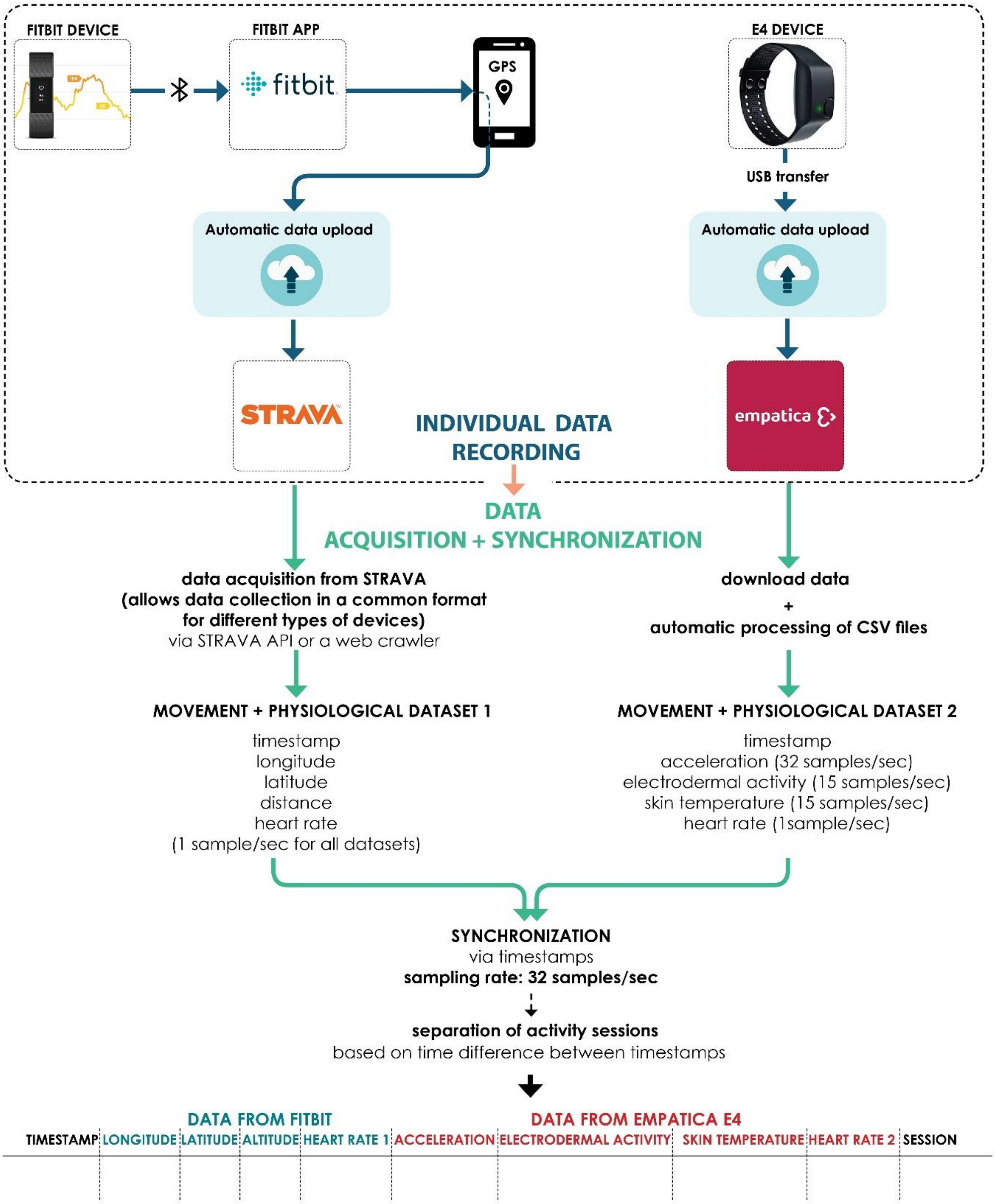


Figure 5.8. The physiological data collection protocol

5.2.3. SPEED AND ACCELEROMETER DATA PRE-PROCESSING

5.2.3.1. ANALYSIS OF SPEED DATA

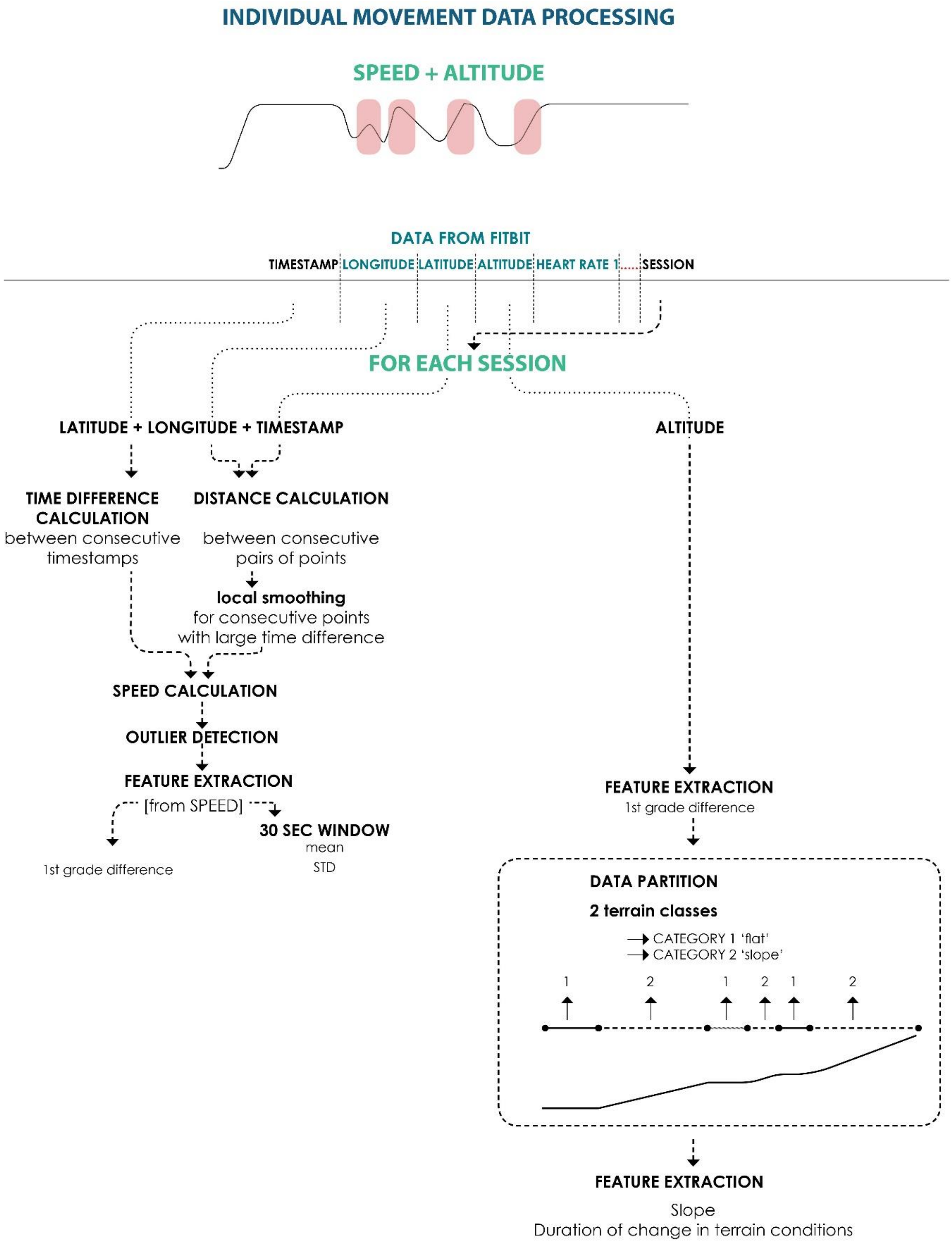


Figure 5.9. The analysis of speed and altitude data

The GPS data is processed in this phase for the extraction of speed data. This data is not used in the scheme for the classification of physiological responses, but it will be useful for other parts of the analysis.

The speed is calculated from the combined analysis of the GPS data and the timestamps. If the time difference exceeds 10 seconds, a local smoothing is applied by averaging the distances in the neighbourhood of data points. A Savitzky-Golay filter is also applied for smoothing the data.

After that, the speed data are resampled at 1 sample/sec, and the first order derivative is extracted. The mean and STD values are also extracted for data segments derived using a non-overlapping 30-second window.

As for altitude data, the first order derivative is used to identify if there is a slope. The data is classified accordingly, and two features are extracted (slope and duration of the change in terrain conditions). As mentioned in section 5.2.2, the altitude data is derived from Strava.

This component leads to the construction of a dataframe for each user, containing the features extracted from speed and altitude data. The process is depicted in Figure 5.9.

5.2.3.2. PROCESSING THE ACCELEROMETER DATA FOR ACTIVITY CLASSIFICATION

The analysis of the accelerometer data is primarily conducted for analysis of the activity. This task is necessary for identifying the different phases of activity intensity.

This component is heavily based on the utilisation of a model for activity classification. The construction of this model was an integral part of this research, and it was based on the different algorithmic approaches presented in relation to this task in Chapter 4. The data collected in the indoor activities was used to construct a supervised ML model, which was able to label three different activities (‘sitting’, ’walking’ and ‘intense movement’) with very high precision. Different ML models were tested for this purpose, and a deep neural network (DNN) model was determined as the best performing one, achieving 97% accuracy. This model was also compared to a threshold-based model, which was based on filtering different features of the accelerometer data. The best performing version of the threshold-based model achieved 89% accuracy. Based on these experiments, the best-performing supervised ML model was selected as the most suitable option. The overall experimentation is presented in Appendix E.

The tasks related to this component are designed as follows:

5.2.3.2.1. CREATION OF THE 'ACTIVITY INTENSITY' FEATURE

The accelerometer data from the Empatica E4 sensor is first processed with the selected activity classification model (the DNN model with the 6 hidden layers), leading to the identification of three phases of activity intensity. The feature 'activity intensity' is created in this way.

5.2.3.2.2. CREATION OF THE 'CHANGE IN ACTIVITY' FEATURE

The extracted phases of activity intensity are further processed towards the identification of the changes in activity intensity. The classes of the 'activity intensity' feature, derived from the activity classification system, are recoded using a numerical scale (1-3) representing the activity intensity.

Then, the first order derivative of the 'activity' class is extracted. The data points between two points where the derivative is not zero are marked as points with the same activity intensity. In this way, the data is split into segments. Consecutive points which have the same activity intensity are grouped and separated from neighbouring points with a different activity intensity.

Each point of change in activity is evaluated by calculating the duration of the previous segment of activity intensity. The data within a window starting 5 seconds before the change in activity, and ending a few seconds after the change in activity (determined by an adaptive buffer), is marked as a 'change in activity'.

The adaptive buffer is determined by the characteristics of the change in activity. The principle that guided the creation of the adaptive buffer was that the impact of a change in activity on physiological responses might be related to the duration of the change, and the presence of a steady state of activity before the change.

The duration of each buffer was decided following the literature review and after extensive experimentation. The literature reviewed in Chapter 3 (section 3.3.3) suggests that changes in HR are expected within one minute from the onset or end of the exercise, while postural changes can bring an HR increase within seconds. The information for EDA data was less concise; therefore, the accelerometer and EDA data collected in the indoor experiment were examined. The visual analysis of the data showed that an EDR sometimes appeared within 5 to 10 seconds from a very short change in activity. It was observed that as the duration of the previous activity and the activity changes increased, the time window within which one or more EDRs appeared after the change also increased. The buffers were thus determined experimentally by monitoring the time of appearance of EDRs after different types of activity changes. Very short changes in activity (less than 3 seconds) have the shortest buffer (10 seconds). Changes of a larger duration have a larger buffer (20 seconds). The largest buffer (1 minute) is when the change in activity follows a steady state. The same buffers were adopted for both EDA and HR data analysis, but more research is needed to calibrate them for HR data analysis.

5.2.3.2.3. DURATION OF ACTIVITY

The 'duration of activity' feature is constructed by calculating for each data point the seconds passed from the beginning of the activity. This feature is later used to identify data points where the duration of activity is above a predefined threshold.

5.2.3.2.4. OTHER FEATURES RELATED TO ACTIVITY

The two features introduced until now ('activity intensity' and 'change in activity' are the main features related to activity. Some other features were also extracted to assist in constructing the adaptive buffer in the 'change in activity' feature. They were constructed to allow the analysis of the changes in activity at a finer level in the inferential analysis presented in Chapter 6. These features are the following:

- 'steady state' (indicating the presence of steady-state activity)
- 'change in activity state'
- 'spontaneous movement'

The ‘steady state’ feature is created to allow the construction of the ‘change in activity state’ feature. It contains data points with no change in the ‘activity intensity’ feature for two minutes or more.

The ‘change in activity state’ feature was created to store the most significant changes in activity. It is a subclass of the ‘change in activity’ feature, and contains the data points within one minute after the end of a ‘steady state’. Based on the literature reviewed in Chapter 3, the change from a state to another is considered a stressor; this feature may be, therefore, associated with a higher impact on physiological responses in comparison to other changes in activity.

The ‘spontaneous movement’ feature is another subclass of the ‘change in activity’ feature. It contains the changes in activity which have a very short duration (less than 3 seconds). This feature was created to assist future researchers in removing all responses that are created during very short-lasting movements and may be movement artefacts. This step is optional and should be decided at a case-by-case basis.

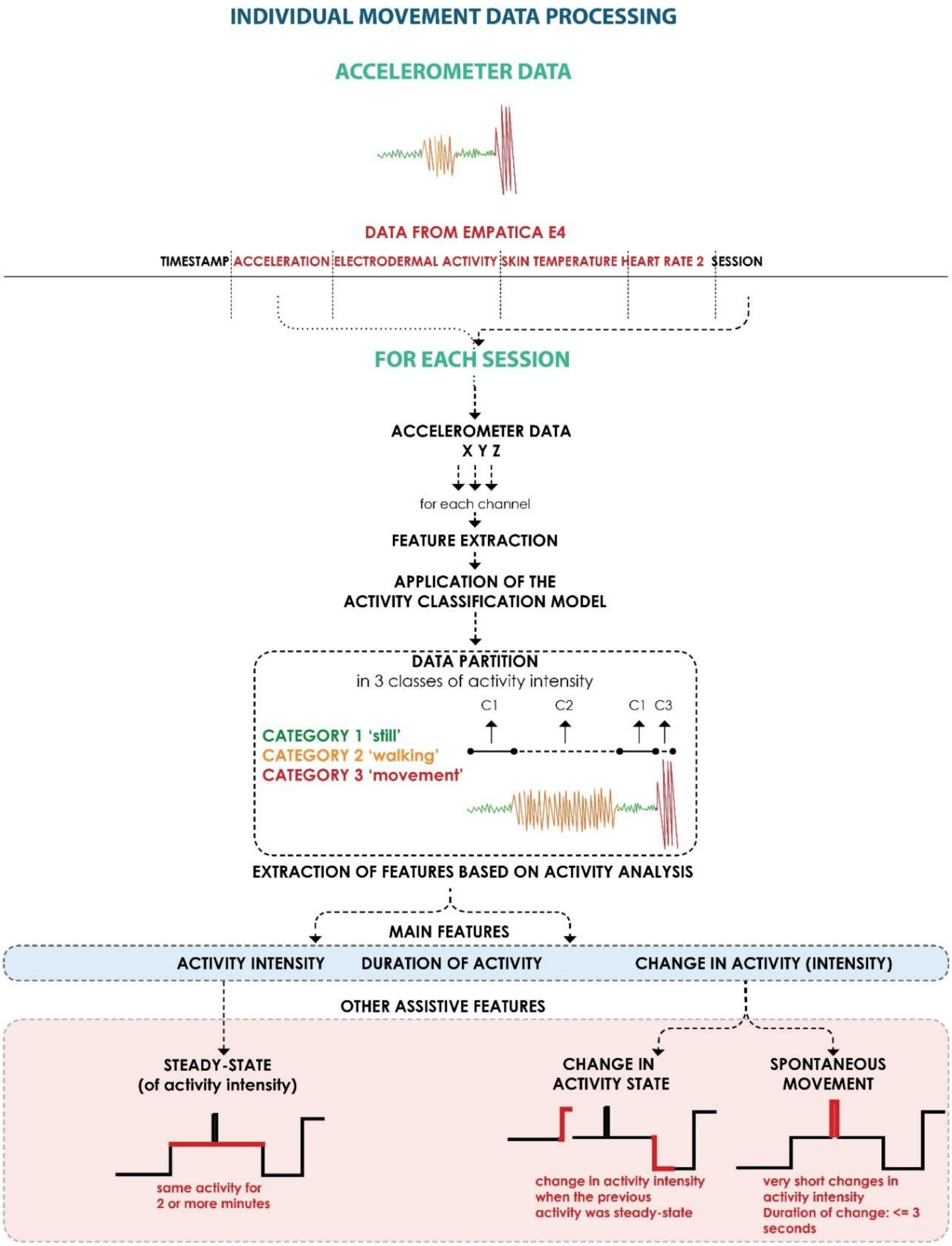


Figure 5.10. Activity analysis after the application of the activity classification model.

The overall process is depicted in Figure 5.10.

Figure 5.11 illustrates the process of extracting classes of activity intensity from the accelerometer data of one user. It also demonstrates the difference between the classification of the 'spontaneous movement' and 'change in activity state' class.

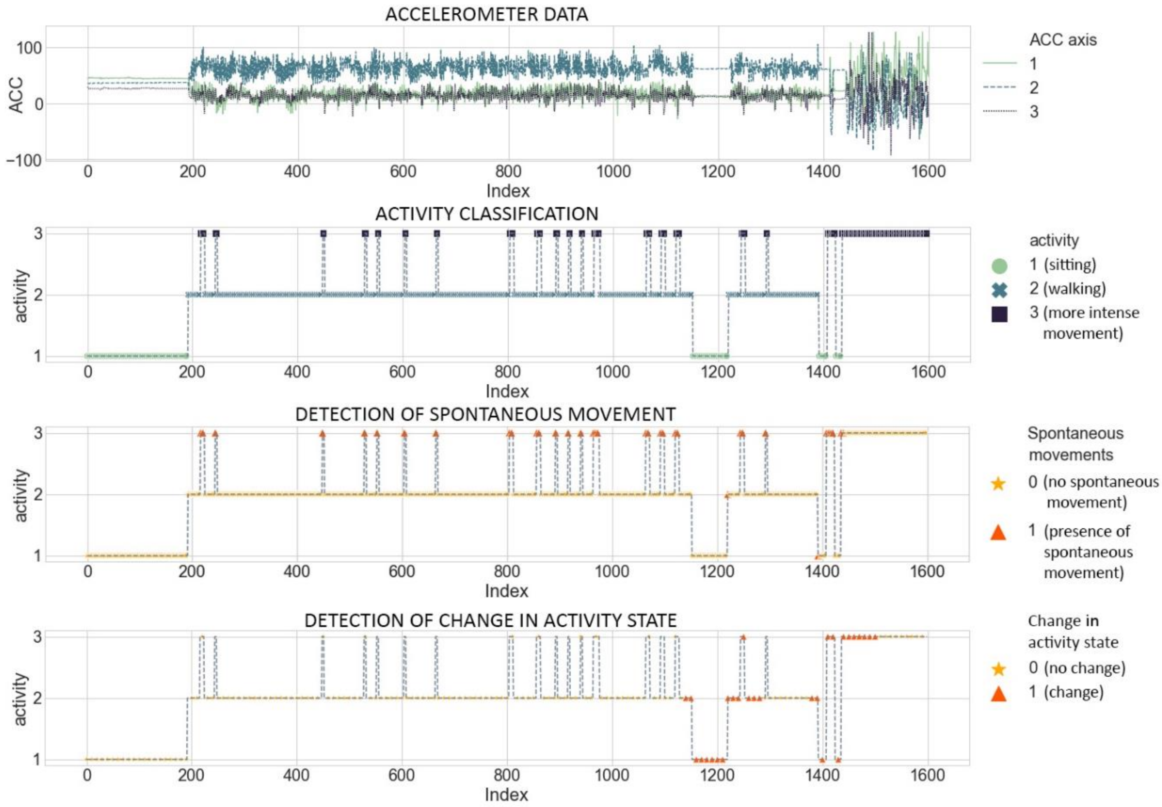


Figure 5.11. The extraction of different features from the analysis of activity

5.2.4. EDA, HR AND SKIN TEMPERATURE DATA PRE-PROCESSING

5.2.4.1. EDA DATA PRE-PROCESSING

5.2.4.1.1. EXTRACTION OF EDRS

For EDA data processing, the EDA signal is resampled at the original frequency of the EDA data. The EDA signal is separated in its tonic and phasic components. The phasic components are identified by applying a peak recognition algorithm based on the signal's first order derivative, following the relevant literature from Chapter 4.

5.2.4.1.2. IDENTIFICATION OF EDA ARTEFACTS

After that, a ML model for artefact recognition is applied to identify artefacts in the signal. This model was built using data collected from the indoor activities. The approach was similar to that followed for the selection of the most appropriate algorithm for activity classification. Different ML models were tested and compared.

The best-performing model was again the DNN model, achieving 96% accuracy. The approach was similar to that followed in Taylor et al. (2015). A detailed presentation of the experiments conducted for constructing the artefact recognition algorithm is provided in Appendix E.

After applying the artefact recognition model and removing the peaks containing artefacts, the remaining peaks are further evaluated to ensure that they fall within the acceptable criteria set for EDR identification in other studies. The main criterion is the minimum threshold for EDR amplitude (set to 0.05μS). A query in terms of the movement characteristics is also applied in a window including 10 seconds before each possible peak, as well as during its onset; if the activity label of these points is 'spontaneous movement', these points are labelled as possible artefacts in terms of EDA measurement.

5.2.4.1.3. CALCULATION OF THE TONIC EDA

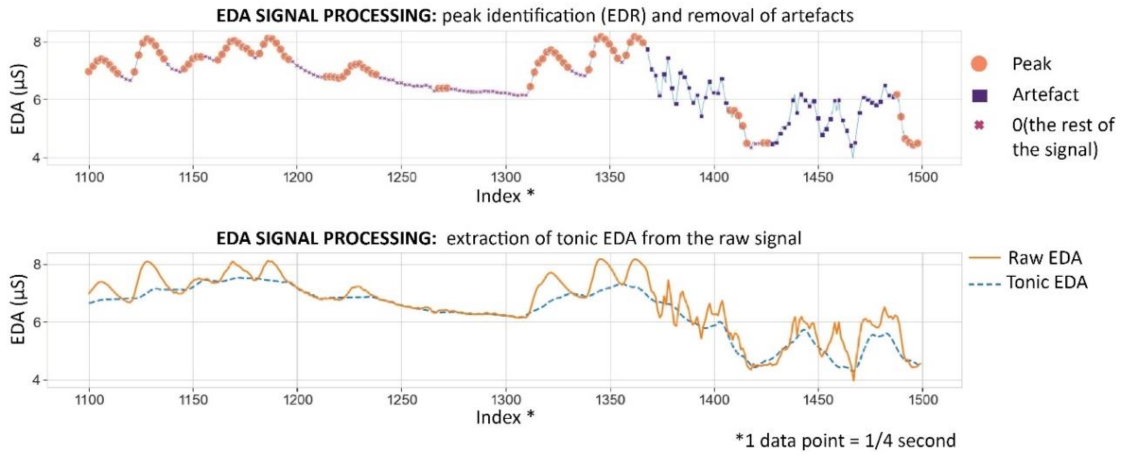


Figure 5.12. EDA signal processing: artefact removal, extraction of tonic EDA and peak identification for extraction of EDRs

Finally, the tonic EDA is calculated by interpolating each peak's starting and ending point and connecting the rest of the signal with the interpolated segments (Figure 5.12). The tonic EDA signal is also smoothed by down-sampling it at 20 seconds. The EDA measures are also normalised after identifying the minimum and maximum EDR amplitude and tonic EDA from all the collected data for this participant. The overall process for analysis of EDA data is presented in Figure 5.13.

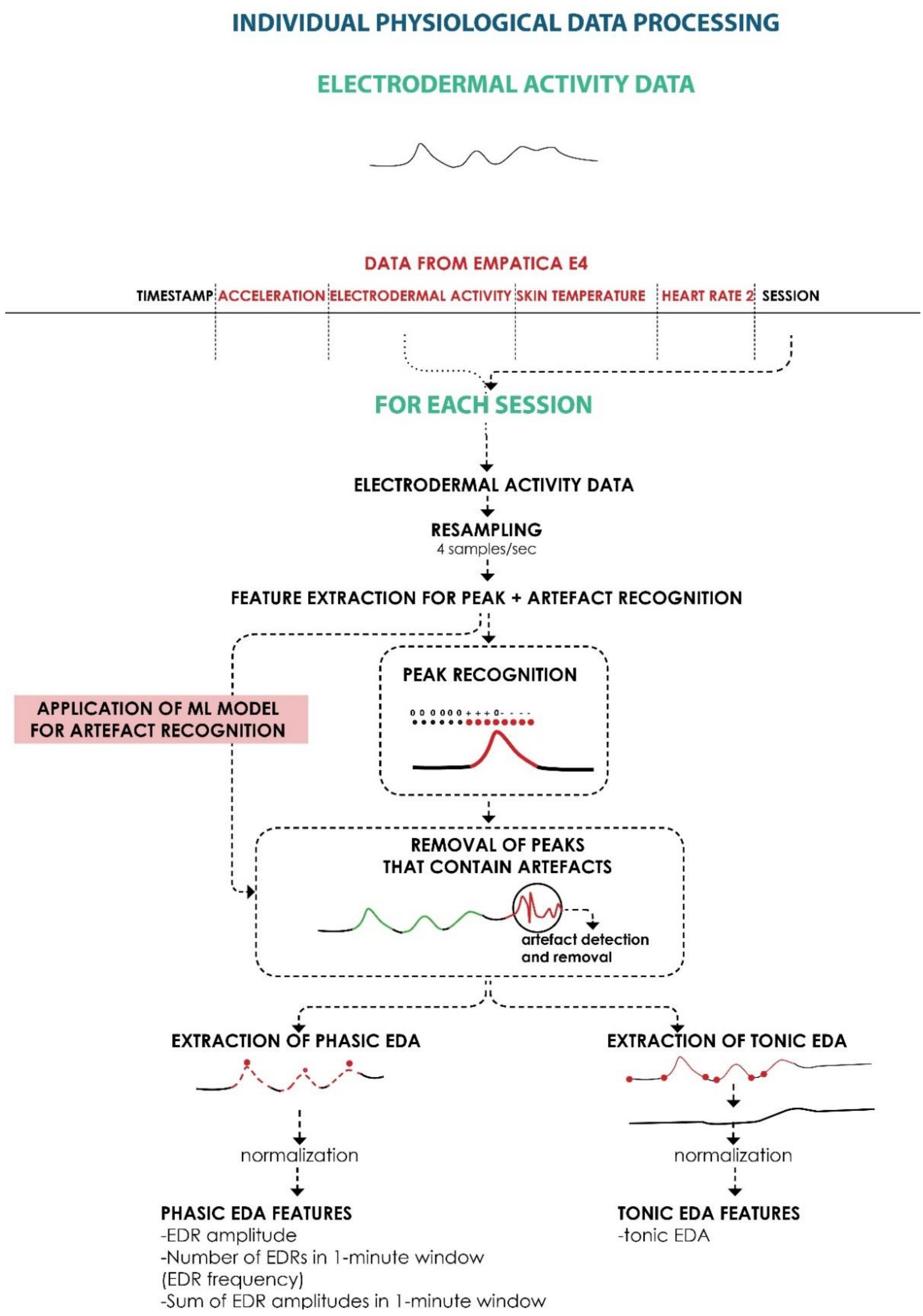


Figure 5.13. The analysis of EDA data

5.2.4.2. PRE-PROCESSING HR DATA

As for the HR data, pre-processing involves smoothing and cleaning by fast Fourier transform. Then, the first order derivative is extracted to be used in peak identification.

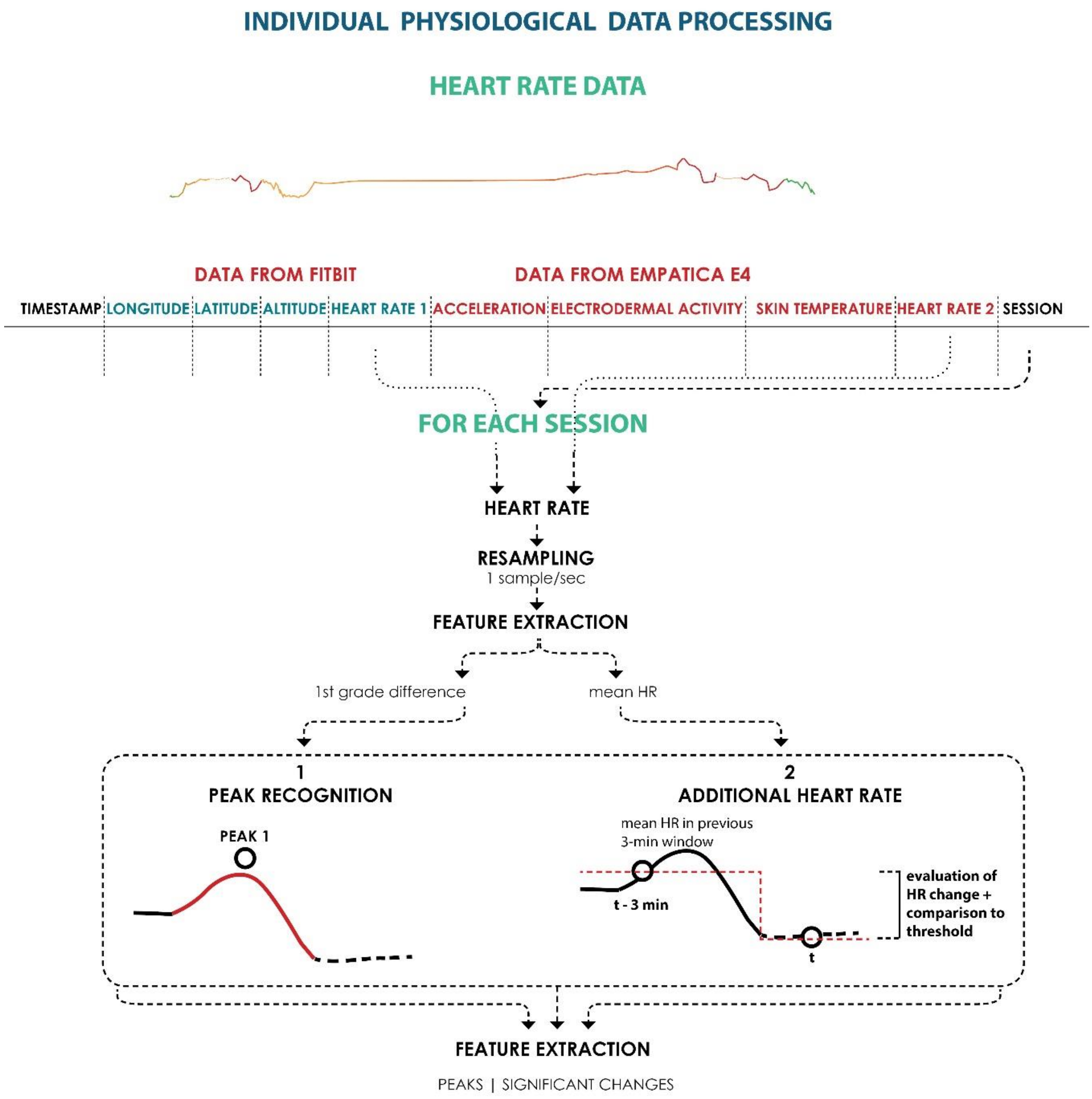


Figure 5.14. The analysis of HR data

5.2.4.2.1. IDENTIFICATION OF CHANGES IN THE HR SIGNAL

Two methods were designed for identifying changes in HR. The first method is the AHR method, proposed by Myrtek (2004) (see section 4.3.2.1). A modified version of this method is adopted here, following the work of Kusserow et al. (2013). The mean HR data (extracted from a 60-second window) is assessed in comparison to the mean HR of the previous 3 minutes. Previous models considered a change larger than 3bpm as a candidate for further inspection. However, this threshold might be low in the context of movement, especially when using devices without high accuracy.

The second method is to process the HR signal by applying a peak recognition algorithm. This algorithm follows the same logic as the one applied for peak identification in the EDA signal. It is again based on identifying the points where the first-order derivative of the signal is zero. An example of the application of the two methods is presented in Figure 5.15.

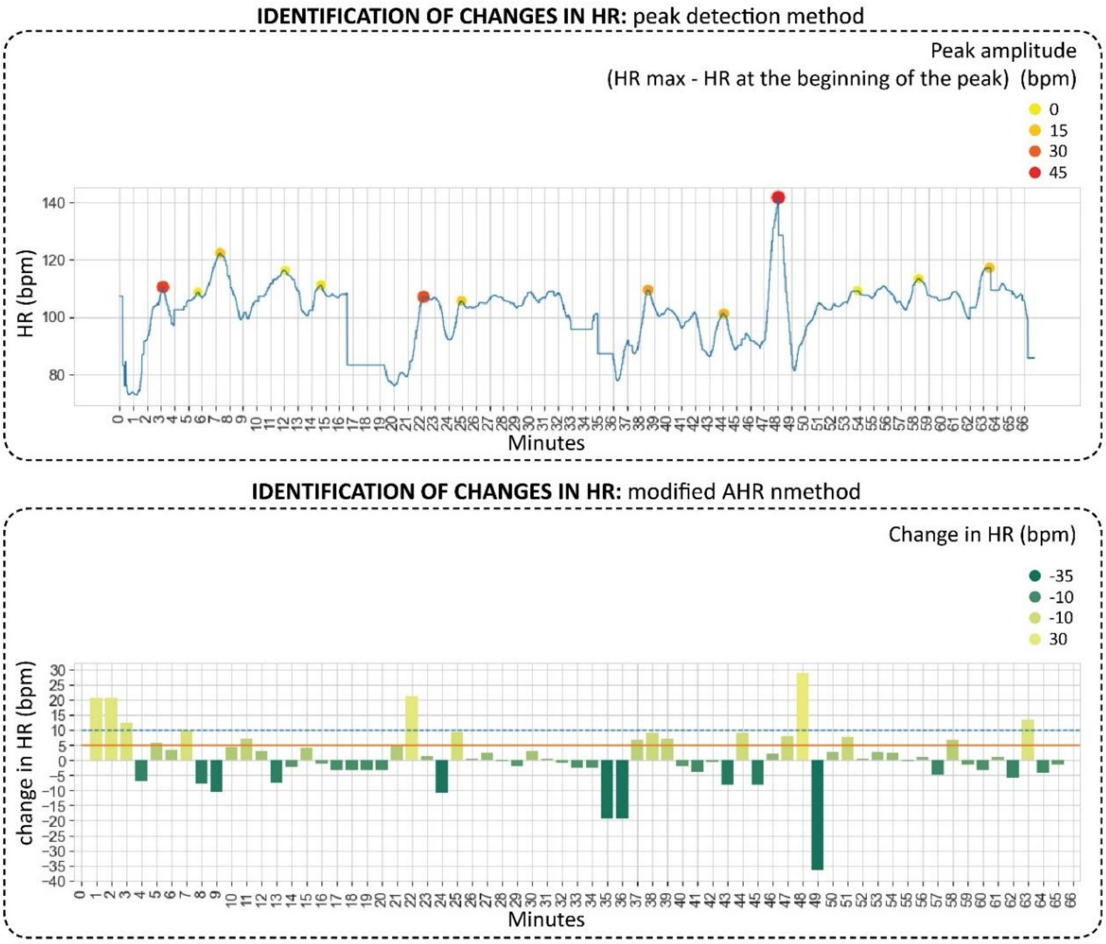


Figure 5.15. Presentation of the two methods for the analysis of changes in the HR data.

The advantage of the peak identification method is that it identifies the change in HR activity as an event with start and end. With the modified AHR method, the characteristics of the whole phase of change cannot be extracted. In both cases, though, the aim is to identify significant changes in HR activity, and both methods achieve this goal. In the next phases, these changes will be assessed by pulling the activity classes from the speed and accelerometer data, as well as the physical and psychological stressors from the spatial database. This interpretation follows the approach of Myrtek (2004) and Kusserow et al. (2013), adding the spatial elements as well.

HRV analysis was not included in the current version of the model, due to the lack of sufficient data for experimentation, but it could be added in the future.

5.2.4.2.2. FUSION OF THE FEATURES EXTRACTED FROM THE PHYSIOLOGICAL DATA

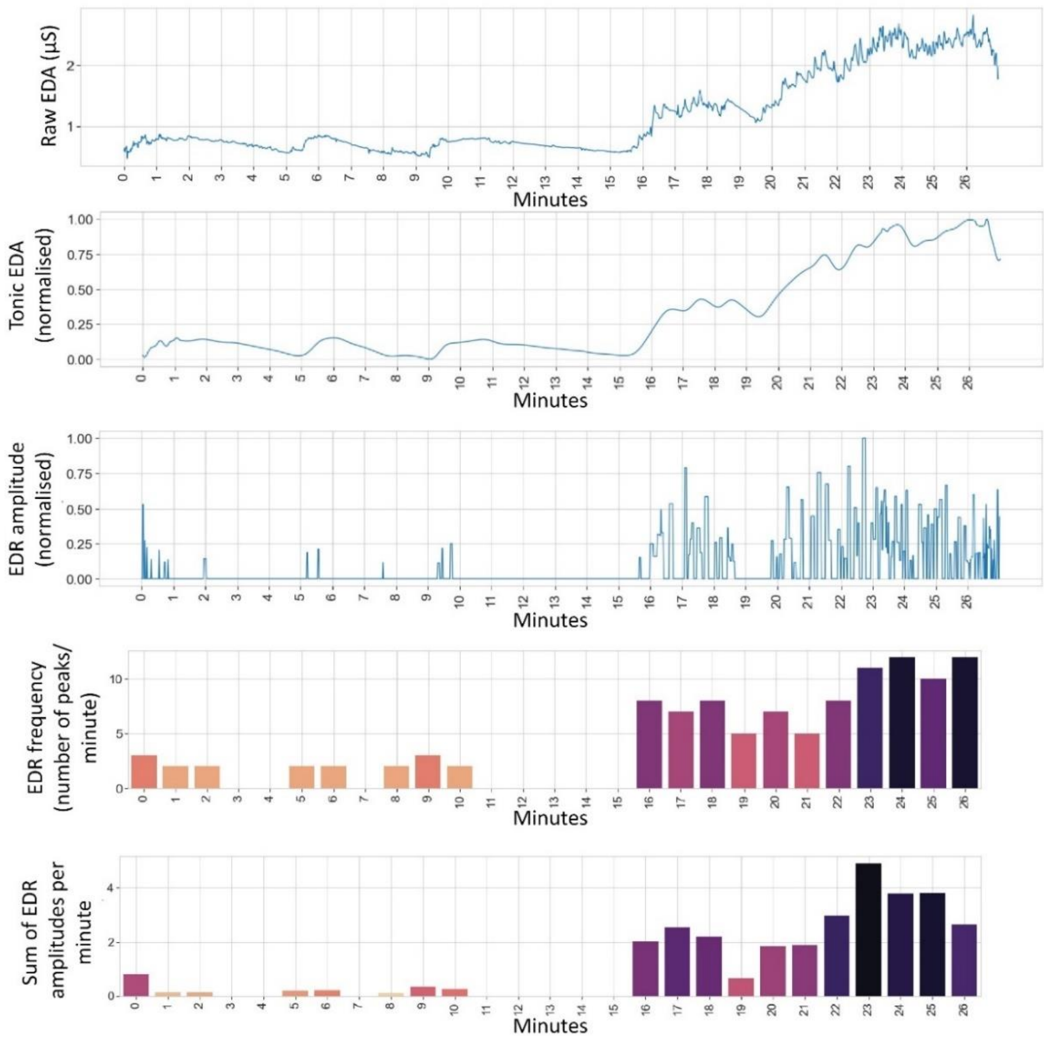


Figure 5.16. An example of the extraction of different features from EDA data

This component ends with a dataframe which contains the following features: timestamp, EDRs, EDR amplitude, EDR frequency (number of EDRs in 1-min windows), the sum of EDR amplitudes in 1-min windows, tonic EDA, mean tonic EDA in 1-min windows, and HR features (amplitude and duration of HR peaks, or change in HR based on the modified AHR method). Figure 5.16 shows an example of the extraction of the different features from the EDA data. The mean skin temperature and its first order derivative are also added. The dataframe is resampled at a sampling rate of 1 value per second, matching the sampling rate of the speed data derived from the consumer activity tracker.

5.2.5. SPATIAL, PHYSIOLOGICAL AND MOVEMENT DATA FUSION FOR INDIVIDUAL ANALYSIS

This stage involves relating the analysed movement and physiological data for each user to the spatial database (containing the processed POI and street network data). The process is depicted in Figure 5.17.

5.2.5.1. DATA FUSION

After importing the movement and physiological data, the closest street network node is found for each GPS stamp, by querying the OSM k-d tree constructed during the initial setup of the spatial database in section 5.2.1. This step allows the identification of spatial characteristics around each GPS point of a route. The properties of the closest node, including POI density, traffic levels, surface conditions) are extracted from the OSM database and inserted in the user database, next to each data point.

This part of the data fusion scheme also includes the fusion of physiological and movement data with ambient temperature data. The assumption of this research is that the setup does not involve any dedicated instrument for collecting this data as a time-series. Therefore, the inclusion of this data is based on accessing historical data for the specified location, which is usually available for download from local governmental sources (e.g., Australian Government Bureau of Meteorology, 2020). The timestamp of the physiological and movement data is used to find the temperature at an hourly resolution (or daily, if the hourly resolution is not available). Many sites also contain historical weather data which is accessible using APIs (e.g., AccuWeather APIs 2020). This option could be considered an alternative that enables access to historical temperature data for a specific date and time. If there is availability of temperature data with a higher resolution from a dedicated portable sensor, this data can also be fused with the physiological and movement data using the timestamps.

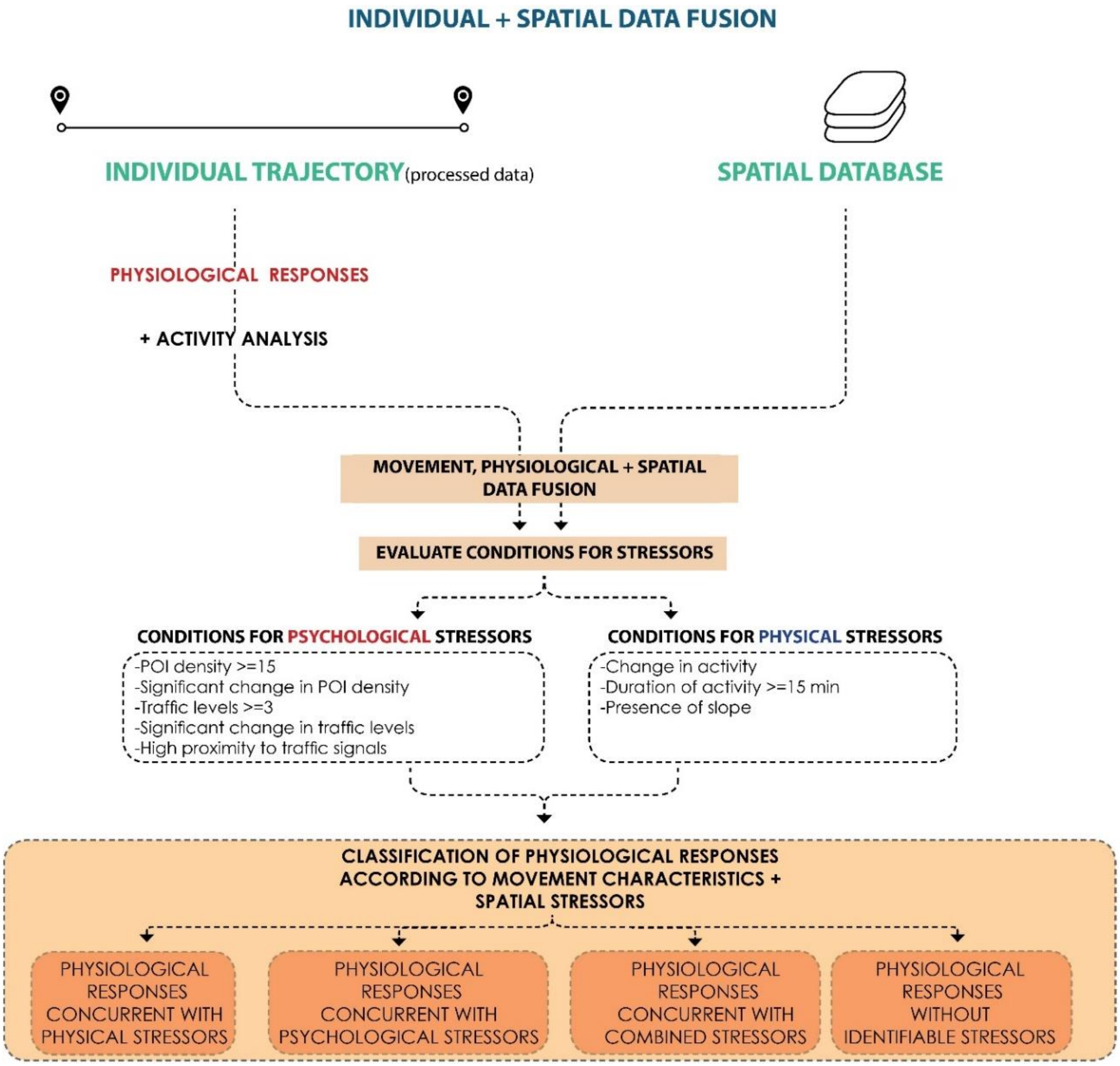


Figure 5.17. The scheme for spatial, physiological and movement data fusion at the final stage of the individual data analysis

5.2.5.2. CALCULATION OF PHYSICAL AND PSYCHOLOGICAL STRESSORS

The calculation of the psychological and physical stressors is conducted by assessing the intensity of the underlying physical and psychological stressors, as well as the change in stressors. For the assessment of changes in activity, this evaluation is conducted for the data points within a buffer starting one minute before the appearance of the response. In these cases, it is possible to know the exact second that these changes happen. However, contextual changes may happen more gradually, and their assessment is based on a rough approximation rather than an accurate estimation. For instance, a pedestrian approaching an intersection with intense traffic levels may perceive changes in the qualities of the surrounding, such as an increase of noise, before reaching this point. Due to these reasons, the buffer for the assessment of psychological stressors is extended to also include the relevant contextual parameters in the minute after the appearance of the response.

The change in stressors is also calculated by splitting the data into 1-minute segments, extracting the mean levels of stressors in each segment and finding the absolute difference between the stressor levels of each segment and its previous one. If the difference exceeds a threshold, the change is marked as significant.

Figure 5.18 shows an example of the extraction of the level of psychological stressors following this process.

The following filters are used to assess the level of psychological stressors:

- POI density larger than 15, or a significant change in POI density
- traffic levels higher than level 2, or a significant change in traffic
- high proximity to a traffic light

For each of these conditions that are satisfied, the level of psychological stressors is increased by 1. The thresholds were determined after iterative experiments and analysis of the distribution of the data in Sydney and Zürich. The data distribution for the data collected in each city and the combined dataset is shown in Figures 6.2a and 6.2b. The threshold for identifying significant changes in POI density was set to 5 (one half of a standard deviation); for traffic, it was set to 1 (approximately one standard deviation). Subclasses of the category 'Psychological stressors' were also created to store the specific contextual conditions for each point (e.g., 'Psychological stressors: Change in POI density').

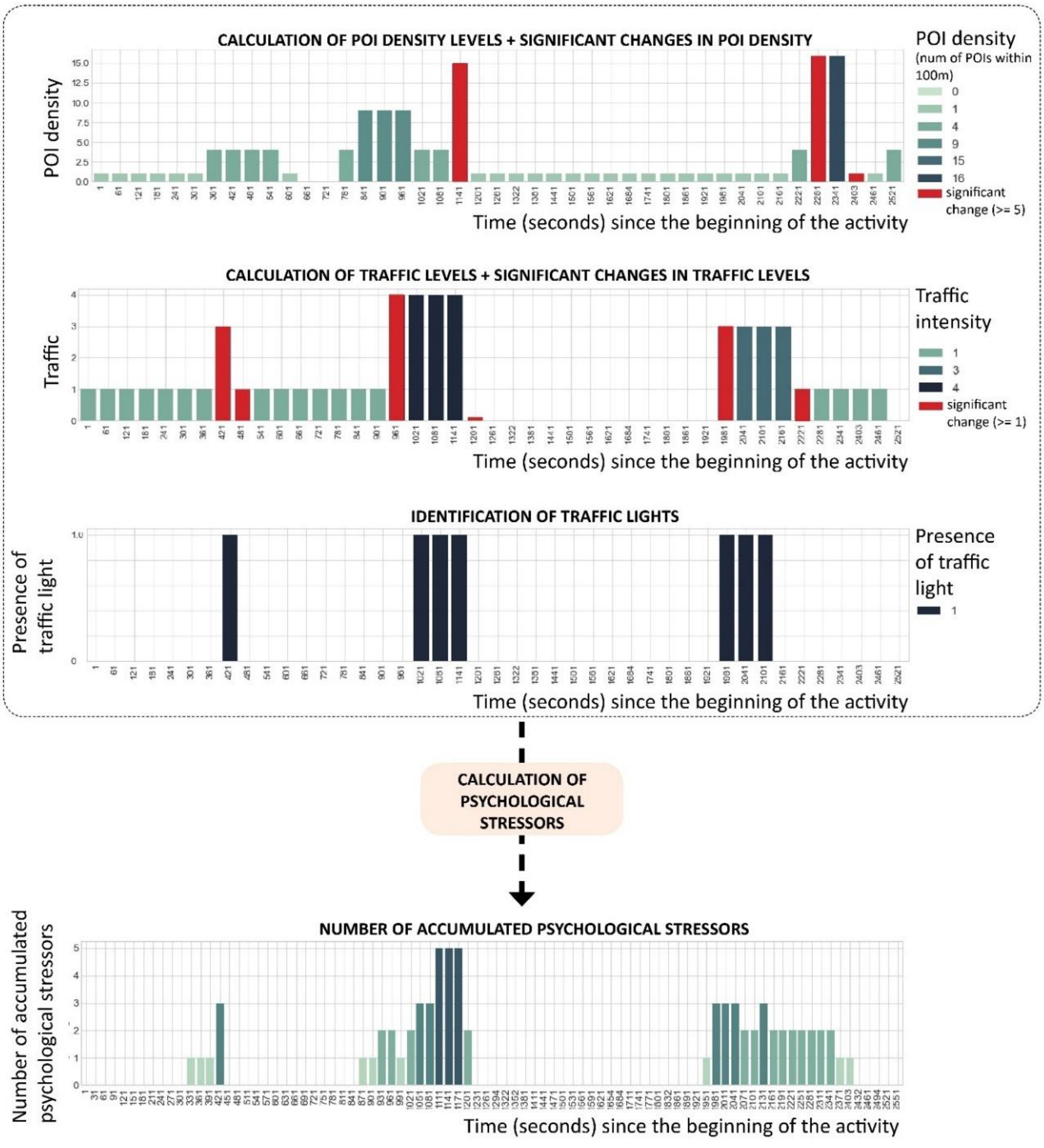


Figure 5.18. The calculation of the level of psychological stressors based on the different contextual features. The changes in the traffic and POI density are also added later to this calculation.

The following filters are used for the classification of physical stressors:

- Change in activity
- Duration of activity > 15 minutes
- Sustained presence (> 1 minute) of activity of high intensity
- Presence of slope (calculated from altitude data processing)
- Presence of traffic light

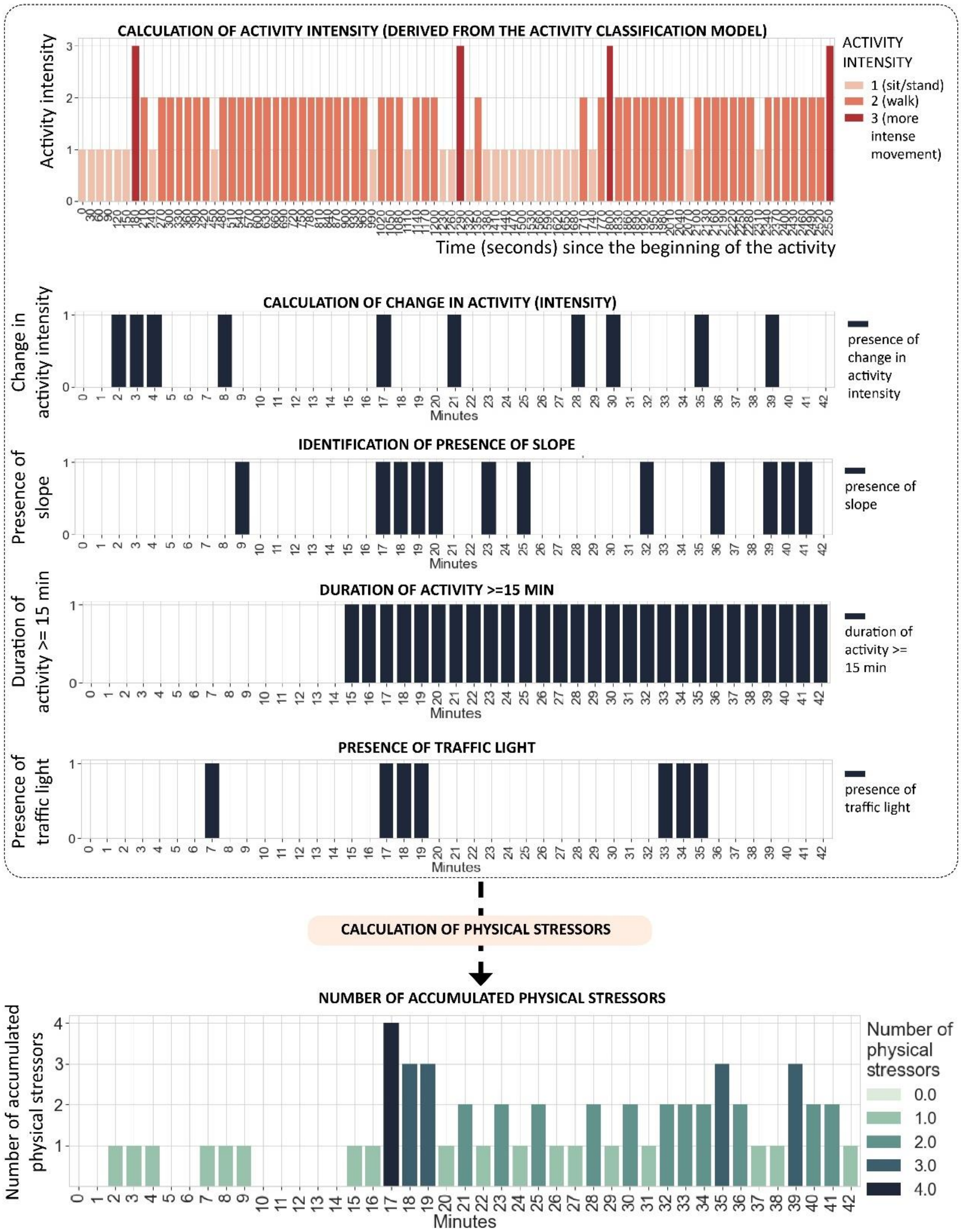


Figure 5.19. Extraction of the physical stressors based on the analysis of activity

For each of the conditions that were satisfied, the level of physical stressors was increased by 1. Figure 5.19 shows an example of this process. The kind of physical stressor was also stored in a subclass (e.g., ‘Physical stressors: Change in activity’).

5.2.5.3. CLASSIFICATION OF PHYSIOLOGICAL RESPONSES BASED ON THE UNDERLYING STRESSORS

The next step of analysis at the user level is the classification of physiological responses. Four main classes are used:

- Physiological responses concurrent only with physical stressors
- Physiological responses concurrent only with psychological stressors
- Physiological responses concurrent with physical and psychological stressors
- Physiological responses with no identifiable source

The class that includes physical stressors includes the subclasses 'duration of activity' and 'change in activity'; therefore, the individual who reads the results can see the specific event classified as a physical stressor.

This classification does not imply that the identified stressors are necessarily the source of the physiological responses. It only suggests that there is a high probability that the changes in sympathetic arousal are related to the identified stressors.

After classifying the physiological responses according to the contextual information, the route can be analysed to calculate the percentage of physical and psychological stressors. Each data point is also geotagged; therefore, the resulting information can be plotted on a map for the identification of places with a high concentration of physical or psychological responses. Examples of this feature will be presented in the next section. The workflow which will be presented in Chapter 7 can also be used for hotspot identification and cluster analysis.

5.3. DEMONSTRATION OF THE METHOD USING DATA FROM 2 USERS

This section illustrates how the method for physiological data collection and analysis works for individual users. The data belongs to two users from the free-living activities dataset (the Phase B of the data collection experiment conducted in Sydney; see section 2.4.2 in Chapter 2).

The presented examples involve graphs and maps showing the spatial concentration of physiological responses and other features. The analysis presented here will focus on

EDA data. For each route that will be analysed, graphs showing the results of the HR analysis will be presented in Appendix G.

The measure used to estimate the intensity of physiological responses based on EDA analysis will be the sum of EDR amplitudes. This feature (sum of EDR amplitudes) is extracted by splitting the data into 1-minute segments and finding the sum of the amplitudes of all the phasic EDA responses (the EDRs) in the segment. The resulting sum of responses is thus used as a measure that reflects both the number and intensity of EDRs. The 1-minute resolution is also appropriate for the purposes of this study, as it matches the level of detail in the contextual data.

The analysis is complemented by photos from spots which were associated with important findings. Relevant information from the notes of the participants is also presented.

5.3.1. USER A

User A is a 30-year-old female. She conducted 21 trips in the period of the data collection (September 2019). Most of her routes took place between 11:00 - 14:00 and lasted more than 20 minutes, with very few exceptions.

The trips of this user which were selected for demonstration of the method and discussion of the findings involve a pair of two routes. The routes have the same starting point and destination, and some common segments. Figure 5.20 displays the spatial distribution of the physiological responses for both routes, and the concurrent physical and psychological stressors.

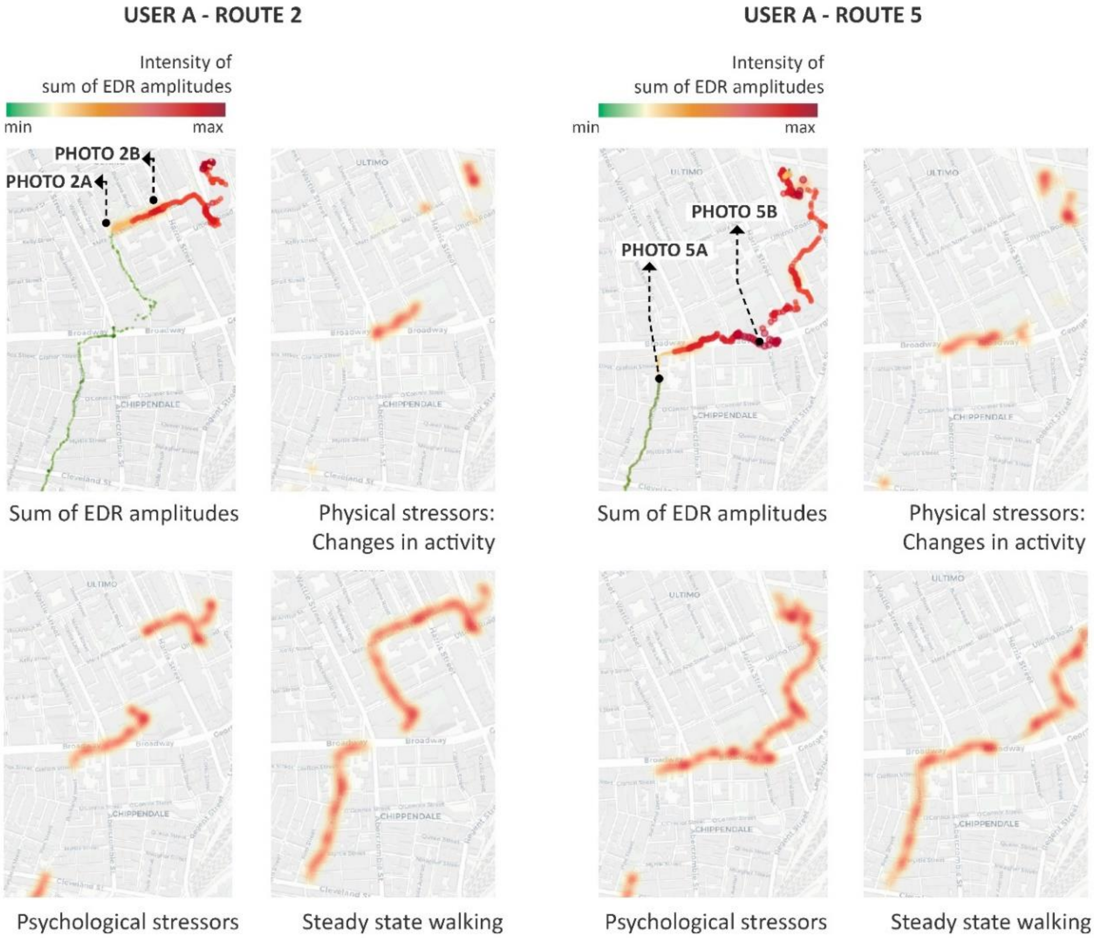


Figure 5.20. The spatial distribution of physiological responses (sum of EDR amplitudes) in routes 2 and 5 for User A.

Figure 5.21. A place which was characterised as a space with a low level of psychological stressors in Route 2 of User A

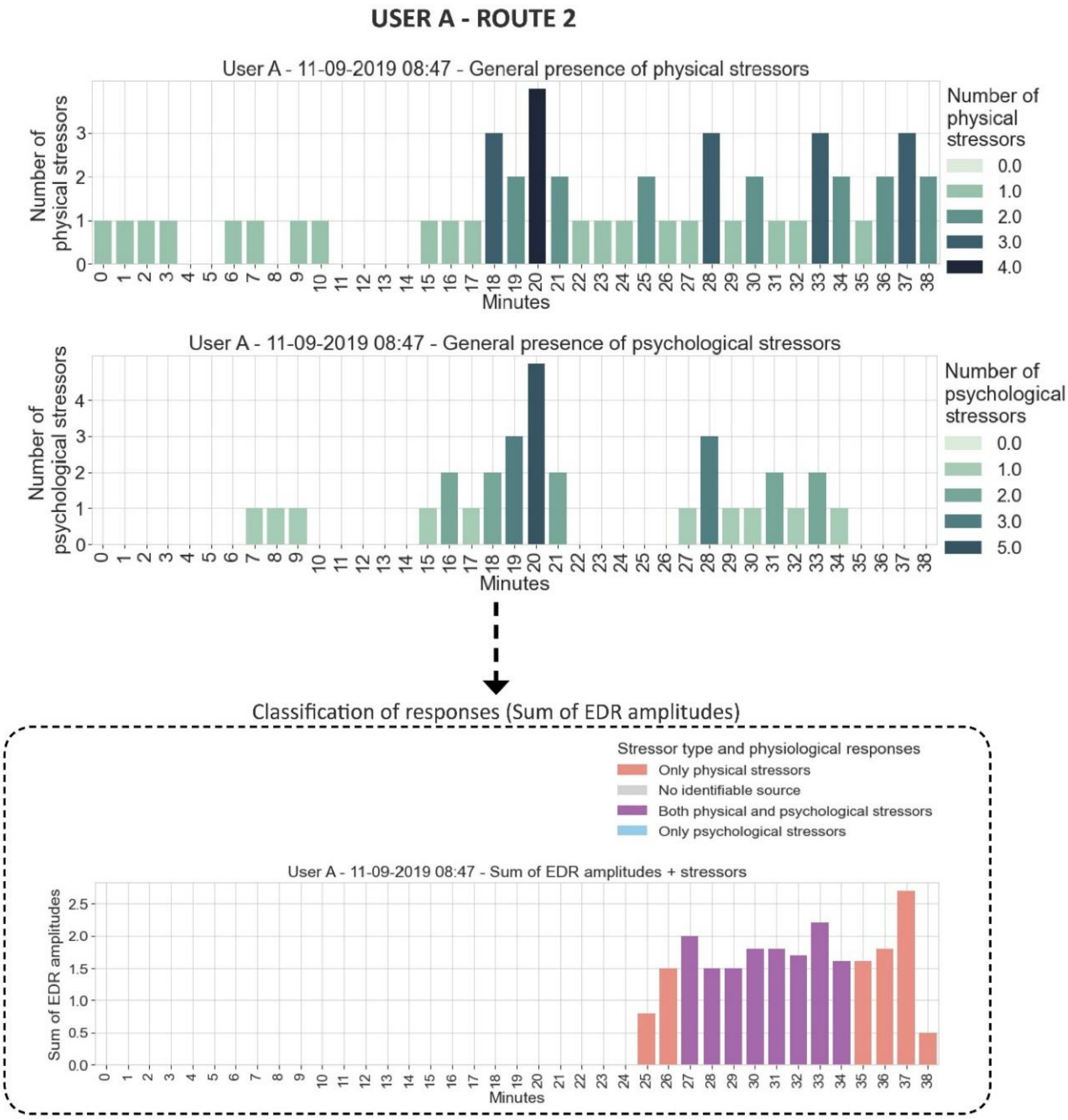


Figure 5.22. Analysis of the physical and psychological stressors for Route 2.

The analysis of Route 2 (Figures 5.20, 5.22 and 5.23) shows that, for the first 15 minutes, the places which the user encounters involve a very low overall presence of psychological and physical stressors, apart from a small cluster of both stressors around the 7th minute. Then, there is an intense increase in both stressors in the middle of the route, between the 15th and the 21st minute. The detailed presentation of the stressors in Figure 5.23 shows the presence of high levels of traffic and POI density during these minutes; a traffic light also appears within this cluster, and there are some changes in activity and the presence of a slope. Then, there is a transition to a tranquil place, presented in Figure 5.21. There are no physiological responses until the 25th minute.

From that point of the initial increase and onwards, the intensity of the physiological responses remains high, with some fluctuations that will be analysed later.

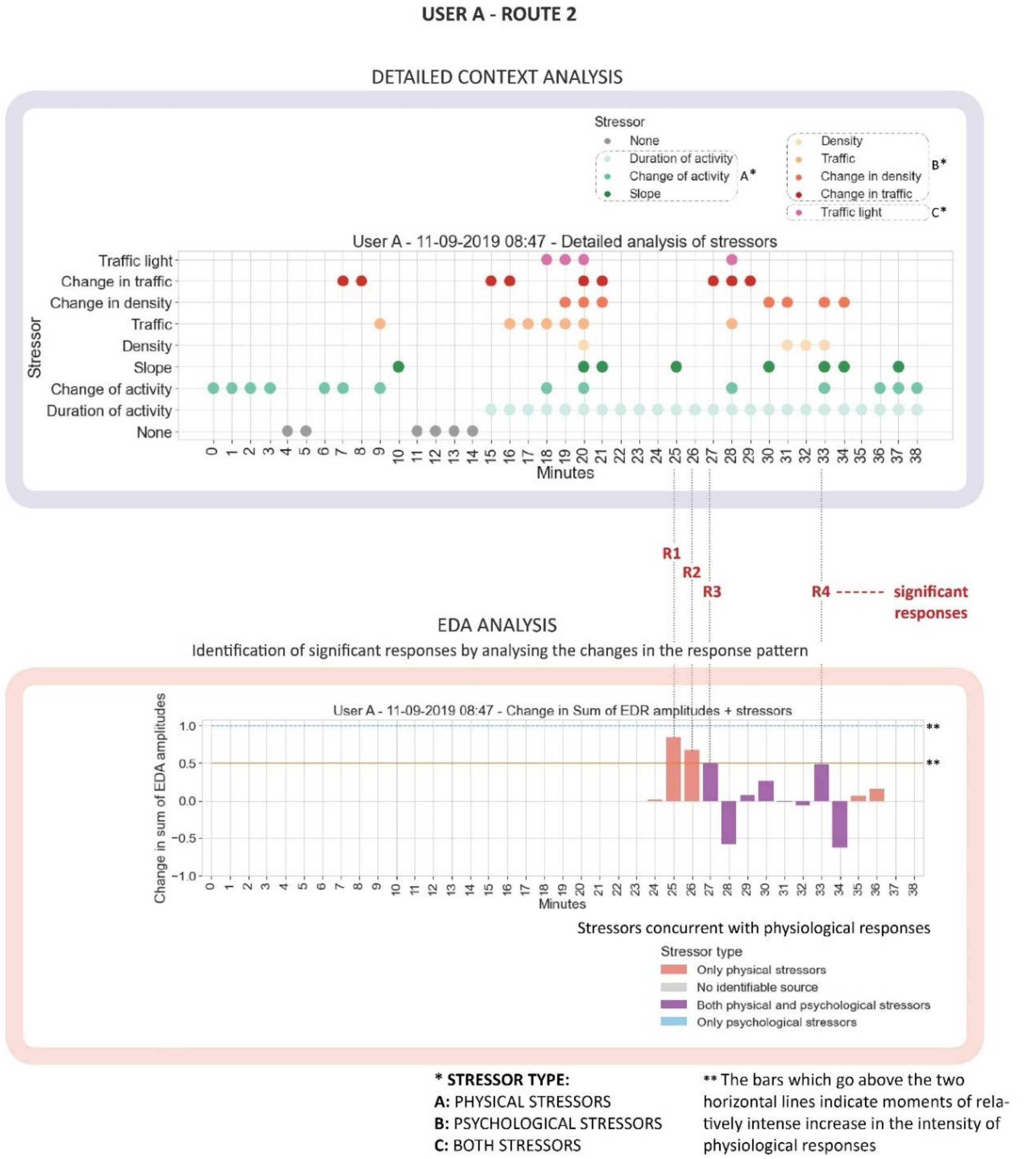


Figure 5.23. The upper graph presents a detailed analysis of the contextual and activity-related stressors.

After the first analysis of the selected measure of physiological responses (the sum of the EDR amplitudes), the change in this measure was also analysed, to find the moments of a significant increase in the intensity of responses. The bottom graph in Figure 5.23 presents the results of this analysis. The significant responses are the ones marked as R1 to R4. The threshold for identifying a significant increase was set at one half of the STD of the measure (based on the data collected from all participants; see Figures 6.2a and 6.2b in Chapter 6). The bars that cross the orange horizontal line in Figure 5.23 show the moments of increase in the intensity of responses which are above this threshold. The blue horizontal line represents one STD of the measure; the bars above this line indicate an even more intense increase in the intensity of responses.

The first two significant increases in the intensity of responses (R1 and R2 in Figure 5.23) happen at a quiet place, with low traffic and POI density. The only concurrent stressors are physical (the duration of the activity and the presence of a slope). The low levels of density and traffic that were identified from the analysis are confirmed in a photo of the location (Photo 2A in Figure 5.24). The other two responses are concurrent with both physical and psychological stressors; R3 is concurrent with a change in traffic, as the user is approaching a place of high traffic levels. Figure 5.24 (Photo 2B) shows the characteristics of this place. R4 is concurrent with an increase in POI density, while there is also a change in activity and a slope, apart from the high duration of activity.

User A - Route 2 - Photo 2A

User A - Route 2 - Photo 2B

Figure 5.24. Photo 2A shows the place where the responses first started appearing in Route 2, for user A.

In the analysis of Route 5 (Figure 5.25), the overall trend of increase in the physiological responses is more visibly connected to the underlying stressors. The first segment of the route is the same as before; this is also reflected in the middle graph in Figure 5.25, which shows the general presence of psychological stressors in this route. There is, again, this small cluster of psychological and physical stressors that was present at the beginning of the other route. This time, there is a physiological response concurrent with this cluster (in the 7th minute of the route). The detailed analysis of responses in

Figure 5.26 shows that this physiological response happened close to a traffic light, when the user first encountered an increase in the traffic levels after the start of the route. Photo 5A (Figure 5.27) shows the intense presence of stimuli in this place. After that, the user followed a different path before reaching the same destination as in Route 2.

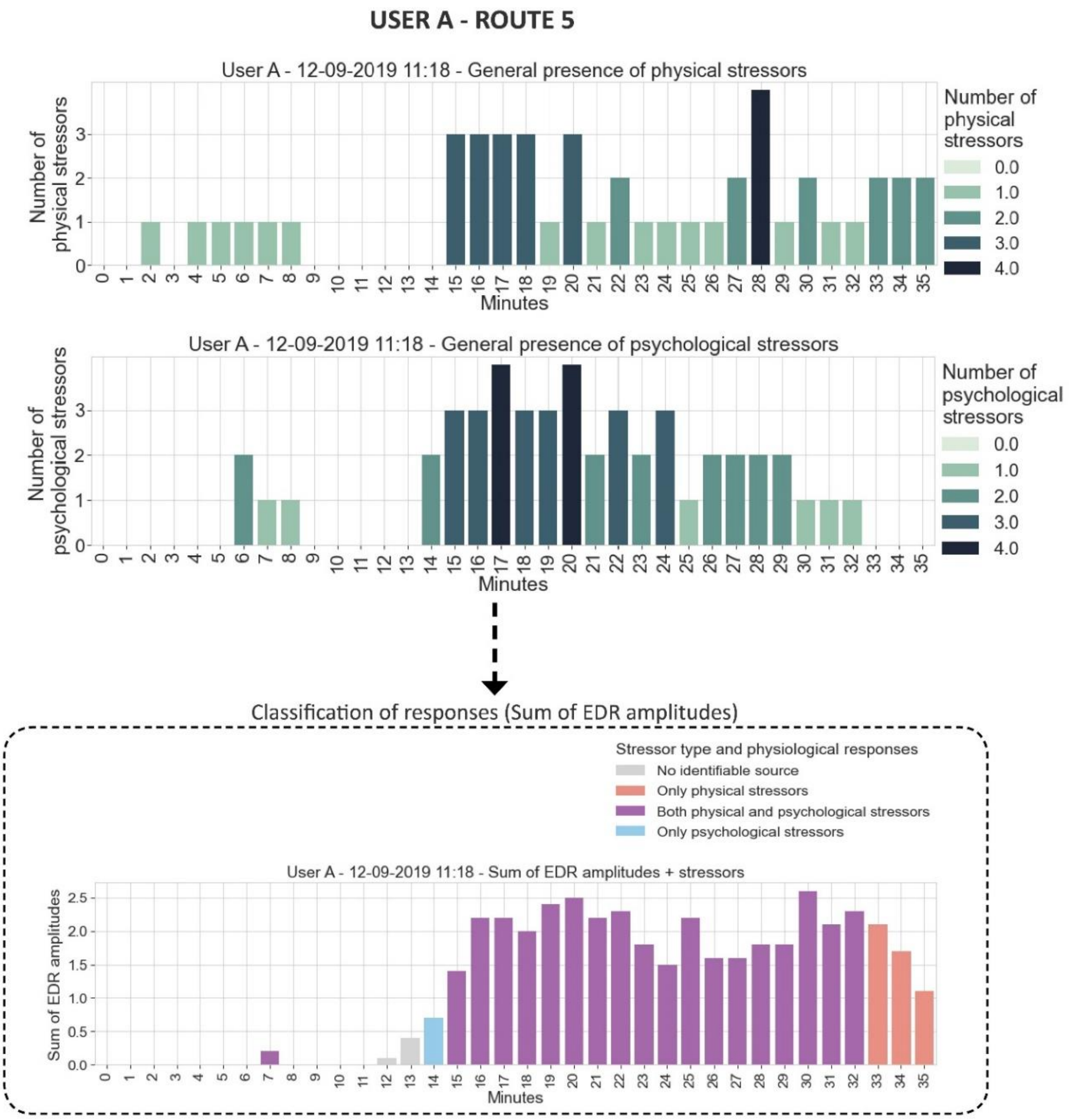


Figure 5.25. Analysis of the physical and psychological stressors for Route 5.

The comparison of the two routes showed that in Route 5, there was a higher overall presence of psychological stressors. The physiological responses were also elevated for more time in that route (21 minutes in Route 5, as opposed to 13 minutes in Route 2). The analysis of the physiological responses after applying the classification scheme showed that Route 2 involved a high percentage of physiological responses generated during physical stressors (40%, as opposed to 12% in route 5). In other words, the main stressors identified from the analysis were related to movement. Route 5, on the other hand, involved a higher percentage of physiological responses generated during exposure to combined physiological and physical stressors (73%, as opposed to 59% in route 2). The higher presence of psychological stressors in route 5 is also confirmed in the maps presented in Figure 5.20.

An interesting finding was that, despite the differences in the physiological responses that were revealed from the analysis, the experience was characterised by the participant as ‘active and exciting’ for both routes, according to their notes.

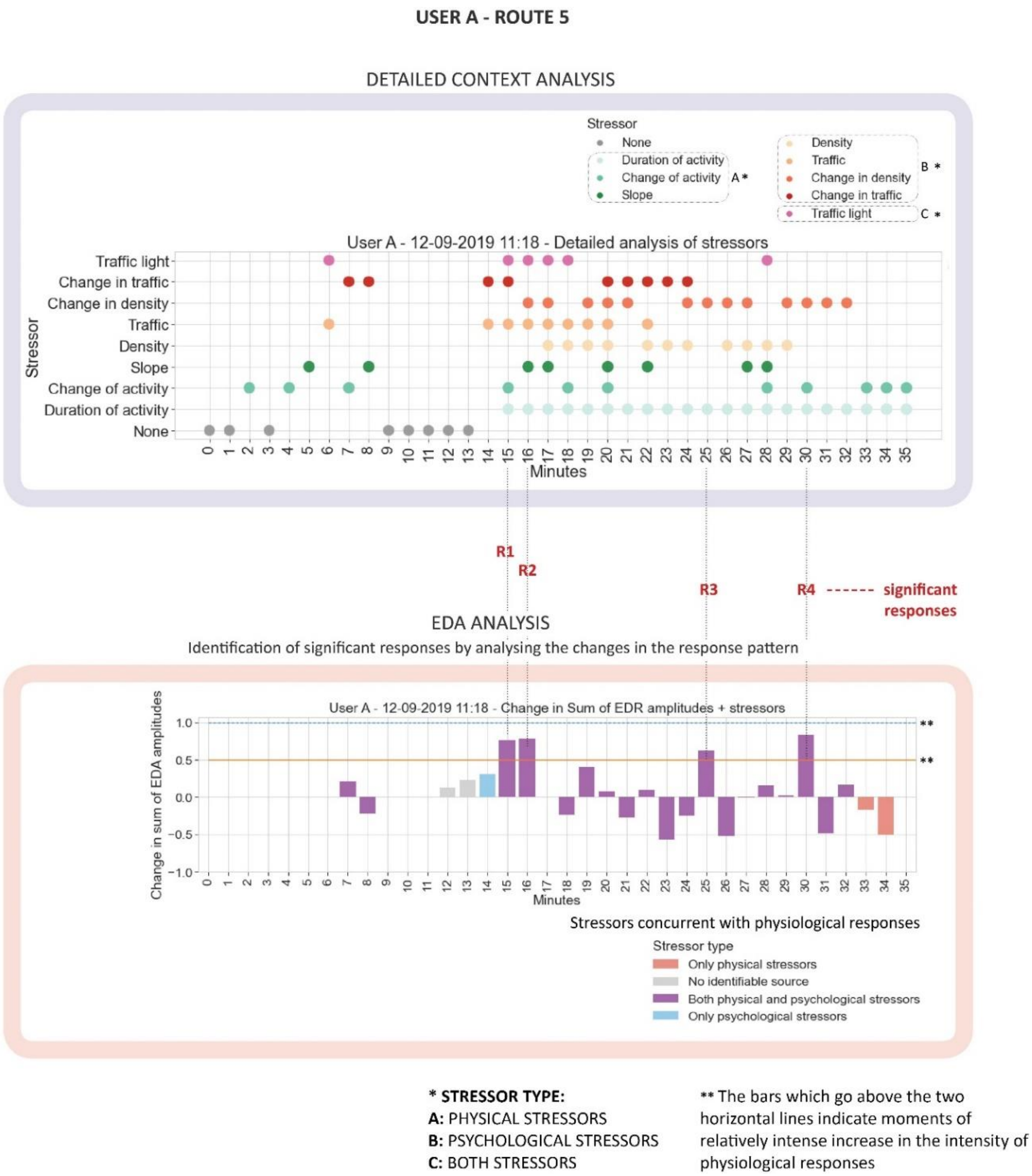


Figure 5.26. A detailed analysis of the contextual and movement-related stressors, in parallel to the analysis of the change in the physiological responses.

The analysis of the moments of a significant increase in the intensity of physiological responses for Route 5 (Figure 5.23) showed that the most significant responses (R1 to R4 in Figure 5.26) were concurrent with both types of stressors. The first significant increases in the intensity of responses (R1 and R2 in Figure 5.26) happened when the user entered an area with high POI density and traffic. There was also a change in activity, possibly associated with a traffic light that was nearby. Photo 5B (Figure 5.27) shows the high presence of stimuli in this area. In the third significant response (R3), the underlying physical stressor was only the duration of the activity. In the last significant response (R4), there was a change in activity and a change in density. The presence of high POI density levels stopped in the minute before this response, and there was no presence of traffic, indicating a transition to a less busy place.

User A - Route 5 - Photo 5A

User A - Route 5 - Photo 5B

Figure 5.27. Two of the places with high levels of psychological stressors that User A encountered during Route 5. Photo 5A is taken from Google Street View (15 Broadway street)

5.3.2. USER B

User B is a 35-year-old male. He conducted 11 trips in October 2019. The route presented here (Figure 5.28) was described as a leisure visit to Rushcutters Bay park for running.

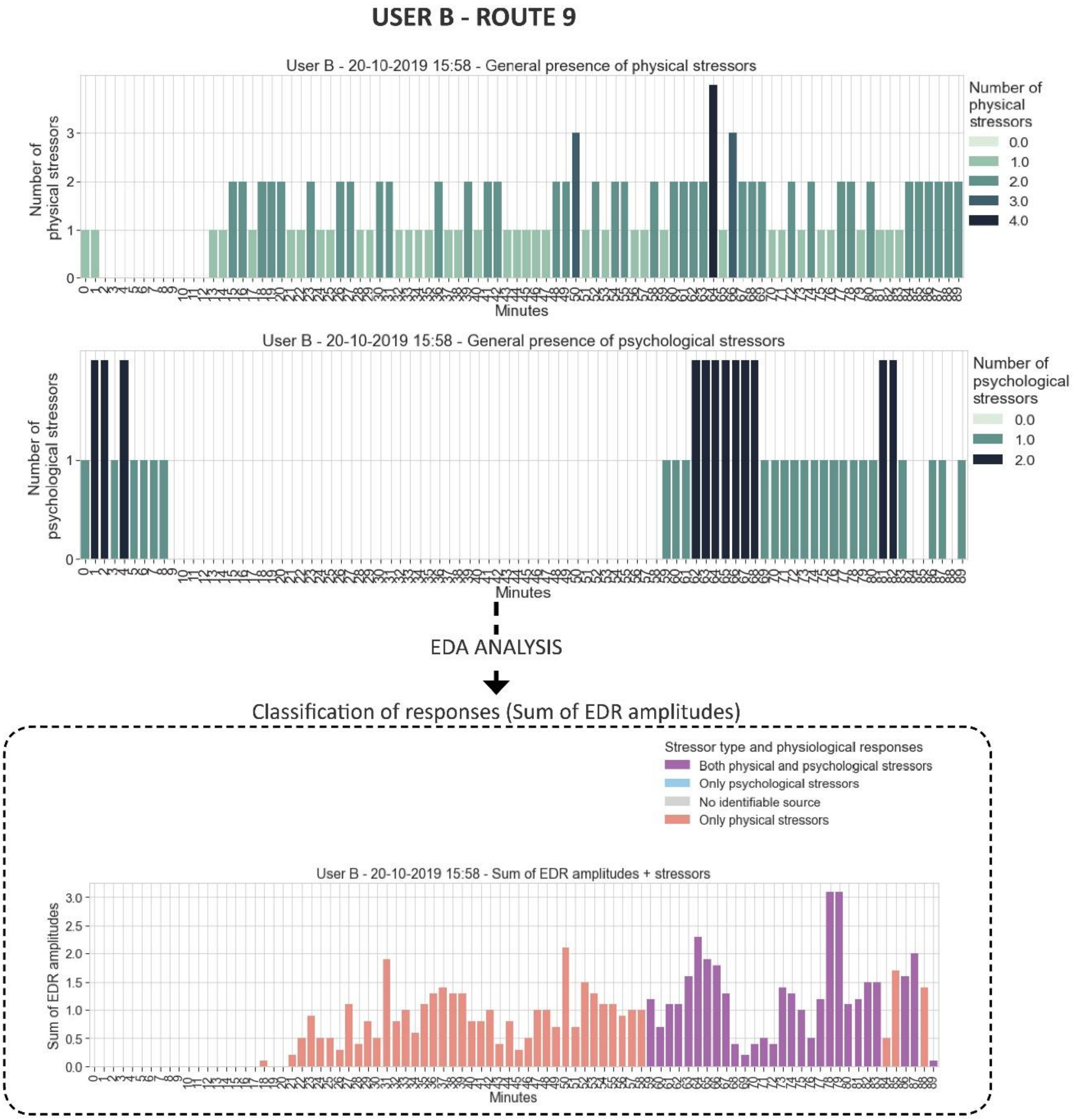


Figure 5.28. Analysis of the physical and psychological stressors for Route 9.

In this route, the spatial characteristics involved mostly residential land use (resulting in very low POI density for a significant portion of the route) and high proximity to nature. Here, physical activity alone was the main underlying factor influencing physiological responses for more than one half of the route. Figure 5.28 shows the significant presence of physical stressors in the first part of the route; in this portion, the physiological responses were most likely elicited due to the exercise. The detailed analysis of the significant changes in the intensity of responses confirms that (Figure 5.29).

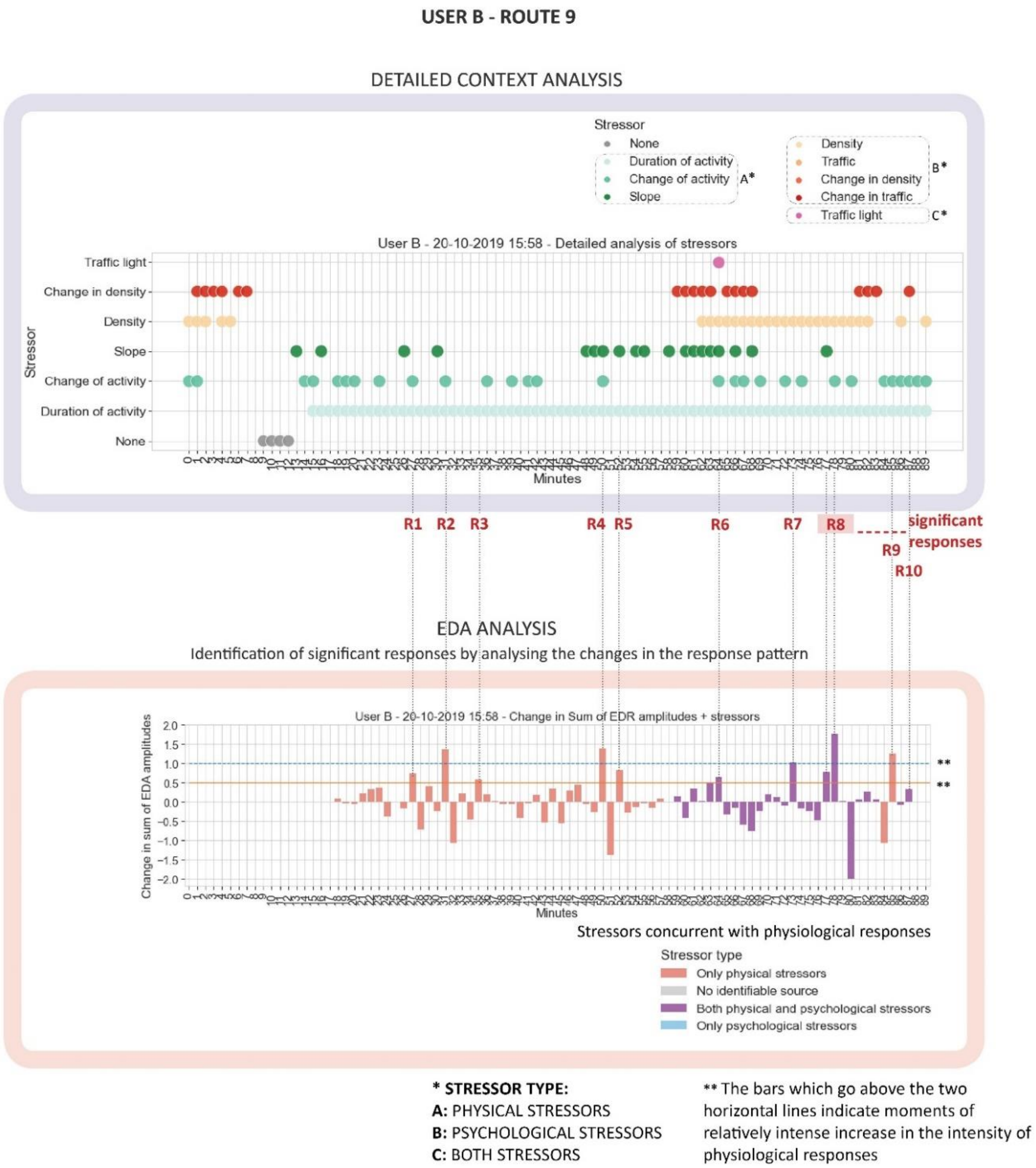


Figure 5.29. A detailed analysis of the contextual and movement-related stressors for Route 9, in parallel to the analysis of the change in the physiological responses.

All the moments of a significant increase in the intensity of responses (R1 to R5 in Figure 5.29) are connected to physical stressors (the duration and change of activity). The absence of psychological stressors is also visible in Figure 5.30, which shows that they are concentrated in an area and only occupy a small part of the route.

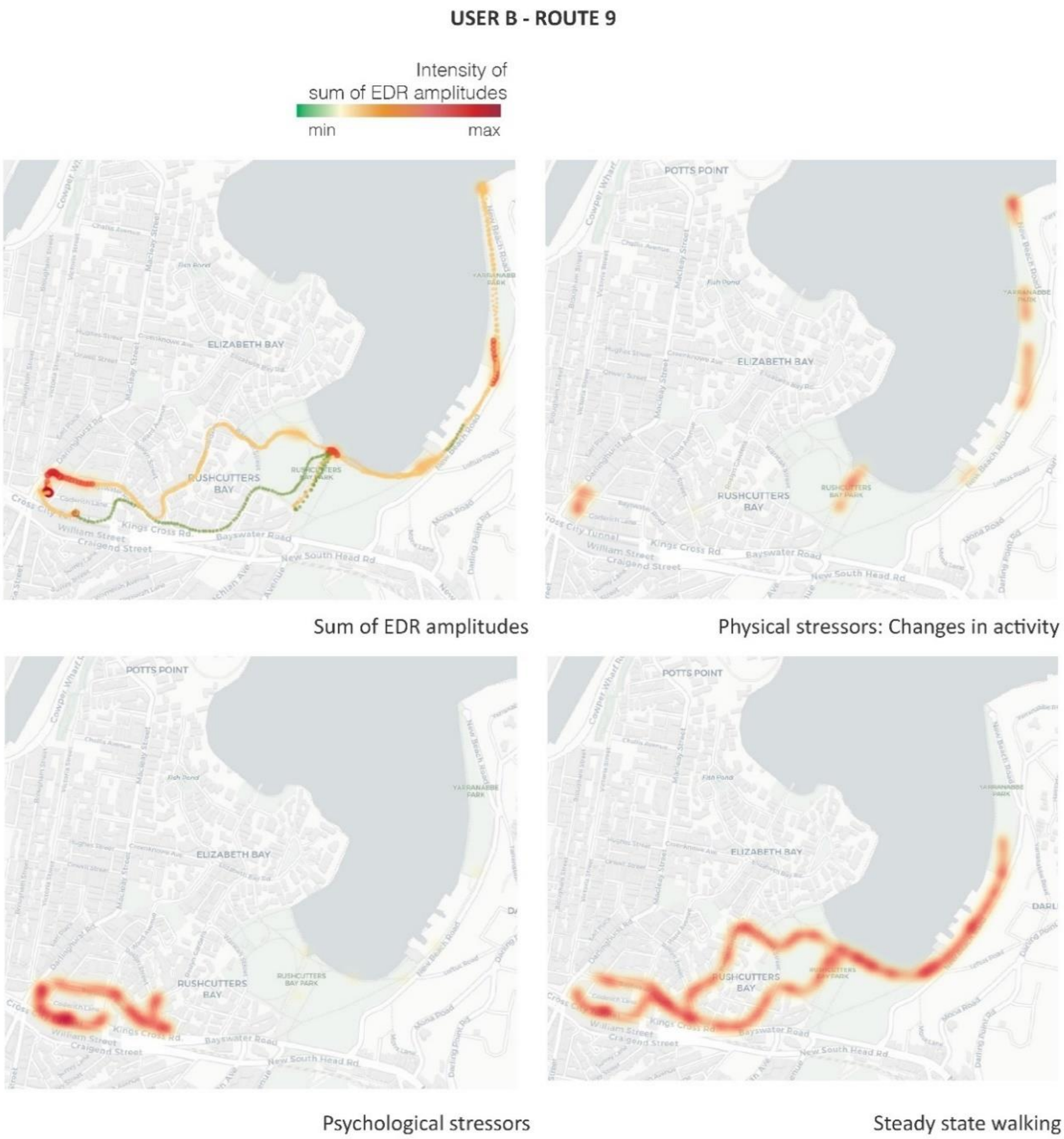


Figure 5.30. The spatial distribution of physiological responses (sum of EDR amplitudes) in route 9 for User B.

The described experience of the user also indicates more physical rather than psychological stress. The overall experience is perceived positively and incorporates a degree of fascination, as well as a recognition of the effect of exercise: *'The grass feels good beneath my feet (..). In the end of the first/second jogging felt a bit exhausted,* *hadn't warmed up yet. Then more jogging/running, found more or less a rhythm. Felt hot after the 2 last runs. Leaving the area feels nice, first park (lots of people but not annoyingly so), then an area that seems like Malibu or something, palms and large empty streets and big houses. Then, from William street onward feels like neighborhood, the area loses this air of exotic holidays. Calm and cosy still*.'

Figure 5.31. William Street-Kings Cross.

Figure 5.32. Rushcutters Bay

There was also a small part of the route where there was a combination of psychological and physical stressors, concurrent with the route's most intense physiological responses. The corresponding response is marked as R8 in Figure 5.29, showing the presence of high POI density, a change in activity and a slope in parallel to the significant increase of physiological arousal. The location is shown in Figure 5.31. Figure 5.32 shows the contextual characteristics of Rushcutters Bay park for comparison.

The places shown in Figures 5.31 and 5.32 have significant differences in their character, yet they both elicited intense physiological responses. The proposed classification scheme was able to identify differences in the possible underlying stressors. A significant percentage (61%) of physiological responses was concurrent only with physical stressors, while combined psychological and physical stressors were present in 38% of the responses. Without this classification, the intense physiological responses during activity might have been misinterpreted as psychological stress.

5.4. DISCUSSION

The proposed scheme includes physiological responses derived from both HR and EDA analysis. The current work was based on tests conducted with two wristbands (FitBit Charge 2, Empatica E4) and relevant information from the literature presented in Chapter 3. The EDA sensor of the Empatica E4 has high accuracy, but the HR measurements of both wristbands were sometimes inaccurate during activity, agreeing with the findings of the literature presented in Chapter 1 (section 1.2.5.3). For these reasons, it was decided to focus on the EDA signal analysis for the demonstration of the method in section 5.3, and specifically on the sum of amplitude of EDRs as the main source of physiological responses. The methods involving HR analysis need more calibration, especially regarding the threshold for detecting significant changes in the HR signal. A more detailed analysis of phasic EDA could also be provided using shorter time windows if more detailed contextual data are included in the scheme at a high resolution. Such data could be noise or other environmental data, coming from portable sensing systems. The presented methods were designed following a componential logic, and each component can be modified or extended to cover specific needs.

As shown in section 5.3, the presented model for the analysis of contextual, movement and physiological data was able to identify different qualities in the circumstances surrounding the physiological responses. After extracting detailed data at a high resolution, such as the POI density, the traffic levels and the traffic lights, the qualities of the routes were grouped in physical and psychological stressors. The analysis of the routes of the two participants in section 5.3, and especially the last example, showed that this categorisation was useful for understanding why physiological responses may occur in places where there is the absence of obvious psychological stressors related to space.

The comparative analysis between similar routes of the same participant also has potential at the user and the city level. The analysis of different instances of the same route of an individual can show if there are spots where the physical space causes repeatedly intense physiological responses. This analysis could take place as a part of an application where the user submits their data for analysis and identifies spaces associated with more intense responses, and their characteristics. For individuals who are more sensitive to external stimuli due to health conditions, this analysis could help identify places during their routes that may affect them negatively. The identification of physical stressors during a route could also be helpful for individuals with kinetic problems. This analysis could be applied in that case to calculate the overall exposure to physical stressors during different routes and select the most comfortable ones. Chapter 7 will later demonstrate methods for analysing the results at a city level; Chapter 9 will also provide methods that can be used proactively for avoiding places with high levels of physical or psychological stressors.

The inclusion of the activity in the analysis of physiological data was one of the most important parts of the presented work in this chapter. Two notable studies which acted as a significant influence concerning this aspect was the activity-aware stress recognition model of Sun et al. (2012) and the model for stress arousal monitoring in the wild of Kusserow et al. (2013). This study has a different aim compared to the work of Sun et al. (2012), as their model results to a classification of the stress versus the baseline condition, while the work presented here results to a classification of possible physical or psychological stressors in parallel to the identified physiological responses. In this aspect, the work is closer to the overall approach of Kusserow et al. (2013).

However, that study only presented a very brief mention of the process of the analysis of activity. It was also operating in a different context, as it focused more on different daily-life conditions such as indoor public speaking, or stress events during a musical performance. This study included, for the first time, a structured analysis of all aspects related to the effects of activity, and it was more focused on the urban environment, as opposed to the two studies mentioned above.

The main limitation of this approach is that the model evaluates the levels of stimulation of the surroundings, but these are based on estimations and not on analysis of continuous data describing the actual fluctuations in stimulation levels during the route. For instance, the model can recognise that the user is passing from an area expected to have a high pedestrian activity or high traffic, but it cannot identify the exact moments that the user encountered a car or other pedestrians in the street. An analysis of such events would require video feedback or at least continuous noise measurement.

Furthermore, the model can only identify a list of different movement-related and contextual conditions that describe the circumstances while a physiological response occurs. It is difficult to say which element among these is responsible for any resulting physiological responses. For this reason, it was decided to calculate the exposure to possible stressors and classify the contextual conditions accordingly, without claiming that the physiological responses are necessarily generated from these factors. In this way, the proposed classification model only outlines some possible factors that may have affected physiological responses without establishing causality.

While it would be very difficult to pinpoint the exact source of physiological responses, it is still possible to analyse them and try to find meaningful patterns. The repetition of a pattern of responses at the same place might indicate that some conditions related to this place are responsible for this pattern. This analysis could be complemented by requesting feedback from the users. This gap was covered in this study by the notes that the participants were asked to keep. They were specifically asked to include anything significant that happened during their routes, including frightening or exciting incidents. The notes were very helpful for understanding how the participants perceived their experience. They also assisted in excluding the presence of other psychological stressors related to family, work or other issues. Future iterations of the designed methods could involve an app for covering this gap by asking the participants to give feedback or rate specific places and experiences.

A factor that needs to be more researched is the selection of the appropriate temporal threshold for the identification of relevant contextual parameters. At the moment, the model is evaluating contextual parameters or factors that appeared within one minute before each response. If there is a significant change in the POI density or traffic, for instance, within that minute, this parameter will appear as a possible event that might have affected a physiological response generated during that minute. However, the inspection of the graphs of the participants showed that, sometimes, the pattern of generation of physiological responses seemed to be more related to a chain of events or changes in activity and context that happen over a few minutes, rather than events happening only in the last minute before the response. Future research will look into these patterns and re-examine the temporal threshold for detecting relevant events if needed.

Another parameter that needs more consideration concerns the incorporation of traffic lights in the scheme for the analysis of the encountered contextual parameters. The designed algorithm currently identifies if there is a traffic light nearby. This information becomes available in the detailed context analysis, indicating the presence of a possible physical and psychological stressor. However, due to the resolution of the OSM data, and the lack of consistency in the quality of reporting sufficient information regarding pedestrian pathways, it is sometimes possible that the identified traffic light is on the other side of the road, and the user may not be affected by its presence. While this is a limitation that has to be considered in the interpretation of the contextual analysis, it is partially compensated by the movement analysis of the user, provided by the analysis of the accelerometer data. The movement analysis shows the changes of activity in the movement pattern in parallel to the context; this information can, therefore, be used to confirm if the user stopped very close to a traffic light or not, limiting the possibilities of a wrong interpretation.

The current role of ambient temperature in the data fusion scheme should also be discussed here. The temperature was included in the scheme because it is a necessary feature for other components of the methodology (component 3 for the prediction of physiological responses). It is currently not included in the classification of physical and psychological stressors in component 1, because the available data during the experimentation with the algorithms was at a low resolution. Therefore, temperature could only be added in this version of the scheme as a general underlying stressor that affects the overall levels of sympathetic arousal. Future research could include a more active inclusion of this factor in the scheme.

Another limitation is that the model currently does not recognise if the user is walking alone or has company. As stated in Chapter 3, social interaction may affect the psychological state of the user; talking can also influence physiological responses. This study attempted to gather relevant data by asking users to note down if they are alone or with company during their routes. Future analysis could involve using the collected data towards the construction of the model for the identification of social interaction.

Future work should also re-examine the threshold set for identifying the duration of activity as a physical stressor. The inclusion of this factor was based on the presented literature in Chapter 3; however, it was not clear if this factor affects both signals. The experiments conducted in the context of this research suggest that this factor has a strong influence on EDRs. Relevant evidence will be presented in Chapter 6, showing that after 15 minutes, there was a small to medium effect of the duration of activity on the sum of EDR amplitudes. A more appropriate solution, though, might be the adoption of an adaptive threshold. The current threshold can be kept as an indicator, while more research is conducted in this direction. As for the relevance of this factor for HR analysis, it was not possible to investigate this point due to the lack of high-quality HR measurement sensors. It was thus decided to mark this factor as mainly relevant for the EDA analysis for the time being.

The threshold set for identifying high POI density (and significant changes in this stressor) in section 5.2.5.1 should also be re-examined after the collection of data from more participants and different contexts. The analysis which will be presented in

Chapter 6 will show that an increase of 15 units in POI density was connected to a medium increase in the sum of EDR amplitudes for one of the datasets (the predefined route in Sydney; see section 6.4). However, the effect was smaller in the combined dataset (see section 6.4 and the discussion in section 6.5). The value of 15 units in the POI density variable represents the presence of 15 POIs within 100m; this value is close to one half of the maximum POI density identified in the collected data. This value was used as the threshold for the identification of high POI density in section 5.2.5.1. Future research will include collecting and analysing more data, and the proposed threshold will be modified accordingly if needed.

Another point which needs to be considered is that some of the analysed parameters may have a stronger effect on physiological responses than others. The next chapters and the appendix present evidence that the following parameters had a stronger relationship with measures of electrodermal activity: *duration of activity, change in activity,* and *POI density*, with the activity-related features having the strongest effects. Chapter 10 (section 10.2.2) presents an overview of the related findings. More evidence is needed to solidify the identified trends; if this happens, the scheme for analysis could be modified so that the effect of the more influential parameters is emphasised.

The scheme for the analysis of OSM tags may also be revisited in the future after more experimentations. An earlier version of the scheme presented in section 5.2.1.3.1. contained some tags which may be associated with a higher physical effort during walking (e.g., 'steps') in the category of physical stressors. The number of lanes in the streets and the maximum speed limits were also used as additional information for the extraction of the traffic levels in this earlier version. The adopted principle was that a higher number of lanes and the maximum speed limit would indicate a higher level of traffic intensity. However, few nodes had these tags in the analysed OSM data. It was thus decided to adopt a simpler version of the scheme, based on similar existing work, until more experiments are conducted. Since the OSM tagging system is not always followed strictly and may change in the future, a point for further development could also be to include a component for automatic classification of the tags, by evaluating the semantic similarity of new tags with the tags contained in the existing hierarchy.

Another point that has not been studied yet is the novelty factor during interactions with stimuli. A future addition could, therefore, be a component for analysis of the similarity between trajectories (following the approach of Xiao et al. 2010, outlined in Chapter 4, section 4.3.3.1) towards the separation of routes which are conducted frequently or places which are visited a lot, from less visited places. Semantic analysis of the POI data could also be included in the future, to better understand the characteristics of the places that the users encounter and the purpose of visit. Future work could also involve adding a component for the detection of travel mode and purpose of the route, based on the combination of speed, accelerometer and HR data.

To conclude, the presented model for the analysis of contextual information and separation of physical and psychological stressors is a significant step towards understanding the links between urban space, activity and physiological responses. The work presented in the next chapter will present work directed towards this aim. The methods outlined in this chapter are especially useful for promoting physical activity and separating its effects on physiological responses from those of other stressors. Sympathetic arousal due to physical activity is a state of the organism which has potential benefits in the long term. At the same time, the combination of physical activity and overstimulation may create a conflict between beneficial and potentially harmful effects of stressors. Our understanding is still limited in terms of long-term effects of such interactions, but in any case, this research is a significant step towards understanding where and when these interactions take place.

6

EXAMINING THE CONNECTION BETWEEN MOVEMENT, CONTEXTUAL PARAMETERS AND PHYSIOLOGICAL RESPONSES IN THE URBAN ENVIRONMENT IN SYDNEY AND ZURICH

6.1. INTRODUCTION

The previous chapter examined methods for analysing physiological responses of individual users, based on the collection of movement and contextual features. This chapter extends this work by utilising the data fusion model presented in the previous chapter to analyse data collected in Sydney and Zürich.

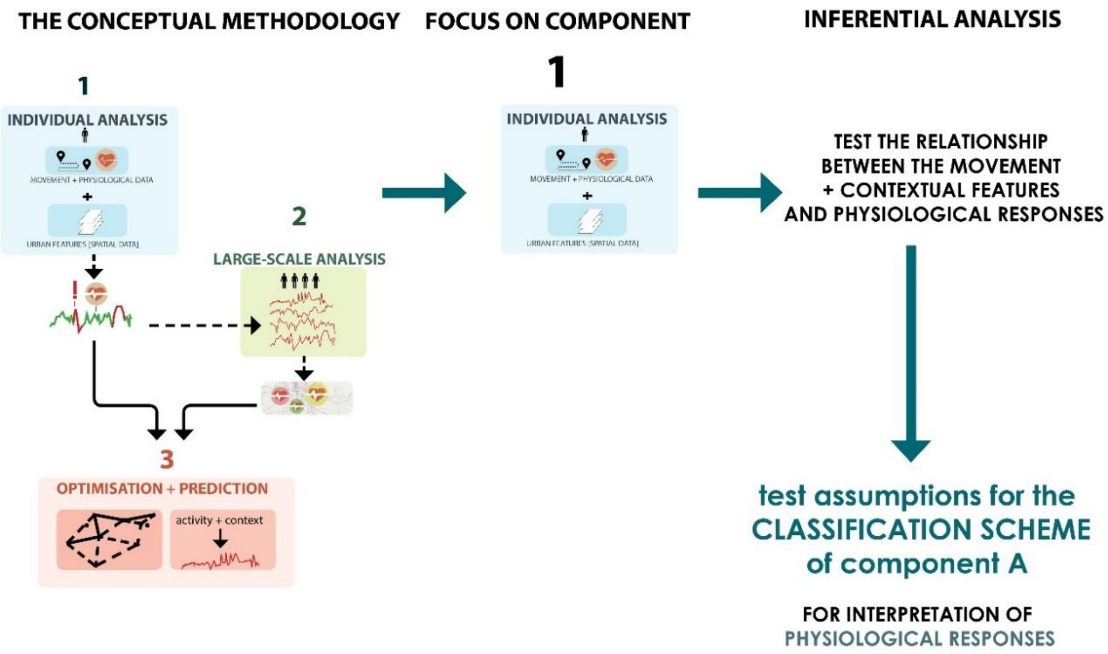


Figure 6.1. The aim of the chapter and the connection with the conceptual methodology.

The aim is to enrich the proposed methodology by investigating some assumptions used to construct the classification scheme in the previous chapter (Figure 6.1).

These assumptions were based on the conceptual framework created in Chapter 3. While the literature presented in Chapter 3 indicates possible connections between physiological responses, activity, temperature, stimulus intensity and complexity, and other parameters, this literature was based mostly on laboratory experiments. The separate and combined effect of these factors has not been studied in real-world experiments and different contexts.

The chapter does not question if the examined features generally affect physiological responses, as the evidence presented in Chapter 3 showed that they are connected to fundamental bodily processes linked to physiological responses. The focus is, instead, on examining the applicability of the same factors in different conditions.

The datasets that will be examined for this purpose include all the data collected during outdoor routes in Sydney. This includes the outdoor predefined route from Phase A of the designed experiments, as described in Chapter 2, and the free-living activities from Phase B (see section 2.4.2 in Chapter 2). The predefined route data collected in Zürich by the research team of Ojha et al. (2019) are also included.

The data collected during a predefined route in Sydney and Zürich come from semi-controlled experiments and are similar in their setup. The free-living activities dataset reflects the participants' physiological responses in a setting where there is no control or influence from a research team and is thus as close as possible to a typical scenario of exposure to stressors during daily activities.

The three datasets will be analysed separately and together, to expand our knowledge of the links between context, movement, and physiological responses in different ways.

The rest of the chapter is organised as follows: section 6.2 analyses the datasets in terms of their contextual and activity-related characteristics, showing their differences and similarities. The main comparison is conducted for the two datasets collected in Sydney and Zürich, while the participants were walking on a predefined route. The same parameters are also analysed for the free-living activities dataset collected in Sydney, although they are presented separately. Section 6.3 elaborates on the methods used for knowledge extraction and the statistical analysis plan. Section 6.4 presents the results, and section 6.5 elaborates on the implications of the findings.

6.2. DATASET CHARACTERISTICS AND CONTEXT ANALYSIS

6.2.1. DESCRIPTION OF THE EXPERIMENT SETUP IN SYDNEY AND ZÜRICH

As mentioned in Chapter 2, the dataset collected in Sydney contained data from 18 users (age = 31.3 ± 5.3 yrs.) that participated in the predefined route experiment. From those, 15 also took part in the free-living activities experiment. One user was a non-responder, exhibiting very low values of tonic and phasic EDA, and their data were not used.

Each participant conducted the predefined outdoor route in Sydney alone, around 5 to 10 minutes after completing the first 10-minute indoor test (see the description of Phase A in Chapter 2, section 2.4.2). The protocol of the indoor test is described in detail in Appendix C (section C.1.1.). The length of the route was approximately 2 km. The route lasted 40 minutes. The participants were given a short overview of the route and a map with directions, and they were asked to come back to the same room when they finished the trip. The route was designed as a sequence of street segments which expose the participants to different spatial characteristics. The first part involved approaching the Central Park tower from Broadway street, and going to the backyard of the building, where the users were asked to sit for 5 minutes. This segment reflects the transition from a noisy environment with a significant presence of mixed-use and intense traffic conditions, to a place with high presence of natural characteristics. Then, the users passed through a pedestrianised segment, where construction works were undertaken until approximately the end of August 2019; after that, a segment with relatively low traffic followed, containing some traffic lights and intersections with busy roads. The users then reached the Goods Line, a popular local example of an activated urban space with appealing architectural features. The final segment involved passing through the Central Station tunnel, climbing a small slope and returning to UTS after passing by the Railway Square on Broadway street.

As stated in Chapter 2, the participants were also asked to complete a questionnaire concerning their experience during the predefined route in Sydney, based on a variation of the PANAS test for measurement of the affect. A template of the questionnaire is presented in Appendix D. The results are briefly reported in this chapter (section 6.4.1), and in Appendix B (section 3.1.5), where the results of the predefined route in Sydney are discussed in detail.

For the data collection during free-living activities in Sydney, one Empatica E4 wristband was given to each participant for tracking EDA data along with accelerometer data, skin temperature, and HR data. Only EDA data were analysed in this study. The participants were asked to wear the wristband each time they went out of the house for any purpose, and take it off when they reached their destination. The data collection was thus conducted only during outdoor walks for commuting, exercising, or visiting a place for leisurely purposes. GPS data were collected with the smartphones of the participants. The participants were asked to return the equipment after 7 to 10 days according to their schedule.

The dataset collected in Zürich contained data from 30 users. The mean age was 28.8 years (± 7.5). From those, only 20 users generated usable data. The rest of the derived datasets were excluded due to the high percentage of artefacts. The data collection was conducted while the participants were following a predefined route in a local neighbourhood. The route's length was 1.3km, and it involved places of different urban characteristics in terms of street width, noise and presence of green. The experiment was conducted during the springtime. The data collection was spread among different days, and in each day, multiple participants conducted the experiment separately, in a sequential manner.

The final sample sizes were thus the following:

a) Separate sample size for each dataset:

- N = 17 for the predefined route in Sydney
- N = 14 for the free-living activities in Sydney (a subset of the 17 participants from the predefined route in Sydney)
- N = 20 for the predefined route in Zürich

b) Sample size for the combined dataset, including Zürich and Sydney data:

- N = 37

6.2.2. DATA COLLECTION AND ANALYSIS

The collection of movement and contextual data in Sydney was conducted with the methods described in Chapter 5 for these tasks. The physiological, movement and environmental data in Zürich had already been collected by the authors of that study (Ojha et al. 2019) and uploaded to the publicly available repository of the ESUM project (ESUM 2018). They were thus acquired from the ESUM repository to be used in this study.

The collection of the physiological data and the accelerometer data was conducted with the same instrument (Empatica E4) in Sydney and Zürich. The only difference was that a dedicated GPS sensor was used instead of GPS tracking with a smartphone in Zürich. Environmental sensors were also used in Zürich for the continuous collection of environmental data at a high resolution. The data from the environmental sensors was not analysed in this study, apart from the ambient temperature. The authors of the study in Zürich provide further details regarding their approach in terms of data collection and analysis in Ojha et al. (2019).

The analysis of the physiological, movement and contextual parameters for the Sydney and Zürich data was conducted using the methods described in Chapter 5. The physiological variable which was examined was the sum of EDR amplitudes extracted from 1-minute windows. The approach was the same as in the demonstration of the data from different users in section 5.3 of Chapter 5.

One difference between this study and the study of Ojha et al. (2019) was the choice of an appropriate threshold for the detection of EDR responses. The threshold was set at 0.05μS here, as opposed to 0.01μS in the study of Ojha et al. (2019). The choice of the lower threshold instead of the selected one would not have a significant impact on the results, as both thresholds are still much lower than the highest values that were observed in this study.

FEATURES	Unit/meaning	SYDNEY									
		DATASET 1: PREDEFINED ROUTE					DATASET 2: FREE LIVING ACTIVITIES				
		Mean	*Median*	*Min*	*Max*	*STD*	*Mean*	*Median*	*Min*	*Max*	*STD*
Sum of EDR amplitudes	Sum of the EDR amplitudes for the examined time window	0.9	0.68	0	4.6	1	0.6	0.07	0	7.2	0.9
activity intensity	intensity of activity [1-3]	1.8	1.9	1	3	0.4	1.8	1.8	1	3	0.6
Duration of activity (Time since the beginning)	minutes	20	19	0	53	12	50	30	0	419	61
Temperature	°C	21	20	15	30	4	21	21	12	32	3
Change in activity	The intensity of any change in activity [0-1]	0.28	0.34	0	1	0.47	0.38	0.42	0	1	0.5
Speed	m/s	3	3.7	0	6	2.1	3.6	3.7	0	6	4.6
Steady state activity	if the performed activity during the examined minute is a part of 'steady state' [0-1]	0.5	0.6	0	1	0.4	0.4	0.22	0	1	0.4
POI density	number of POIs within 100m	13	15	1	30	7	11	10	0	48	10
Traffic	traffic intensity [0-4]	1.3	1	0	4	1.2	1.3	1	0	4	1.2
Traffic light	presence of traffic light [0-1]	0.1	0	0	1	0.2	0.1	0	0	1	0.3
Change in activity state	presence of a change from a 'steady state' of activity to another activity intensity [0-1]	0.13	0	0	1	0.2	0.1	0	0	1	0.2

Figure 6.2a. Feature description for the datasets collected in Sydney

FEATURES	Unit/meaning	DATASET 3: ZURICH					DATASET 4: ALL COMBINED				
		Mean	*Median*	*Min*	*Max*	*STD*	*Mean*	*Median*	*Min*	*Max*	*STD*
Sum of EDR amplitudes	Sum of the EDR amplitudes for the examined time window	0.4	0	0	5	0.8	0.5	0.08	0	7.2	0.9
activity intensity	intensity of activity [1-3]	1.6	1.6	1	2.1	0.2	1.8	1.8	1	3	0.5
Duration of activity (Time since the beginning)	minutes	27	27	20	33	3	50	26	0	419	64
Temperature	°C	17	17	10	26	3	21	21	10	32	4
Change in activity	The intensity of any change in activity [0-1]	0.43	0.45	0	1	0.49	0.7	0.41	1	3	0.8
Speed	m/s	3.3	2.4	0	6	1.4	3.5	2.6	0	6	4.3
Steady state activity	if the performed activity during the examined minute is a part of 'steady state' [0-1]	0.2	0	0	1	0.3	0.4	0.2	0	1	0.4
POI density	number of POIs within 100m	14	13	4	30	5	12	12	0	48	10.5
Traffic	traffic intensity [0-4]	0.4	0.4	0	1.7	0.3	1.3	1	0	4	1.2
Traffic light	presence of traffic light [0-1]	0.02	0	0	1	0.1	0.12	0	0	1	0.27
Change in activity state	presence of a change from a 'steady state' of activity to another activity intensity [0-1]	0.07	0	0	0.7	0.1	0.1	0	0	1	0.2

Figure 6.2b. Feature description for the dataset collected in Zürich and the combined dataset

Figures 6.2a and 6.2b show the variables which were included in the statistical analysis. Some of the variables included in the table (*steady-state activity, traffic light, change in activity state*) were initially coded as categorical variables, based on the data fusion scheme in Chapter 5. Traffic was also coded as an ordinal variable. The categorical variables had two possible values; the value of 0 indicated no presence of this feature, while 1 indicated its presence. The statistical analysis that will be presented in this chapter (section 6.4) involved experimentations with these variables in their initial (ordinal or categorical) form, as well as after transforming them to continuous ones. This transformation was conducted by splitting the data in time windows lasting 120 seconds and extracting their mean values for each time window. The result was a representation of the degree of presence of each feature in each time window. For instance, the 'traffic light' feature had values between 0 and 1 after its transformation to a continuous feature. A value of 0.3 would indicate the presence of a traffic light for 30% of the time window. Figures 6.2a and 6.2b present the distribution of these variables in their continuous form. A presentation of the frequencies for each level of the same variables coded as categorical is included in Figures H1 and H2 in Appendix H.

6.2.3. ANALYSIS OF CONTEXTUAL AND ACTIVITY-RELATED CHARACTERISTICS FOR THE PREDEFINED ROUTE IN SYDNEY AND ZÜRICH

This section focuses on the data collected during walking on a predefined route in Sydney and Zürich and presents a descriptive analysis of the differences and similarities between the two study areas. The two cities are perceived as very different environments from many aspects; Sydney is a city of extremities regarding the spatial distribution of its population, considering the differences between the CBD, which is populated by skyscrapers and the low-density suburbs. While its architectural history does not span more than two centuries, the city is rich in terms of different architectural styles, including typical two- to four-story suburban buildings, juxtaposed with Federation houses, Victorian and neo-Gothic examples, and skyscrapers. The study area is located at the heart of the city centre, which is buzzing with life and acts as a significant attractor of human activity due to the vibrant presence of commercial and retail use.

Zürich, on the other hand, is much less populated and does not have such intense differences in the concentrations of residential density. The city is composed of a small number of districts or neighbourhoods, with different degrees of historical character and concentration of activities. The study area is located in Wiedikon, a residential area with an increasing presence of shops and cafes in the past few years. The city is characterised by a broader diversity in the age and architectural style of the buildings, which include examples from the medieval period, intertwined with modern buildings. Zürich thus generates the feeling of a much older city to the eyes of the pedestrian, compared to Sydney.

These differences affect the perception of the urban fabric and the diversity of observed elements during a walk. The most striking difference is in the sense of continuity in the skyline that characterises the study area in Zürich, as opposed to its counterpart in Sydney. There is larger homogeneity in various elements of the urban fabric in the study area Zürich, most notably in the scale, while the volumetric differences in the Sydney CBD are much more intense in comparison.

Another critical difference between the two cities is the weather. The climate is generally colder in Zürich than Sydney; Sydney has a humid subtropical climate, with warm summers and mild winters, while Zürich has an oceanic climate, with colder summers and temperatures close to zero in the winter. The maximum temperature based on historical data between 1981 and 2010 was 24°C (Meteoswiss 2014).

These parameters shall be further discussed in the following sections from a quantitative perspective, based on the collected data from the two cities. Additionally, the activities conducted in the two contexts shall be analysed in terms of parameters related to movement. This analysis is guided by the theoretical and conceptual framework presented in Chapter 3.

6.2.3.1. CLIMATE CONDITIONS: TEMPERATURE

As mentioned in section 6.2.2, temperature data were already included in the Zürich dataset, measured by a custom sensor. The temperature data introduced in the data fusion model for Sydney were historical weather data from a local weather station (Australian Government Bureau of Meteorology 2020).

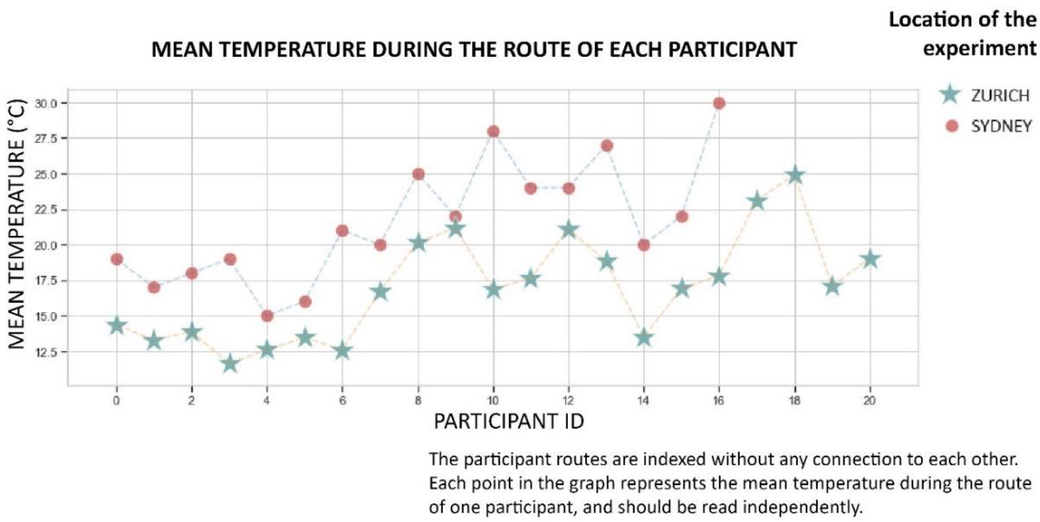
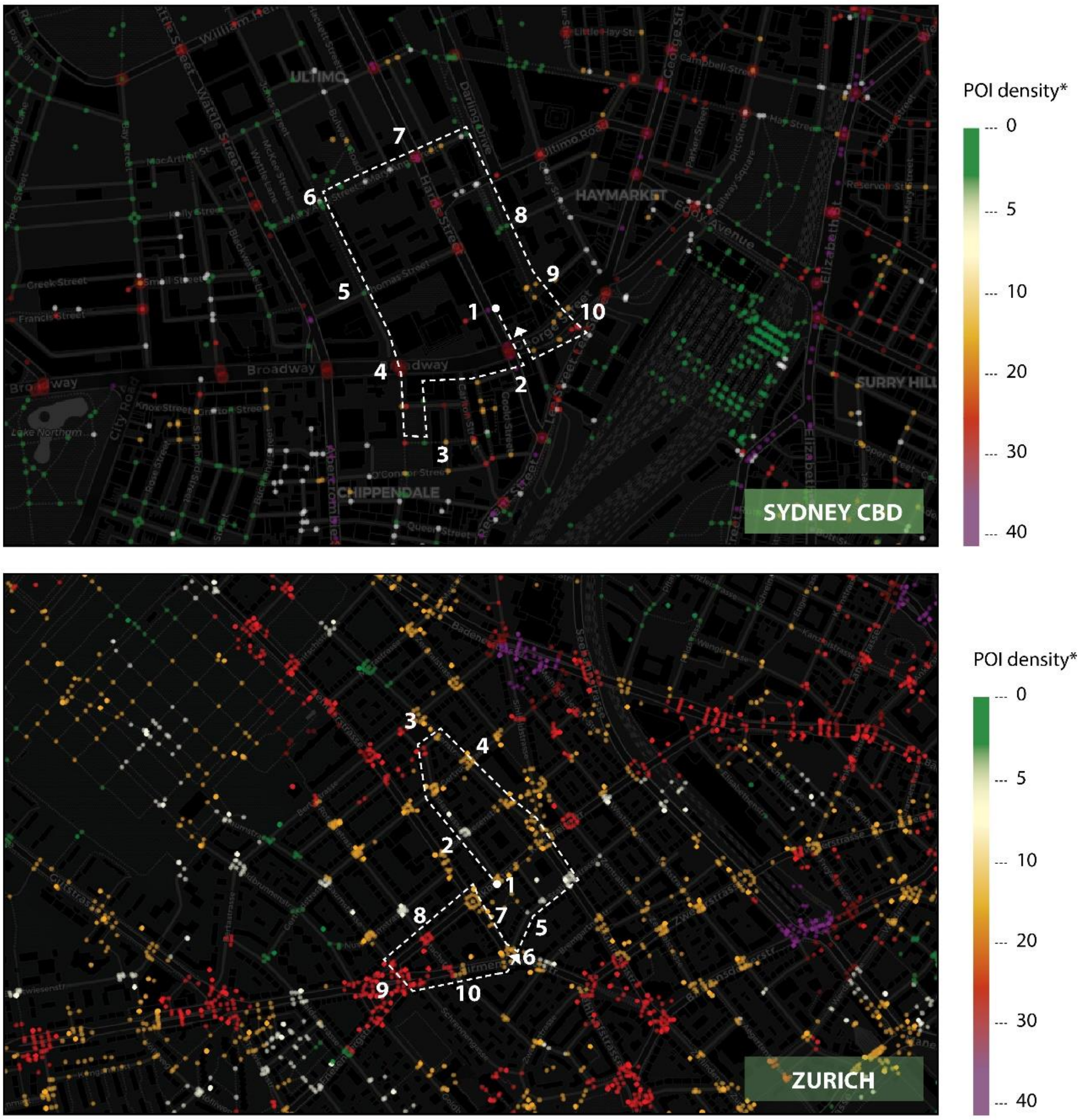


Figure 6.3. Mean temperature data for each participant, for the predefined routes in Zürich and Sydney.

The data collection in Zürich was conducted during springtime, with a mean temperature of 17 °C (min=10, max=26). The data collection in Sydney captured the transition from winter to summer, with a mean temperature of 21 °C (Figure 6.2a). Figure 6.3 shows the mean temperature during the route of each participant.

6.2.3.2. URBAN PARAMETERS: POI DENSITY AND TRAFFIC



* number of POIs within 100m of each point

Figure 6.4. Poi density data in the studied areas in Zürich and Sydney.

The studied route in Zürich is mostly populated by residential buildings with five floors, with some instances of mixed-use frequently populating the ground floor (Figure 6.5).

According to the POI density map for Zürich (Figure 6.4) and the observation of photos taken from Google Street View (Figure 6.5), points 3, 6, 8, 9 and 10 appear to be places which are more populated with shops, cafes and other elements which attract human activity.

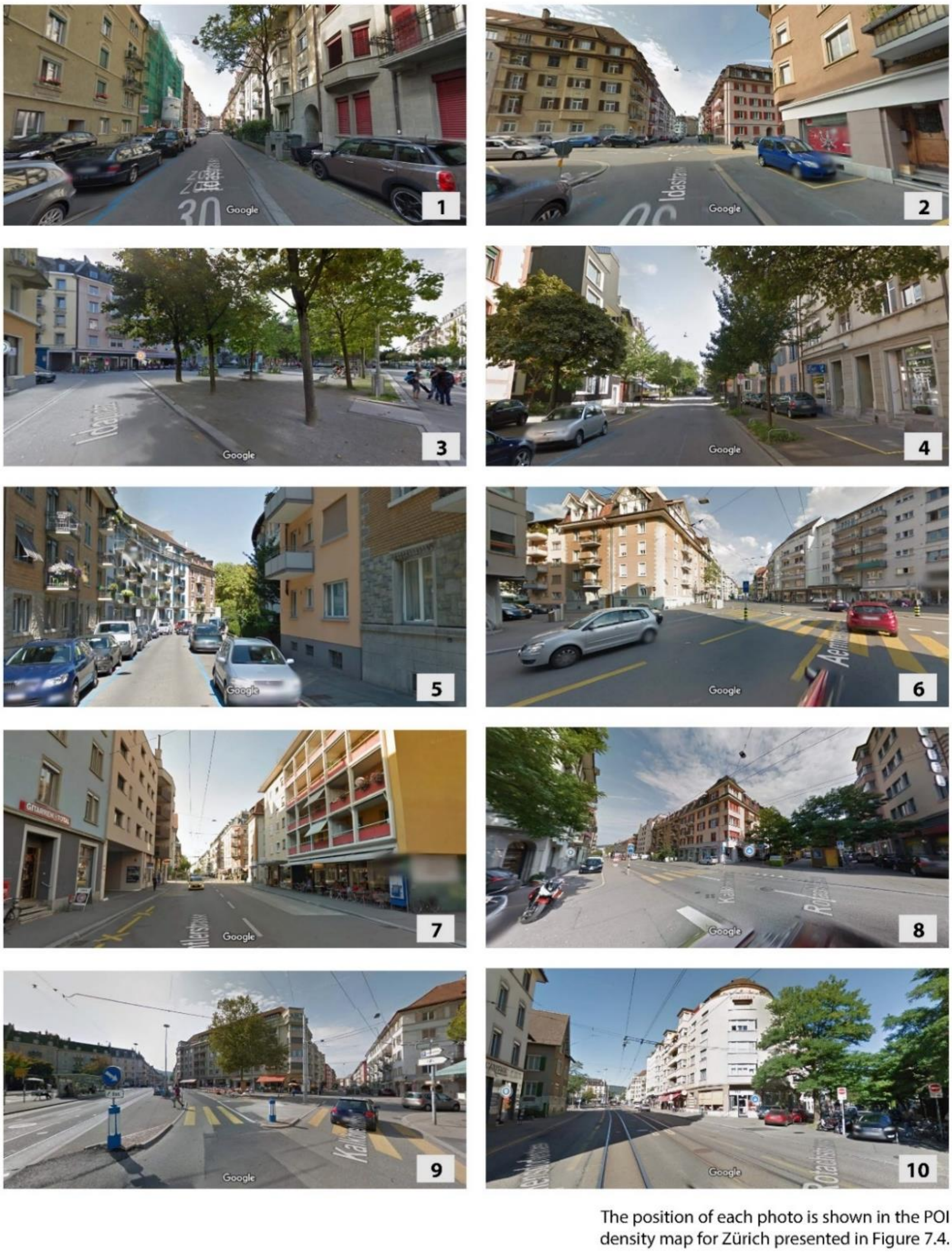


Figure 6.5. Photos from the route in Zürich. The photos were obtained from Google Street View (Google Maps 2020).

Some notable places in terms of their contextual qualities are Idaplatz, a small square with cafes and high presence of green (Point 3 in the map; Photo 3 in Figure 6.5); also Point 9 which is a relatively busy area, and a critical intersection where many streets meet, with a high presence of mixed-use and wide views. Point 5 is a local example of a place with lower POI density, belonging to a mostly quiet residential part of the neighbourhood.

As shown in Figure 6.6, there is much more diversity in the building heights in the route in Sydney. The photos from points 2,4 and 10 are taken from Broadway street, which is very close to the Central Station and is one of the busiest streets in Sydney. As the photos show, this street contains buildings of medium height, with 4 to 6 floors, and skyscrapers. These points, along with point 7, are also places where the traffic levels are relatively high, as shown from the number of lanes in the photos. Points 3,5 and 6 are relatively quieter environments; Point 3 is a green area at the back of the Central Park skyscraper, and points 5 and 6 represent a transition to a more residential area of the neighbourhood, with buildings of a lower height and relatively higher presence of green. Points 8 and 9 are on the Goods Line, an urban park which was formerly a rail corridor. A segment-wise analysis of the POI density and traffic levels for the predefined route in Sydney is also presented in Appendix B (section 3.1.1.).

The position of each photo is shown in the POI density map for Sydney presented in Figure 7.4.

Figure 6.6. Photos from the route in Sydney. Photos 8 and 9 were taken by the author; the rest were obtained from Google Street View (Google Maps 2020)

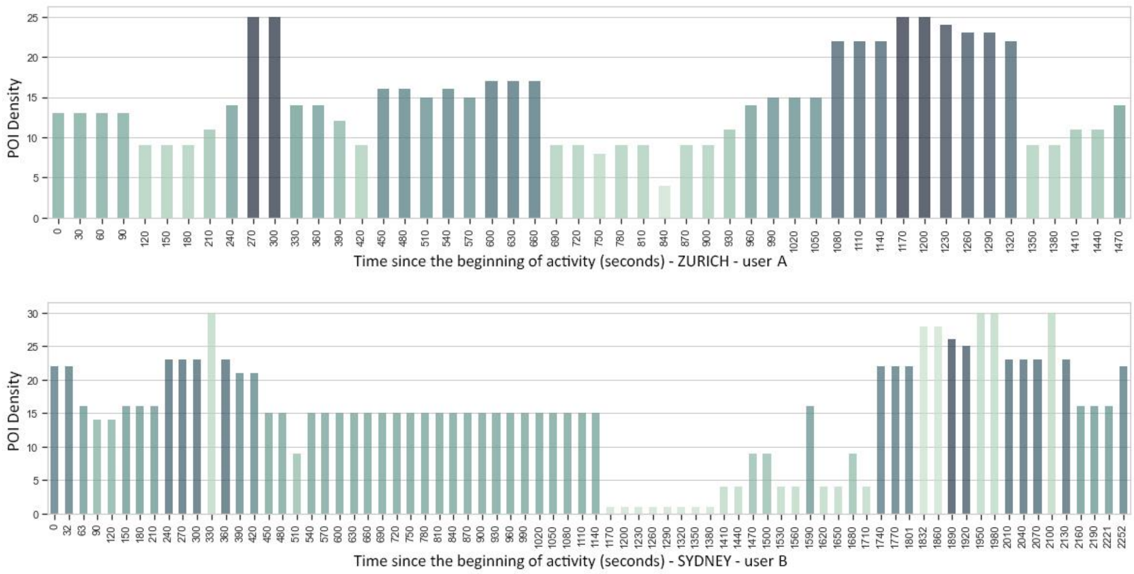
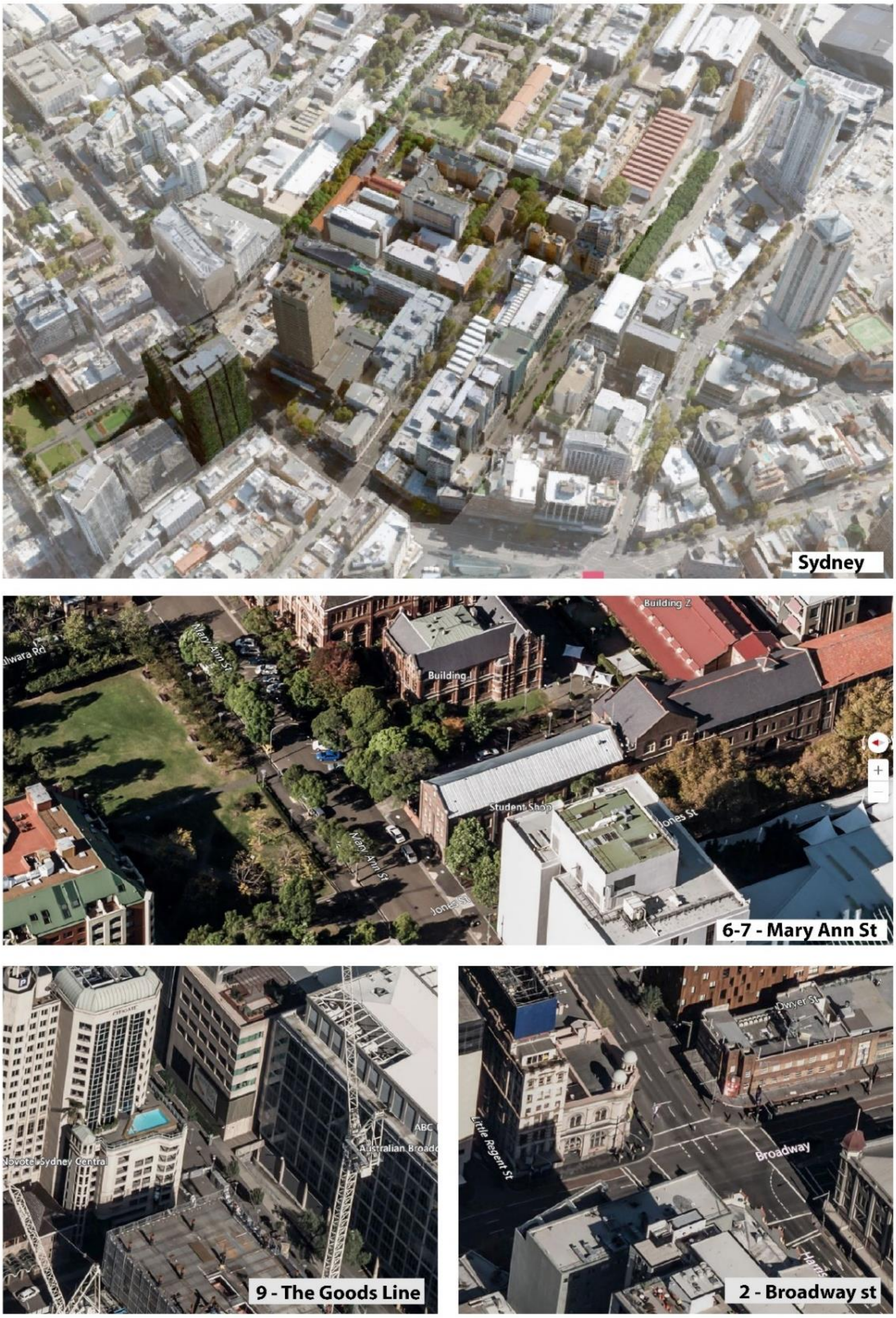


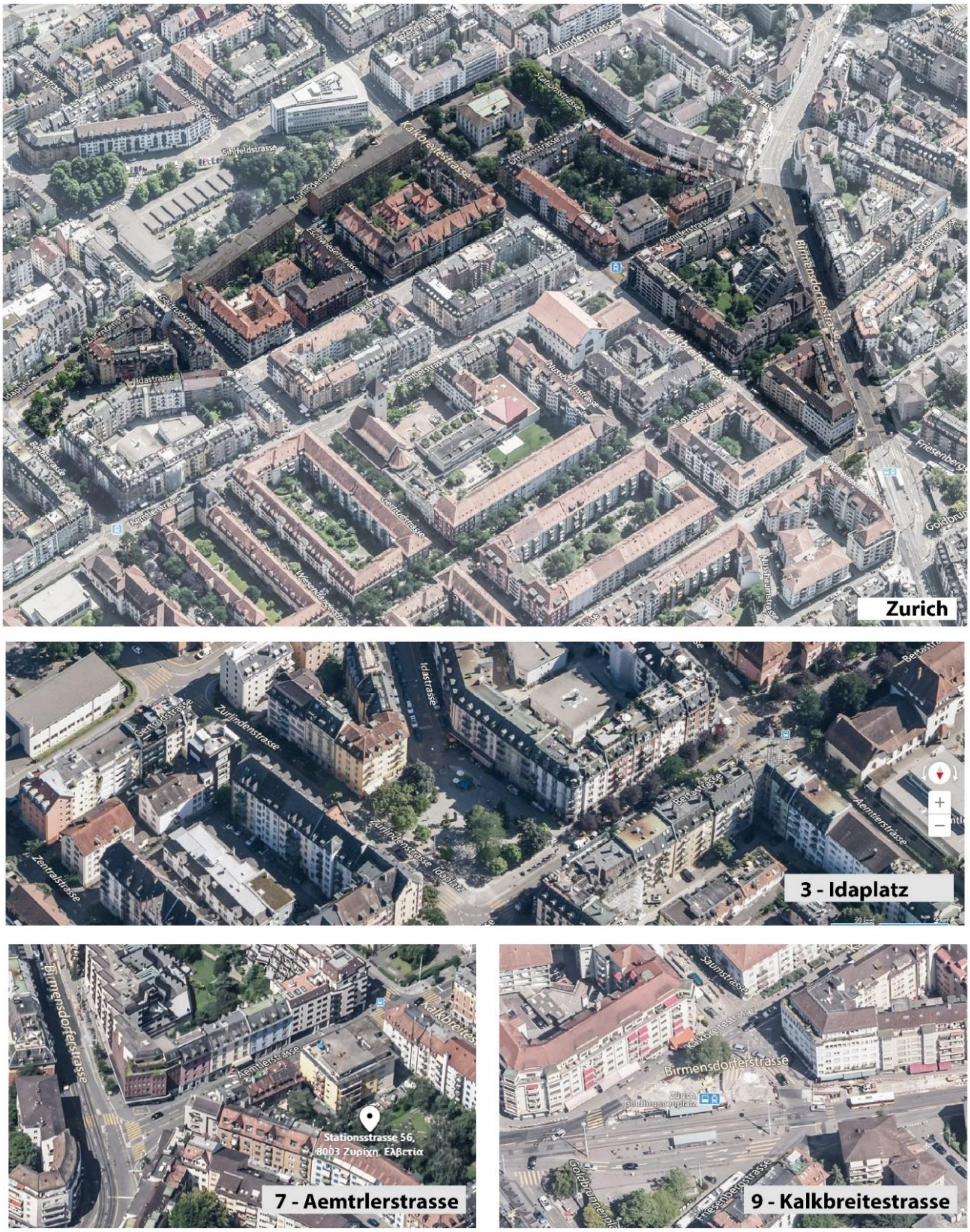
Figure 6.7. POI density time-series data for one user in Zürich and another user in Sydney.

As shown in Figures 6.2a and 6.2b, the mean and STD values of POI density are similar for the predefined route in Sydney and Zürich. The time-series graphs in Figure 6.7 show the different levels of POI density experienced in different parts of the route. The overall POI density pattern has a similar trend in both cases, as shown in Figure 6.7. The route starts with medium POI density, towards the middle of the route the POI density is lowered (more significantly in the case of the Sydney route, and less intensely in the Zürich route) and towards the end the POI density levels become high. However, as the photos showed, the transitions seem to be more intense in the case of Sydney. The differences in the structure and the degree of diversity in the building size in the two cities become apparent in Figures 6.8 and 6.9.



The position of each photo is shown in the POI density map for Sydney presented in Figure 7.4.

Figure 6.8. Screenshots from a 3-dimensional model of the studied area in Sydney (3d city models of Sydney 2017).



The position of each photo is shown in the POI density map for Zürich presented in Figure 7.4.

Figure 6.9. Screenshots of the studied area in Zürich (Bing maps 2020).

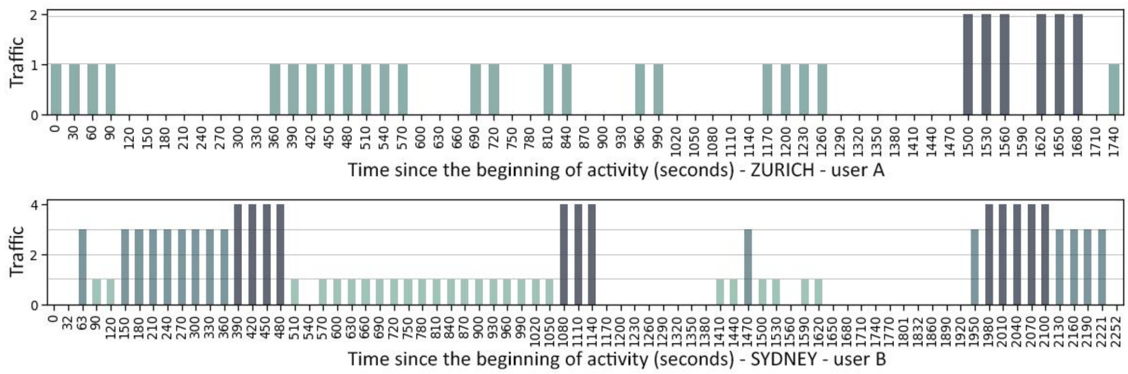


Figure 6.10. Traffic time-series data for one user in Zürich and another user in Sydney.

As for the traffic levels, the route in Sydney involves some short encounters with high traffic intensity, in the start, middle and end of the route (Figure 6.10). Between these points, there are also parts with low traffic levels. In Zürich, on the other hand, the traffic levels encountered during the route appear to be relatively lower, with a small increase towards the end.

6.2.3.3. ACTIVITY

As Figures 6.11 and 6.12 show, the two datasets collected during a predefined route in Sydney and Zürich are very different in terms of the participants' movement pattern. The walk in Sydney was continuous, apart from one point where the participants were asked to sit for 5 minutes, and a few times that they had to stop due to a traffic light. A segment-wise analysis of the activity for the predefined route in Sydney is also presented in Appendix B (section 3.1.1.).

The walk in Zürich was a sequence of multiple small bouts of walk and stops, each lasting 1-2 minutes. It was also slightly shorter in terms of duration, lasting approximately 30 minutes while the predefined walk in Sydney had a mean duration of 40 minutes.

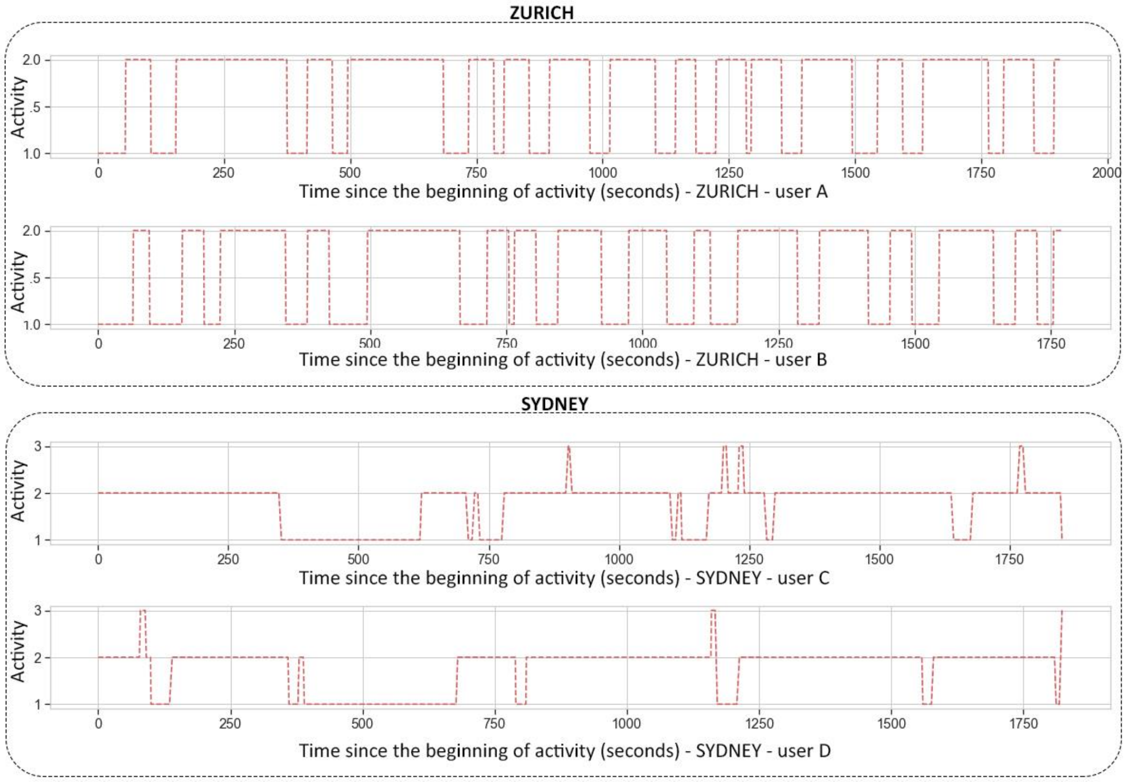


Figure 6.11. Example of the activity intensity data collected during walking on a predefined route in Zürich and Sydney.

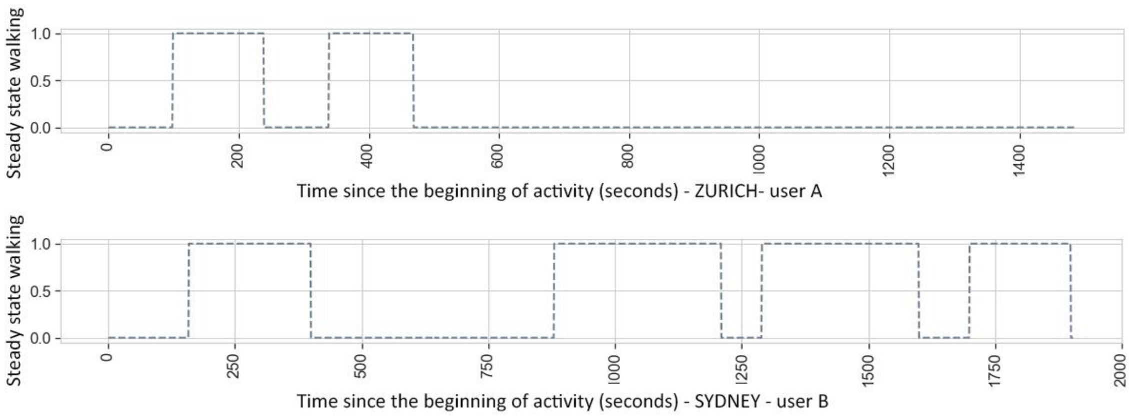


Figure 6.12. Steady-state walking (time series) data for one user in Zürich and another user in Sydney.

There was thus a different sequence of bouts of walking and stopping, and a different presence of steady-state walking in the two routes. The steady-state walking feature was extracted by filtering the 'steady state' feature and selecting the data points where the activity intensity was 2 (corresponding to the 'walk' class). In the predefined route in Sydney, the participants were in the steady-state walking phase for an average of 17 minutes (adding the corresponding minutes for each separate bout of steady-state walking), as opposed to an average of 5 minutes in the walk in Zürich.

Since the duration and intensity of exercise may affect its influence as a stressor, the identified differences in the qualities of movement may create different patterns in the generation of physiological responses.

6.2.3.4. PHYSIOLOGICAL DATA

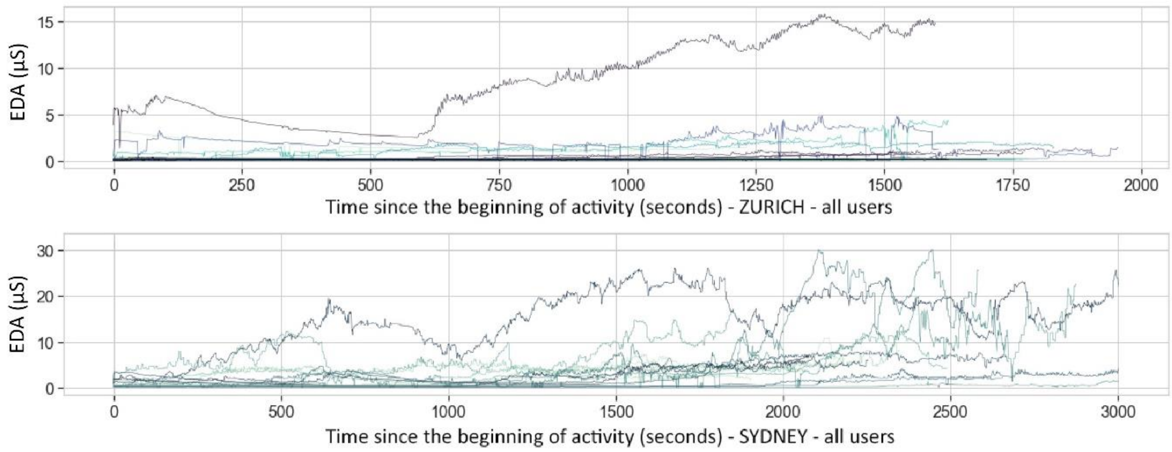
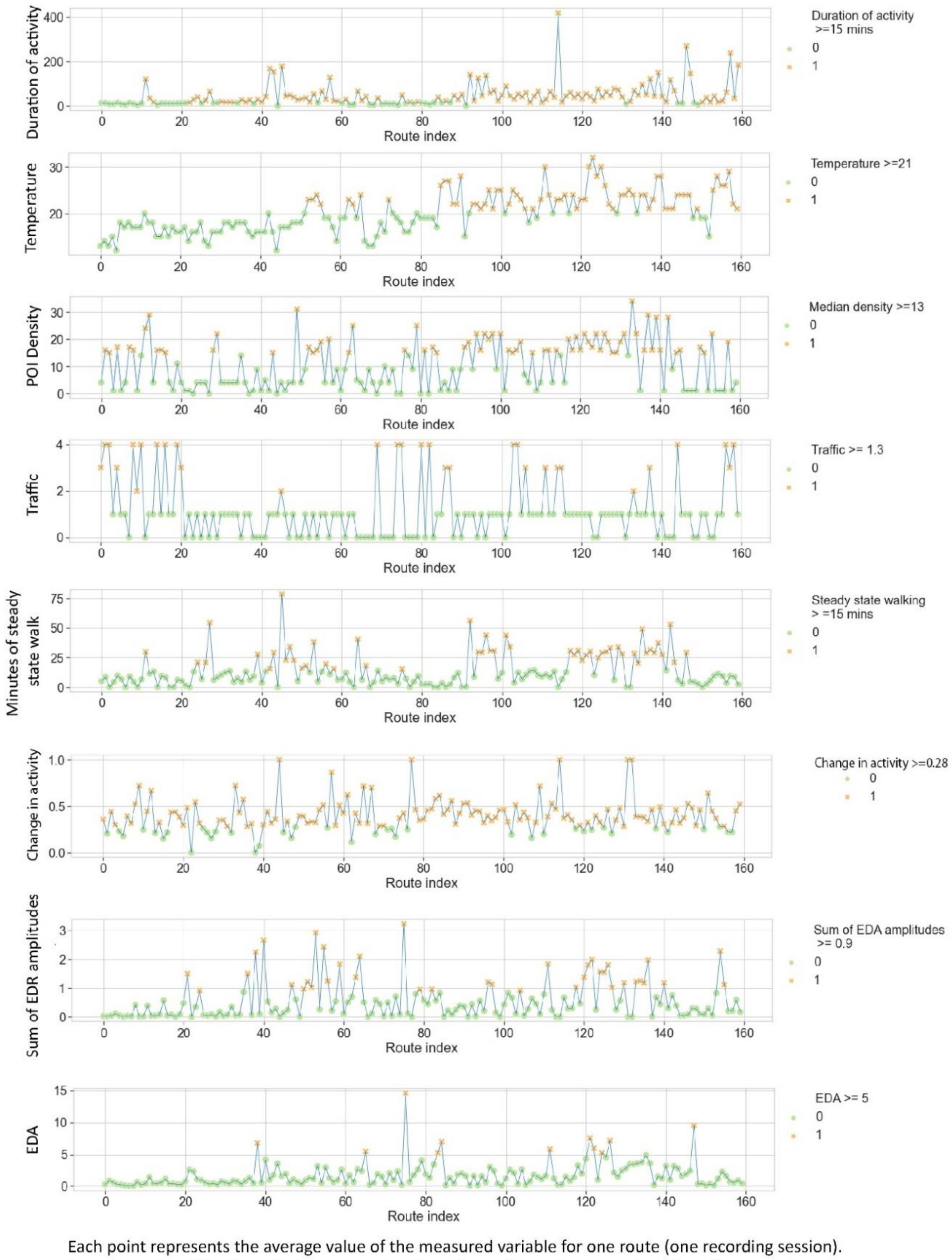


Figure 6.13. Raw EDA data from all users in Zürich and Sydney.

The visual inspection of the raw EDA data for the predefined route in Zürich and Sydney showed that the raw EDA values were generally lower in the data collected in Zürich, compared to Sydney. It might not be appropriate to examine the differences in the raw EDA values between the two cities, due to the significant interindividual differences generally found in the range of values in this signal. The main physiological measure examined in this chapter (the sum of EDR amplitudes) can be compared, as it is generated after normalisation of the values. The descriptive analysis conducted for the sum of EDR amplitudes showed that the trend identified in the raw EDA data was also found there (mean = 0.4, std = 0.8 for Zürich; mean = 0.9, std = 1 for Sydney).

6.2.4. ANALYSIS OF CONTEXTUAL CHARACTERISTICS FOR THE FREE-LIVING ACTIVITIES DATASET IN SYDNEY



Each point represents the average value of the measured variable for one route (one recording session). In each graph, a filter is applied by comparing the values with a reference value. The reference value corresponds to the values of the predefined route in Sydney (Figure 7.2).

Figure 6.14. The movement-related and contextual characteristics of the free-living activities dataset.

The free-living activities dataset contains data from 160 sessions (separate trips) that were recorded in Sydney. Figure 6.14 shows the characteristics of several contextual and movement-related factors, averaged for each route. Each point in the graph represents one route, and the sessions are arranged in the X-axis with respect to time, progressing from winter to summer. The 'duration of activity' feature in this graph corresponds to the maximum duration of each route.

As Figure 6.14 shows, almost half of the recorded sessions (n=70) lasted less than 21 minutes. The temperature was less than 21^{o}C for around half of the sessions. More than half sessions had lower median POI density than that of the predefined route in Sydney. Approximately one-third of the sessions had a median POI density less than 5, which is typical for residential neighbourhoods and streets with low levels of human activity. Most sessions had low average traffic values, corresponding to streets which do not have high-speed limits or many traffic lanes. Almost two-thirds of the sessions also contained less than 15 minutes of steady-state walking. The presence of changes in activity was generally comparable to that observed in the predefined route in Sydney, and much smaller than that in the predefined route in Zürich.

6.3. METHODS

The statistical analysis plan that was followed investigates the research question of this chapter; if a generalisable model can be created to describe the link between urban and environmental features, movement and physiological responses. This question will be explored using a linear mixed model for examining the relationship between the target physiological variable (sum of EDR amplitudes) and the features related to contextual and movement parameters. The utilisation of the different datasets in the statistical analysis is visualised in Figure 6.15.

Since the dataset contains multiple data points generated by the same participant, there are dependencies in the independent variable of interest that had to be taken into account in the chosen inferential model for this part of the statistical analysis. The difference in the overall context of the experiment (Sydney versus Zürich) also had to be taken into account. For these reasons, the linear mixed model was used here, as it takes into account the user-related interdependencies between samples, including their possible organisations in different groups.

Four models were constructed; one for Zürich, one for the dataset collected in Sydney while the participants were following a predefined route, one for the dataset collected in Sydney during free-living activities, and one for all the datasets combined. The main reason for adopting this strategy was to allow the examination of the results separately for each dataset.

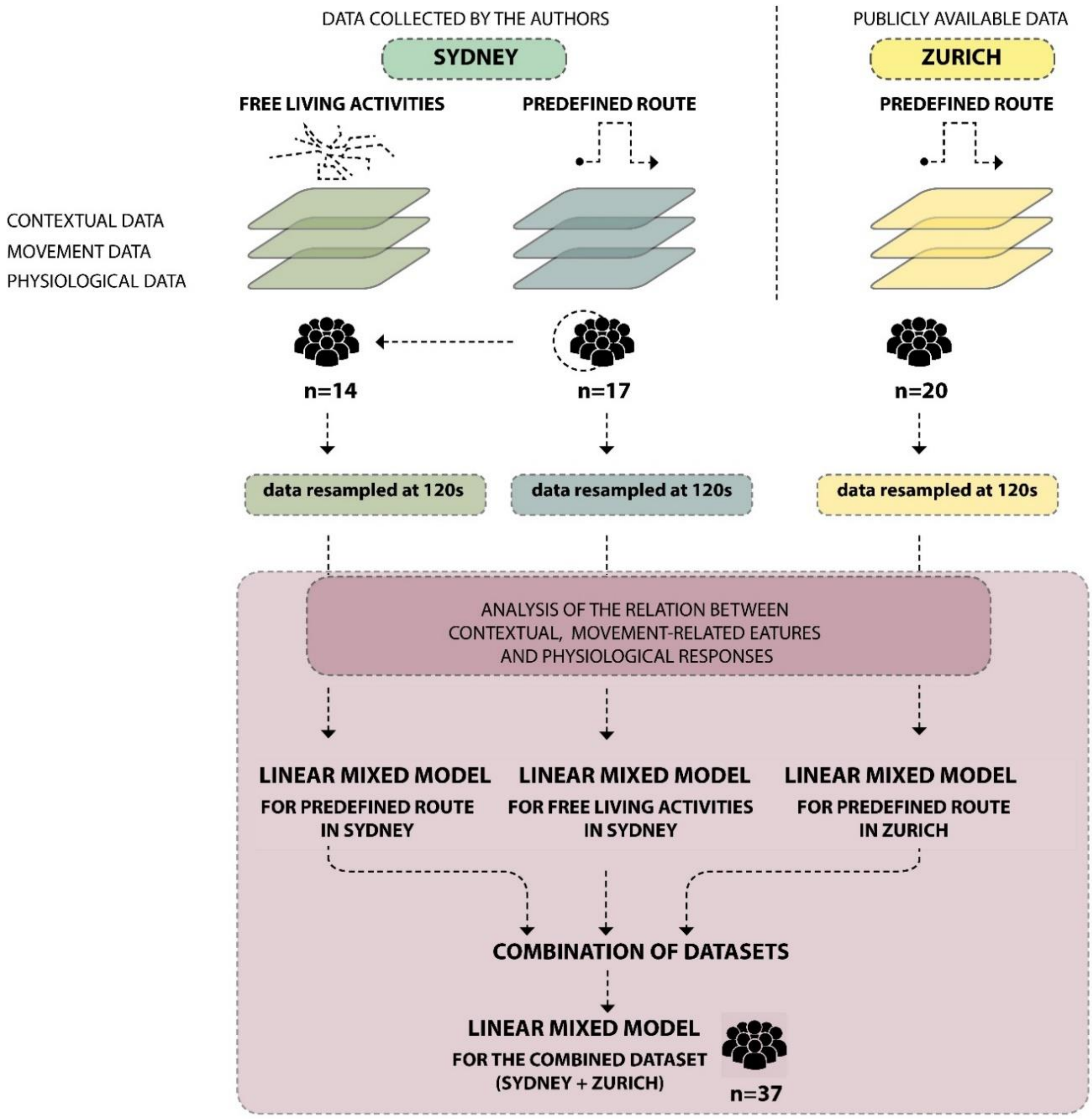


Figure 6.15. The statistical analysis approach followed in this chapter

In the first three models, where the datasets are separated according to place and context of activities, the parameters related to movement and context were used as fixed effects, and the subject's ID was used as a random effect. The participants' age was initially included as a random effect, but after experimentation, it was decided to omit it, since its inclusion did not improve the model fit, and there were accuracy concerns regarding this variable in the Zürich data (as explained in Chapter 2). The sex of the participants was initially included as a random effect only for the Sydney data, as it was not known for the Zürich data. In the end, it was also excluded for the same reasons as in the 'age' variable.

In the final model which contained the combined datasets, the place (Sydney and Zürich) was also added as a random effect. The datasets were resampled at 120 seconds for this analysis. The transformation of categorical or ordinal variables to continuous ones (as described in section 6.2.2) was conducted by extracting their mean values for each time window of 120 seconds.

The experiments with linear mixed models were also repeated at a different resampling (60 and 30 seconds) with very similar results.

The Moran's I test was also conducted to check for spatial autocorrelation in the data. The test indicated that there was a statistically significant presence of hotspots of the measured variable. Spatial autocorrelation was also found in the analysis of the residuals in the initial application of the linear mixed models. This finding would normally lead to the application of a spatial regression model (Anselin 2009), but this approach could not be followed here, since the dependencies between the data of the same participants have also to be taken into account. It was, thus, decided to use the linear mixed model, while also including a spatially lagged variable for the sum of EDR amplitudes as a predictor, to account for the spatial autocorrelation in the dataset. This variable was calculated by constructing a matrix with the spatial weights, describing the spatial relations between points based on their proximity.

The experimentation also showed that the initial model for free-living activities in Sydney did not satisfy the assumption of normality of the errors. For this reason, a square root transformation was applied to the dependent variable (sum of EDR amplitudes). This transformation is usual in the context of analysis of EDA, according to Boucsein (2012). Since this choice had a vast improvement on the residuals of the free-living activities model, the square root transformation was consequently used for all models for a more consistent approach.

As for the features used as dependent variables, all the features presented in Figures 6.2a and 6.2b were initially considered as possible candidates. Different combinations were tested after making sure that there was no issue of multicollinearity by checking the variance inflation factor. The general formula had the following form:

$$Yi = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_x X_x + \gamma_{01}$$

where Yi was the dependent variable (the square root transformed sum of EDR amplitudes) and the parameters X_1 to X_x were the other parameters included in Figure 6.2a and 6.2b, as well as the spatially lagged variable (X_x = *sum of EDR amplitudes_lag)*. The variable γ_{01} corresponds to the random intercept for each subject.

The presented results are based on a set of features that produced an acceptable result for all cases. The features which did not have an effect on the studied variable or bring any improvement to the model fit when added (e.g., *traffic lights*) were omitted. The statistical tests were conducted using R.

6.4. RESULTS

The parameter combination that led to an acceptable result for all models was the following: *lagged sum of EDR amplitudes, POI density, duration of activity, change in activity state*, *speed, traffic, temperature*.

The following sections show the coefficients for each separate model, and their statistical significance, ending with the model that was fitted to the combined dataset for both cities.

The tests showed that the models had a better performance when the change in activity state was coded as a categorical feature. Therefore, the coefficients presented for this feature in Figures 6.16 – 6.21 refer to it as a categorical one (with ‘1’ indicating its presence, as mentioned before).

6.4.1. SYDNEY: PREDEFINED ROUTE

LMM model for the predefined outdoor route in Sydney					
	Coef.+++	p-value+	95% CI (lower)+++	95% CI (upper)+++	Unit
Intercept	-0.543	0.1279	-1.242	0.157	
Sum of EDR amplitudes_lag	0.008	0.8672	-0.081	0.096	
Duration of activity	0.022	<0.00001***	0.019	0.025	effect of 1 minute increase in duration of activity
POI Density	0.011	0.0005***	0.005	0.017	effect of presence of 1 more POI per 100m
Traffic	-0.002	0.9279	-0.036	0.033	effect of 1 level increase in the traffic intensity scheme [0-4]
Speed	0.029	0.0082**	0.008	0.050	effect of increase by 1 m/s
Change in activity state(1)++	0.006	0.8921	-0.077	0.088	0 (no change) or 1(change)
Temperature	0.030	0.0851	-0.005	0.064	effect of 1 °C increase in temperature

+ *P-values coded as follows: p<0.05: *; p<0.01: **; p<0.001: ****

++ *The coefficient corresponding to 'Change in activity state =1', signifying the presence of a change in activity state*

+++ *The coefficients and confidence intervals show the effect of each parameter on the variable with the square root transform*

Figure 6.16. The parameters of the selected linear mixed model for the predefined route in Sydney.

In the linear mixed model that was fitted for the predefined route in Sydney, the features which were important in terms of statistical significance were POI density (β=0.011; p=0.005), duration of activity (β=0.022; p<0.00001) and speed (β=0.029; p=0.0082). The ambient temperature was also marginally significant (β=0.03; p=0.08).

These coefficients correspond to the effect of each parameter on the transformed variable. Section 6.5 will involve a discussion of the effects of all the models after reversing the square root transformation.

This dataset was also analysed in more detail compared to the others, by breaking the route in different segments and analysing the transitions between pairs of consecutive segments. The results are presented in detail in Appendix B (section 3.1.1.). The most notable finding was that the two statistically significant increases in the sum of EDR amplitudes happened in parallel to increases in the traffic and POI density, after the participants had been walking for some time in a quiet segment with low levels of stimulus intensity and complexity. In one of the two steep increases, there was also a transition from a bout of steady-state walking to a traffic light, which created a significant change in activity. Hotspot analysis was also conducted for this route, presented in Appendix B (section 3.1.2.). The results showed that the clusters of change in the EDA measures coincided with changes in POI density, traffic, or activity.

As stated in section 6.2, the participants were also asked to report their experience during each segment of the route, using the template of the PANAS test for the measurement of the affect. The results (Appendix B, section 3.1.5) showed a gradual increase in the negative affect, in parallel to the time passed since the beginning of the activity. There were no significant changes in the positive affect; however, there was a notable trend of increase when the participants entered the segment with the lowest values in terms of POI density.

6.4.2. ZÜRICH: PREDEFINED ROUTE

LMM model for Zürich

	Coef.[+++]	p-value[+]	95% CI (lower)[+++]	95% CI (upper)[+++]	Unit
Intercept	-0.875	0.0002***	-1.324	-0.426	
Sum of EDR amplitudes_lag	-0.006	0.92	-0.123	0.111	
Duration of activity	0.016	<0.00001***	0.009	0.023	effect of 1 minute increase in duration of activity
POI Density	0.007	0.16	-0.003	0.016	effect of presence of 1 more POI per 100m
Traffic	-0.004	0.95	-0.131	0.123	effect of 1 level increase in the traffic intensity scheme [0-4]
Speed	-0.014	0.40	-0.046	0.019	effect of increase by 1 m/s
Change in activity state(1)[++]	-0.051	0.35	-0.157	0.056	0 (no change) or 1(change)
Temperature	0.056	<0.00001***	0.031	0.080	effect of 1 °C increase in temperature

[+] *P-values coded as follows: p<0.05: *; p<0.01: **; p<0.001: ****

[++] *The coefficient corresponding to 'Change in activity state =1', signifying the presence of a change in activity state*

[+++] *The coefficients and confidence intervals show the effect of each parameter on the variable with the square root transform*

Figure 6.17. The parameters of the selected linear mixed model for the predefined route in Zürich.

The significant features in the linear mixed model which was fitted for the predefined route in Zürich (Figure 6.17) were the duration of activity (β=0.016; p<0.00001) and the ambient temperature (β=0.056; p<0.00001).

6.4.3. SYDNEY: FREE-LIVING ACTIVITIES

LMM model for the free living activities in Sydney					
	Coef.+++	p-value+	95% CI (lower)+++	95% CI (upper)+++	Unit
Intercept	-0.4616	<0.00001***	-0.6032	-0.3199	
Sum of EDR amplitudes_lag	0.2964	<0.00001***	0.2654	0.3274	
Duration of activity	0.0006	0.0023**	0.0002	0.0011	effect of 1 minute increase in duration of activity
POI Density	0.0014	0.115	-0.0003	0.0030	effect of presence of 1 more POI per 100m
Traffic	0.0014	0.825	-0.0111	0.0140	effect of 1 level increase in the traffic intensity scheme [0-4]
Speed	0.0241	<0.00001***	0.0175	0.0306	effect of increase by 1 m/s
Change in activity state(1)++	0.0971	<0.00001***	0.0643	0.1299	0 (no change) or 1(change)
Temperature	0.0292	<0.00001***	0.0233	0.0350	effect of 1 °C increase in temperature

+ *P-values coded as follows: p<0.05: *; p<0.01: **; p<0.001: ****

++ *The coefficient corresponding to 'Change in activity state =1', signifying the presence of a change in activity state*

+++ *The coefficients and confidence intervals show the effect of each parameter on the variable with the square root transform*

Figure 6.18. The parameters of the selected linear mixed model for the free-living activities in Sydney.

For the dataset containing the data collected during free-living activities in Sydney, the parameters which had a significant effect on the sum of EDR amplitudes data were the following (Figure 6.18): duration of activity (β=0.0006, p=0.0023), change in activity state (β=0.097, p<0.00001), speed (β=0.0241, p<0.00001) and temperature (β=0.0292, p<0.00001).

6.4.4. COMBINED DATA FROM SYDNEY AND ZÜRICH

LMM model for all the available data combined					
	Coef.+++	p-value+	95% CI (lower)+++	95% CI (upper)+++	Unit
Intercept	-0.5146	<0.00001***	-0.6475	-0.3817	
Sum of EDR amplitudes_lag	0.2947	<0.00001***	0.2662	0.3232	
Duration of activity	0.0007	0.0005***	0.0003	0.0011	effect of 1 minute increase in duration of activity
POI Density	0.0021	0.0113*	0.0005	0.0037	effect of presence of 1 more POI per 100m
Traffic	0.0002	0.976	-0.0116	0.0120	effect of 1 level increase in the traffic intensity scheme [0-4]
Speed	0.0252	<0.00001***	0.0189	0.0314	effect of increase by 1 m/s
Change in activity state(1)++	0.0875	<0.00001***	0.0574	0.1176	0 (no change) or 1(change)
Temperature	0.0343	<0.00001***	0.0288	0.0399	effect of 1 °C increase in temperature

+ *P-values coded as follows: p<0.05: *; p<0.01: **; p<0.001: ****

++ *The coefficient corresponding to 'Change in activity state =1', signifying the presence of a change in activity state*

+++ *The coefficients and confidence intervals show the effect of each parameter on the variable with the square root transform*

Figure 6.19. The parameters of the selected linear mixed model for the combined dataset from Sydney and Zürich.

In the combined dataset, which contained data from Sydney and Zürich, all parameters presented in Figure 6.19 were statistically significant at $p<0.05$, apart from traffic.

6.5. DISCUSSION

This part of the research aimed to investigate how differences in contextual circumstances affect physiological responses, and what is the role of each urban or movement-related feature in modulating physiological responses.

A visual and descriptive analysis of the different datasets was presented in section 6.2. The analysis of the two predefined routes (section 6.2.3). showed considerable differences in many contextual and activity-related parameters. Similar differences were also found among routes from different users, in the free-living activities study in Sydney (section 6.2.4).

PREDICTORS	SYDNEY PREDEFINED ROUTE	SYDNEY FREE LIVING ACTIVITIES	ZURICH PREDEFINED ROUTE	ALL COMBINED	Unit
	Coef.	*Coef.*	*Coef.*	*Coef.*	
Duration of activity	0.022	0.0006	0.02	0.0007	effect of 1 minute increase in duration of activity
POI Density	0.011	-	-	0.0021	effect of presence of 1 more POI per 100m
Traffic	-	-	-	-	effect of 1 level increase in the traffic intensity scheme [0-4]
Speed	0.029	0.0241	-	0.0252	effect of increase by 1 m/s
Change in activity state (1)		0.0971	-	0.0875	0 (no change) or 1(change)
Temperature	0.030	0.0292	0.06	0.0343	effect of 1 °C increase in temperature

Figure 6.20. The coefficients of the significant features for all models.

The statistical analysis presented in section 6.4 was conducted first separately for each dataset, and then for the combined data. Since most of the data points in the final model were from the free-living activities dataset in Sydney, the results of the final model may be more reflective of the trends in that dataset. The specific trends for each context can be identified by examining the coefficients of the different models in Figure 6.20. The coefficients are pulled from the figures displayed in section 6.4.

The coefficients in Figure 6.20 correspond to the effects on the transformed variable. Additional experiments were conducted to understand the effects on the actual variable by generating predictions using the models presented in section 6.4 and inversing the square root transformation. The results are shown in Figure 6.21, presenting each parameter's effect on the sum of EDR amplitude values. The predictions were generated by changing only one parameter each time and keeping all the other parameters stable.

THE EFFECT OF DIFFERENT PARAMETERS ON THE SUM OF EDR AMPLITUDE VALUES

4 models are used for prediction of corresponding values:
-One for the predefined outdoor route in Sydney
-One for the free living activities in Sydney
-One for the predefined outdoor route in Zurich
-One for all the data combined
Each row represents the results from the corresponding model

Effect size
small
small to medium
medium to strong

Location	Description of activities	Manipulated parameter				
		Effect of duration of activity		Effect of change in activity state	Effect of temperature	
		After 15 minutes	*After 30 minutes*	*After a change in activity state*	*After 6 ° C increase (from 15 ° C to 21 ° C)*	*After 12 ° C increase (from 15 ° C to 27 ° C)*
Sydney	Predefined	0.21±0.13	0.62±0.27	0.005±0.002	0.04±0.07	0.14±0.15
	Free living	0.004±0.002	0.008±0.004	0.05±0.02	0.05±0.04	0.16±0.08
Zurich	Predefined	0.16±0.11	0.43±0.22	-0.04±0.02	0.06±0.16	0.34±0.13
Combined dataset		0.006±0.004	0.012±0.008	0.06±0.03	0.07±0.08	0.24±0.17

Location	Description of activities	Manipulated parameter					
		Effect of speed		Effect of POI Density		Effect of traffic	
		After 2.5m/s increase (from 1m/s to 3.5m/s)	*After 5m/s increase (from 1m/s to 6m/s)*	*After increase of 15 POIs per 100m*	*After increase of 30 POIs per 100m*	*After increase of 2 levels of traffic intensity (0 to 2)*	*After increase of 4 levels of traffic intensity (0 to 4)*
Sydney	Predefined	0.02±0.03	0.05±0.06	0.08±0.07	0.23±0.14	-0.001±0.0001	-0.002±0.0002
	Free living	0.02±0.01	0.05±0.02	0.009±0.004	0.02±0.009	0.001±0.0006	0.002±0.001
Zurich	Predefined	-0.01±0.01	-0.03±0.03	0.06±0.05	0.14±0.1	-0.003±0.0003	-0.007±0.0007
Combined dataset		0.03±0.02	0.07±0.05	0.03±0.02	0.07±0.05	0.0002±0.0001	0.0004±0.0003

Figure 6.21. Analysis of the effect size for each parameter

Instead of calculating the effect of the change of one unit in each parameter, it was decided to study the effect of the change from low to moderate, and from moderate to high values of each parameter on the sum of EDR amplitudes. This approach was followed since the square root transformation is not linear, and the calculation of the change per unit would be misleading. Another reason for adopting this approach was to analyse the effect of significant contextual or movement-related changes which might be observed in typical outdoor activities. For instance, the effect of temperature was analysed by considering how the sum of EDR amplitudes value is affected by three different situations: a relatively cold environment (15^{o}C), compared to a comfortable (21^{o}C) and a relatively hotter one (27^{o}C). The effect of POI density was analysed by considering an environment without any POIs nearby, compared to an environment with 15 POIs within 100m (equal to half of the highest POI density found in the predefined routes in Sydney and Zürich) and an environment with 30 POIs within 100m (the highest POI density in the predefined routes in Sydney and Zürich). The effect of exposure to traffic intensity levels was analysed by having as input the lowest level, as well as the maximum and one half of the maximum level. The effect of a change in activity state was also included; as for the effect of speed, three different speeds were considered, corresponding to very slow movement (1 m/s), moderate walking pace (3.5 m/s) and fast walking pace (6 m/s). The calculation of the effect size was calculated separately for each dataset (Figure 6.22), based on the standard deviation values of the sum of EDR amplitude variable, extracted from Figures 6.2a and 6.2b.

CALCULATION OF EFFECT SIZE
BASED ON STD VALUES FOR THE SUM OF EDR AMPLITUDE DATA IN THE DIFFERENT DATASETS

Effect	**CALCULATION OF THRESHOLDS BASED ON STANDARD DEVIATIONS**	**EXTRACTED THRESHOLDS**		
		ZURICH *STD = 0.8*	**SYDNEY**	
			FREE-LIVING ACTIVITIES *STD=0.9*	**PREDEFINED ROUTE** *STD = 1*
small	<0.2*STD	<0.16 µS	<0.18 µS	<0.2 µS
small to medium	>=0.2*STD & <0.5*STD	[0.16-0.4 µS)	[0.18-0.45 µS)	[0.2-0.5 µS)
medium to strong	>=0.5*STD	>=0.4µS	>=0.45µS	>=0.5µS

Figure 6.22. Calculation of effect size based on the std values for the sum of EDR amplitude data

As shown in Figures 6.20 and 6.21, some common trends emerged across different models. Most notably, the overall duration of activity was a significant feature in all the models. Chapter 3 showed that physical activity is considered a stressor, and the findings here are in line with these suggestions. Figure 6.21 shows that the effect of this parameter was small for the combined dataset and the free-living activities dataset, and medium to strong in the two predefined routes in Sydney and Zürich. The differences in the size of the effect are also reflected in the coefficients presented in Figure 6.20 for this variable. The coefficients are similar for the two predefined routes in Sydney and Zürich, and higher than the coefficients for the combined dataset and the free-living activities.

The ambient temperature was also a crucial feature for all models. Temperature is again a physical stressor which influences sympathetic activity, based on the literature presented in Chapter 3. The analysis presented in Figure 6.21 shows a small effect of this variable when comparing a relatively cold (15°C) to a comfortable environment (21°C) and a small to medium effect when comparing a comfortable environment to a hotter one (27 °C). The coefficients presented in Figure 6.20 are similar among the different datasets, being slightly higher in Zürich and the combined dataset. The interpretation of this study's findings is that ambient temperature can act as a modulating factor that generally creates more intense responses in amplitude and frequency in mild to hot conditions compared to colder ones. It is also important to note that this research did not involve very cold conditions, walking during rain, or abrupt transitions from a high to a low temperature, and these conditions should also be covered in future research.

In terms of contextual features, traffic was not statistically significant in any model. POI density was significant in the predefined route in Sydney and the combined dataset. Based on the analysis presented in Figure 6.21, the impact of very small changes in POI density would be trivial. The effect was small when comparing the exposure to an environment without any POI and an environment with medium POI density (15 POIs within 100m). The same applied when comparing an environment with medium POI density and one with high (30 POIs within 100m). The effect size was slightly larger in the predefined route in Sydney.

Speed was an essential feature for all models that contained data collected in Sydney. This feature is related to the activity intensity. Its effect on the sum of EDR amplitudes was small, based on the analysis presented in Figure 6.21. The change in activity state was significant in the free-living activities and the combined dataset; the effect was also small in this case, for all the designed models. The other similar variable which was sometimes tested (‘change in activity’), was also statistically significant in some of the additional experiments that were not reported in the tables presented here. It is unclear if the most critical feature between these two is the general change in activity intensity or the change from a steady state to another activity intensity. According to the literature presented in Chapter 3, the transition from a steady state to another fits the definition of a stressor. The analysis of the indoor experiments, presented in Appendix C, showed that the change in activity had a particularly strong impact on the sum of EDR amplitudes when there was a change from steady-state walking to standing. However, this was observed only in the second indoor experiment, when the participants' sympathetic activity was already elevated from the outdoor activity. The reactions to the same parameter were very low, or even non-existent in some cases, in the indoor test before the outdoor activity. The effects of the change in activity (or the change in activity state) on physiological responses may, therefore, be amplified during the existence of other parameters which act as stressors, such as a high duration of the activity. This interpretation is in line with the theory of the synergistic effect of multiple stressors (presented in Chapter 3).

Similar reasons might explain why the POI density had a larger impact on the predefined route in Sydney. This route lasted for a longer time and contained more bouts of steady-state walking than the predefined route in Zürich, as shown in section 6.2. Similarly, in the free-living activities dataset in Sydney, there was high variation in the duration of the bouts of steady-state walking, and some routes had short overall duration, as shown in Figure 6.14. One possibility is that the combination of the overall time of activity and the presence of many or long bouts of steady-state walking might create higher levels of sympathetic activation. When a route of a participant satisfies these conditions and some time has passed since the beginning of the activity, a change in activity or stimulation may have a higher impact at that point, than at the beginning of the activity. Furthermore, in the predefined route in Sydney, there were more extreme variations in POI density, including places with very high and very low POI density, while in Zürich the differences were relatively smaller. Since there are links between POI density and stimulus complexity (following the analysis presented in Appendix A), this suggests that the predefined route in Sydney might have contained more marked differences in the complexity of the environment. These differences in complexity may be one of the reasons that the positive relationship with POI density was identified in this route and not in the others.

One limitation was that the statistical analysis used each route's average ambient temperature and did not take into account any differences in the local microclimate, which might influence the result. This parameter should be added in future studies.

Another limitation was that the presence of slope was not included in the models, because the two predefined routes in the two cities were mostly flat. It was, therefore, decided to exclude this variable from the analysis and focus on all the other variables which had a presence in all datasets. Future work shall involve more dedicated analysis of the influence of this variable as well.

Another point for future improvement should be the investigation of other ways of modelling and analysing the variables. The relationship between the variables examined here, and physiological responses might be better described as a more complex sequence or pattern of parameters that have to coexist in order to provoke physiological responses. One such variable that may not have been sufficiently described in the linear mixed models is the ‘steady state’ variable. The results of the cluster analysis in section 6.4.1 and the findings of the analysis of the indoor data (presented in Appendix C) suggest the existence of a possible link between the overall duration of the activity, duration of steady-state walking and physiological responses. The variable created for the representation of ‘steady state’ in the dataset was not identified as significant in the linear mixed model analysis, but this could have to do with the modelling of this variable. Alternative representations for future experiments could include a lagged variable describing the past existence of a steady state, or the minutes of steady-state walking in the current bout of activity, and the total bouts of steady-state walking until each time point.

In conclusion, the presented results suggest that some of the features (most notably, the overall duration of activity and the ambient temperature) which were identified as significant in the context of Sydney do not have this behaviour exclusively in this local environment, but have similar effects at least in one other context. The combined findings from the three phases of the analysis suggest that there are multiple parameters in different scales that play a role in the generation of physiological responses. While the large-scale contextual differences (mainly ambient temperature in this study) may affect physiological responses to a certain extent, small-scale differences may also be found within different neighbourhoods of the same broader context. These differences may also be modulated by the movement pattern and several factors related to that. When there is also diversity in the yearly weather pattern of a city, apart from diversity in the urban fabric, there may be large-scale seasonal effects on the physiological responses, apart from small-scale spatiotemporal patterns, within the same city.

These findings expand our existing knowledge on the link between urban environment, activity and responses. They also suggest that the conceptual framework which was proposed in Chapter 3 is in the right direction. The presented results provide evidence that supports the choice of some of the features which were used as physical and psychological stressors in the data fusion model presented in Chapter 5. The significance of the features related to activity was highlighted.

This chapter also played another role apart from the presentation of the statistical analysis and the examination of the role of different features. The analysis of the datasets (section 6.2), showed that the datasets utilised in this research capture a wide range of contextual circumstances and activity-related differences. The chapter also demonstrated that the methods of component 1 of the methodology (used here for data collection and analysis) are applicable in more than one context.

The work presented in this chapter concludes the presentation of material related to component 1 of the methodology for the collection and analysis of physiological data in the urban space. The remaining chapters shall present the methods related to the two other components.

7

METHODS FOR SPATIAL ANALYSIS OF PHYSIOLOGICAL RESPONSES IN THE URBAN ENVIRONMENT

7.1. INTRODUCTION

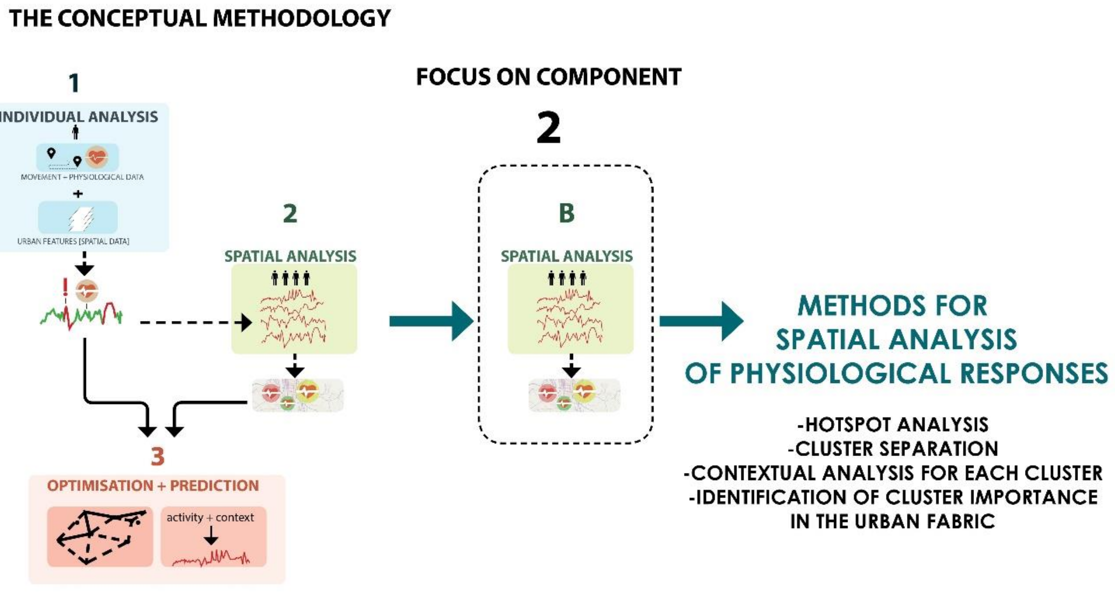


Figure 7.1. Flowchart outlining the aim of the chapter and the connection with the conceptual methodology.

After presenting the methods related to component 1 of the methodology in Chapter 5, and providing evidence that supports these methods in Chapter 6, this chapter shifts the focus on component 2 of the methodology for collection and analysis of physiological data in the urban environment (Figure 7.1). This component contains methods for spatial analysis of physiological responses.

The extrapolation of spatial patterns of physiological responses is an essential step of the analysis of physiological data. Some methods that have been used for this purpose include averaging the physiological responses in grid cells or segments (Shoval et al. 2018), constructing heatmaps based on the density of physiological responses (Zeile et al. 2016), or identifying hotspots with the Getis-Ord Gi* method (Kyriakou & Resch 2019). Among these methods, the latter has the advantage of examining the statistical significance of the emerging clusters so that the researchers can filter the results accordingly. As these projects showed, the identification of spatial patterns in the physiological responses is one of the most significant parts of the analysis, as it enables the identification of areas which have a higher or lower intensity of responses than others. In EDA analysis, high intensity of EDA responses is connected to high sympathetic arousal, which may indicate physical or psychological stress, as shown in Chapter 3. For this reason, past studies have used the identification of spatial concentrations of EDA responses of high intensity as a way of understanding the spatial dimension of stress and physiological arousal in the urban environment.

While past studies have been successful in demonstrating the beneficial aspects of spatial analysis of physiological responses, the main output of this stage was usually a visualisation of the hotspots. The hotspots were not separated into different clusters, which would be the logical next step. Without this information, it is difficult to include a quantitative analysis of each cluster's contextual circumstances. There are many precedents of algorithms used for spatial cluster identification (e.g., Hwang et al. 2013). The application of such algorithms, though, requires the calibration of many parameters. These parameters affect cluster separation and their interpretation in terms of their role in the urban fabric. The same algorithm can result in clusters with the size of a neighbourhood or a small urban square, just by altering some parameters. Therefore, some experiments need to be conducted to define how cluster separation can be integrated as the next step after hotspot analysis in the workflow of spatial analysis of physiological data. This part of the analysis is necessary for understanding if there are differences in each cluster and what kind of circumstances may be behind the physiological responses. The lack of this step hinders the connection of hotspot analysis with further inferential analysis and decision-making processes at an urban planning level. If there is no understanding of each cluster's specific conditions, no actions can be taken to mitigate stress hotspots in the urban space.

Furthermore, when it comes to clusters of stressful responses in a large study area, it would be difficult for the local governmental agencies to take action simultaneously at all spots, in a scenario where many such clusters are identified. One obstacle in the process of decision making is thus the lack of measures to analyse the importance of each cluster of physiological responses in the context of the urban network. If the area of analysis is small, it is easy to conduct a visual assessment of the clusters emerging from the analysis, for an analyst that has knowledge of the area. However, as the area of analysis and the number of clusters increase, this process becomes complicated.

One possible solution to this problem could be to add a step after the creation of clusters of physiological reactions, for ranking them according to different metrics. One such metric could be the intensity of responses in the cluster or the number of users who experienced a strong response. Another idea could be an assessment based on the cluster's significance in the urban network in terms of pedestrian activity. The last two metrics are based on the idea that a cluster of physiological reactions may have a more significant impact if it is expected to affect a larger population compared to other clusters. Some studies have already incorporated similar steps that suggest that the user-based assessment method has significance in the urban context. Hijazi et al. (2016) included a manual analysis of each cluster's data points to ensure that the physiological responses were generated from different people. Shoval et al. (2018b) incorporated user analysis in a visualisation of the physiological responses in the form of grid cells, which had different heights according to the number of users in each cell.

While the calculation of the two first metrics is explicit, the third metric requires local knowledge of the mobility patterns of the city, for its practical implementation. While in small cities it might be easy for the local planning officers to visually assess a map with the emerged clusters and pinpoint areas are most prone to be visited, this becomes much more difficult as the area of analysis increases. One alternative way would, therefore, be to integrate into the tools of spatial analysis either the actual pedestrian activity data if they exist, or a method for predicting pedestrian mobility. In this way, the actual or estimated mobility data would be analysed, and the most visited areas would be automatically inferred and combined with the cluster analysis. A method that could be used for this assessment is the estimation of pedestrian mobility from urban network analysis. This method of analysis is considered a well-established approach for predicting spatial interactions in the urban domain (Batty 2004).

In this context, this chapter investigates methods for analysis and knowledge extraction from the spatial concentrations of physiological responses at a city scale. A method for spatial analysis of physiological responses shall be presented, starting with hotspot analysis, and proceeding with cluster ranking for the identification of clusters which may have a more significant impact at a city scale, in terms of urban health and wellbeing. The ranking step is followed by the analysis of the contextual attributes of each cluster. The cluster ranking methods shall include user-based and pedestrian activity-based ranking methods. The proposed methods are tested on the free-living activities dataset collected in Sydney, and the dataset collected in Zürich. These two datasets exemplify how this method can be incorporated in different contextual circumstances, including the size of the study area, the size of the dataset and the diversity in the conducted activities. The focus is on constructing a workflow that can be applied by future practitioners in this area.

The chapter starts with a brief description of the dataset and the methods used for hotspot analysis and prediction of mobility patterns based on network analysis (section 7.2). Section 7.3 demonstrates the results of this method in the context of Sydney and Zürich and discusses the findings in the local context. Finally, section 7.4 elaborates on the benefits and limitations of the proposed method and discusses future directions. The code created for the execution of the methods designed for this component can be found in GitHub[7].

[7] https://github.com/ddritsa/PhD-Thesis-repository/tree/main/2nd%20component

7.2. METHODS

7.2.1. DATASET CHARACTERISTICS

The datasets that were analysed to demonstrate the described methods are the free-living activities dataset from Sydney and the dataset collected in Zürich from Ojha et al. (2019) during a predefined route. The two datasets show the applicability of the methods in two different setups: a semi-controlled experiment on a predefined route, where the study area is small, and its boundaries are known to the research team, and in a completely uncontrolled scenario where the only prior knowledge is the city where the experiment is conducted. In the constrained route, all participants face the same obstacles that affect movement; therefore, there is some control over the activity pattern. Previous studies have focused only on this setup (except Lee et al. 2020).

The dataset characteristics are the same as presented in Chapter 6 (Figure 6.2a and 6.2b). The variable which will be analysed as an indicator of physiological responses is the *sum of EDR amplitudes*, and its change (mentioned as '*change in the sum of EDR amplitudes')*. All features are extracted before this step with the data fusion model of Chapter 5.

7.2.2. NETWORK ANALYSIS

This section provides a brief background on network analysis in the urban context. This background is necessary for understanding the network-based cluster ranking method that will be outlined in section 7.2.3.3.

The application of network analysis in urban networks is based on graph theory principles. The urban network is treated as a graph, composed of streets and intersections, which act as the graph links and nodes respectively. The streets can also be analysed as nodes and the junctions as links, using the dual graph approach, as proposed in the space syntax theory (Hillier & Hanson 1984). Node centrality measures are then used as metrics of the performance for different nodes and links of the network. This approach allows the identification of nodes which are essential for the network and facilitate connectivity between its components; for this reason, node centrality measures have been used extensively for defining which nodes play a central role in the network and what is the number of trips expected between them. Urban network analysis has been integral for various types of studies of socio-spatial phenomena, such as the spatial analysis of the rate of crime, or the prediction of cycling and walking flows (Baran et al. 2008; Jiang & Claramunt 2004; Klarqvist 1993; Nourian et al. 2018).

This study uses betweenness centrality as a measure which expresses the potential level of pedestrian activity at each network node (Sevtsuk & Mekonnen 2012). In network analysis, the betweenness centrality of a node is calculated by extracting the shortest paths between pairs of nodes and estimating the number of times each node is included on a shortest path, in relation to the overall number of shortest paths in the network (Freeman 1977). In the context of street network analysis, the 'shortest path' analysis usually incorporates the actual length of the streets as a weight which affects the calculation on top of the topological characteristics of the network. Other attributes can also be incorporated, such as land use, the path's straightness, or other urban characteristics. The 'shortest path' thus expresses the path which a pedestrian is expected to take when travelling from one point of the city to another, taking into account the time needed to reach the destination as a minimum criterion for selecting their route. If a node has high betweenness centrality, many 'shortest paths' are expected to pass from this node.

The area which was selected for analysis in this chapter had the Central Station, Sydney as its centre and contained the street network nodes within 4km of this point. The majority of the data points of the free-living activities dataset in Sydney were contained in these boundaries. The selected area for network analysis in Zürich was slightly smaller, containing all street network nodes within 2km of the route's middle point. The network analysis was conducted with the python module *osmnx* (Boeing 2017a). The derived betweenness values were integrated into the spatial database that was previously created with the methods presented in Chapter 5 since the spatial database was also generated by analysing the same OSM data. This process was repeated for each city. A visual demonstration of the resulting betweenness centrality values for Sydney is provided in Figure 7.2.

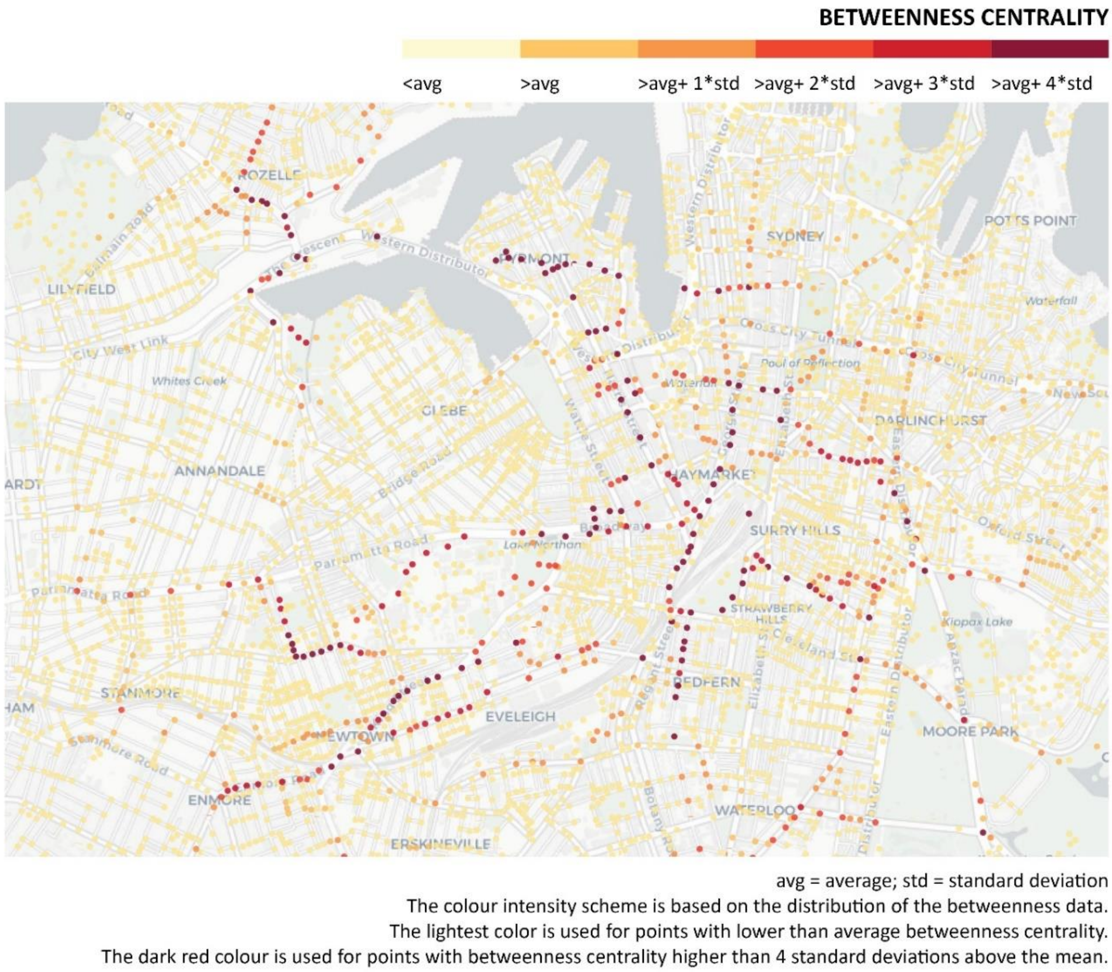


Figure 7.2. The results of betweenness centrality analysis for the studied area in Sydney.

7.2.3. THE PROPOSED METHOD FOR HOTSPOT IDENTIFICATION, CLUSTER SEPARATION AND USER RANKING

The proposed method can be applied to a dataset containing the processed physiological responses and geolocation information for each data point. The applied node centrality metric (node betweenness) also has to be calculated beforehand for the city's street network. The overall workflow is presented in Figure 7.3.

Figure 7.3. The proposed workflow for spatial analysis of physiological responses

7.2.3.1. HOTSPOT IDENTIFICATION

The identification of hotspots in the methods designed for component 2 is based on the extraction of the Local Moran's I value for each point. This index is a measure of local spatial autocorrelation, and it examines the degree of similarity between the neighbouring samples of a dataset (Anselin 1995). It has been widely used for hotspot identification in various studies, including identifying air pollution hotspots (Zhang et al. 2008) and virus outbreaks (Sugumaran et al. 2009).

The Local Moran's I index results in identifying four kinds of clusters; points of high values that are concentrated together, points of low values that are concentrated together, points of low values gathered around points of high values and the opposite. The statistical significance is also calculated for each value, allowing the identification of clusters which are not a result of noise in the data. In this case, the focus was on the concentration of high values close to other high values; in other words, on hotspots where points of intense physiological responses (or significant change of responses) were clustered together.

7.2.3.2. CLUSTER SEPARATION WITH THE DBSCAN ALGORITHM

The previous step allows the extraction of hotspots of physiological responses which are statistically significant. While the local Moran's I value signifies the presence of points which have similarly high values and are proximal, there is still no specific identifier for each separate cluster. It is crucial to mark each hotspot's spatial boundaries, as, without this step, it is not possible to extract any metric with regards to the spatial characteristics of the different hotspots.

For this purpose, the DBSCAN algorithm (introduced in Chapter 4) is applied to separate the points in clusters based on the density in the spatial distribution of the points. Another approach would be to use the DBSCAN algorithm from the beginning, instead of the local Moran's I value, but in that case, it would not be possible to have the values of statistical significance for each cluster that the local Moran's I index provides.

7.2.3.3. CLUSTER RANKING

The different methods for cluster ranking that are proposed, are based on analysing the impact of each cluster based on two metrics: the number of users that were impacted during the study, and the expected degree of pedestrian activity in the area, based on the cluster's position in the urban fabric. The resulting rankings are referred to in the rest of the chapter as the *user based ranking*, and the *betweenness centrality based ranking*.

The calculation of the user based ranking is conducted by measuring for each cluster the number of unique participants whose physiological responses are contained in the cluster. Only the physiological responses with relatively high values are included, as these calculations are based on the subset of points that had high values next to other high values, as identified by the Local Moran's I analysis.

The betweenness centrality based ranking estimates the expected degree of pedestrian activity for each point in the hotspots. It is calculated by extracting the betweenness centrality metric for each node. For this purpose, a k-d tree (see Chapter 4, section 4.2.3) is constructed, containing information regarding the spatial distribution of the street network nodes based on proximity. The k-d tree is then queried for each point belonging to a hotspot of physiological responses. The purpose is to find the five closest nodes for each point and get the betweenness centrality value of these nodes. The average betweenness centrality for these five nodes is then calculated, and the resulting value is assigned to the cluster.

Each ranking results in the assignment of weights based on the position of the cluster on a scale. The scale is based on the minimum and the maximum values for this ranking.

7.2.3.4. PARAMETER CALIBRATION

The general workflow, as presented until now, is composed of a series of simple steps. Many parameters have to be specified, though, during the analysis, such as the parameters related to the DBSCAN algorithm. Small changes in the choice of values for each parameter may have significant differences in the result.

One question here is if the focus should be on the signal of interest (*sum of EDR amplitudes* in the experiments described in this chapter) or the changes in the signal, or both.

Another parameter is the identification of an appropriate resampling rate for the target signal. If no resampling is applied, the time of processing becomes high in large datasets, such as the free-living activities dataset in Sydney; at the same time, a resampling at a rate of more than 1 or 2 minutes may result to the loss of valuable information. For studies at a city scale, an appropriate rate or range of rates has to be specified to allow fast processing and assure that no information will be lost.

Another question is if some methods for outlier correction and data transformation should be applied in order to ensure that the result would not be skewed by a few data points with very high values of physiological responses. For this purpose, a cut-off could be applied based on the mean and standard deviation values or using the 3rd upper quartile of the values as a threshold.

Finally, the DBSCAN algorithm requires the specification of a maximum distance for the identification of neighbouring points. This choice affects the resulting number of clusters and the number of data points in each cluster and influences how the results are interpreted in the urban context. For instance, a large distance may result to the creation of clusters that correspond to a whole street or a neighbourhood, while a small distance results to the emergence of clusters that correspond to an urban network node.

Various experimentations were conducted to test all these parameters for both Zürich and Sydney. The results are presented in section 7.3.

7.2.3.5. EXTRACTION OF CONTEXTUAL INFORMATION

The final stage of the methods for spatial analysis of physiological responses includes the extraction of contextual information for each cluster, for understanding differences and similarities between the clusters.

7.3. RESULTS

This section demonstrates the results of the application of the algorithms for the two datasets, first for the predefined route in Zürich, and then for the free-living activities dataset in Sydney.

7.3.1. SPATIAL ANALYSIS OF PHYSIOLOGICAL RESPONSES IN ZÜRICH

The first phase of the experimentation with the Zürich dataset involved the calibration of two parameters: the resampling rate and the cut-off value. The cut-off value was a threshold that was defined with the purpose to detect and reduce any data points which may have abnormally high values of the target signal. The cut-off was applied to the physiological response data. The experimentations for the resampling rates were conducted for the following rates: 10, 30 and 60 seconds. The different cut-off values that were tested were based on standard deviations above the mean.

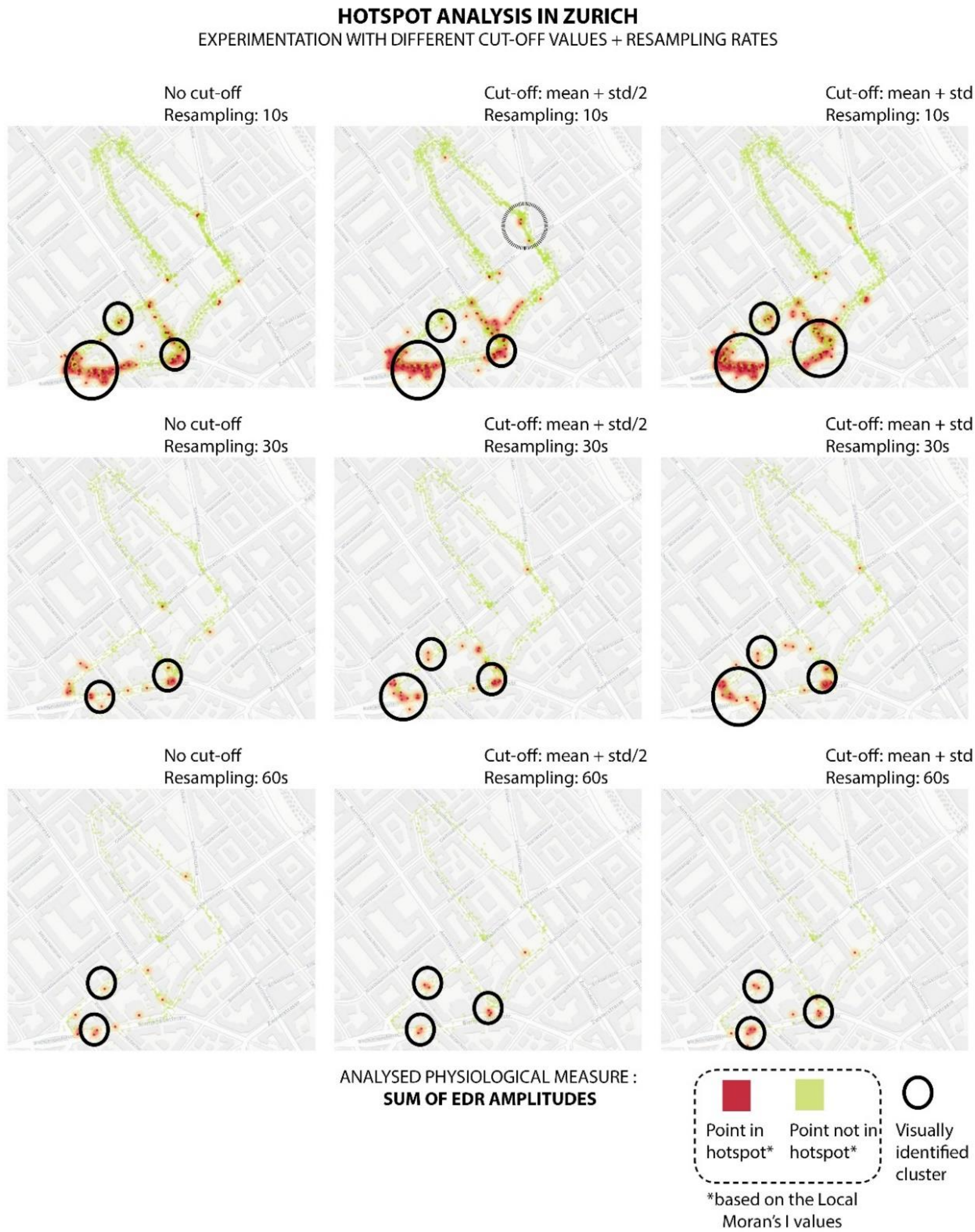


Figure 7.4. The results of the hotspot identification based on the Local Moran's I values for the Zürich dataset.

Figures 7.4 and 7.5 show the results of the experimentation with different resampling rates and cut-off values for two cases: In the first case (Figure 7.4), the sum of EDR amplitudes signal is analysed, but in the second case (Figure 7.5), the change in the signal is analysed instead.

As Figure 7.4 shows, there is not much difference in the results of the different experiments and the resulting number of clusters for the *sum of EDR amplitudes* data. The only difference is that the data points become fewer than before, and the minimum number of samples needed for the detection of a cluster in the DBSCAN algorithm has to be adjusted accordingly.

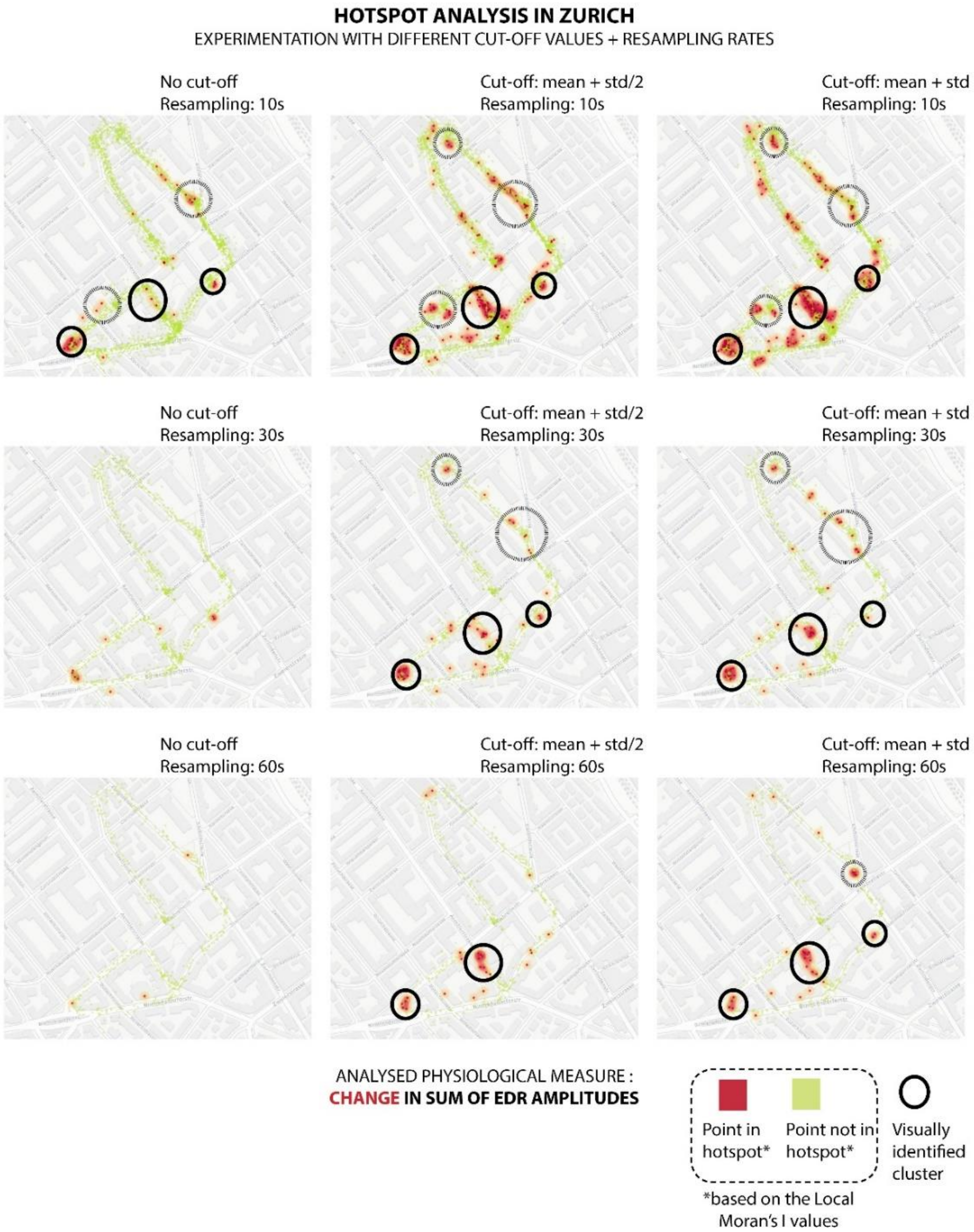


Figure 7.5. Experimentation with different resampling rates and cut-off values for the change in the sum of EDR amplitudes data.

Figure 7.5 shows though that the results are different for the *change in the sum of the EDR amplitudes* data. Here there is some small variation in the resulting number of clusters, as in the more conservative resampling rate (10 seconds), some clusters are not visible in the last row of images, where the resampling is at 60 seconds. The application of the cut-off values for improving the distribution of the data was also preferable compared to the data without cut-off, as it made more prominent the existence of some clusters that would be otherwise not detected, particularly in the higher resampling rates. The locations of the most prominent clusters are also very close for the two analysed signals (the *sum of the EDR amplitudes* data, and the *change in the sum of the EDR amplitudes*).

After calibrating the algorithm for the detection of statistically significant hotspots using the data from the predefined route in Zürich, the algorithm was applied for hotspot analysis in the predefined route in Sydney. The results are presented in Appendix B (section 3.1.2).

The next phase of the experimentation with the Zürich dataset involved the calibration of the maximum distance threshold for detecting clusters in the DBSCAN algorithm. For this experimentation, the *change in the sum of the EDR amplitudes* data was used as the studied variable. The same method can still be applied for the analysis of the other signal.

For the application of this algorithm in the context of studying urban space and its effect on physiological responses, it is essential to think what is the rate of change in contextual parameters that can affect physiological responses, and how this rate is expressed in the urban fabric, in terms of distance metrics. For instance, two points that belong to the same street segment will be perceived as parts of the same environment when traversing this street segment as a pedestrian. This behaviour applies to the variables which are studied here, such as the levels of POI density, traffic intensity and presence of traffic lights. These points should be included in the same cluster, as they have similar contextual parameters. It is unlikely that these parameters will undergo a meaningful change within the same street segment, but in distances above that, factors such as traffic may change. In that case, it would make sense to assign these points in different clusters as parts of environments with different contextual circumstances.

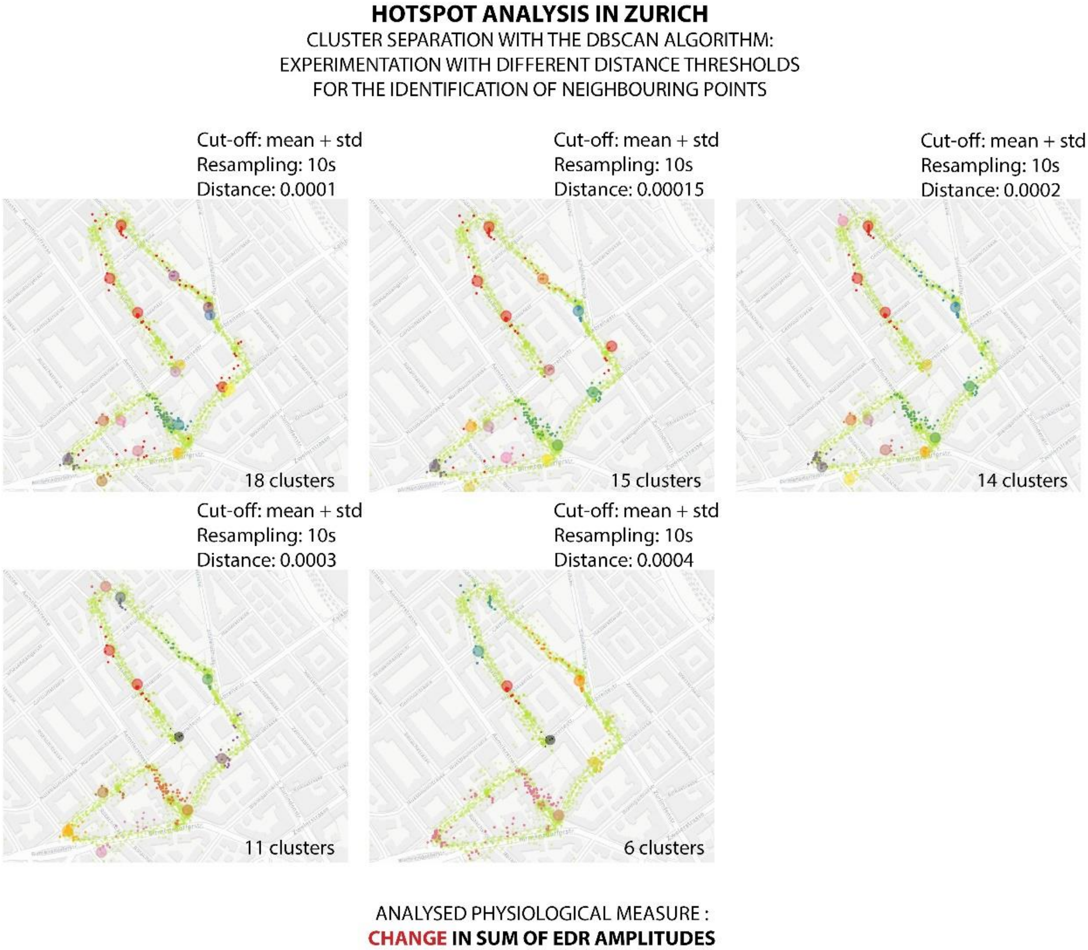


Figure 7.6. The results of parameter testing for the cluster separation phase with the DBSCAN algorithm applied to the Zürich dataset.

A range of different distances was tested with these principles kept in mind, and the results are presented in Figure 7.6. As shown in the figure, the distance thresholds within a range of 0.0001-0.0002 resulted in the identification of too many clusters (n=18). The clusters were also sometimes very close to each other. The distance threshold set at 0.0004 also seemed to work oppositely, grouping together some points which belong to different street segments and may have different contextual parameters. The selected option was that with the distance threshold set at 0.0003.

This threshold still resulted in too many clusters (n=11), but the ranking methods which were applied afterwards were able to filter out the redundant information and highlight the most significant clusters. As shown in Figure 7.7, clusters A and B were the ones which had the most significant impact in terms of the number of users that experienced an intense response. The locations of the clusters are presented in Figure 7.8, and indicative photos from each location are shown in Figure 7.9.

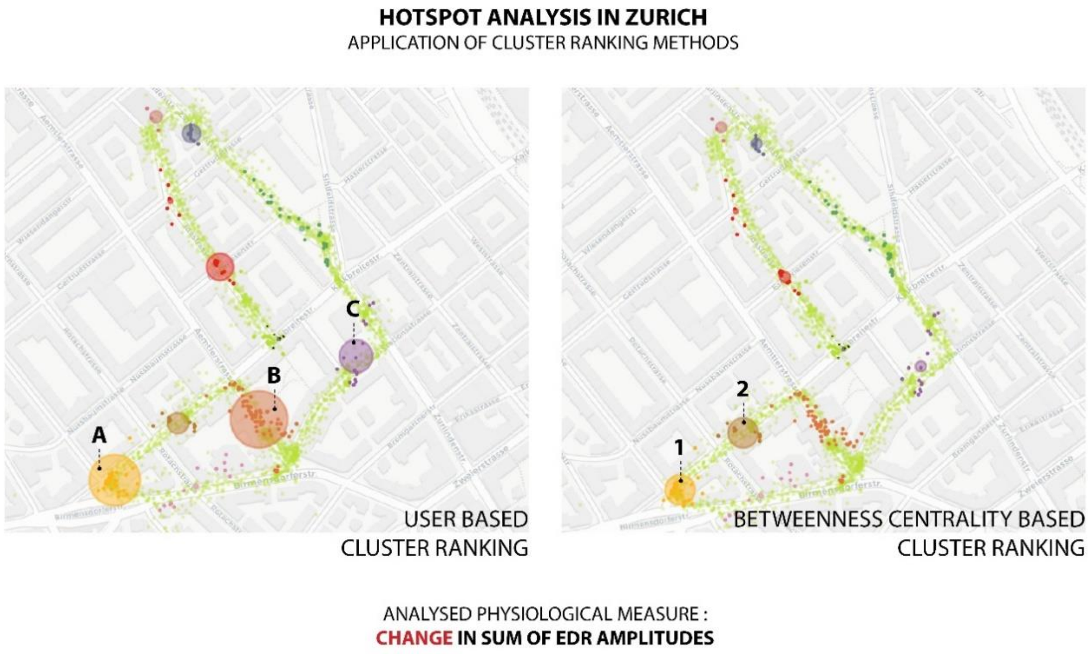


Figure 7.7. Application of cluster ranking methods on the route in Zürich

Cluster A is located in an area with high POI density in the route, located close to Goldbrunnenplatz. Cluster B is located towards the end of the route and is also close to shops and amenities. Cluster C is located in a quieter street and was closer to the start of the route than the others.

The clusters which were identified as most important in terms of high betweenness centrality were clusters 1 and 2 in Figure 7.7. Cluster 1 is the same as cluster A, which means that this is a place with a significant role in the urban fabric, where many users had relatively intense responses.

Figure 7.8. The locations of the most important clusters in Zürich.

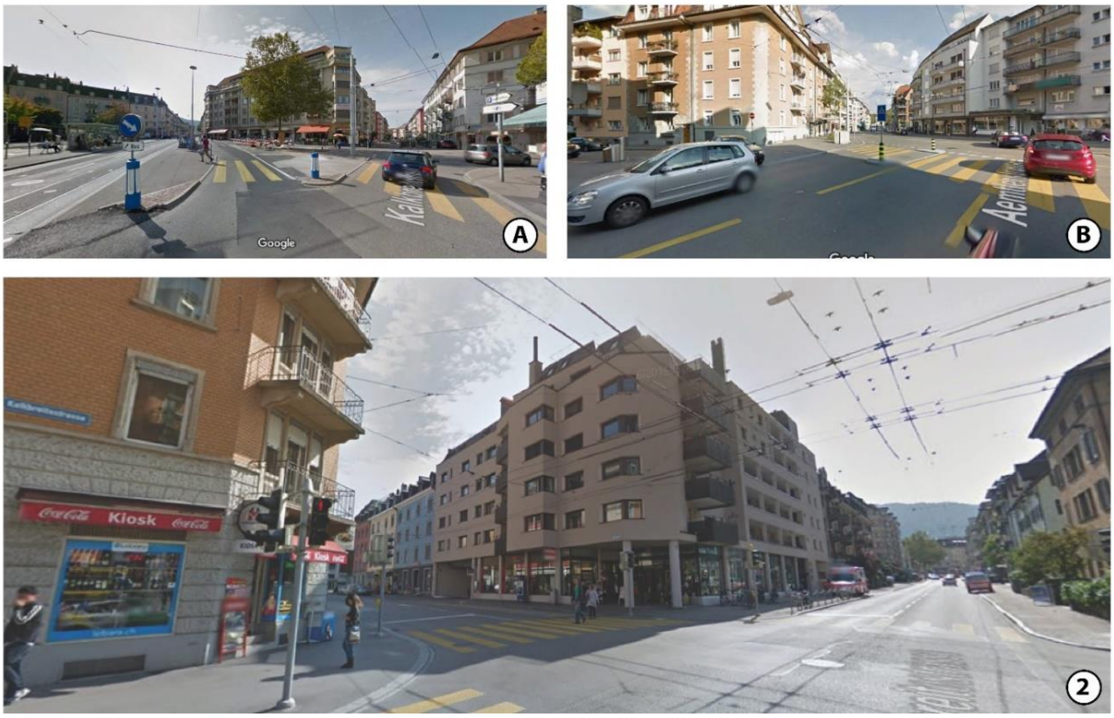


Figure 7.9. Photos of the locations corresponding to the critical clusters in Zürich. The photos are taken from Google Street View (Google Maps 2020)

7.3.2. SPATIAL ANALYSIS OF PHYSIOLOGICAL RESPONSES IN SYDNEY

This section presents the results of the application of the clustering and ranking methods for the free-living activities dataset in Sydney.

Figure 7.10. The results of the hotspot identification with Local Moran's I values for the free-living activities dataset in Sydney.

After the documentation of the experiments in Zürich, the parameters that were adopted were a resampling rate of 10 seconds, a cut-off set at one standard deviation above the mean, and a maximum distance threshold of 0.0003 for the DBSCAN algorithm. The results of resampling at 30 seconds are shown in Figure 7.10 for comparison.

As Figure 7.10 shows, the analysis of the *sum of EDR amplitudes* data resulted in the identification of continuous street segments as hotspots, while the analysis of the *changes in the sum of EDR amplitudes* data highlighted clusters at a street node scale. Both kinds of analysis are of interest, but the first is more applicable for analysing and comparing street segments rather than street network nodes.

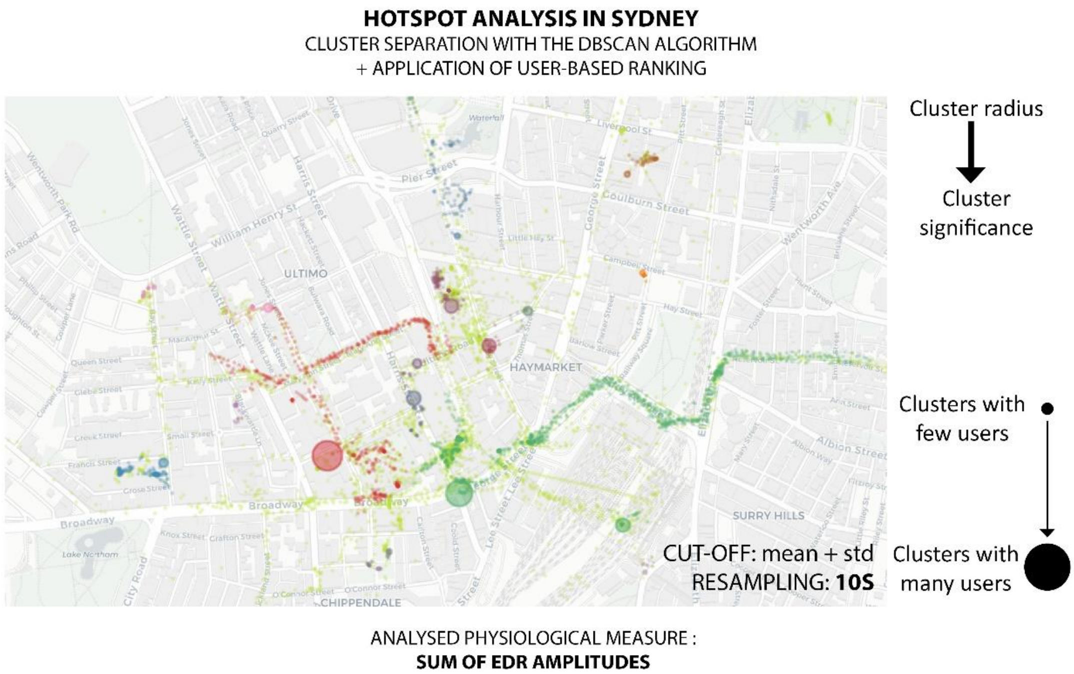


Figure 7.11. Result of the DBSCAN algorithm applied on the sum of EDR amplitudes, with user-based ranking applied.

The problem created by analysing the raw signal, instead of the change in the signal, becomes very obvious in Figure 7.11. The figure shows the results of the DBSCAN algorithm applied for the sum of EDR amplitudes data. In this case, the DBSCAN algorithm groups together route segments, and the resulting clusters resemble paths as opposed to more circular shapes. The most probable reason for this grouping is the temporal and spatial autocorrelation in the signal. This analysis shows that, due to this effect, in some cases, it would be preferable to focus on the study of the changes of the signal, where there is more contrast in the neighbouring data points of each user, as opposed to using the signal itself.

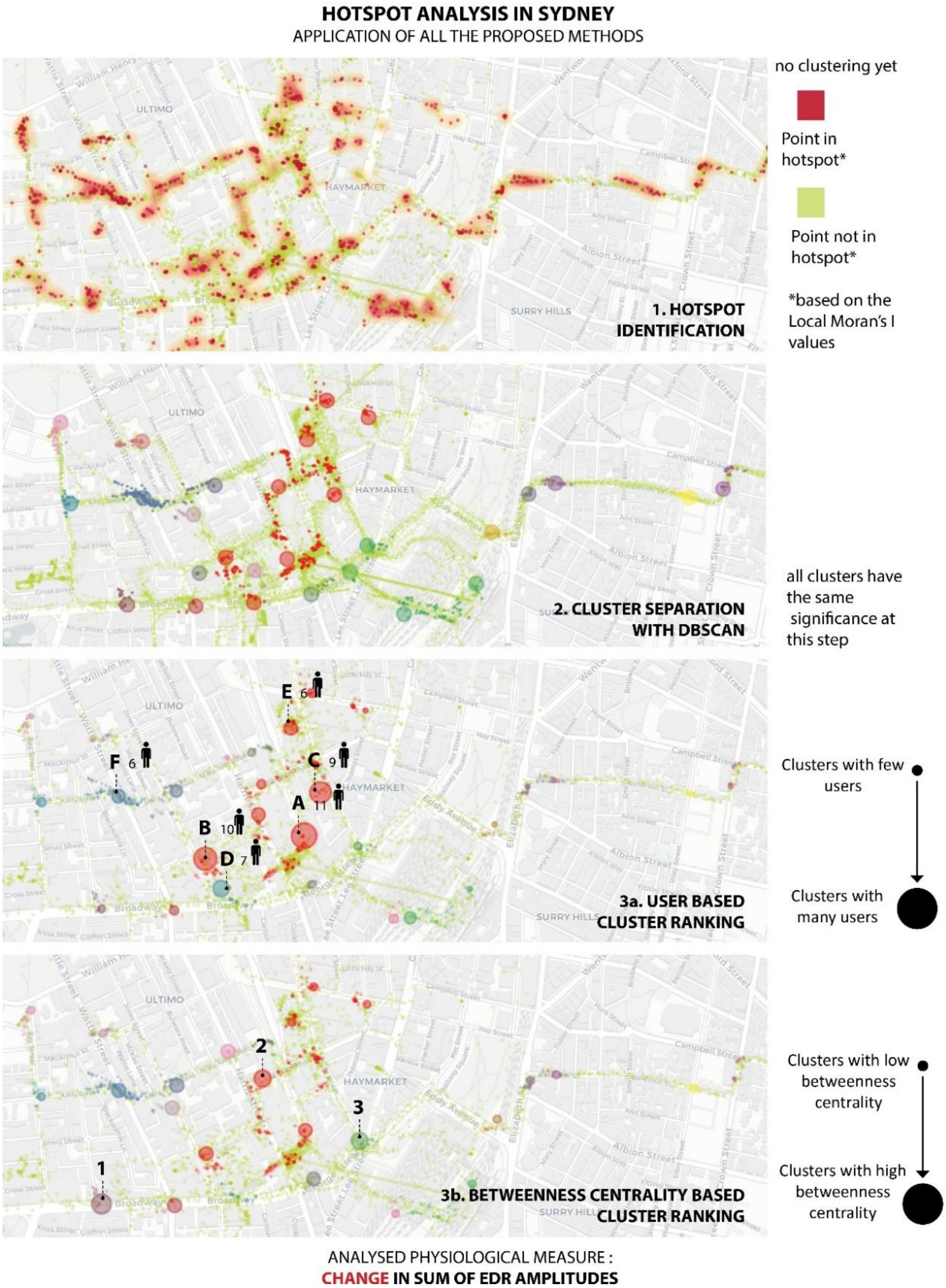


Figure 7.12. The proposed workflow for spatial analysis applied to the change in the sum of EDR amplitudes data collected in Sydney.

The results of the analysis of the change in the signal (sum of EDR amplitudes) are presented in Figure 7.12. It is visible that the clusters are more meaningful here. The figure also presents the results of the different ranking methods that were applied for the extracted clusters in Sydney. As shown in the figure, a large number of clusters were initially identified from the hotspot identification and the DBSCAN algorithm, but the ranking methods were able to highlight a few that are of higher significance. The clusters containing data from only one or two users are visualised with a smaller radius in the user based ranking map (Figure 7.12), to highlight the clusters with more users.

Figure 7.13 shows the locations of the most significant clusters for each ranking method.

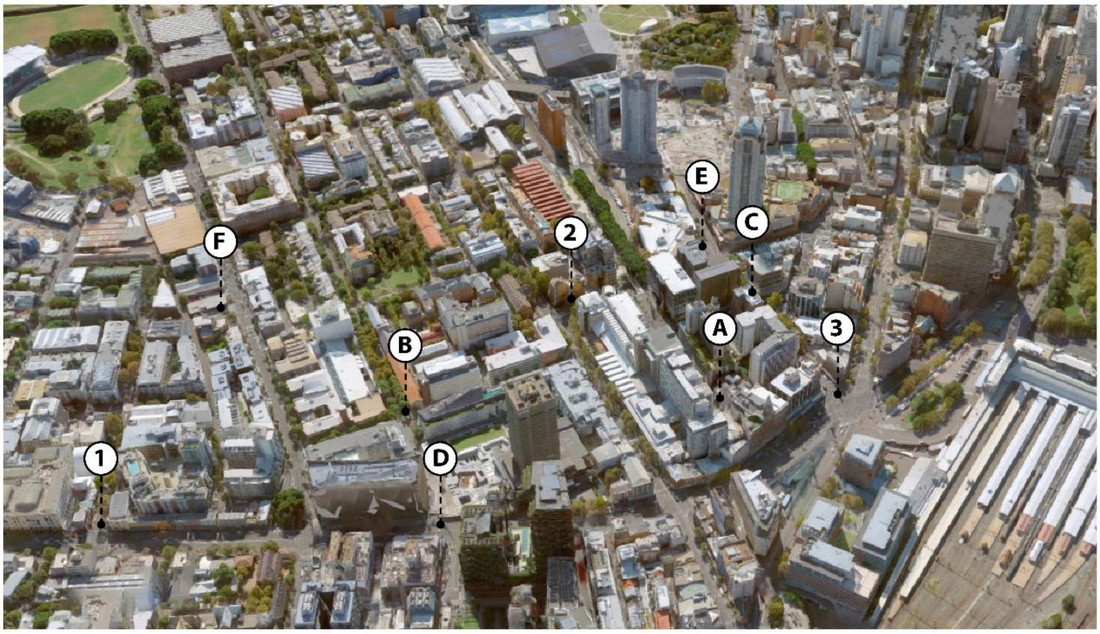
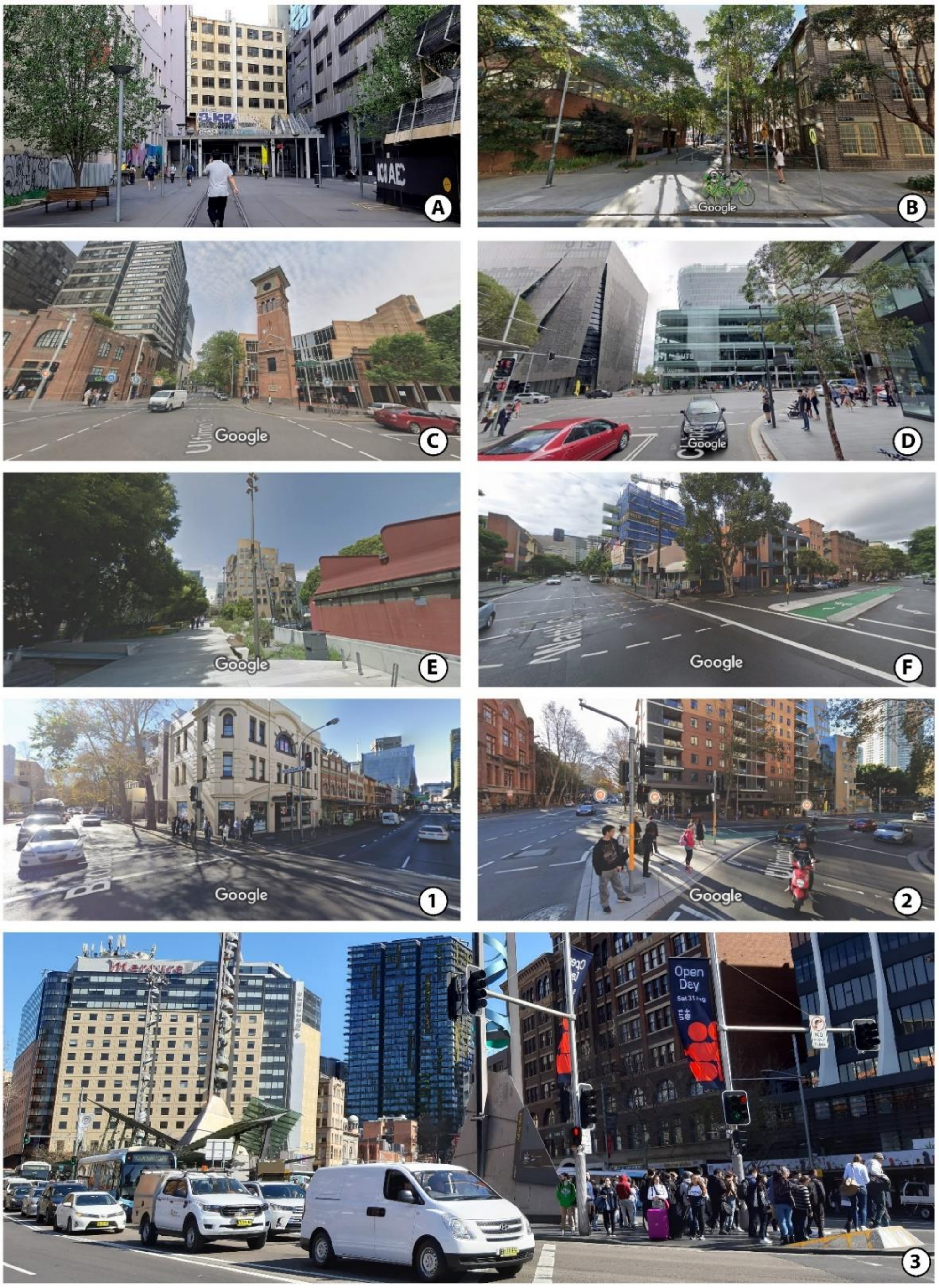


Figure 7.13. The locations of the most important clusters in the studied area in Sydney.

As the participants were affiliated with the local university, it was expected that their paths would converge at some points. Clusters A, D and C, are on quite busy spots in terms of pedestrian activity; cluster A is on the Goods Line, and very close to the exit of the tunnel leading to the Central Station of Sydney. It was expected that many participants would visit this spot as a part of their daily commuting. Cluster B is on

Broadway Street, and cluster C is on Ultimo Rd and Quay St, close to the library and the buildings of the local university.



The index of the clusters is the same as in Figures 8.12 and 8.13.
Locations A-F: Significant clusters derived from the user-based ranking
Locations 1-3: Significant clusters derived from the betweenness centrality based ranking

Figure 7.14. Photos depicting the contextual circumstances in the significant clusters. In Sydney. The photos are taken from Google Street View (Google Maps 2020), apart from photos A and 3 that were taken by the author.

The three clusters with the highest ranking in terms of betweenness centrality are located on Broadway Street (cluster 1), George Street (cluster 3) and Harris Street (cluster 2). These streets are indeed among the busiest in terms of pedestrian activity in the studied area. Figure 7.14 shows the contextual circumstances for all the locations identified as significant. The clusters that were highlighted with this ranking method are not the same as the clusters identified as significant with the user based ranking; the highlighted clusters from the user-based ranking in Figure 7.12 have 6 to 11 users, while the significant clusters from the betweenness centrality-based ranking have 3 to 4 users. These differences are expected, as the user-based ranking is a measure reflecting the responses of the studied population, while the betweenness centrality-based ranking reflects the potential future impact.

Figure 7.15 shows the results of the extraction of contextual information for each cluster. In this case, the contextual analysis of each cluster is supported by quantitative data that assist the researchers in extracting patterns in the spatial behaviour of physiological responses. Until now, this analysis had to be conducted manually by finding photos for each cluster. The quantitative analysis was rare and involved comparing all hotspots with all non-hotspots, without extracting unique information for each cluster. This part of the analysis is thus one of the most valuable features enabled with the cluster separation with the DBSCAN algorithm, as it allows the abstraction of meaningful contextual information for each cluster and the comparison of this information between different clusters.

The information presented in the figure shows that clusters A, C and D are similar in all the presented parameters (POI density, traffic, activity, changes in activity, changes in traffic, changes in density). The changes in activity, traffic and POI density are at a low level for all parameters; the traffic is at low to medium levels, and the POI density is at medium levels. This observation suggests that among the studied parameters, the possible contextual stressors at these three clusters were the POI density levels. Cluster D also has very high traffic levels, which is an additional potential stressor in that case. These characteristics can be confirmed from the photos shown in Figure 7.14.

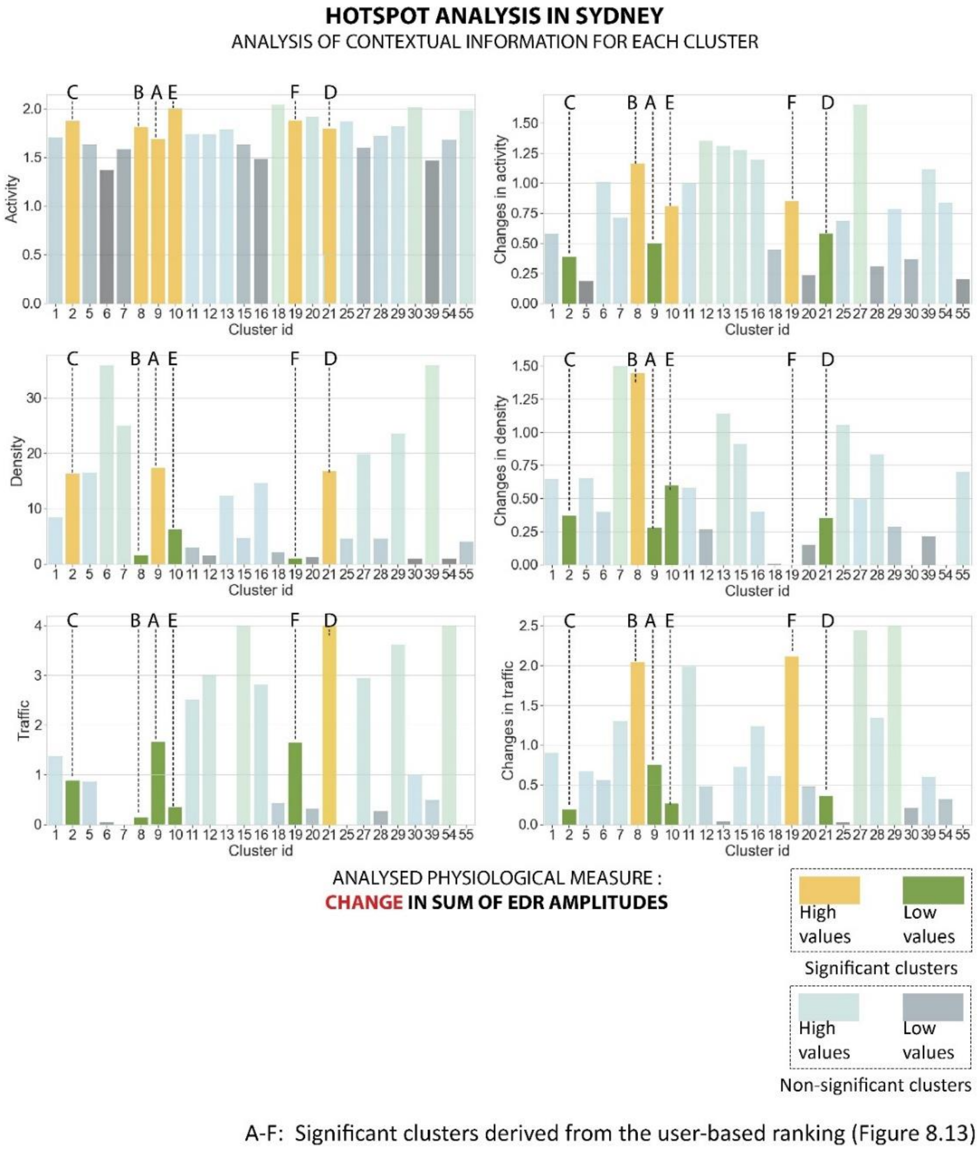


Figure 7.15. Extraction of contextual parameters for each cluster.

Clusters B, E and F, are characterised by lower POI density and traffic (apart from F which has slightly higher traffic). In these three clusters there are more profound changes in activity compared to the other three clusters (A, C and D). In clusters B and F, there are also significant changes in traffic, meaning that the participants' routes contained some points with very different traffic levels before arriving at that cluster. Cluster B is also characterised by intense changes in activity and POI density. As shown in Figure 7.14, cluster B is located on a quiet street with a high presence of vegetation. This street is surrounded by places with high traffic, pedestrian activity and presence of cafes and retail, and these factors explain the significant changes in POI density that were identified from the analysis of this cluster, as the users have to traverse the highly busy points before arriving at the quiet area in cluster B.

Clusters A, C and D thus seem to be possible sources of overstimulation due to their high degree of mixed-use, as captured by POI density levels. In these cases, some possible interventions could include enhancing the green space, redesigning the urban space in a way that reduces the visual complexity and intensity of stimulation, or lowering the intensity of retail and commercial use in the area. Clusters B and E, on the other hand, contain lower levels of sources of stimulation but are characterised by more changes in activity and stimulation levels compared to the other three clusters. In these clusters, the physiological responses may be more related to changes in activity that occur either due to nearby urban factors such as traffic lights or personal factors and decisions.

7.4. DISCUSSION

The methods for spatial analysis of physiological responses which were analysed in this chapter compose component 2 of the designed methodology. As demonstrated with the two examples presented in this chapter, the proposed methods for cluster identification and spatial analysis helped extract meaningful knowledge from the provided data. The cluster separation and ranking methods were very assistive for filtering out redundant information; this was particularly important for the Sydney dataset, which contained a high volume of data that was sometimes only reflective of the activities of one or two users. The contextual analysis based on each cluster's attributes was also able to integrate activity recognition in the cluster analysis.

The ranking measures that were used for cluster importance analysis have a different interpretation when the study is conducted in a predefined route, as opposed to an unconstrained setting where the participants follow their daily routines in different parts of the city. In the predefined route setting, the user based ranking is, in this case, a good indicator of impact among the studied group, as there are no differences in the paths of the participants. The betweenness centrality based ranking was not of high importance there, as the study area was small, and it was easy to identify which areas have higher pedestrian activity with some research of local sources. The calculation of a response intensity-based ranking could be added as a third measure here.

In the second scenario of the free-living activities setting, the user based ranking tended to prioritise points where there is a convergence of users. In studies focused on people who belong to the same organisation, the clusters with most users are expected to be found around this environment. This effect should be taken into account in order to avoid any misinterpretation of the results. As for the betweenness centrality based ranking, this method is more meaningful in this scenario than the predefined route setup, as in the free-living activities scenario there is a high volume of data points and many emerging clusters. The betweenness centrality based ranking can help identify which clusters are positioned in a critical place in the urban fabric, and if combined with the other rankings, it can be a useful filter for selecting the most important clusters from all aspects. The combination of rankings is the most meaningful approach for identifying which places would be in the most urgent need for intervention. Finally, the response intensity-based ranking that was proposed before in the context of the predefined route study should not be trusted in the free-living activities scenario. In this case, the duration of activity and the ambient temperature may influence the responses, as shown in Chapter 6. Clusters with a less intense average response thus could be the result of an activity that does not involve the same exertion levels, or that was recorded during a less hot day. For this reason, the response intensity-based ranking was not implemented in this chapter, but its application is relatively straightforward and can be considered for studies where it makes sense.

One advantage of this method is that it is closely connected to network analysis methods. This link creates future opportunities for using the derived information and embedding the cluster locations in the street network data to enrich network analysis. This integration could be conducted by finding the closest cluster for each network link or node and embedding in the network data the information of the cluster (such as the intensity of the physiological responses) as additional attributes of the corresponding link or node. This information can be then used in multiple ways; for instance, in studying if network centrality metrics are related to physiological responses, or selecting the optimal route based on avoiding stress hotspots and minimising stress levels. Chapter 9, which focuses on pathfinding methods, provides an example of route optimisation, which includes integrating physiological responses into network analysis.

Future experiments could involve the calibration of the proposed methods so that they can be used for the analysis of other physiological data, such as HR. Another point for further development is the inclusion of more urban features as attributes in the calculation of betweenness centrality. Other centrality measures could also be added or considered as alternatives. Another approach could be to include other forms of estimation of pedestrian activity, such as an analysis based on social media data (Beiró et al. 2016). The actual pedestrian activity data can also be used if it can be retrieved from providers such as Google or local authorities. These possible improvements can happen without affecting the other cluster analysis methods.

Finally, it should be pointed out that the chosen values for several of the parameters that were considered for the calibration of the clustering and ranking methods are based on the characteristics of the studied data. For best results, some brief experiments for recalibration should be conducted before applying these methods in a different scenario. This study was able to show the different results that each range of parameters may create, and give some guidelines in terms of matters that need to be considered in future experimentations. Some other parameters or choices in terms of algorithms were held constant for the time being, and future experimentation should also cover these aspects. For instance, the identification of hotspots was based on the extraction of the Local Moran's I values, but the Getis Ord Gi* method could also be used for this purpose. The choice of the number of minimum samples for the identification of a cluster in the DBSCAN algorithm should also be finetuned in studies which contain massive datasets and more users. Future experiments shall extend the current work and cover these aspects wherever possible.

After concluding the presentation of methods related to component 2 of the proposed methodology for collection and analysis of physiological responses in the urban environment, the next chapter shall present work related to component 3.

8

MACHINE LEARNING METHODS FOR PREDICTION OF PHYSIOLOGICAL RESPONSES IN THE URBAN ENVIRONMENT

8.1. INTRODUCTION

The previous chapter presented work related to the spatial analysis of physiological responses, connected to component 2 of the proposed methodology for collection and analysis of physiological data. The methods presented in that chapter are most useful for analysing data collected from multiple users, although they can also be used to analyse data from an individual, after small modification.

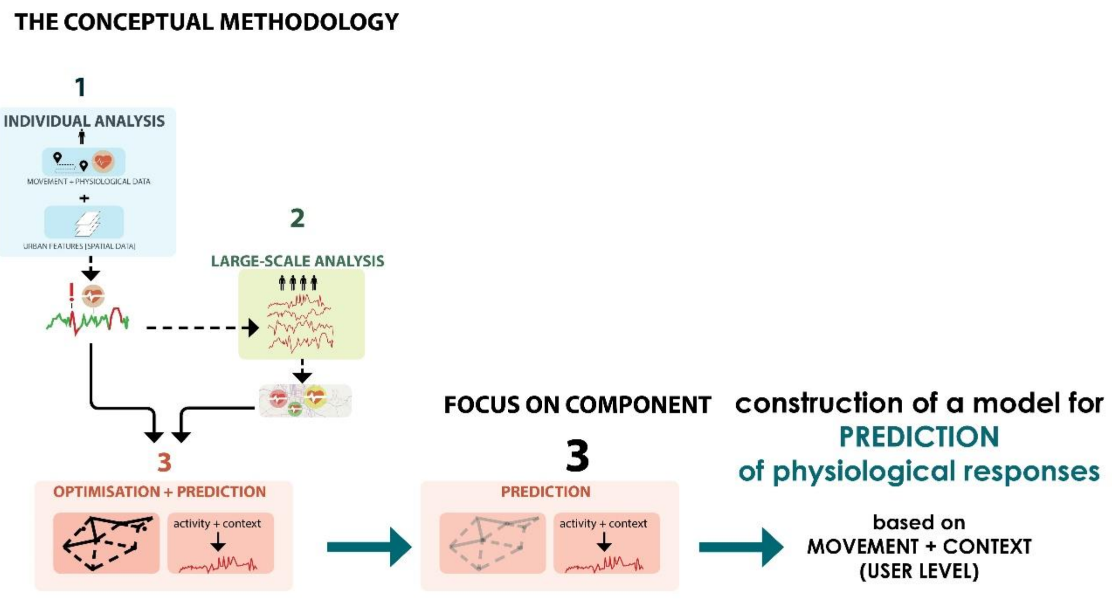


Figure 8.1. The aim of the chapter and the connection with the conceptual methodology.

This chapter moves the focus to the user scale by exploring methods for predicting physiological responses during individual routes based on movement and contextual features. The contribution of this chapter to the proposed methodology is related to component 3 (Figure 8.1). The methods for prediction of physiological responses which will be presented here compose one strand of this component. The other strand, which is related to pathfinding methods, will be presented in the next chapter.

As discussed in Chapter 1, most studies on physiological responses collected with wearable technologies in the urban space used the collected data to infer which urban or environmental features may affect physiological or affective responses. Chapter 6 also adopted a similar approach; the goal there was to identify if there is any relationship between urban context, activity and physiological responses, following the conceptual framework presented in Chapter 3. As explained in the research methodology (Chapter 2), this information helps understand how the urban environment influences the human body.

This chapter explores similar grounds but uses a different framing of the problem. The task at hand here is to identify if it is possible to obtain a satisfactory prediction of physiological responses, given a set of urban and contextual variables. The focus this time is on producing a model that everyday users can use to analyse how they interact with their environment, and estimate their physiological responses based on their activity data, intertwined with contextual information. The term prediction, in this context, does not refer to forecasting future physiological responses, but to estimating physiological responses from data obtained in routes conducted in the past. In a real-world application, this type of analysis would allow a user to know how intense were the estimated physiological responses of a user during a walk outside, based on the different qualities of the urban environment and other features.

The focus of this chapter will be on the prediction of the sum of the EDR amplitudes. This feature is used as an indicator of the intensity of physiological responses. It was also used in the inferential analysis in the previous chapter, and in the demonstration of the methods of component 1 using data from two users in Chapter 5. The term 'physiological responses' in this chapter will be used referring to this feature.

Since EDA features are widely used indicators of stress levels, the knowledge of their intensity levels during different environments and activities is essential for understanding how different circumstances affect our bodies. This knowledge would be particularly useful for individuals who suffer from stress or anxiety-related disorders and would like to avoid circumstances which make their experience stressful. The percentage of the population that owns an EDA tracking wristband is though currently small. Thus, it would be of use if this gap could be covered by a model that would indicate the intensity of physiological responses without having any physiological data in its input features. The question is, therefore, if there exists an underlying structure between contextual characteristics, activity and physiological responses, and if it can be captured adequately by a predictive model.

While it is evident that predictive modelling has a lot to offer from the perspective of predicting stress, emotions or physiological arousal based on the context, very few studies have incorporated predictive analysis of physiological responses in the outdoor environment. Most of these studies approached this as a classification problem towards predicting physiological arousal (Ojha et al. 2019; Yates et al. 2017), and emotions (Kanjo et al. 2018b; Flutura et al. 2019). Benita and Tunçer (2019) also framed it as a regression problem for the prediction of physiological measures. EDA was used in all these studies as an indicator of stress or emotional or physiological arousal. The contextual features which were most commonly used were noise, temperature and other environmental data, which were collected as time series data in parallel to movement and physiological data monitoring. Ojha et al. (2019), for instance, used environmental features as input for the prediction of physiological arousal and achieved high accuracy. Benita and Tunçer (2019) used urban and environmental features, and their results were promising with moderate predictive power. Air temperature appeared to be particularly important, highlighting the importance of shading and green space. Kanjo et al. (2018b) experimented with different modalities (physiological, environmental and location data) for the prediction of emotions. In their study, the combination of all modalities led to significantly better accuracy compared to using only one of the data categories. In Yates et al. (2017), the best results for the prediction of arousal were obtained by using physiological and movement data.

In this context, the paper explores different models for predicting physiological responses in the outdoor environment, using a multimodal dataset which combines movement and contextual data. The main focus is on machine learning (ML) models, as the few previous studies that incorporated predictive analysis indicated that ML approaches were the most suitable for handling the complexity of the task at hand.

It is also important to note that the predictive analysis conducted in this chapter is not mutually exclusive with the inferential analysis conducted in Chapter 6. On the contrary, the previous inferential analysis and the current predictive analysis are seen as two pieces belonging to the same puzzle and complement each other, while being able to operate independently for different purposes. The goal of the inferential analysis presented in Chapter 6 was to understand the relationship between different features and physiological responses. The aim of the predictive analysis presented in this chapter is to predict physiological responses based on a combination of the input features, having as a goal the maximisation of the accuracy of the model. In the case of predictive analysis, there is more freedom in terms of experimentation with different combinations of variables without having to fix issues of multicollinearity. The relationship between the variables and the output is sometimes examined, but it is not the primary focus. Predictive modelling techniques often include 'black box' models that involve unexplainable functions. These models may increase the predictive ability, but they cannot be used for understanding the underlying process that drives the phenomenon. The inferential analysis of the previous chapter was, thus, more focused on the relationship between the variables, while the predictive analysis of this chapter aims at the construction of a model with satisfactory predictive power.

The rest of the chapter is organised as follows: section 8.2 elaborates on the dataset characteristics, the methods used for feature preparation, the separation of the initial problem in a classification and regression task, and the ML models which were used. Since the focus was on constructing a model with a good predictive performance and not on inferential analysis, the study was not constrained by the use of interpretable models, but a feature importance analysis component was also added for the models that allowed it. Section 8.3 presents the results of the classification and the regression tasks, comparing the performance of the different models and elaborating on the outcome of the feature importance analysis. Finally, section 8.4 discusses the overall findings and presents conclusions and future directions. The code related to the methods designed for this component can be found in GitHub[8].

8.2. METHODS

8.2.1. DATASET

The dataset which was used for the predictive analysis in this chapter was the combined dataset, containing all the available data from Sydney and Zürich, from 37 users in total. This dataset contains the data collected in Sydney during a predefined route and free-living activities, and the data collected in Zürich from the team of Ojha et al. (2019), during a predefined route. The combined dataset thus includes data which correspond to the same route conducted multiple times, as well as different completely unrelated routes.

Some sessions which mostly contained data collected while the participants were sitting while using public transport were omitted. After removing these sessions and combining the data from the free-living activities and the predefined walking routes, and resampling at 1 second, the combined dataset had 490711 samples. From those samples, 34658 data points belonged to data collected in Zürich; 41971 belonged to data collected in Sydney during the predefined route experiment, and the rest were collected during free-living activities in Sydney. The majority of the data points thus come from the free-living activities dataset in Sydney.

8.2.2. DATA ANALYSIS

The predictive task that was the objective of this study was approached in two different ways: as a classification and a regression problem. In the regression problem, the aim was to predict the sum of EDR amplitudes. As explained in the previous chapters, this

[8] https://github.com/ddritsa/PhD-Thesis-repository/tree/main/3rd%20component/Prediction

feature provides a combined description of the frequency and intensity of EDRs, as it is based on the summation of all EDR amplitudes in 1-minute time windows.

In the classification problem, the task was to predict if the sum of EDR amplitudes would be above zero or not in each data segment. If the sum of EDR amplitudes was above zero, this meant that there was at least one EDR in this segment, thus suggesting the presence of a physiological response.

The dataset contained physiological, movement and contextual data. The input and target variables were extracted using the data fusion model described in Chapter 5. The methods described in this chapter, therefore, presuppose the application of the methods described in Chapter 5 (excluding the final step of the classification of physiological responses, presented in section 5.2.5.3). The data fusion was conducted separately for the data collected in Sydney and Zürich, and then the two datasets were combined.

For the regression task, the target feature ('sum of EDR amplitudes') was log-transformed and normalised. Before the log transformation, a constant value (1) was added to the data to avoid having zero values. The regression task was split into two approaches that were tested sequentially. The first approach that was followed did not include any biometric data in the input features. The second approach involved the prediction of the sum of EDR amplitudes feature as the first step, using a time window size of 240 seconds, and then the utilisation of the predicted sum of EDR amplitudes of the previous three minutes as an additional input feature for the final prediction.

For the binary classification task, two classes were created; one class ('class 0') for the segments where the mean value of the target feature ('sum of EDR amplitudes') was at zero levels, and one ('class 1') for the segments where the mean value of the target feature was greater than zero. This classification was used to identify any segment where there was an EDR amplitude. Class 0, therefore, indicated the absence of a physiological response, and Class 1 indicated its presence. The two classes were relatively balanced (48-52% presence in each class) in all the classification experiments presented here.

A non-overlapping window was used for the segmentation of the time series. The window size ranged from 10 to 240 seconds in the experiments conducted for the classification task and 60 to 360 seconds for the regression task. The lower and upper bounds of the time window size were chosen experimentally for each task, after determining that there would be no improvement if these limits changed significantly.

Some additional features were also computed during this segmentation. This included some other features describing the distribution of the 'POI density' variable (*mean POI density, STD of POI density*) and some lagged features (*previous activity intensity, previous POI density, previous traffic light*). The new features related to POI density were constructed by extracting descriptive statistics for POI density (mean, minimum, STD) for each time window. Then they were log-transformed. The lagged features were constructed by extracting the values of each feature from the previous time window. For instance, the 'previous activity intensity' feature for a time window contained the values of the 'activity intensity' feature of the previous window.

Two features related to change in POI density and traffic (*POI density change, traffic change*) were also added. These features were calculated by splitting the data into 1-minute segments and finding the absolute difference between the feature in each segment and its previous one. Binary coding (0,1) was used to indicate the presence of a change. If the change was significant (exceeding one STD based on the values presented in Figure 6.2a and 6.2b), the feature was given the value of 1. The same procedure was followed in Chapter 5 for the calculation of significant changes in physical and psychological stressors (section 5.2.5.2).

Other transformations which were applied specifically for the predictive models included raising the 'duration of activity' feature (which expressed the minutes since the activity started; see section 5.2.3.2.3 in Chapter 5) to the power of four, and then applying a log transformation. Normalisation was also applied to all the features. These transformations were applied to the data only for the predictive modelling methods in this chapter. They were selected after multiple experiments for finetuning each parameter and were added to achieve better predictive performance. Nineteen features were selected as input variables. These features can be organised in two modalities (movement and contextual data). Each modality contained the following features:

- *Movement data: Duration of activity, activity intensity, change in activity, change in activity state, speed, steady-state, derivative of steady-state, derivative of activity intensity, previous activity intensity, previous speed.*
- *Contextual data: mean POI density, traffic, traffic change, POI density change, previous POI density, STD of POI density, traffic light, previous traffic light, ambient temperature.*

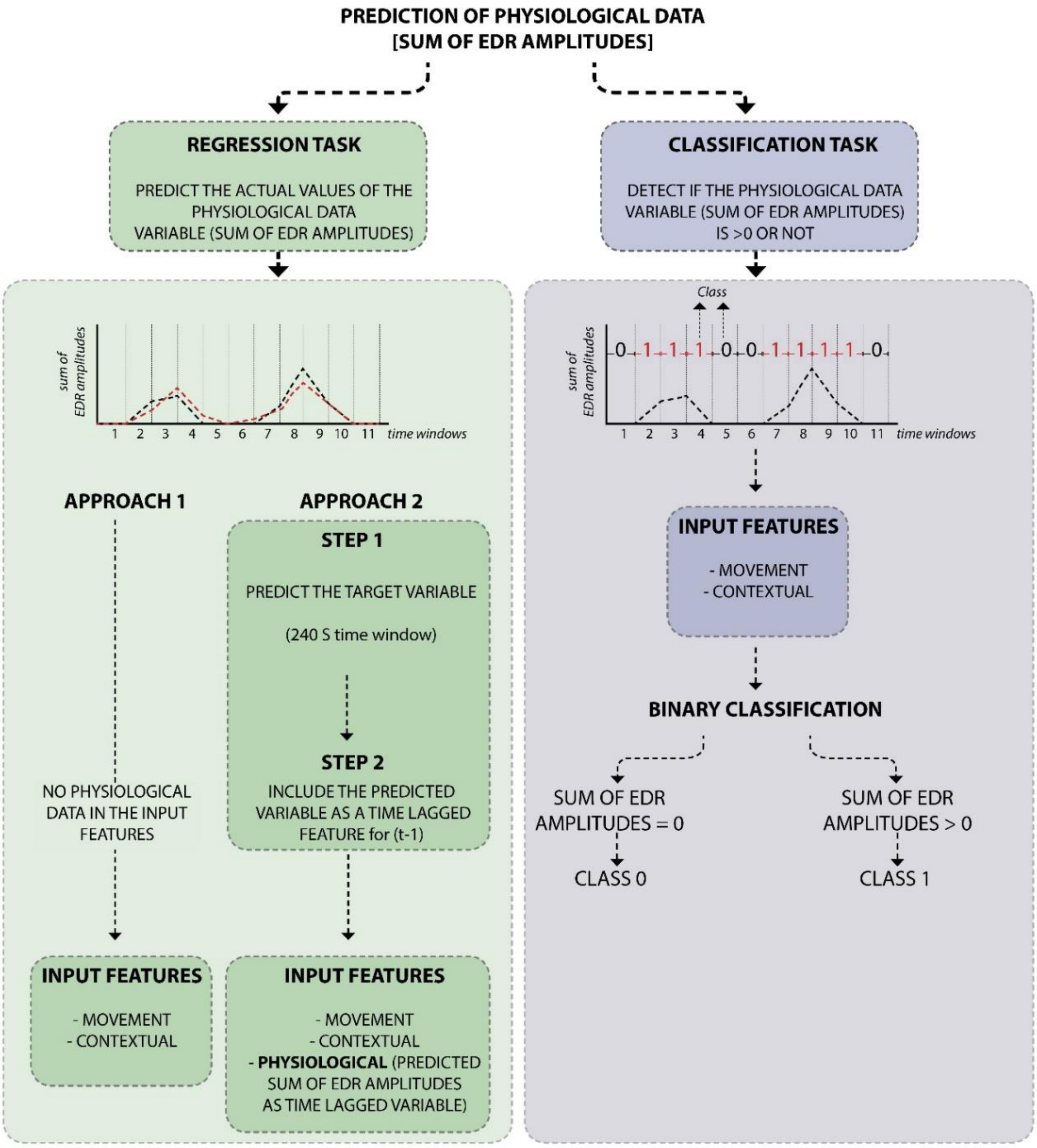


Figure 8.2. Description of the workflow adopted for the prediction of the target variable

The characteristics of the features are reported in Figure 6.2a and 6.2b in Chapter 6. The characteristics of the lagged features are not reported there, but they are the same as in the features from which they originated.

The overall workflow is presented in Figure 8.2.

Figure 8.3 provides further clarification of the two scenarios that were tested in the regression task and the underlying assumptions regarding the context of the prediction.

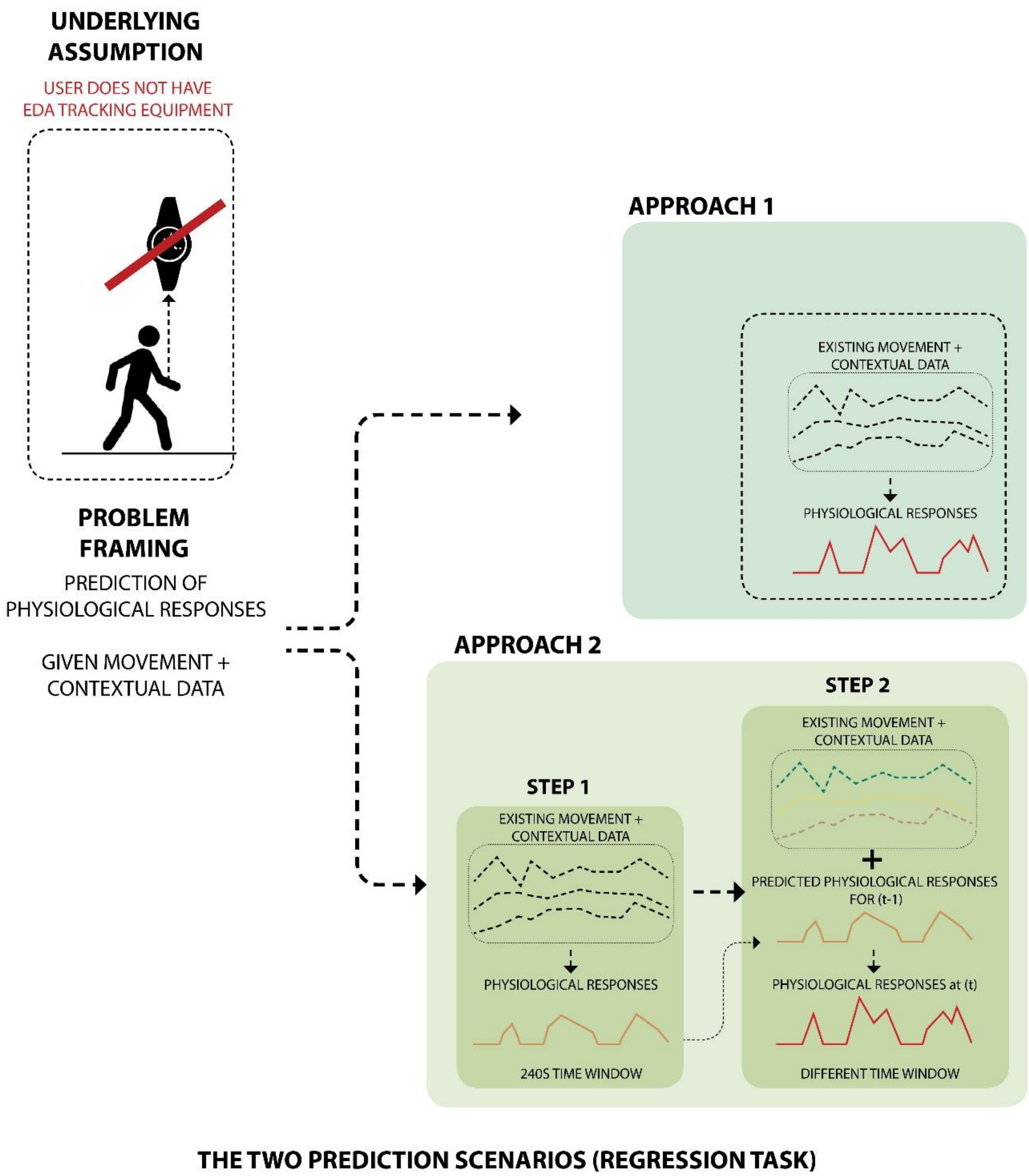


Figure 8.3. Presentation of the two approaches that were followed in the regression task.

The idea behind the second approach in the regression task was based on some initial experiments, where the problem was framed as a one-step-ahead forecast scenario. These experiments showed that the inclusion of a time-lagged feature (describing the sum of EDR amplitudes value in the previous two or three minutes before the moment of the actual prediction) resulted in a tremendous improvement in the prediction, with very small mean squared error values. In real-world circumstances, this kind of prediction would be a part of a different scenario, where the user has an instrument that collects EDA data, and while they are walking, this algorithm would take the current EDA data and use that as input for the prediction of the target feature in the next minute. This setup would thus be a prediction on-route, like a scenario where a user wants to predict their physiological responses in a few minutes from now, based on the current physiological responses. An example is given in Figure 8.4.

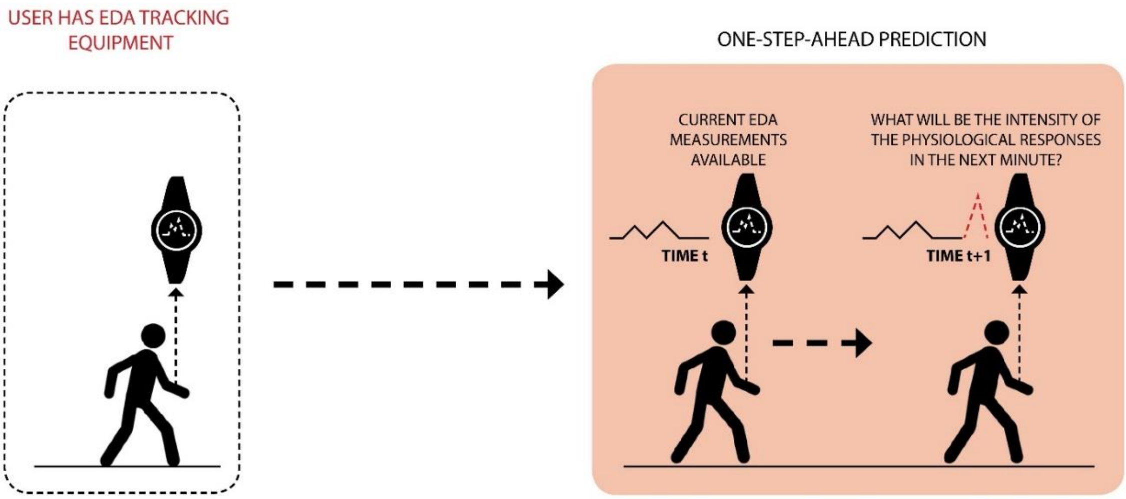


Figure 8.4. An alternative problem framing that can be considered in the future.

In this study though, the aim was to predict the target feature (sum of EDR amplitudes) without having any EDA data, apart from those collected during routes conducted in the past, from other users. The scenario presented in Figure 8.4 was thus not explored further. The framing of the problem which was adopted (presented in Figure 8.3) was chosen since the wristbands that track EDA are not as widely used as those that track HR, and an algorithm that would make an on-the-spot prediction of future values based on current EDA features would be less applicable than an algorithm without any EDA features. The other scenario can be certainly considered in the future when the wearable EDA trackers will become more popular and affordable.

8.2.3. MACHINE LEARNING METHODS

Six supervised ML algorithms were tested for each of the predictive modelling tasks; support vector machine (SVM), k-nearest neighbors (k-NN), random forests (RF), convolutional neural network (CNN) and long-short term memory network (LSTM). The models were introduced in Chapter 4 (section 4.2.2.2). RF and XGBoost are ensemble methods, while the CNN and LSTM models are classes of deep neural networks.

The rest of this section provides a brief description of the architecture and hyperparameters of the models. For the SVM, RF, k-NN and XGBoost models, the hyperparameters were tuned with randomised grid search.

In the SVM models for regression and classification, the radial basis function (RBF) was used in terms of the kernel parameter. In the SVM regressor, the gamma was also set to 0.0005. In the k-NN regressor and the k-NN classifier models, the number of neighbours was set to 10. In the RF regressor, the number of trees was set to 300, the maximum depth of the tree was 4, and the minimum samples for the leaf nodes were 5. The RF classifier used the same setup. In the XGBoost regressor, the number of trees was 1000, the maximum depth of the tree was 6, the L1 regularisation parameter was set to 0.01, the gamma parameter was set to 3, and the learning rate was 0.01. The hyperparameters for the XGBoost classifier were as follows: the number of trees was set to 100, the maximum depth of the tree was set to 6, the L1 regularisation parameter was set to 0.01, the gamma parameter was set to 10, and the learning rate was 0.1.

For the two deep learning models (CNN and LSTM), the initial experiments involved models of different depth and width, until the selection of the best-performing ones. The selected structure of the CNN model contains two convolutional layers, each followed by a max-pooling layer of size (2,) and a dropout layer (0.2). The first convolutional layer has 256 filters, and the second has 64. A dense layer of 64 neurons follows, then another dropout layer (0.5) and an output layer of one neuron. This setup (shown in Figure 8.5) was followed for both tasks, with the only modification being the addition of another neuron in the output layer for the classification task.

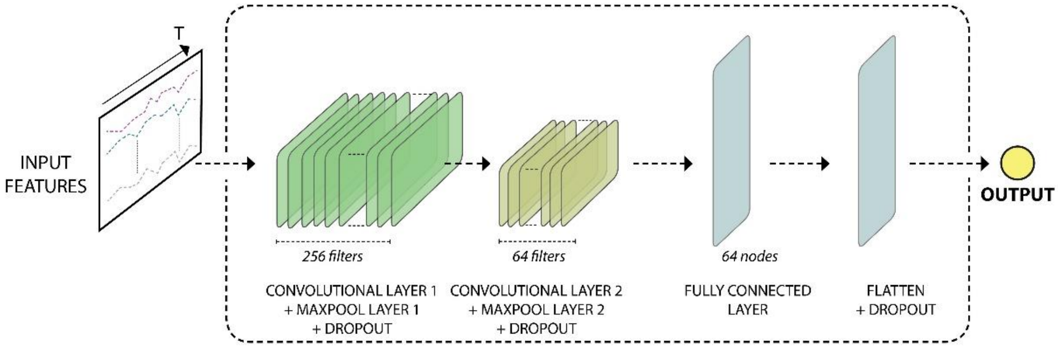


Figure 8.5. CNN architecture

The LSTM model selected for comparison with the other models consists of an LSTM layer of 256 units, followed by a dense layer with 64 neurons, and an output layer with one neuron (or two neurons in the classification task). The state of the network was manually reset after each training epoch. The online training method was used, with each batch containing data from a single time window. The model architecture is presented in Figure 8.6.

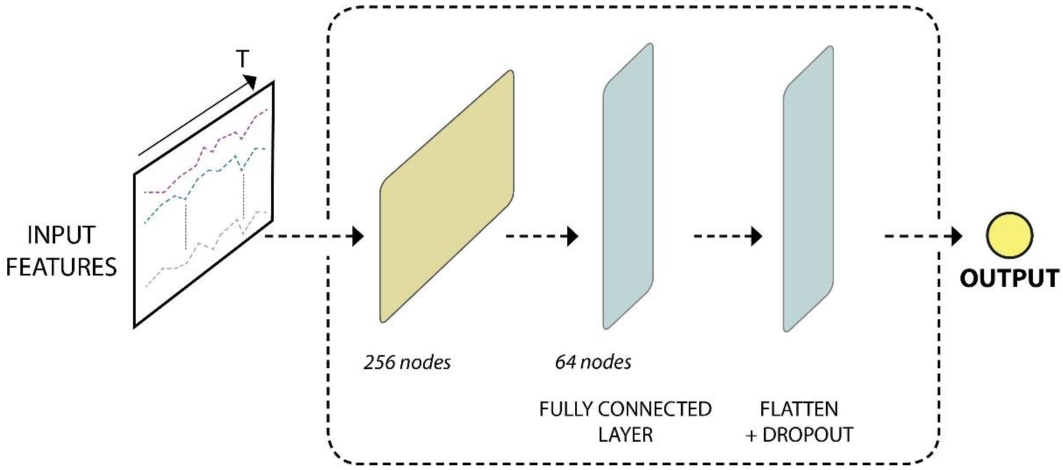


Figure 8.6. LSTM architecture

The *scikit-learn* Python library was used for the RF, SVM and XGBoost models, and the *Keras* Python library was used for the LSTM and CNN models, with Tensorflow as backend. The ADAM algorithm was used for optimisation. The mean squared error

(MSE) loss function and the binary cross-entropy function were used as the loss function in the regression and the classification task, respectively.

The predictive performance of the models was assessed with 4-fold and 5-fold cross-validation in the classification and regression tasks, respectively. The 80:20 ratio was used for the creation of the training and testing dataset. Each time, data from 29 to 31 different participants were used to develop a predictive model, and new data from 6 to 8 users were used to test the model's performance. This variation in the number of users in each fold was adopted since some users generated more data than others, and the 80:20 ratio had to be kept. Finally, the metrics used for performance assessment of the classification models were the *accuracy, precision, recall and F1 score*.

8.2.4. FEATURE IMPORTANCE IDENTIFICATION

The selection of significant features for the best-performing algorithms was conducted with the feature importance module of the *scikit-learn* API. The algorithm was applied to the most successful algorithm for each task if the algorithm allowed it, and the process was repeated for different window sizes, from 60 seconds to 360 seconds. A rank was given to each feature based on its score in that window size, reflecting its importance. The rank was based on the number of standard deviations above the mean value of the extracted array of feature importance values; the rank 0.5 was given to features that had a score that was higher than 0.5 STD above the mean, and so on, with the maximum rank being 5 (equal to 5 STD above the mean).

8.3. RESULTS

8.3.1. CLASSIFICATION

8.3.1.1. MODEL COMPARISON

As Figures 8.7 and 8.8 show, the model which had the best performance was the RF classifier, achieving 72.5% to 73% accuracy for all the studied window sizes. The XGBoost classifier achieved the second-best performance. The other models had accuracy between 60% and 70% for all window sizes, with the CNN model achieving 63-67% accuracy and the LSTM and k-NN models achieving between 60-63% accuracy.

	FREQUENCY	CNN P	CNN R	CNN F1	LSTM P	LSTM R	LSTM F1	RF P	RF R	RF F1
Class 0	30s	0.69	0.5	0.57	0.55	0.57	0.6	0.73	0.63	0.66
Class 1		0.67	0.82	0.73	0.67	0.55	0.6	0.73	0.8	0.74
Accuracy		65%			62.5%			72.5%		
Class 0	60s	0.7	0.57	0.62	0.61	0.75	0.67	0.75	0.68	0.7
Class 1		0.65	0.77	0.69	0.69	0.52	0.58	0.73	0.77	0.73
Accuracy		67%			63%			73%		
Class 0	90s	0.67	0.58	0.61	0.63	0.88	0.73	0.76	0.71	0.72
Class 1		0.62	0.7	0.64	0.66	0.3	0.4	0.71	0.75	0.72
Accuracy		63%			62%			72.5%		

	FREQUENCY	KNN P	KNN R	KNN F1	SVM P	SVM R	SVM F1	XGBOOST P	XGBOOST R	XGBOOST F1
Class 0	30s	0.57	0.56	0.56	0.74	0.52	0.6	0.68	0.63	0.64
Class 1		0.64	0.66	0.64	0.7	0.82	0.73	0.72	0.76	0.73
Accuracy		60%			67%			70%		
Class 0	60s	0.68	0.66	0.65	0.7	0.62	0.64	0.72	0.68	0.69
Class 1		0.61	0.62	0.59	0.65	0.72	0.67	0.71	0.74	0.73
Accuracy		63%			67%			71%		
Class 0	90s	0.62	0.69	0.65	0.68	0.69	0.67	0.75	0.65	0.68
Class 1		0.62	0.56	0.58	0.66	0.64	0.64	0.71	0.73	0.71
Accuracy		63%			66%			71%		

Figure 8.7. Presentation of different metrics for all models at three window sizes

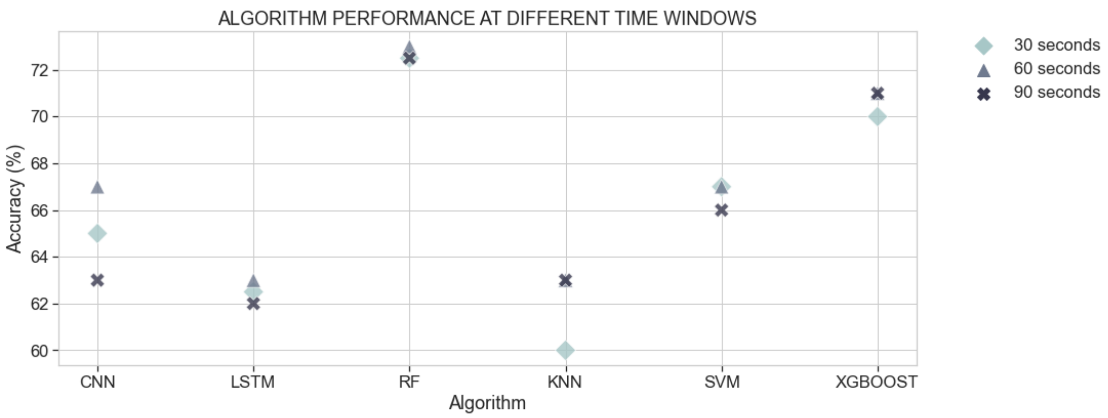


Figure 8.8. Comparison of accuracy levels for all models

Furthermore, as shown in Figures 8.7 and 8.9, the RF and the XGBoost classifiers had the most consistent performance in the different metrics, having similar scores for the recall values at all time window sizes, while the other models showed considerable differences in the recall values of the two classes. The LSTM model, for instance, had a particularly bad performance in the recall values when the window size was 90 seconds, with the recall score being 0.88 for Class 0 and 0.3 for Class 1 (Figure 8.7).

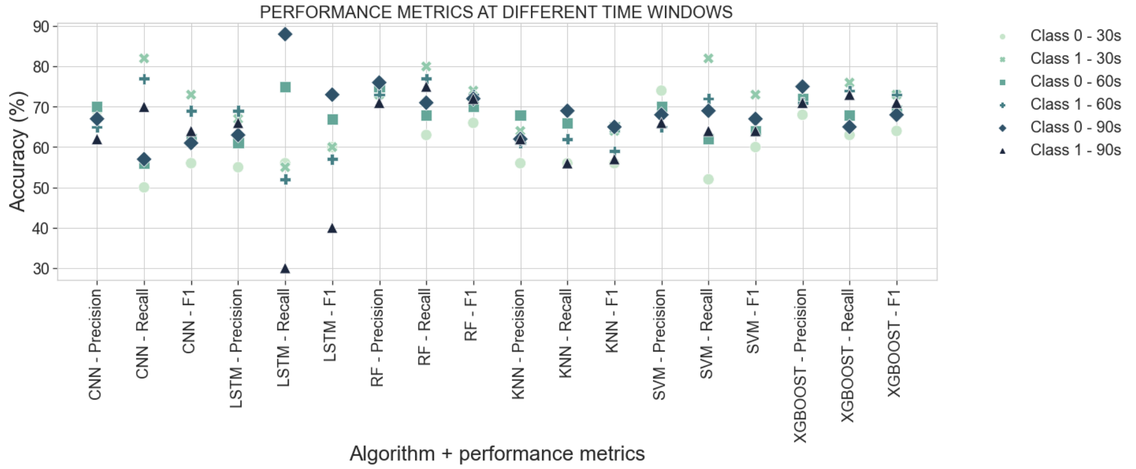


Figure 8.9. Performance metrics at different time windows for all models

After identifying the RF classifier as the most successful for the tested time window sizes, more experiments were conducted with this model, using the same setup in terms of hyperparameters, and a higher range of time window sizes. 4-fold cross-validation was used for testing the performance of the algorithm in different user groups.

RF Parameters: n_estimators=300,max_depth=4, min_samples_leaf=5

	TIME WINDOW														
	10s	**20s**	**30s**	**40s**	**50s**	**60s**	**70s**	**80s**	**90s**	**100s**	**110s**	**120s**	**150s**	**180s**	**240s**
User group 1	0.68	0.68	0.7	0.69	0.69	0.72	0.7	0.69	0.69	0.69	0.7	0.7	0.69	0.72	0.71
User group 2	0.71	0.7	0.71	0.72	0.71	0.72	0.71	0.71	0.72	0.72	0.72	0.73	0.71	0.75	0.73
User group 3	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.76	0.74	0.75	0.71	0.75	0.71	0.69	0.73
User group 4	0.72	0.75	0.74	0.73	0.74	0.74	0.74	0.74	0.75	0.74	0.74	0.73	0.73	0.72	0.7
Avg	0.715	0.72	0.725	0.7225	0.7225	0.7325	0.725	0.725	0.725	0.725	0.7175	0.7275	0.71	0.72	0.718

Figure 8.10. Accuracy score of the RF classifier for different time windows

As Figure 8.10 shows, the performance was similar for the majority of the tested time window sizes. User groups 3 and 4 had slightly better scores than user groups 1 and 2, but these differences were expected as there was significant diversity in the parameters of the activities that the user groups were performing. The average accuracy score from all user groups for each window size ranged from 0.71 (at a time window size of 150 seconds) to 0.7325 (at a time window size of 60 seconds).

TIME WINDOW	FEATURES									
	Current activity (intensity)	*Duration of activity*	*Previous activity intensity*	*Previous speed*	*Temperature*	*Speed*	*Traffic change*	*Mean POI density*	*Traffic light*	*Traffic*
60s	5	5	2	1	2	1	0	0	0	0
120s	5	5	2	2	3	2	0	0	0	0
180s	5	5	5	3	3	2	0.5	0	0	0
240s	5	5	4	5	3	0	1	0.5	1	0.5
300s	5	5	5	5	2	4	0.5	0.5	0.5	0
360s	5	5	5	5	1	4	1	2	1	1
Sum	30	30	23	21	14	13	3	3	2.5	1.5
Avg	5.00	5.00	3.83	3.50	2.33	2.17	0.50	0.50	0.42	0.25

TIME WINDOW	FEATURES									
	Change in activity (intensity)	*Previous POI density*	*Previous traffic light*	*STD of POI density*	*Steady state*	*POI Density change*	*Derivative of activity intensity*	*Change in activity state*	*Derivative of steady state*
60s	0	0	0	0	0	0	0	0	0
120s	0	0	0	0	0	0	0	0	0
180s	0	0	0	0	0	0	0	0	0
240s	0	0	0.5	0	0	0	0	0	0
300s	0.5	0	0	0	0	0	0	0	0
360s	0.5	1	0.5	0	0	0	0	0	0
Sum	1	1	1	0	0	0	0	0	0
Avg	0.17	0.17	0.17	0	0	0	0	0	0

Figure 8.11. Results of feature ranking according to their importance in different time windows

8.3.1.2. FEATURE IMPORTANCE ANALYSIS FOR THE CLASSIFICATION TASK

The final step in the classification task was the identification of features which had the highest importance in terms of predictive value. The RF classifier was used again, with the same hyperparameters as before. One test was conducted for each window size, and the features were ranked according to their score. The average and sum values of the scores for all window sizes for each feature reflect its importance among all window sizes. As shown in Figures 8.11 and 8.12, the most important features were the following: *current activity intensity*, *duration of activity*, *previous activity intensity* (the array of activity intensity values of the previous time window), *previous speed* (the array of speed values of the previous time window), *temperature* and *speed*. Figure 8.13 shows the feature importance ranking separate for each time window size, visualising the data presented in Figure 8.11. As shown in the figure, *current activity intensity* and the *duration of activity* were significant for all window sizes.

The lagged features (*previous activity intensity* and *previous speed*) were more significant in time windows of size 180 and 360 seconds, and *speed* was more important in time windows of a size larger than 240 seconds. Some contextual features (*traffic* *change, mean POI density, traffic light, traffic*) were also crucial in time windows larger than 180 seconds.

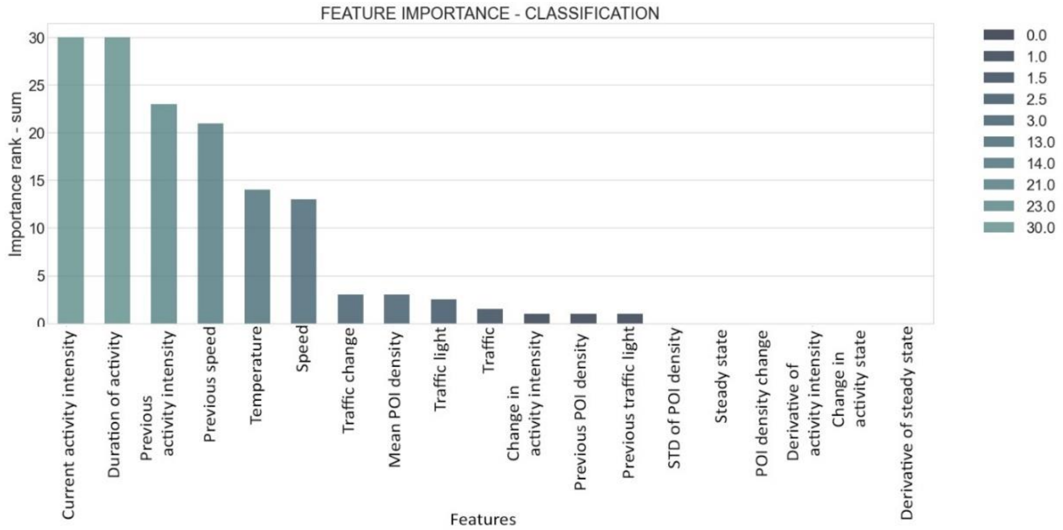


Figure 8.12. The sum of importance scores for each feature, based on the scores presented in Figure 8.11.

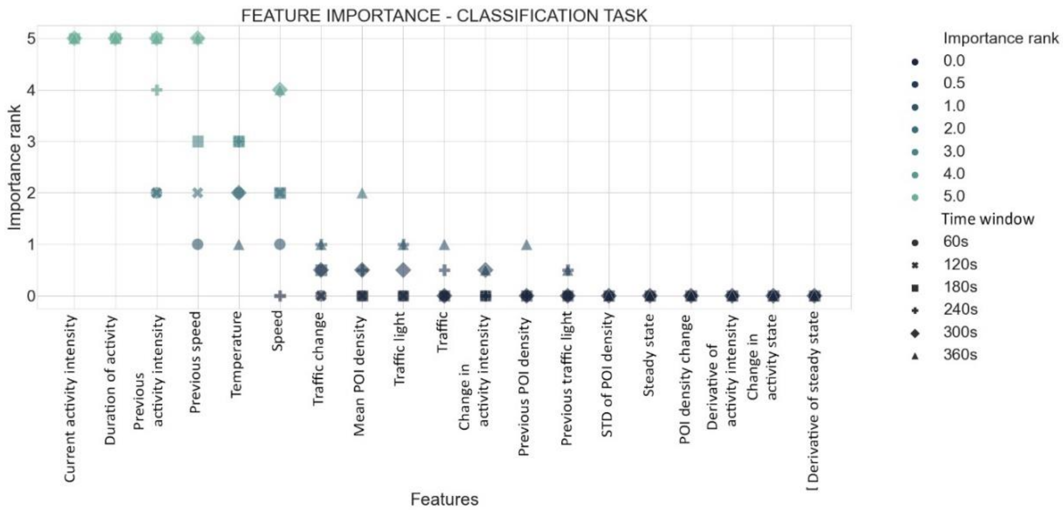


Figure 8.13. Detailed importance score for each feature.

8.3.2. REGRESSION

8.3.2.1. MODEL COMPARISON

This section elaborates on the results of the experiments related to the regression task. As shown in Figures 8.14 and 8.15, the tested algorithms had similar performance in terms of the obtained mean squared error (MSE) values. These results reflect the average performance from all five user groups together, obtained from the 5-fold cross-validation. The only exceptions were the performance of the SVM model at 180s window size, and of the CNN model at 360s window size; these two scores were much higher than the others (indicating worse performance), as shown in Figure 8.15.

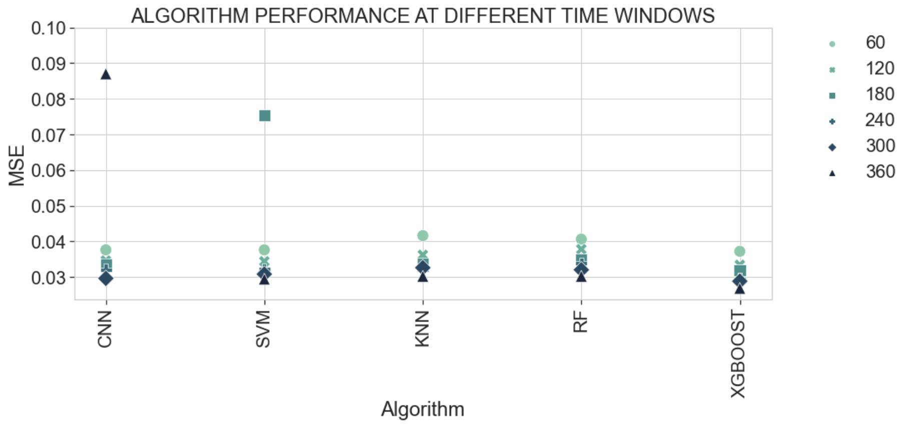


Figure 8.14. Presentation of the MSE scores for each model.

TIME WINDOW	MODEL				
	CNN	*SVM*	*KNN*	*RF*	*XGBOOST*
60	0.038	0.038	0.042	0.041	0.037
120	0.035	0.034	0.036	0.038	0.033
180	0.034	0.075	0.034	0.035	0.032
240	0.032	0.032	0.032	0.034	0.029
300	0.030	0.031	0.033	0.032	0.029
360	0.09	0.03	0.03	0.03	0.03
AVG	**0.042**	**0.040**	**0.034**	**0.035**	**0.031**

Figure 8.15. Presentation of the MSE scores for each model, at different window sizes.

The XGBoost model had the best performance, with average mean squared error equal to 0.031 and mean absolute error (MAE) equal to 0.12. The XGBoost model was followed by the k-NN model (MSE=0.034, MAE=0.143), the RF model (MSE =0.039, MAE=0.149), the SVM model (MSE =0.039, MAE=0.141) and the CNN model (MSE = 0.042, MAE=0.151).

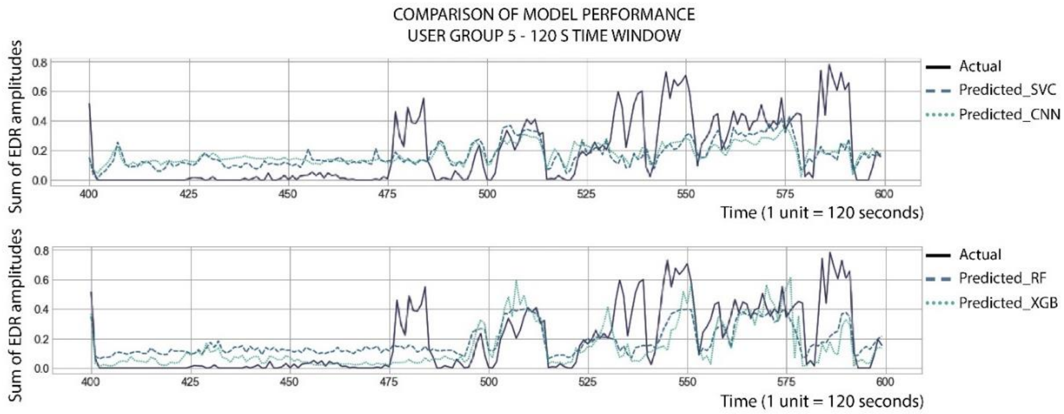


Figure 8.16. The actual and predicted values from the different models that were tested.

The ability of the tested models to predict the variations in physiological responses was also evaluated by observing the visual relationship between the actual and the predicted data. Figure 8.16 shows an example of this relationship using time windows of 120 seconds for one user group (containing data from 9 users). The graphs in Figure 8.16 were obtained during cross-validation, and show the performance of the models on unseen data, from the test dataset. Each data point in the figure presents the mean sum of EDR amplitudes data obtained from a single time window for one user. As shown in the figure, the models were able to capture the main underlying trends in the physiological responses and identify moments where the signals were elevated.

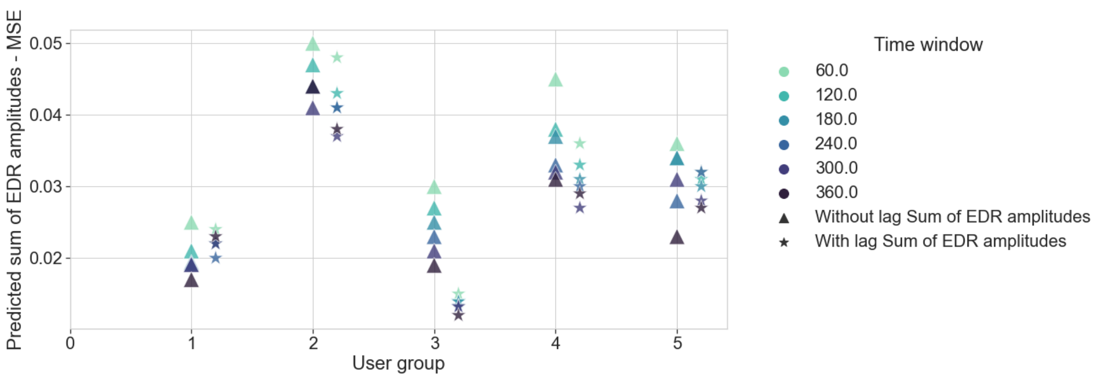


Figure 8.17. The MSE scores for each user group, using the XGBoost model, at different window sizes.

Based on these results, the XGBoost model was selected for further experimentation. The next phase of experiments involved testing the second approach that was introduced in section 8.2.2. The second approach had as its first step the construction of a model (‘Model A’) for predicting the target variable (sum of EDR amplitudes) using time windows of 240 seconds. Model A was then used during the preparation of the input features, for predicting the target value of the previous 240 seconds, and then using it as a lagged value and adding it to the input features. A new XGBoost model (Model B) was then constructed for the final prediction; the new model had, therefore, 20 features, as it included the new lagged value as predicted from Model A, and it was constructed using the same range of window sizes as before. The results of this approach are presented in Figure 8.17, next to the results of the model without the predicted lag feature.

As shown in the figure, the results of the different user groups in the 5-fold validation for the XGBoost algorithm vary. Groups 1,3, and 5 have a lower error in comparison to the other two groups. These slight differences were expected, and this method of cross-validation was used to identify such variations and test the behaviour of the algorithm in different groups that may have different contextual circumstances and varying intensities of physiological responses.

The second approach, with the introduction of the predicted physiological responses of the previous minute as a lagged variable, yielded better results for the majority of the predictions and was able to lower the average MSE of the two user groups that had slightly higher errors. More specifically, the second approach resulted in average 0.027 MSE compared to 0.031 MSE error without the lag feature. At the same time, the exploration of the second approach was experimental and there are concerns regarding the possibility of increased error in the final prediction, when there is significant error in the predicted lag feature. It could be considered as an option in studies on predictive modelling for physiological responses, but more experimentation is needed.

Figure 8.18 shows the performance of the selected XGBoost model against the actual (log-transformed and normalised) sum of EDR amplitudes values, confirming the model’s ability to capture the significant trends.

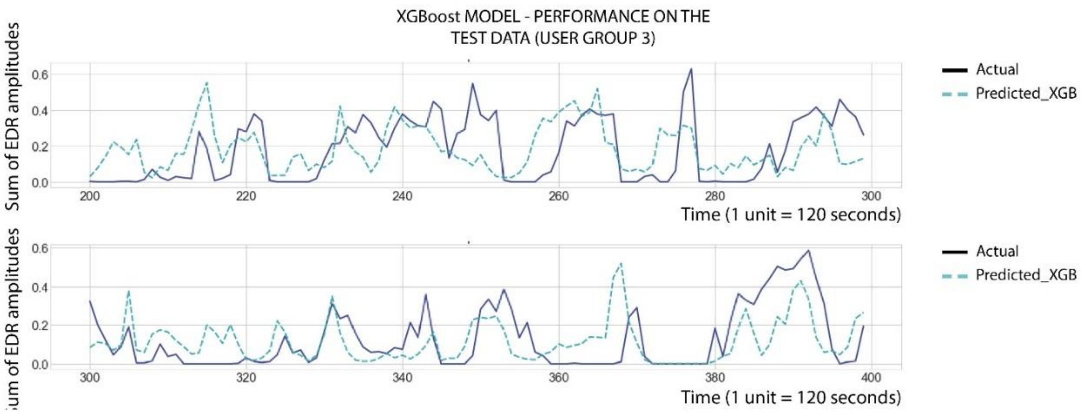


Figure 8.18. Comparison of the actual and predicted values for the selected XGBoost model.

8.3.2.2. FEATURE IMPORTANCE ANALYSIS FOR THE REGRESSION TASK

Finally, the process described in section 8.2.4 for feature importance identification was followed to understand which movement-related and contextual variables were the most crucial components in the process of generation of physiological responses, according to the selected XGBoost model.

The results of feature importance identification for the regression task are shown in Figure 8.19 and visualised in Figure 8.20. Figure 8.21 shows the sum of ranks for each feature, which indicates how important is this feature for all window sizes.

TIME WINDOW	FEATURES									
	Duration of activity	*Previous activity intensity*	*Previous activity*	*Temperature*	*Previous speed*	*Change in activity (intensity)*	*Previous POI density*	*Speed*	*STD of POI density*	*Traffic change*
60s	5	5	5	3	0.5	0.5	0.5	0	0.5	0
120s	5	5	5	4	2	0.5	0.5	0.5	1	0.5
180s	5	5	5	5	5	4	4	1	2	1
240s	5	5	5	5	5	3	3	1	1	1
300s	5	5	5	5	5	5	4	3	2	2
360s	5	5	5	5	5	5	3	4	2	4
Sum	30	30	30	27	22.5	18	15	9.5	8.5	8.5
Avg	5	5	5	4.5	3.75	3	2.5	1.58	1.42	1.42

TIME WINDOW	FEATURES								
	Steady state	*Mean POI density*	*Traffic*	*POI Density change*	*Previous traffic light*	*Traffic light*	*Derivative of activity intensity*	*Change in activity state*	*Derivative of steady state*
60s	0	0	0	0.5	0	0	0	0	0
120s	0.5	1	0.5	0.5	0.5	0.5	0.5	0	0
180s	1	1	1	1	1	1	1	0	0
240s	1	1	1	0	1	1	0	1	0
300s	1	2	1	2	1	1	1	1	0
360s	5	3	3	2	2	1	0.5	0.5	0
Sum	8.5	8	6.5	6	5.5	4.5	3	2.5	0
Avg	1.42	1.33	1.08	1.00	0.92	0.75	0.50	0.42	0.00

Figure 8.19. Feature importance analysis for the regression task, for each time window

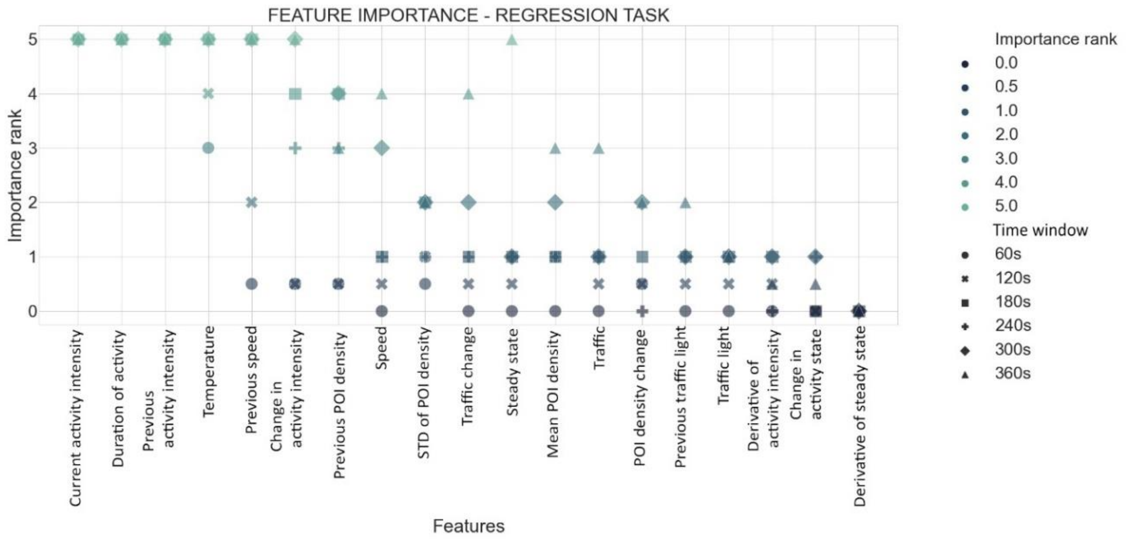


Figure 8.20. Visualisation of feature importance ranking for the regression task

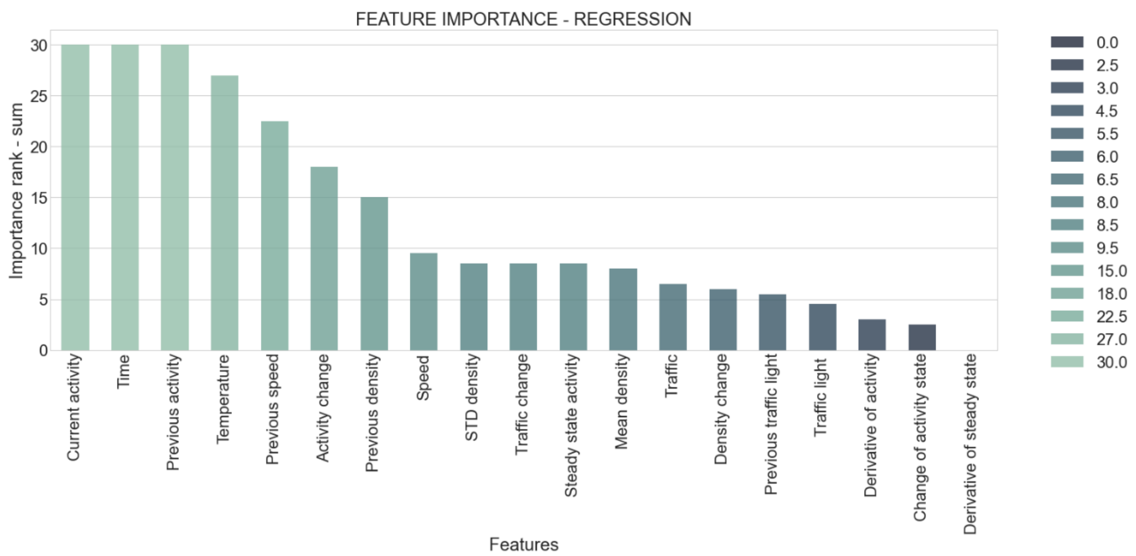


Figure 8.21. Visualisation of feature importance ranking for the regression task: The sum of ranks for each feature, based on Figure 8.19.

As shown in Figure 8.21, the most significant features according to this analysis were mostly parameters related to the activity (*current activity intensity, duration of activity, previous activity intensity, previous speed* and *change in activity intensity*). The ambient temperature was also a feature of high importance, and POI density (specifically the *previous POI density*, the lag feature describing POI density values in the previous time window) was the most critical feature in terms of contextual parameters.

It is also interesting to look at the influence of different time window sizes on the identification of significant features. The parameters *current activity intensity, duration of activity* and *previous activity intensity* were identified as the most important for all the tested time window sizes, and *temperature*, as well as *speed*, were among the most important for most of the tested time window sizes. The *change in activity intensity* and the *previous POI density* were most important in time window sizes between 180 and 360 seconds. Other contextual parameters describing stimulation intensity levels or changes in stimulation (i.e., *STD of POI density*, *traffic change, mean POI density, POI density change, traffic light, previous traffic light*) were of lesser importance. They had only a small influence in time window sizes between 180 and 360 seconds. The same applied to some other features related to movement (*speed, steady-state*, *derivative of activity intensity, change of activity state*).

8.4. DISCUSSION

The methods for prediction of physiological responses that were presented in this chapter form one strand of component 3 of the designed methodology. The combined findings from the regression and the classification task show that the best performing models in both tasks were able to identify an underlying structure in the way that the physiological responses are generated during interactions with the urban environment. One of the most important contributions of this study is thus the finding that the generation of physiological responses is predictable to a certain extent, given a set of primarily movement-related, and secondarily urban contextual features.

The setup of the study is also unique concerning the combination of data from two cities and the incorporation of a very diverse dataset. The majority of the data came from free-living activities that were not related to each other. The data used in previous studies were from activities that were conducted in the same city and on the same route. The predictive models created with this study are an important step towards making more generalisable models in terms of applicability in different contexts and during outdoor activities of different qualities.

The majority of the tested models in the regression task, and particularly the selected XGBoost model, were able to provide a prediction of the physiological responses which followed the main trends. While the classification model also identifies portions where the responses are not zero, the regression model also estimates the magnitude of the response, with a level of error that is acceptable in the context of this study. The model thus satisfies its primary purpose. There is certainly room for improvement, but at the same time, it would be almost impossible for a model to be able to predict the physiological responses at any circumstances without any error. There are always random events that cannot be captured easily or expected beforehand. The addition of a component for extraction of stressors from live camera feed could be a solution that would provide more sophisticated analysis. However, in that scenario, the privacy issues would prohibit a large-scale implementation of such a monitoring system. The setup used in this study is preferable from this perspective, as it forms a minimal and unobtrusive sensing system.

The results of the feature importance analysis for both tasks are also meaningful in the context of understanding the link between urban and movement parameters and physiological responses. The main focus of this chapter was on investigating if the physiological responses can be predicted from the given set of features, and not on the detailed contribution of each feature. However, the implemented algorithms for feature importance analysis expanded our previous knowledge also on this aspect. The identification of duration of activity, speed and temperature as significant features, is in line with the results of the linear mixed models presented in Chapter 6. The activity intensity calculated from the accelerometer data, as well as the activity intensity of the previous time window, were also among the most important features for both the classification and regression tasks. These features had high predictive power for all the tested window sizes.

The contextual features related to POI density, traffic and traffic lights, played a secondary role in comparison to the movement-related features, but they were still able to add value to the selected regression model. This finding suggests that the collection of this information, combined with the movement data, is valuable in the context of predicting the intensity of physiological responses in outdoor routes. Their predictive power was higher in window sizes between 240 and 260 seconds, suggesting that these features might be more related to slower rather than rapid changes in physiological responses.

Additionally, the features which were used as input here can be easily collected with devices that are already widely used. Speed and accelerometer data can be easily tracked with smartphone sensors, and the other features are based on OSM data which are freely available for any part of the world. Other previous studies used environmental parameters tracked with special sensing equipment, or physiological parameters from expensive wristbands. This distinction is important for the implementation of a predictive model in a real-world scenario; models which use data that are readily available from sensors and devices that are widely used will have broader applicability as more individuals will be able to use them.

While this study was able to create a model that had a good fit on the different user groups for both the regression and the classification tasks, more experiments need to be conducted in more diverse contextual circumstances. In the future, the final models could be possibly implemented in activity tracking applications that already collect and analyse movement data, and offer an estimation of physiological responses in the analysis of data from past routes. For the time being, the models presented here are more applicable for contexts similar to Zürich and Sydney, and only after repeated testing and improvement should any generated predictive models be deployed. The next steps should involve the inclusion of data from more users and places with much lower or higher temperatures than the tested ones. The models which were selected as the best performing in this chapter may also be outperformed by the deep learning models, if the described experiments are repeated using a much larger dataset. Further experiments shall, therefore, be conducted if a larger dataset becomes available.

After elaborating on methods for predicting physiological responses in this chapter, the next chapter shall conclude the presentation of the designed methodology by proposing methods for finding the best route for minimising exposure to stressors.

9

LINKING PHYSIOLOGICAL RESPONSES IN THE URBAN SPACE TO PATHFINDING: ALGORITHMIC METHODS FOR IDENTIFYING THE LEAST STRESSFUL ROUTE

9.1. INTRODUCTION

The previous chapters addressed multiple issues related to physiological responses in the urban space, at multiple scales. Chapter 6 examined the links between urban features, activity and physiological responses; Chapter 7 demonstrated methods for component 2 of the proposed methodology, related to the spatial analysis of physiological responses at a city scale. Chapter 8 proposed models for component 3 of the methodology, related to the prediction of physiological responses based on contextual and movement-based attributes. In the last chapter, there was a shift from a city-oriented approach to a user-based one, as the predictive models which were described in that chapter were primarily applicable for individuals who can use them to understand the intensity of physiological responses during their routes.

This chapter operates in similar lines and follows a user-oriented approach; this time focused on pathfinding. The methods presented in this chapter compose the second strand of component 3 in the proposed methodology (Figure 9.1).

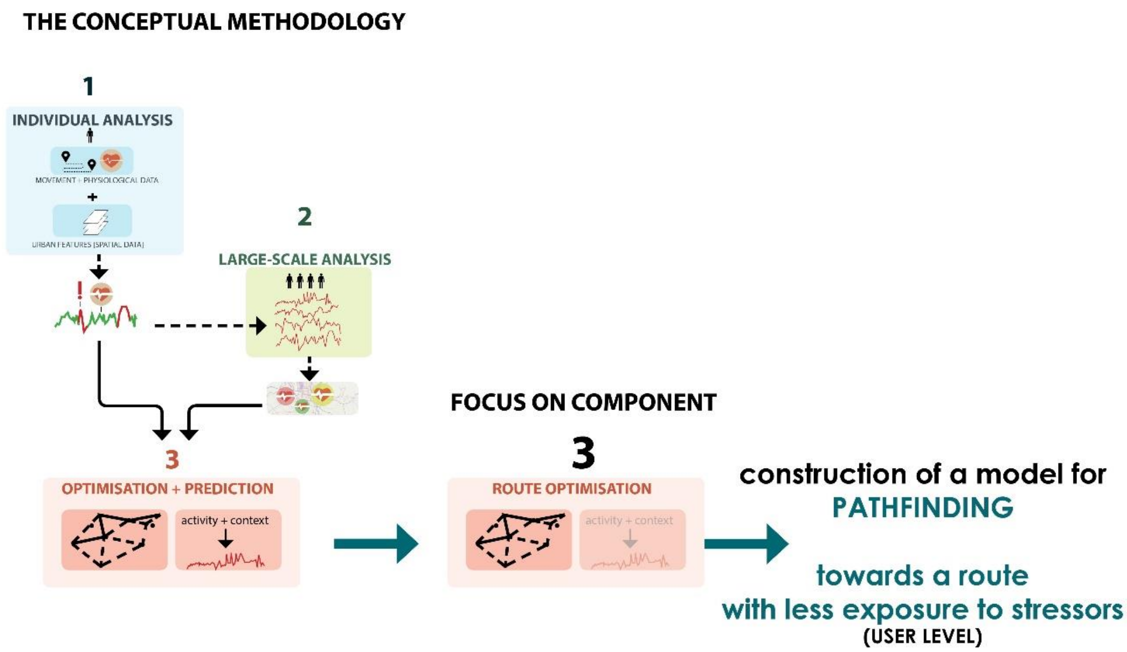


Figure 9.1. Flowchart outlining the aim of the chapter and the connection with the conceptual methodology.

Algorithmically assisted pathfinding is usually approached as a route optimisation problem. The objective is to find the 'shortest path', which is the optimal path according to one or more criteria. The main criterion usually is the identification of the shortest route in terms of trip time. Some studies have proposed the 'simplest' path, which minimises the complexity of instructions instead of the route distance (Duckham and Kulik 2003). Other approaches involve the computation of the number of turns, scenic features and interactions between bicycle and car (Hochmair & Fu 2009), or the cognitive complexity of instructions, the slope angle and the degree of familiarity with the area (Nourian et al. 2015). Very few studies have incorporated environmental parameters connected to urban health as criteria, though there are exceptions such as the study of Su et al. (2010) who have included the minimisation of exposure to air pollution. There have also been lately a few studies that address route optimisation from a health-oriented perspective; for instance, Sharker et al. (2012) have presented a route selection model which identifies the 'health-optimal route'. The model incporporates environmental and urban variables, such as walkability, segment complexity and street safety in terms of crime, as well as individual variables (BMI, calorie target, walking speed and time constraint).

These studies show that significant steps were taken in the past few years towards the construction of pathfinding models that can enrich pedestrians' experience in many aspects. However, there is still no link with the parallel advances in physiological response mapping in the urban environment. This gap was first presented in the literature review presented in Chapter 1. The physiological responses act as an indicator of how the body perceives the environment and reacts to different stressors. Since physiological responses are an indicator of physical or psychological stress, the minimisation of the intensity of responses could be used as the main objective in a pathfinding algorithm for the identification of the least stressful route. This approach towards pathfinding would add new knowledge in existing approaches to route selection, which currently ignore affective criteria. Some studies propose the incorporation of criteria that are related to stress in the urban environment, though their link to stress is not explicitly mentioned. For instance, Nourian et al. (2015) propose the inclusion of slope as a criterion related to comfort. Su et al. (2010) include the minimisation of exposure to air pollution as a criterion, along with increasing proximity to green space. Russig and Bruns (2017) propose a model for minimisation of heat stress. The pedestrian comfort model of Dang et al. (2013) also takes into account heat stress and pedestrian discomfort due to congestion. The interactive pathfinding system of Novack et al. (2018) allows pedestrians to select their preferences among a few criteria that include greenness, presence of human activity, and noise. All these criteria have links to physiological responses according to the literature presented in Chapter 3. A few studies also have incorporated a personalised and experience-based approach; Huang et al. (2014), for instance, addressed the need to incorporate people's affective responses in route planning services. Their proposed method uses subjective self-reported data, employing a mobile application which gathers crowdsourced geotagged data on people's perceived level of comfort in relation to urban space. Jonietz (2016) has also pointed out the need to consider the varying physical and cognitive abilities that affect pedestrian movement. Their study proposed a method for assessing the capability of the user from prior trajectory data. Up to now, these studies have not been taking into account physiological data. This chapter thus aims to cover this gap by linking physiological response mapping to algorithmic methods for pathfinding.

In this context, this chapter aims to demonstrate a method for pathfinding from a physiological response-based approach, for the identification of the least stressful route. The main objective is the minimisation of exposure to stressors. The method builds on the literature presented in Chapter 3 and the knowledge inferred in Chapter 6 and 8, regarding the links between urban features, activity and physiological responses. Multiple scenarios are tested, regarding the importance of urban features, the inclusion of time as an influencing factor and the incorporation of existing hotspots of physiological responses. The scope of this chapter is limited to the demonstration of these scenarios in artificial examples situated in Sydney. The analysis of the benefits and drawbacks of each scenario includes a quantitative comparison of exposure to stressors in each case. The observation of the contextual qualities is also included in each example. The rest of the chapter is organised as follows: section 9.2 elaborates on the adopted method for pathfinding, provides reasoning for the selection of relevant features in the context of stress mitigation, and describes the process of incorporating the selected features in the algorithm. Section 9.3 demonstrates how these methods would work in the context of Sydney and examines multiple routes generated between random pairs of points in Sydney. Section 9.4 elaborates on the results and discusses the limitations and future considerations. The code related to the methods designed for this component can be found in GitHub[9].

9.2. METHODS

9.2.1. TYPICAL APPROACHES TO PATHFINDING IN THE URBAN SPACE

The route optimisation problem is typically approached in relevant literature by conducting network analysis and finding the shortest path in a graph G = (V, E) with weighted edges. The streets and junctions of the studied urban network are again transformed to nodes (V) and edges (E) of a graph (as in the calculation of betweenness

[9] https://github.com/ddritsa/PhD-Thesis-repository/tree/main/3rd%20component/Route%20Optimisation

centrality in Chapter 7), and each of the graph edges has a weight w_i. The edge weights are any relevant criteria in the context of walking routes, such as the duration of the route, the number of turns, the aesthetic attributes, or the path straightness. The weights act as a penalty or a cost; for instance, if the objective is to find a route that minimises exposure to traffic, the highest cost (weight value) is assigned to edges that are proximal to high traffic levels, and edges with low traffic levels get a weight value close to 0. The final edge weight is constructed by accumulating the values of the different features. The values may also be modified with a multiplier according to their relative importance or the preferences of the individual that selects the route.

The objective is, then, to find a path between the starting and the ending node, which has the minimum accumulated weight of edges.

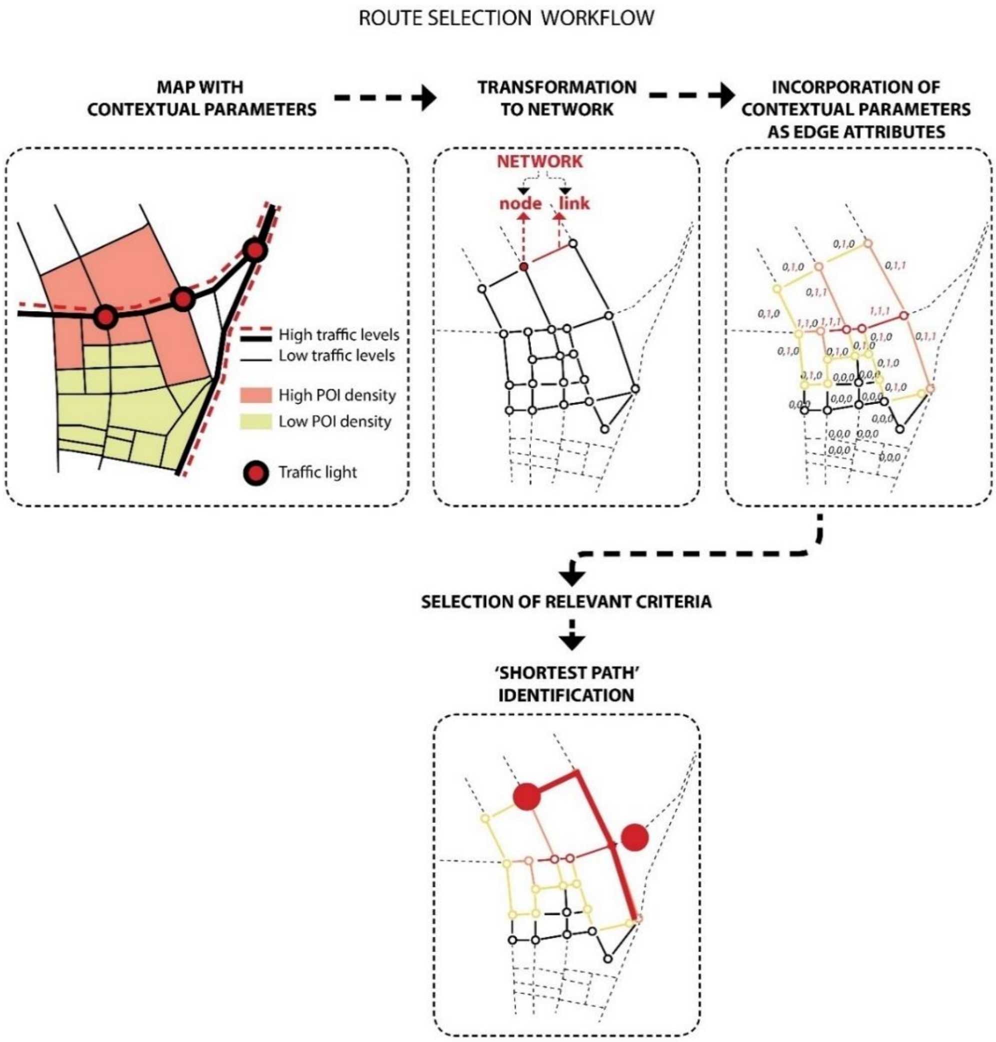


Figure 9.2. The procedure typically followed for solving pathfinding problems in the urban space.

This procedure (illustrated in Figure 9.2) is the backbone of algorithmic approaches for pathfinding problems in the urban space (e.g., Novack et al. 2018; Russig & Bruns 2017). The contextual parameters presented in Figure 9.2 (traffic, POI density, traffic lights) are related to the context of this study but can be replaced with any other attributes.

9.2.2. INCORPORATING URBAN AND ACTIVITY-RELATED FEATURES AS ATTRIBUTES

As shown in the previous chapters, the most influential features (regarding their relation to physiological responses) in the two studied cities were the duration of the activity and the activity intensity (or speed), as well as the change in activity intensity and state. The ambient temperature was of high importance as well. POI density and traffic, acting as indicators of stimulus intensity and complexity, were of lesser importance, but they still influenced physiological responses sometimes.

The experiments presented in the previous chapters were focused on the EDA signal and did not involve an examination of HR. However, at least some of these parameters (traffic, activity intensity, and change in activity intensity) also have well-documented effects on the HR signal, based on the literature presented in Chapter 3.

From those features, the ones that can be most explicitly associated with the properties of the urban fabric, and related to existing features from the spatial database, are the following: *duration of activity, POI density* and *traffic*. The *duration of activity* is related to the length of the path. It is also determined by the purpose of the route, but this is a characteristic defined by the individual and cannot be modelled in relation to the urban fabric. The length of the paths and the other two features (*POI density* and *traffic*) are already contained in the spatial database that was constructed in Chapter 5.

As for the rest of the features, the urban environment elements that affect movement and are primarily associated with an undesired change in activity intensity are *traffic lights*. This feature is also included in the spatial database.

Figure 9.3 describes the process of feature selection and groups the attributes in the category of physical and psychological stressors according to the literature presented in Chapter 3.

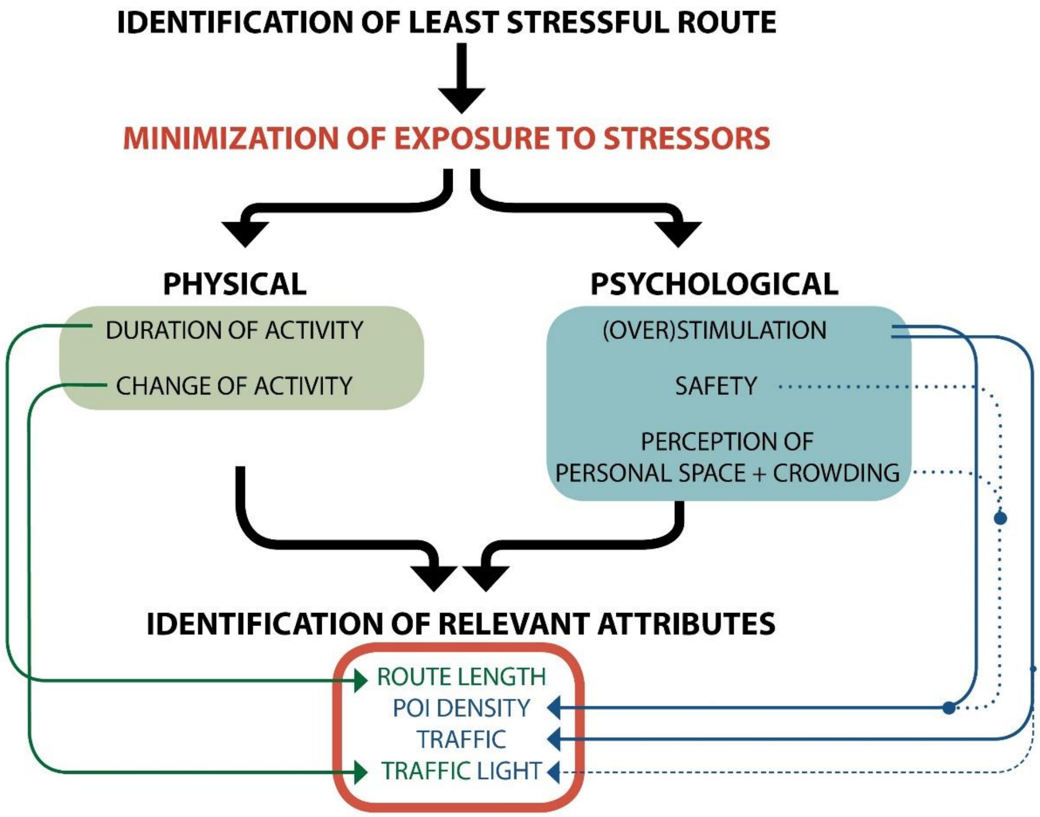


Figure 9.3. The selection of relevant attributes for the pathfinding algorithm, and their grouping in two categories.

It should be mentioned here that physical activity is a stressor which can be beneficial for the organism in the long term; from this perspective, the inclusion of features could have focused only on the psychological stressors. However, the ‘route length’ attribute, (related to the duration of activity) could not be removed, since the length of the trip is one of the most significant parameters in general route optimisation models, as discussed in the introduction. The parameter related to the change in activity intensity (the traffic lights) is also related to psychological stressors. It was, therefore, decided to keep both parameters related to physical stressors. However, the algorithmic approach, which is will be presented in section 9.2.4. incorporates multipliers which define the relative importance of each parameter, and allows removing or minimising the influence of the parameters related to physical stressors, if there is interest in focusing only on the psychological stressors.

9.2.3. POSSIBLE APPROACHES TO THE PATHFINDING PROBLEM

The incorporation of physiological responses in pathfinding is a concept that can be approached in many ways. The different approaches can be divided into two groups, based on how the attributes are calculated in the network representing the urban fabric; in the first group of approaches, there is no incorporation of actual physiological data, and the model can be based on existing theoretical knowledge. The second group, on the other hand, involves the collection and incorporation of physiological responses as additional information.

Figure 9.4 illustrates some scenarios from both groups. Scenario A belongs to the first group, scenarios B and C belong to the second group, while scenario D can be used in combination with all the other scenarios.

More specifically, scenario A is based on assessing the presence of urban features that may affect physiological responses and incorporating the results in pathfinding algorithms.

Scenario B can be imagined as a future setup, where there are already multiple users of EDA tracking equipment in a city. The algorithmic approach in this scenario could be based solely on avoiding stress hotspots derived from the data of other users. Alternatively, the stress hotspots could be included as an additional attribute on top of the existing urban features (extending Scenario A).

Scenario C operates on similar lines and involves a user who has EDA tracking equipment. In this case, it could be possible to add a layer of personalisation by incorporating existing individual stress hotspots. These hotspots would indicate how the body of this specific user responds to a route, apart from general trends.

Finally, scenario D is a modification of scenario A, with the difference that it incorporates a higher penalty for attributes that act as stressors if they are placed towards the end of the route, since the duration of activity may act synergistically with the other stressors and create a more intense combined effect there.

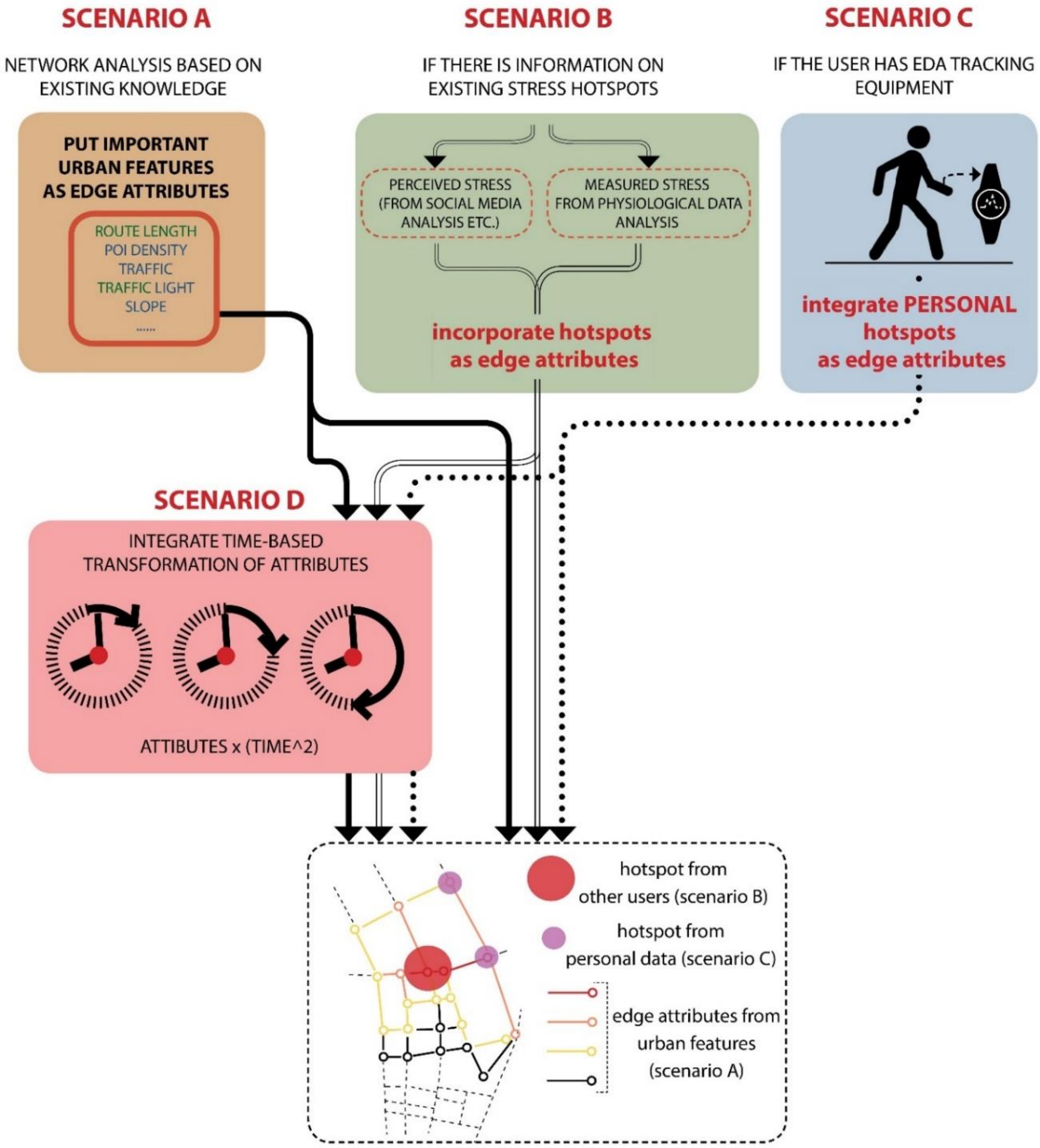


Figure 9.4. The different scenarios for pathfinding for the identification of the least stressful route

All these approaches should be considered, as they have different strengths and applicability. Scenario A can be thought of as the generalised approach, which relies on theory and does not require any EDA tracking equipment; Scenario D is one possible extension of scenario A, and scenarios B and C add new evidence-based information, which is more relevant to specific contexts or people.

The next section will start from scenario A and then explain how this approach can be extended to scenario D, by adding a time-based transformation of the features, and then modified to create scenario B, by adding existing stress hotspots from already collected physiological data as attributes.

The algorithmic approach to scenario C is the same as that followed in scenario B. The only difference is that the personal stress hotspots would be included as attributes with higher weights in the algorithm in that case. This scenario will not be demonstrated with an example here and shall be investigated in the future.

9.2.4. DESCRIPTION OF EACH ALGORITHMIC APPROACH

9.2.4.1. SCENARIO A: THE GENERALISED APPROACH

As described in section 9.2.3, scenario A is a typical approach to a pathfinding problem, where the weights of the network are static. The features used as edge weights for the network analysis are the following: *(street segment) length, POI density, traffic,* and *presence of traffic light*. The features are retrieved from the spatial database that was constructed in Chapter 5. The steps for constructing the spatial database in the data fusion scheme, described in section 5.2.1. of Chapter 5, are thus prerequisites for this part of the pathfinding algorithm. These features were indexed in the relational spatial database for each network node; therefore, their values are transferred to the network edges by finding the two neighbouring nodes for each edge and averaging their values.

The next step is the normalisation and accumulation of all features. The final weight for each edge of the network, representing a street segment, is the following:

$$W_i = l \times w_{Li} + d \times w_{Di} + t \times w_{Ti} + s \times w_{Si} \quad (1)$$

The terms w_L, w_D, w_t and w_s, are the normalised values of the segment for *length*, *POI density, traffic* and *traffic light,* respectively. The terms *l, d, t* and *s,* are multipliers used to control the influence of each attribute. The experiments conducted here involved many iterations of this algorithm. In the first iteration, the same multiplier (1) was used for all attributes. Another version included focusing only on one feature and setting the multipliers of the other features to 0. The other iterations followed similar lines. Finally, the calculation of the shortest path is conducted with the Dijkstra algorithm (Dijkstra 1959).

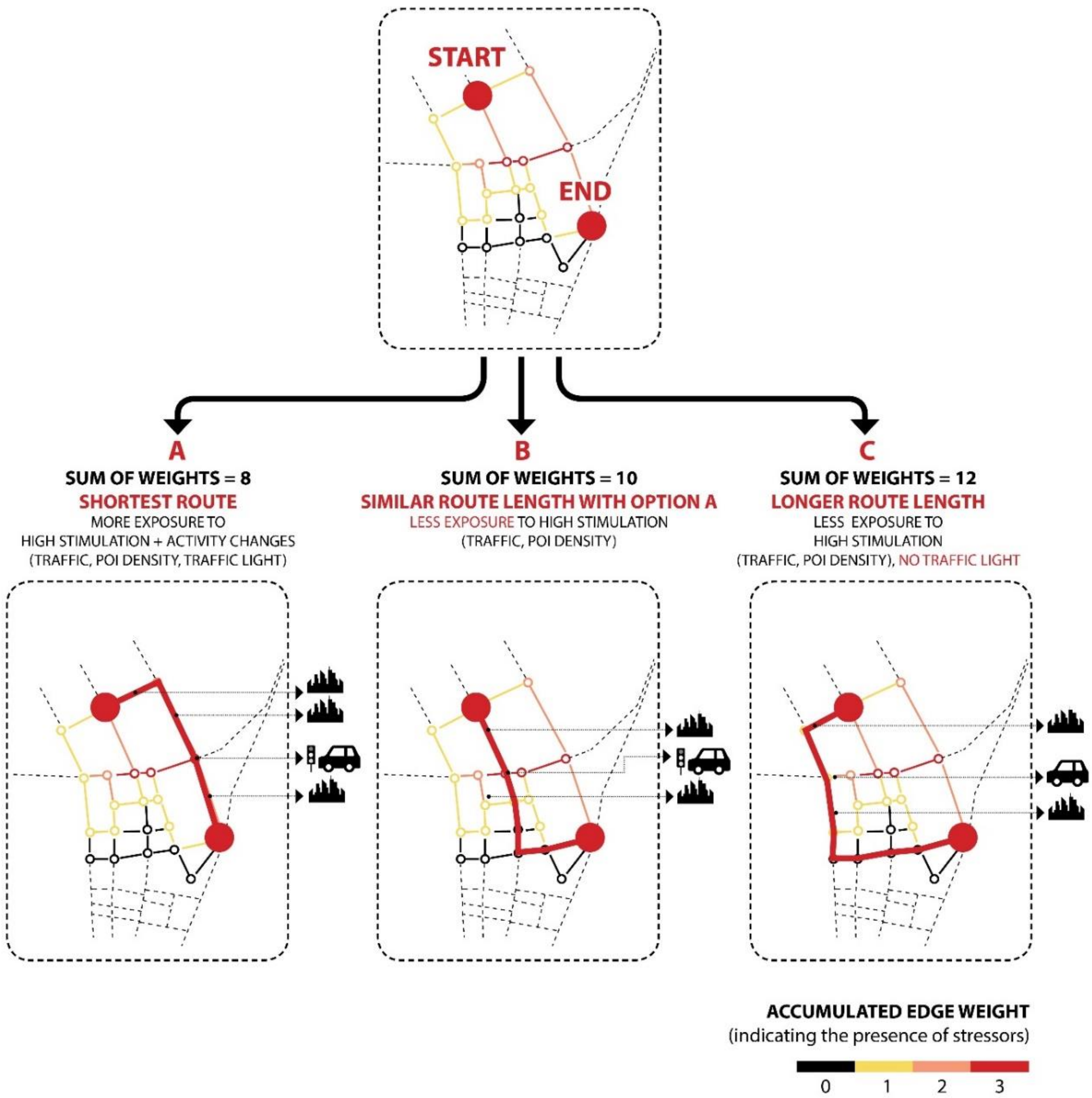


Figure 9.5. An example of Scenario A applied to a network constructed for demonstration purposes.

An example of the application of Scenario A on an artificial network is given in Figure 9.5. As shown in the figure, the route with the lowest amount of accumulated weights according to all the criteria is A. This route is the shortest, but it involves exposure to all kinds of stressors. Route C involves the lowest exposure to stressors, but it is much longer. As this example demonstrates, there is a trade-off between route qualities and time, which should be considered when finetuning the multipliers in equation 1.

9.2.4.2. SCENARIO B: INTEGRATION OF STRESS HOTSPOTS AS ATTRIBUTES

Scenario B is very similar to scenario B, with the only difference being the addition of the stress hotspots in the calculation of the edge weights.

The stress hotspots are derived from the analysis of EDA data of other users in the same city, following the methods described in Chapter 7. Each hotspot contains a set of geotagged points which resemble intense physiological responses in this area. The first step in this scenario is connecting the hotspot data to the network nodes and edges. Since the network nodes have geographical coordinates, the closest network node can be identified for each geotagged hotspot point. A k-d tree is used for the identification of the closest node. This procedure leads to the identification of nodes that are contained in hotspots. A new attribute is created for describing node proximity to hotspots. The nodes belonging to a hotspot are given the highest value (1) for this attribute, and the other nodes are given the lowest value (0). In this way, the algorithm penalises points contained in existing hotspots and will try to avoid them.

Equation 1 is slightly transformed in order to incorporate the new attribute, leading to equation 2, which describes the accumulation of weights for each edge in a hotspot-based scenario:

$$W_i = l \times w_{Li} + d \times w_{Di} + t \times w_{Ti} + s \times w_{Si} + h \times w_{Hi} \qquad (2)$$

The term w_H is the new *'hotspot'* attribute for each edge, and the term *h* is a multiplier used to describe the relative influence of this attribute compared to the others. A high value in this multiplier will assist in maximising the chances of avoiding these spots. In a future scenario where there is rich existing information in terms of stress hotspots from other users, the other parameters could even be omitted, leaving only the length and the hotspot attributes as the ones that control the pathfinding process. Finally, the calculation of the shortest path is conducted in the same way as before.

The same steps would be followed for the addition of the personal stress hotspots in scenario C.

9.2.4.3. SCENARIO D: INTEGRATION OF A PENALTY DEPENDENT ON TIME (ISOCHRONE-BASED APPROACH)

Scenario D was created following the findings of the analysis presented in Appendix C, which indicated that the duration of activity might affect the intensity of physiological responses during exposure to other stressors. The controlled experiments in the laboratory, presented in Appendix C, showed that the applied stressors (particularly the change in activity intensity) had a more significant impact on physiological responses when the participants had already spent some time exercising. In contrast, the responses were much less intense, or even not existing, at the start of the experiment. The hotspot analysis of the predefined route in Sydney (presented in Appendix B, section 3.1.2.) also showed that the contextual stressors had a more considerable impact towards the end of the outdoor route.

Scenario D thus aims to implement these findings in the algorithmic methods for pathfinding, by incorporating a numerical transformation of the features based on the time needed to reach each node. For this purpose, the network attributes need to be enriched with information which is relative to the characteristics of each route, describing how far each node is from the starting point of the route in question.

The first step is the calculation of the time needed to reach each edge of the network from the starting point. This process involves calculating travel time isochrones that describe which nodes are reachable within a given time. An example of the procedure followed for the generation of isochrones is given in the study of Allen (2018). At the end of this process, all nodes and edges are given a *'time'* attribute, reflecting the different route times. The *'time'* attribute takes a value between 5 minutes and the time needed to reach the most distant nodes. The values are successively increasing with a step of 5 minutes.

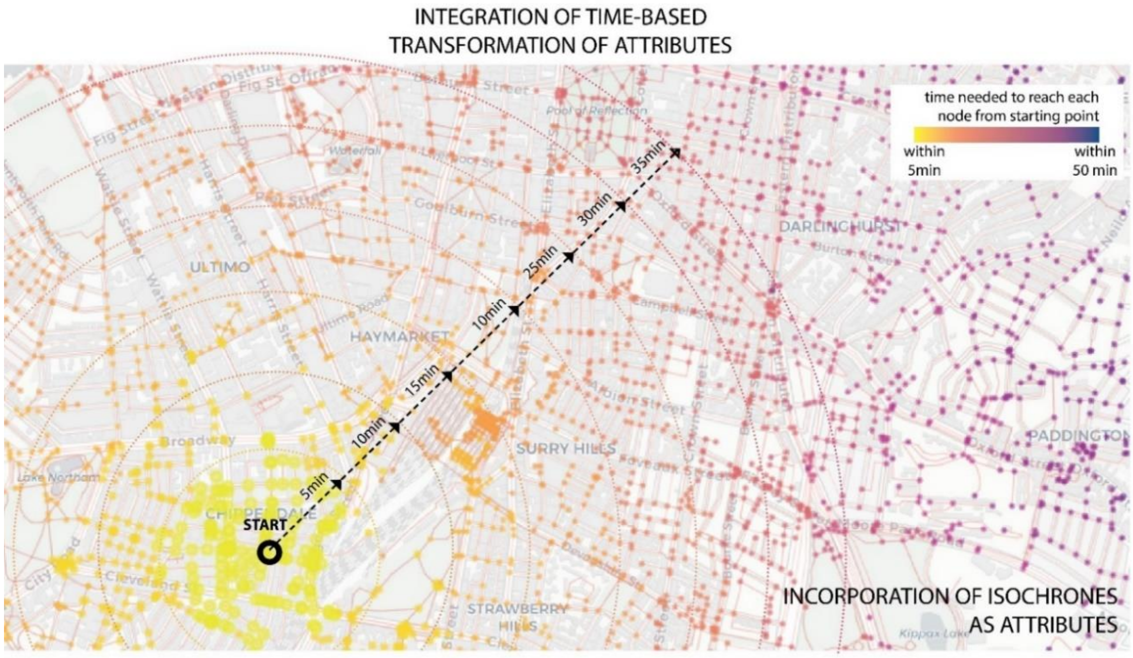


Figure 9.6. An example of nodes coloured according to the generated isochrones.

The *'time'* attribute is a temporary feature, different for each route, and reflects only the relationship between the starting point of this specific route and the other network nodes. Figure 9.6 shows an example of network nodes coloured according to the temporary *'time'* attribute, generated from network isochrones using a random starting point as their centre. It should be noted that the circles drawn on the figure show an approximation of the area which is reachable within each time band (5, 10, 15 minutes and so on). The actual reachable area within each isochrone does not have a perfect concentric circle as its boundary, as it is determined by the road distance and not the Euclidean distance. This is also visible in Figure 9.6, where it is shown that while each circle ring has a dominant node colour, a few nodes within each ring are coloured differently.

The next step is the extraction of the weights for each network edge, which are calculated with the following equation:

$$W_i = l_i \times w_{Li} + d_i \times w_{Di} \times T_i^2 + t_i \times w_{T\,i} \times T_i^2 + s_i \times w_{S\,i} \times T_i^2 \qquad (3)$$

Equation 3 is very similar to (1). All the urban features (*length, POI density, traffic, traffic light*) are again included. They are multiplied by the unique 'time' attribute (T_i) of each edge, raised to the power of 2. The 'length' attribute is excluded from this multiplication. This process amplifies the accumulated weights of edges with many stressors when they are located far away from the route's starting point. The multipliers (*l, d, t, s*) can have the same or different value, as explained in section 9.2.4.1.

This scenario can also be combined with scenario B, for the simultaneous inclusion of existing stress hotspots and isochrone-based penalty. Equation 4 describes the calculation of weights for this case, extending equations 2 and 3:

$$W_i = l_i \times w_{Li} + d_i \times w_{Di} \times T_i^2 + t_i \times w_{T\,i} \times T_i^2 + s_i \times w_{S\,i} \times T_i^2 + h \times w_{Hi} \times T_i^2 \qquad (4)$$

Finally, the calculation of the shortest path is conducted in the same way as in scenario A.

9.2.5. EVALUATION OF THE EXPERIMENTS

The different methods were first compared with a qualitative analysis of an example of their application. The example was used to illustrate the strengths and weaknesses of each method. Each of the tested scenarios was applied to the same randomly selected pair of nodes and resulted in a different route. The simulation was conducted using the urban network of Sydney. The qualities of the generated routes were examined as indicators of their performance. The tested scenarios were the following: A, B, D, and B-D combined. The results are presented in sections 9.3.1 to 9.3.3.

After that, the different approaches were systematically compared based on their performance concerning the selected criteria. One thousand random pairs of starting and ending nodes were selected from the spatial database constructed for Sydney, as described in Chapter 5. The pairs that resulted in routes lasting more than two hours were excluded. The final set had 896 pairs of starting and ending nodes. Then, the different methods were applied on each pair for the generation of routes, having as an objective the minimisation of exposure to stressors. The scenarios that were tested were the following: Scenario A (the generalised approach, using Equation 1), scenario B (the hotspot-based scenario), scenario D (the isochrone-based scenario, using Equation 3) and scenario B+D (a combination of the isochrone- and the hotspot-based scenario, using Equation 4). The following multipliers were used: 3 for the *length* criterion, and 2 for the other criteria. These values were chosen following the results of the analysis conducted in Chapters 6 and 8, which showed that the duration of the activity had a stronger influence on the sum of EDR amplitudes than the other parameters. Therefore, it was decided to prioritise the *length* attribute (W_L), while still taking into account the other parameters.

Then, the percentage of exposure to stressors was calculated for each of the generated routes. The routes generated by the shortest path algorithm were used as a benchmark. This evaluation method has been used before in similar studies (e.g., Russig & Bruns 2017). The results are presented in section 9.3.4.

9.3. SIMULATION ANALYSIS FOR DEMONSTRATION OF THE PROPOSED METHODS

9.3.1. SIMULATIONS FOR SCENARIO A

Figure 9.7 demonstrates the results of applying scenario A (the generalised approach) on a pair of nodes randomly selected from the street network of Sydney. Four different iterations are shown in the figure; in each iteration, one feature is chosen as the dominant feature, and the multipliers of the other features are set to 0. The iterative testing helps in identifying if the algorithm performs well for one feature at a time, focusing only on one aspect of the route, before combining all features.

As shown in the figure, all iterations resulted in routes with a low presence of the selected stressor. The POI density-based optimisation resulted in a route that passes from two local parks to avoid places with higher concentrations of POIs (and thus higher visual complexity and crowding). The traffic-based optimisation resulted in a path that avoided one of the busiest street segments in terms of traffic levels and selected a much quieter road instead. The traffic light-based optimisation resulted in a route with only three traffic lights, while all the other routes had more. The route that had the highest number of traffic lights was the route created by the length-based optimisation.

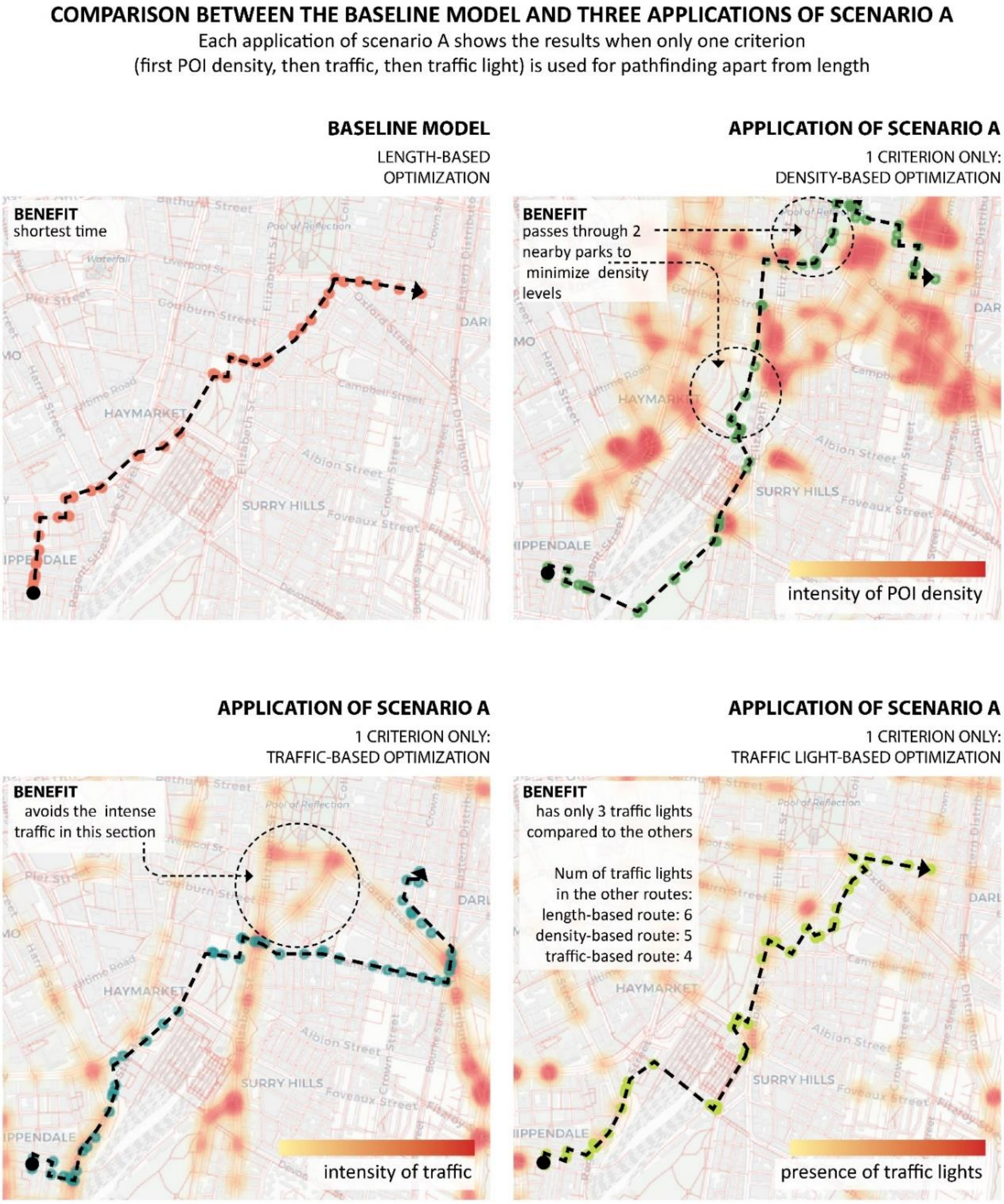


Figure 9.7. Comparison between the baseline model and three applications of Scenario A for a random pair of nodes in Sydney

At the same time, all iterations of the algorithm (apart from the length-based one) resulted in longer trips compared to the shortest one. The route from the length-based optimisation, which was the shortest, would take 33 minutes. The traffic light-based one was the second shortest, with an expected duration of 43 minutes. The traffic-based one would take 47 minutes, and the POI density-based one was the longest with an expected duration of 50 minutes. Finally, Figure 9.8 overlays all the different options and presents the route created from the combination of all criteria. This route is 12 minutes longer than the shortest one and does not incorporate the positive elements of the previous experiments (where the features were handled separately), in terms of avoiding stressors.

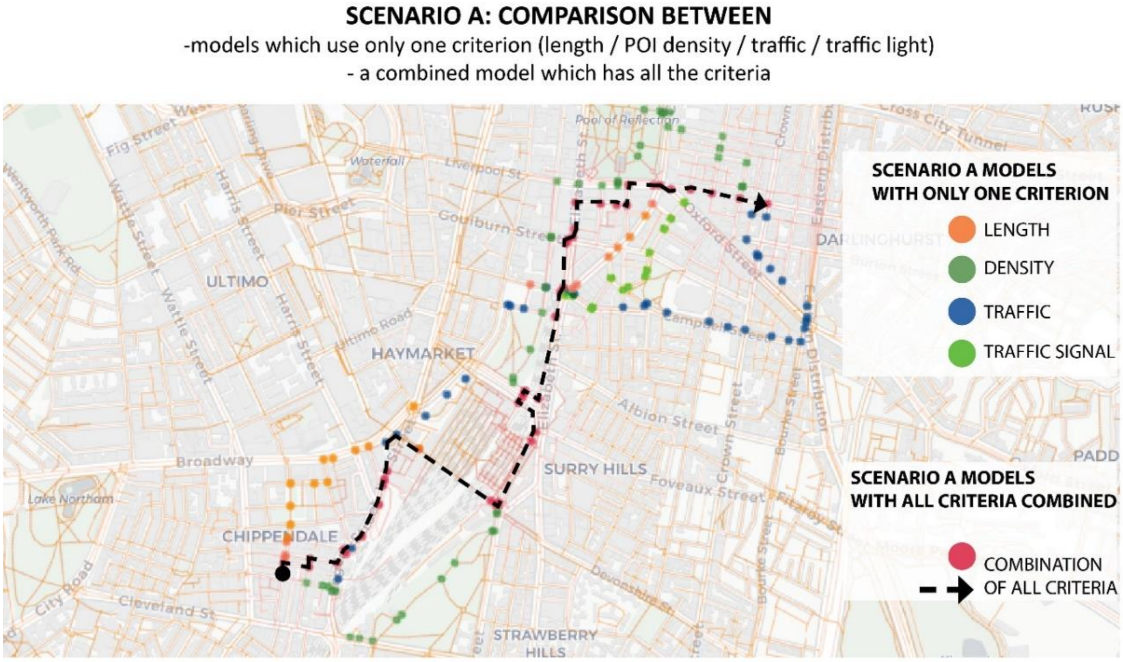


Figure 9.8. The image shows all the routes from Figure 9.7 together. A route generated by incorporating all four criteria from equation 1 is also presented for comparison.

9.3.2. SIMULATIONS FOR SCENARIO D, AND COMPARISON WITH SCENARIO A

The next simulation involved applying the isochrone-based scenario (D) on the same pair of starting and ending nodes. This was the scenario which put a higher penalty on stressors when they were at a greater distance from the starting point, compared to the presence of stressors in network edges which were closer to the start. The generalised scenario (A) was again applied to the same pair of nodes for comparison. Figure 9.9 presents the results for both scenarios.

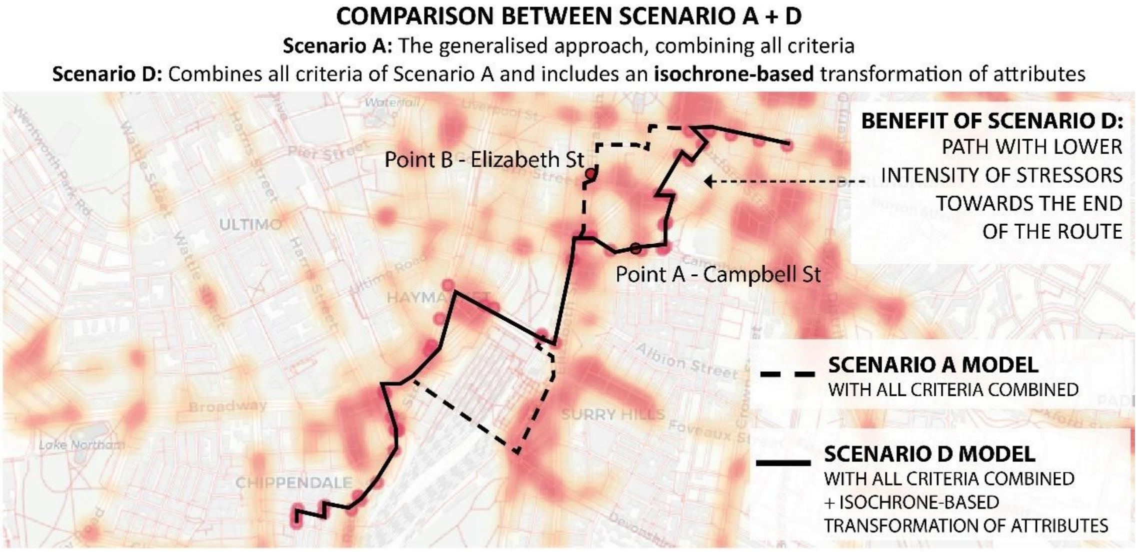


Figure 9.9. Comparison between Scenario A and Scenario D (the isochrone-based approach) applied to the selected pair of starting and ending nodes.

As shown in the figure, the isochrone-based scenario (scenario D) selected a much quieter set of street segments towards the end of the route, compared to scenario A. The application of a higher penalty in the stressors based on the time passed since the beginning of the activity was thus a good strategy for avoiding stressful places when the user may already be slightly exhausted and possibly more susceptible to physical and psychological stressors.

Figure 9.10 illustrates the difference between the two scenarios by showing the contextual circumstances in places belonging to the route generated with each scenario. Point A belongs to the route generated by the isochrone-based approach and is a part of a segment with a lower intensity of stressors. The segment belongs to Campbell Street, a typical residential street with low traffic levels and two-storey houses. Point B belongs to the route generated by scenario A which does not consider the effect of time on physiological responses. Point B is on Elizabeth Street, one of the busiest in Sydney CBD in terms of traffic, pedestrian activity and concentration of commercial activities.

These two places were close to the end of their respective route. A user who would follow these routes would encounter them when their sympathetic activity would be already high from the physical activity. The reactions to any stressors might be, therefore, more intense, due to the high sympathetic activity. Walking through the busier environment presented in Point B could result in the generation of more intense responses, compared to Point A, during this state of high sympathetic activity.

COMPARISON OF ROUTE SEGMENTS DERIVED FROM SCENARIOS A + D
(from the routes displayed in Figure 10.9)
Scenario A: The generalised approach, combining all criteria
Scenario D: Combines all criteria of Scenario A and includes an **isochrone-based** transformation of attributes

Point A is a part of the route **with the isochrone-based transformation** of attributes (**Scenario D**) in Figure 10.9

Point B is a part of the route **without the isochrone-based transformation** of attributes (**Scenario A**) in Figure 10.9

Figure 9.10. Two places which are included in the route with- and without the isochrone-based (time correction) penalty (Google Maps 2020)

9.3.3. SIMULATIONS FOR SCENARIO B, AND COMPARISON WITH SCENARIO D

The final simulation was conducted to test the approach that involves integrating existing stress hotspots in the pathfinding algorithm (Scenario B). This approach was tested against Scenario D, as it was the most successful between the two previously tested scenarios. The algorithm for scenario B, which was tested here, was based on equation 4, which also incorporated isochrone analysis apart from stress hotspots. Figure 9.11 presents the generated routes.

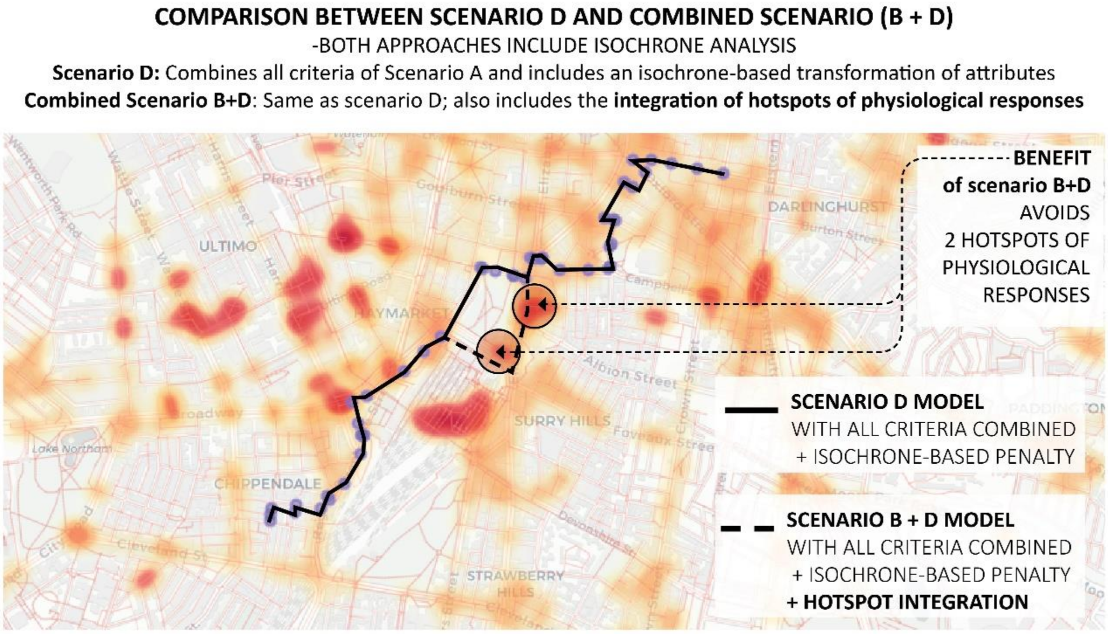


Figure 9.11. Comparison of the results of the isochrone-based scenario D, with and without the integration of stress hotspots (scenario B).

Since both approaches incorporated isochrone analysis to take into account the synergistic effects of the combination of time with the other stressors, the route generated from scenario B was very similar to the route generated from scenario D. At the same time, the algorithm served its purpose in terms of avoiding two stress hotspots, as shown in Figure 9.11.

9.3.4. QUANTITATIVE EVALUATION OF THE PROPOSED MODELS

This section discusses the results of the systematic evaluation of the models based on the comparison of multiple randomly generated paths, as explained in section 9.2.5. Figure 9.12 presents the results of the evaluation.

COMPARISON OF THE RESULTS OF DIFFERENT SCENARIOS
-Each scenario (A,B,D,B+D) is compared with the benchmark model (the shortest path) in terms of exposure to stressors and route time

MODELS	*MEDIAN REDUCTION OF EXPOSURE TO STRESSORS COMPARED TO THE SHORTEST PATH*	*MEDIAN INCREASE IN ROUTE TIME*
GENERALIZED SCENARIO (A)	29%	32%
HOTSPOT-BASED SCENARIO (B)	29%	32%
ISOCHRONE-BASED SCENARIO (D)	24%	47%
COMBINATION OF HOTSPOT- AND ISOCHRONE-BASED SCENARIO (B+D)	24%	43%

Figure 9.12. Comparison of the results of the different scenarios.

The comparison is conducted between the 896 paths generated by the proposed algorithms with the aim of minimising exposure to urban stressors, and the shortest paths generated by the Dijkstra algorithm. The shortest paths were used for benchmarking, and do not incorporate any other optimisation criterion apart from the route length. As shown in Figure 9.12, the paths generated by the proposed algorithms managed to reduce the accumulated exposure to stressors. The generalised scenario (A) and the hotspot-based scenario (B) had a similar performance, with a median reduction rate of 29%. The isochrone-based scenario (D) and the combination of the isochrone- and the hotspot-based scenario (B+D) had a slightly lower reduction rate of 24%. Figure 9.13 demonstrates the accumulated index of exposure to stressors for a subset of the routes. As the figure shows, the exposure is indeed much higher in most cases for the shortest path routes, and the optimised routes perform much better.

At the same time, the optimised paths were considerably longer according to Figure 9.12, resulting in a median increase of travel time by 32% for the generalised scenario (A) and the hotspot-based scenario (B), and an increase of 47% and 43% for the isochrone-based scenario (D) and the combined scenario (B+D) respectively.

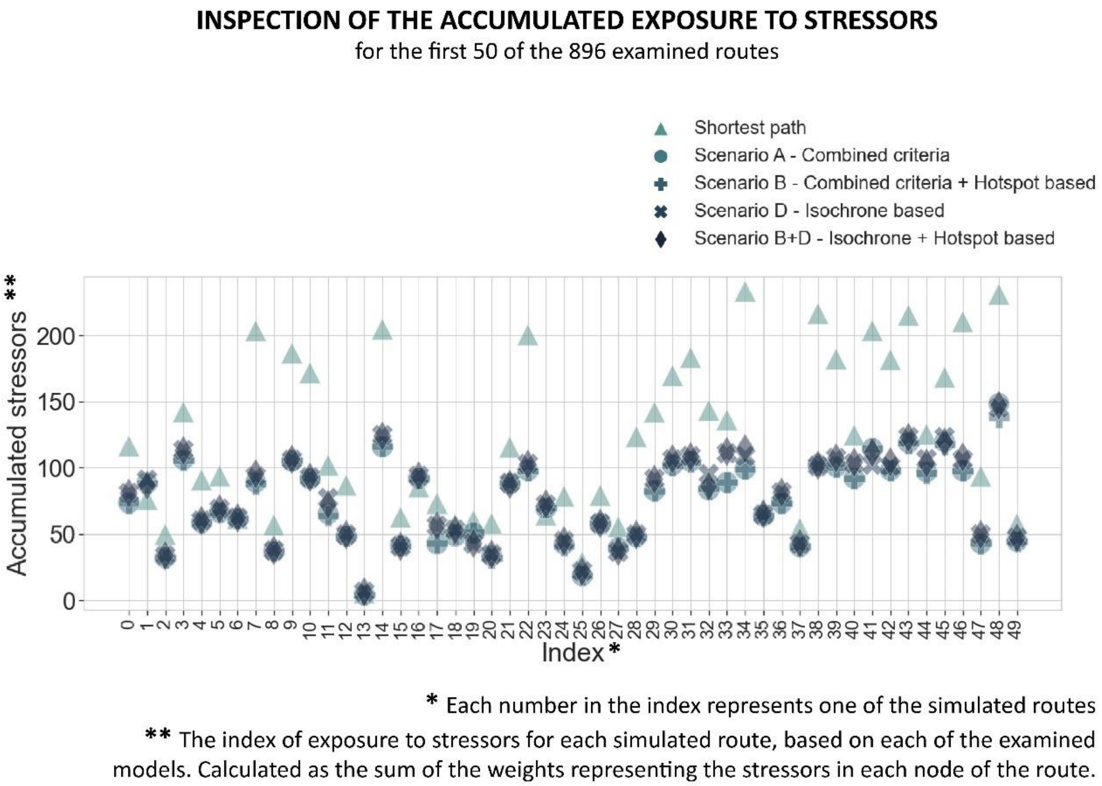


Figure 9.13. The comparison of exposure to stressors for 50 simulated routes.

9.4. DISCUSSION

The methods presented in this chapter were constructed for component 3 in the designed methodology. This component was designed to facilitate a connection between the analysis of physiological responses and computational pathfinding methods for the reduction of exposure to urban stressors.

As demonstrated in section 9.3, the presented methods managed to incorporate several qualities of the urban environment that may be associated with physical and psychological stress. The qualitative analysis of the routes generated with the proposed algorithms in sections 9.3.1 to 9.3.3, showed that each algorithm fulfilled its purpose in terms of reducing exposure to one or more stressors. The quantitative analysis of the algorithms showed a considerable improvement in terms of reducing exposure to stressors compared to the benchmark.

A significant contribution of the study was the incorporation of the effect of time in the isochrone-based scenario, as a factor that may affect the perception of the other stressors when it increases. The algorithm has slightly worse performance than the other models in terms of overall exposure to stressors. However, the analysis presented in section 9.3.2 and 9.3.3 showed that the algorithm managed to reduce exposure to stressors in the last section of the route as planned.

The inclusion of relevant urban features was based on the analysis of the previous chapters, which was conducted on data derived by a small multicultural population sample, aged between 20 and 45 years, with university education (at least in the case of the study in Sydney). Their identified effects may differ among other groups, and they may be more intense for some population groups that are more sensitive to stimulation or activity changes. For instance, older adults with dementia can be negatively affected by excessive environmental stimulation (Kovach et al. 2000). The avoidance of obstacles which affect activities, such as traffic lights, may also be of higher importance for people with difficulties in moving. For this reason, it was decided to include all the relevant urban features in the proposed models, while leaving unspecified the multiplier that determines the relative importance of each feature. The experiments presented in section 9.3 included a predefined multiplier, but the designed methods allow the user to modify this number and prioritise some of the criteria according to their preferences. The character of the route plays an important role when defining the multipliers, especially concerning the criterion that controls the travel time. As the results of the evaluation in section 9.3.4 showed, the proposed models resulted in a significant increase in trip time. When the pathfinding is conducted in the context of a leisure trip, the user may prefer to select a longer route with less exposure to stressors, but when the user is looking for a commuting route, the trip time is an important criterion. The balance between the different objectives can be easily controlled by modifying the multiplier that controls the relative importance of the criterion related to route length, in comparison to the multipliers of the other features. In any case, the proposed models can be integrated into an interface that allows customisation of these parameters by the user, as in the interactive pathfinding system proposed by Novack et al. (2018). In this interface, the user should be able to see different route options generated by modifying the multipliers and compare them based on each route's characteristics, including route time and time of exposure to each stressor.

The proposed models should also be finetuned based on local contextual parameters, before their application in other cities and countries. Some factors that were omitted here need to be considered in future extensions of this study. One such parameter that should be integrated in the future is the presence of slope as a physical stressor that affects the activity intensity. The methods described in Chapter 5 (section 5.2.2) for collecting movement data for each participant only allow the acquisition of altitude data from Strava, for each GPS point of their trajectory. It is possible to integrate elevation data in the spatial database using the *osmnx* Python library (Boeing 2017b), but the process requires acquiring an API key for using the Google Maps Elevation API. It was decided not to include this feature in the spatial database for now, as this data is not freely available. Future work will include the addition of this feature if other open APIs for elevation data are identified.

Another parameter that could be included in the future in the spatial database is the ambient temperature. As it was shown in the previous chapters, the temperature is an important parameter that influences the intensity of physiological responses. The temperature could be added as a multiplier that increases the intensity of the stressor-related attributes. Another variable could be added in the model to take into account the local differences in microclimate. Real-time data could be used for this purpose if there is a local sensor network that gives temperature data at a high spatiotemporal resolution. Alternatively, some built environment features, such as the presence of green and water around a node, could be used as indicators of temperature differences. Future work on the presented algorithms could involve incorporating the proximity to these elements as an attribute in the network data.

It should also be mentioned that POI density (and mixed-use) is an attribute that has both positive and negative interpretations in the context of pathfinding. As shown in the analysis presented in Appendix A (the analysis of the relationship between POI density and complexity), environments with high POI density might be associated with higher complexity and intensity in terms of stimulation, as well as a higher degree of human activity. These attributes are related to experiences of overstimulation and crowding, which can act as psychological stressors. At the same time, the presence of shops, cafes and other elements that attract social life may make a walk more pleasurable (Brown et al. 2007). The increased presence of human activity may also increase the feeling of safety while walking at night. For these reasons, it should be possible to allow the users to select the desired level of incorporation of mixed-use in the user interface, in order to cover all the scenarios mentioned above. More experiments also need to be conducted for the scenario of walking at night. The safety aspect should have a more substantial presence there.

The integration of existing stress hotspots in the pathfinding process is a novel element that will be very useful in the future if EDA tracking wristbands become more affordable and gain popularity. Other kinds of spatiotemporal data related to stress could also be integrated into the pathfinding algorithms in the same way. Recent developments in sentiment and stress analysis in natural language processing allow identifying psychological stress levels from social media data (Lin et al. 2014). This analysis could be combined with an analysis for the identification of spatial stress patterns, and incorporated in the pathfinding algorithm in the same way as in Scenario B.

A critical matter for consideration here is that the existing stress hotspots are an information layer with accuracy relative to the number of users that generated this data. When the sample is small, the identified hotspots may reflect the personal traits of users or preferences in their routes, and should not be taken at face value. It must also be ensured that the tracks of the users cover the area of analysis adequately. Some methods that are useful for removing redundant information from this perspective, and keeping only the most significant hotspots, were presented in Chapter 7 and can be used in this case. Future work here should also involve methods for separating the data within existing stress hotspots according to the characteristics of the activities during the time of data collection. Since factors such the overall duration of the activity and temperature are influential in the process of generation of physiological responses, a model which uses existing data should be based on data points which have similar attributes; otherwise, the results may be misleading.

Another point for future improvement is the incorporation of real-time traffic or noise data. Traffic was used as an indicator of noise levels since noise is a psychological stressor. The OSM data that were used for the extraction of traffic levels were sufficient for the scope of this study, but the incorporation of real-time traffic data would be the best for a more accurate approximation of noise levels and their variations during the day. Real-time human activity data could also be added to enhance the capacity of the algorithm to reflect crowding levels with higher accuracy.

Furthermore, there are vast differences in the structure of the urban fabric of different cities, which may render some of the parameters discussed here irrelevant. The intensities of mixed-use are very different if we compare mega-cities to smaller settlements. While cities such as Sydney have areas with high concentrations of multiple land uses, which might create an overwhelming effect under certain conditions, other cities have much smaller overall levels of mixed-use. The same applies to the intensity of traffic levels, as some cities have a very high presence of pedestrianised zones, and the inclusion of the traffic-related parameters is not of high importance there. In such environments, where the urban fabric is more homogeneous in aspects related to noise and visual complexity, the methods proposed here would not be of much use. At the same time, the application of the proposed methods would not lead to a worse solution in terms of the qualities of the encountered places. Most probably the result would be very similar to the shortest route generated by common pathfinding applications.

Future research on the proposed methods should involve evaluating the different methods regarding their actual ability to produce less intense physiological responses compared to the shortest path. Since this study is focused on the identification of least stressful route, in terms of actual physiological responses, it would be appropriate to complement the tests presented in section 9.3.4, with the organisation of an outdoor experiment for collection and comparison of physiological responses during the different generated routes. It was not possible to include data collection for this aspect in the outdoor experiments organised in this study, as the participants already had to contribute a significant amount of their time for participation in the other data collection activities. Future work will complement the experiments presented in this chapter by collecting physiological data while walking on some of the generated routes.

A subjective evaluation should also be added to identify if the proposed routes are perceived as preferable for the participants.

The work presented in this chapter was related to the last component of the proposed methodology for the analysis of physiological responses in the urban space. The next chapter concludes the thesis by evaluating the proposed methodology with respect to the research questions, discussing the research significance and elaborating on limitations and future directions.

10

CONCLUSIONS AND FUTURE DIRECTIONS

10.1. INTRODUCTION

The starting point for this research was the emergence of physiological data as a source of information that can help us understand how our interactions with the urban environment affect the human body. The literature review in Chapter 1 showed that there is significant potential in using physiological data to understand the links between different urban features and physiological responses; however, this research area is still not well developed. The review also showed potential in utilising physiological data in ways that could directly benefit the users of devices that collect this data. Physiological data analysis could be linked to pathfinding methods for identifying the least stressful route, or predicting the physiological responses during an activity based on movement and contextual data. These areas have been understudied until now.

The lack of a methodology for the analysis of physiological responses that seeks to inform not only urban planners but also the citizens that generate the data, was thus identified as a crucial gap. The primary aim of this research was to address this gap by developing a methodology for the collection and analysis of physiological data in the urban environment.

The literature review also identified other issues that should be addressed in order to increase the efficiency and scalability of the methods used for the analysis of physiological data in the urban space. The lack of inclusion of the effect of movement on physiological responses, the lack of a theoretical and conceptual framework for feature selection, and the heavy reliance on image-based methods for contextual data analysis, among others were identified as issues which needed addressing. The research utilised these critical issues as secondary drivers for assisting in the design of different components of the methodology.

After describing each component of the methodology in the previous chapters, this chapter revisits the primary research question, aim and objectives, and discusses the presented work in relation to the research goals that were established in Chapter 2.

Section 10.2 revisits the research aims and questions and discusses the designed methodology with respect to each objective set in Chapter 2. The findings of the research are also discussed in section 10.2 in relation to the broader research question of how the urban environment affects physiological responses. Section 10.3 discusses the methodological, theoretical and practical research contributions. The limitations of the research are then discussed in Section 10.4. Section 10.5 elaborates on the implications of the findings for urban design and planning. Finally, section 10.6 closes the chapter by outlining possibilities for future work related to the research.

10.2. REVISITING THE RESEARCH AIMS AND OBJECTIVES

10.2.1. THE DESIGNED METHODOLOGY AS A RESPONSE TO THE PRIMARY OBJECTIVES

The presented work was driven by the following overarching research question:

How does the urban environment affect physiological responses, and what is the role of different urban and environmental characteristics and activity in this process?

Following the broader research question, the research aim was to design a methodology for collection and analysis of physiological data in the urban space, which should act simultaneously for the benefit of the user and the city. The designed methodology incorporated three components and was first outlined in Chapter 2. The methods for each part were presented in detail in Chapters 5 (component 1), 7 (component 2), 8 and 9 (component 3).

Each of the three components of the methodology responds to one of the primary research objectives, as stated in Chapter 2:

(1) *To integrate the user-generated physiological data with other geotagged open data related to urban health, using scalable methods*
(2) *To establish methods for deriving patterns of physiological data responses and interpreting them at a user and a city level*
(3) *To identify how the acquired information can be linked to computational models that can promote urban and individual health and wellbeing*

Component 1 responds to the first objective by presenting a unique data fusion scheme which combines physiological, spatial and movement data. Within the broader agenda of urban health, the study focuses on identifying ways of capturing and analysing physiological responses to urban stressors. The data fusion scheme includes the analysis of activity, covering a gap that had been identified in previous studies. A machine learning model for the classification of activity was developed for this purpose after extensive experimentation. OSM and POI data are also analysed to extract the levels of traffic, the distribution of mixed-use represented by the POI density, and the presence of traffic signals. This component leads to the classification of physiological responses based on the underlying physical or psychological stressors. It responds thus to the second objective as well, as it provides a method for identifying potential contextual and movement-related sources that may be responsible for the physiological responses.

Component 2 (presented in Chapter 7) responds to the second objective by presenting methods for spatial analysis of physiological responses based on hotspot analysis and clustering methods. The physiological responses are first processed to identify statistically significant hotspots. Then, the hotspots are separated into clusters, and the clusters are analysed and ranked based on their possible impact.

Component 3 responds to the third objective by including two strands. The first strand includes methods for predicting physiological responses based on collected physiological and contextual data. The experiments presented in Chapter 8 showed that the physiological responses could be predicted with an acceptable degree of accuracy using the proposed urban and movement-related features as input. The regression model showed a considerable capacity to predict moments of increased levels of physiological arousal.

The second strand of component 3 also responds to the third objective by focusing on pathfinding methods for the identification of routes that minimise exposure to stressors. The presented methods are based on network analysis and utilise common approaches to finding the shortest path between two network nodes based on some criteria. The proposed methods were tested in terms of exposure to stressors against a benchmark model that used only time as the primary criterion for pathfinding. The results showed that the proposed methods reduced exposure to stressors by 25 to 30%, but they also increased the trip time as expected. For some individuals, the benefits in terms of the reduced exposure to stressors may not be enough to counteract the cost in terms of time; however, this is something that can only be decided on a case-by-case basis.

The three components are linked to each other, creating an efficient information flow that responds to different needs at the user and the city level. Component 1 can be used for individual analysis of physiological responses, while it also serves as the starting point for analysis at the city scale, as it contains the data fusion model. Component 2 links the information derived from component 1 to hotspot analysis. It was designed primarily for use at a city scale, for the benefit of urban planners or researchers, but individual users can use these methods to find and analyse hotspots of their physiological responses. Component 3 links information derived primarily from component 1 (and optionally from component 2) to the pathfinding module and the predictive analysis. The pathfinding module can be used by individual users that want to find a route that avoids exposure to stressors. The predictive models can be used by users who want to find the stress levels of a past route, given geotagged activity data. The overall information flow thus creates a synergy between the individual and the city level, satisfying the research aim.

The designed methodology was tested and refined using data collected from users in Sydney and Zürich. The methods designed for component 1 (presented in Chapter 5), and especially the construction of the spatial database and the data fusion model, were first used to analyse the data of each participant. Then, the hotspot analysis and clustering methods were tested separately for each city, for calibrating several parameters of the algorithms. These experiments are presented in Chapter 7. Finally, the experiments on the prediction of physiological responses, which are related to component 3 and were described in Chapter 8, used combined data from both cities, in order to construct more generalisable models. The inclusion of data from Zürich came at a later phase of the project, but it was a significant step towards ensuring that the designed methods are not only applicable to Sydney.

10.2.2. DISCUSSION OF THE FINDINGS OF THE STATISTICAL ANALYSIS FOR SYDNEY AND ZÜRICH: REVISITING THE CONCEPTUAL FRAMEWORK

The review of existing studies also showed significant methodological issues in past studies that involved continuous measurement of physiological data in the urban domain. One of the most significant gaps that were identified was the lack of the incorporation of the effect of movement on physiological responses. Existing theories in the field of environmental psychology linking urban environment parameters and physiological responses were based on experiments conducted while sitting. Most of the past studies on physiological responses during outdoor movement also focused on comparing green and natural environments, and research on other features was sparse and unstructured. There was a lack of a theoretical and conceptual framework linking together urban features, movement and physiological responses.

While it was not the primary aim of this research to solve this problem, the lack of progress in this area still affected this study. It was necessary for many parts of the methodology to understand which features might affect physiological responses. For instance, the construction of the pathfinding model presented in Chapter 9 required selecting relevant attributes of the urban environment that might act as stressors. The model for classification of physiological responses according to the underlying stressors, presented in Chapter 5, also required understanding which features act as stressors and what are their characteristics.

These gaps in knowledge were addressed by constructing a theoretical and conceptual framework linking contextual features, activity and physiological responses. The theoretical framework was based on identifying contextual parameters that can act as physical and psychological stressors. Its construction was based on relevant literature on stress theory and fundamental functions of the human body. The division to physical and psychological stressors is theoretically sound, as the links between parameters such as activity and stimulation, and physiological responses, have been well established. The framework presented in Chapter 3 is the first that situates urban features and parameters of movement in the urban space under these two categories. Most of the parameters of the outdoor environment can be positioned under one or the other category, or both. The conceptual framework was based on selecting the contextual and movement-related features that were identified as the most significant for this study based on the reviewed literature.

After designing the theoretical and conceptual framework, much thought was given to deciding if it should be taken as a given that these features affect physiological responses, or if the research should treat this as a hypothesis to be tested. The position of this research, derived from the literature presented in Chapter 3, is that the effects of activity and stimulation on physiological are a part of fundamental processes of the organism, as past studies have shown through extensive experimentation in the laboratory. Based on the reviewed literature, it can be assumed that environments that affect activity and stimulation through their features might generally be associated with a higher chance of eliciting physiological responses in the urban environment. From this perspective, one might argue that it was not necessary to conduct the inferential analysis presented in Chapter 6.

At the same time, urban space is a complex milieu, with multiple factors interacting simultaneously. The inclusion of a chapter dedicated to the inferential analysis of the collected data aimed, therefore, to enrich current knowledge on the interplay between different factors and combinations of circumstances, and not to prove that the assumed links exist in the first place. It was also decided that future studies would benefit from presenting proof of the importance of the inclusion of movement in schemes for the analysis of physiological responses since this factor was ignored in previous studies.

The experiments presented in Chapters 6 and 8 showed that the designed conceptual framework relating contextual features and activity with physiological responses was in the right direction. The designed experiments included many kinds of activities, with different degrees of control. Overall, the results of the statistical tests presented in Chapter 6 (and in Appendix C, containing the statistical analysis of the indoor experiments) emphasise the strong influence of activity on physiological responses. The feature importance analysis in the predictive models of Chapter 8 was also in line with the findings of the previous chapters. The duration of activity was a significant feature under all circumstances. The change in activity state was also a feature that had a small (but statistically significant) effect on physiological responses. The results of the controlled indoor experiments, presented in Appendix C, also showed that the effect of the change in activity on physiological responses was significant, especially when the organism had a high degree of activation. The effect size was medium to strong there. The results of these experiments confirm the position that was taken in Chapter 3, indicating that the examined parameters related to movement can have a substantial effect on physiological responses.

The relationship between contextual features and physiological responses seems to be more complicated. The linear mixed model analysis showed that POI density was significant mainly in the predefined route experiment in Sydney. It was also significant in the combined model, which included all the collected data, but the effect was much smaller in that case. This study was the first to investigate the links between POI density (representing the density of mixed-use), and physiological responses; therefore, more research on the links between this feature and physiological responses in different contextual circumstances and activities will be beneficial. Traffic was not a significant feature in any model. However, the links between traffic, noise and psychological stress are well-established, based on Chapter 3, and there is no doubt that this variable should be included in the analysis. The inclusion of traffic lights in the linear mixed models also did not improve the model fit, and this feature was not identified as significant in this phase of the analysis. A possible explanation for the lack of the identification of the expected effect here, especially with regards to traffic lights, was that the presence of this feature might have been found in fewer data points compared to other features. Another possible reason could be that the participants knew where to expect traffic lights during familiar routes, and the element of surprise, annoyance or alarm may have been not significant.

The analysis of feature importance that was incorporated in the predictive models of Chapter 8 also showed that all the contextual features were important in the selected regression model for prediction of physiological responses. Their significance was lower compared to movement-related features, but they still played a role. Another reason that some features such as the presence of traffic lights and steady-state walking did not appear as significant in the mixed model analysis could be that some features might have a more complex relationship with physiological responses.

Some notable characteristics of the inferential analysis presented in this study were related to its setup. The analysis included data collected during multiple different setups, including controlled, semi-controlled and uncontrolled experiments. Previous studies used data collected during a predefined walk, and this study is one of the very few that used data collected during free exploration in the urban space. This mode of monitoring had the advantage of being as close to the actual circumstances as possible, with no intervening or direction from the research team apart from the instruction to use the equipment. The research also included data from two different contexts, which was a first for studies in this research domain, as all previous studies included only data from one area. Chapter 6 included a thorough analysis of the data collected in Zürich and Sydney, during indoor activities, outdoor activities on a predefined route, and free-living activities. The analysis allowed the identification of similarities and differences between different contexts, and various models were created to allow the comparison between the results in different circumstances. The results from the presented models were interpreted by considering the differences in the circumstances and elaborating on how these might have influenced the effect of different factors on physiological responses. For instance, the fact that the contextual stressors did not significantly affect physiological responses during the predefined route in Zürich could be attributed to the shorter duration of the activity and the generally lower temperature.

As a concluding remark in this section, the knowledge gained by reviewing the inferential analysis results was invaluable, especially concerning the effects of physical stressors. Apart from their contribution to the existing knowledge on the links between urban environment, activity, and physiological responses, the findings shall also help design future experiments. The experiments showed that the duration of the activity and the temperature are decisive factors, as they significantly affected the physiological responses in all models. These parameters should, therefore, be considered in the design of studies in this area. Section 10.5.2. will include further elaboration on this topic. The investigation of links between some features of the conceptual framework that were not significant or not examined (traffic, traffic light, slope) and physiological responses should be included in future research with a larger population sample and inclusion of different contexts. The visual analysis of the data also showed that some effects of urban and movement-related features might be amplified in moderate to hot climates during long-lasting activities, while not appearing at all in colder conditions and during relatively short walks. The inclusion of interactions between duration of activity, temperature and the other features did not improve the linear mixed model analysis, but future studies can consider this point.

10.3. RESEARCH CONTRIBUTIONS

10.3.1. METHODOLOGICAL AND PRACTICAL CONTRIBUTIONS

10.3.1.1. DESIGN OF A METHODOLOGY FOR THE ANALYSIS OF PHYSIOLOGICAL RESPONSES IN URBAN SPACE

The primary contribution of this research is the designed methodology, which enriches current research on physiological responses in the urban space from a methodological perspective. As discussed in Chapter 1, the synergy between the user and the city level covers many existing gaps, such as the utilisation of physiological data in predictive and pathfinding models, and paves the path towards more efficient future research in this area. The designed components can be used in different combinations and contexts.

For instance, components 1 and 2, which involve methods for construction of the data fusion scheme and spatial analysis of responses, could be used by a research team for the analysis of data from multiple users. Individual users could use all components for analysis of their personal physiological responses, identification of personal hotspots of intense responses, route finding and prediction of responses based on past route data.

Furthermore, all the necessary tasks were designed as components coded in a programming language (Python). This approach was chosen as a response to previous issues related to efficiency and the lack of a streamlined approach. Most of the tasks can be executed automatically using this approach, as a part of a structured workflow, instead of having to use special software which requires domain knowledge for different tasks. The effort required for the execution of many time-consuming tasks is thus significantly reduced.

The second reason for using a code-based approach for the design of the components was the possibility of using this work to build a dedicated application or web platform for the analysis of physiological data in the future. In this way, the designed components could be used as the basis for the construction of a data visualisation dashboard open to the public, connected with an application for collection of and analysis of personal data. There is still much work to be conducted towards this purpose, but this step will be critical for allowing the methodology to operate optimally at the individual and urban scale and serve different stakeholders.

10.3.1.2. INCLUSION OF MOVEMENT ANALYSIS IN PHYSIOLOGICAL DATA ANALYSIS

Some parts of the components of the methodology are also original contributions to existing research related to their respective domains. One of the most significant steps was the inclusion of movement effects in the physiological data analysis in the urban space. The work presented here is among the few, if not the first, that included a thorough analysis of activity-related events in the context of urban space. Only a recent study (Benita & Tunçer 2019) included speed as a possible explanatory feature. Past studies that ignored movement effects might have misclassified many physiological responses as the result of other parameters.

In this research, this module was used as a part of a broader classification system that includes a division to physical and psychological stressors. However, the method proposed for identification of movement-related responses in Chapter 5 does not have to be used necessarily in the context of this particular classification system. For instance, if a research team is focused only on stimulus-related responses, this method could be used for the exclusion of movement-related effects. Since the method uses accelerometer data for activity recognition, they can be used in indoor and outdoor environments.

10.3.1.3. DESIGN OF METHODS FOR ROUTE OPTIMISATION FOR MINIMISATION OF EXPOSURE TO STRESSORS

The development of algorithms for route optimisation from a stress-oriented perspective was another significant contribution that enriches current research on algorithmically assisted pathfinding methods. The incorporation of physiological data in route optimisation models, and the isochrone-based analysis for the incorporation of the effect of time on the other attributes, are novel approaches that have not been included in computational models for pathfinding up to now.

The methods designed for this module (outlined in Chapter 9) could also be used out of the context of the proposed methodology, in navigation systems embedded in platforms such as Google Maps. The proposed methods could be easily implemented in an application dedicated to route finding. This part of component 3 includes approaches that are based on findings of past experiments and relevant literature, and do not require necessarily physiological data of a specific user. These approaches were included to make the methods applicable also for people who do not have any device for measuring physiological data. The approach that includes physiological data is, in this sense, an enhancement of the basic approach that is based only on the identification of spatial stressors according to relevant theory. As it was elaborated in Chapter 9, this part of the research could be used to create a navigation tool for people with high sensitivity to external stressors.

10.3.1.4. DESIGN OF METHODS FOR PREDICTION OF PHYSIOLOGICAL RESPONSES BASED ON ACTIVITY AND CONTEXTUAL DATA

The design of the component for the prediction of physiological responses was a significant contribution connected to the application of machine learning algorithms for the analysis and prediction of physiological signals. This study is the first that presents a relatively successful model for prediction of responses based on data that is easily available using only accelerometer and GPS sensors, combined with freely available OSM and POI data. The significance of this part of the research is thus high, as very few studies have been conducted on this topic. There is certainly room for further development, but the presented models were an essential first step towards future research in this area.

The models can also be used out of the context of the methodology. For instance, they could be incorporated in an application that tracks geotagged accelerometer data, connects it with contextual data using methods from Chapter 5, and predicts physiological responses for a user's past route using on the collected data. Individuals can use these models to estimate how different past route choices affect their body and inform future choices accordingly. The predictive analysis is not personalised, as it is based on samples generated from other users. However, its significance is high for users that cannot afford a sophisticated EDA tracker, as explained in Chapter 8.

10.3.1.5. DESIGN OF METHODS FOR THE CONSTRUCTION OF A SPATIAL DATABASE OF THE IDENTIFICATION OF PHYSICAL AND PSYCHOLOGICAL STRESSORS IN SPACE, USING OSM AND POI DATA

Another contribution of the research was the construction of a spatial database for the identification of physical and psychological spatial stressors, based on OSM and POI data. This part of the research was a significant step towards solving practical issues of past approaches and ensuring that the designed methods are scalable. Previous studies were heavily based on image analysis, while this approach is based on acquiring and processing data that is already available online for free for many cities. The inclusion of POI density for the representation of the stimulus complexity in the environment was also justified by the analysis between POI density and complexity (presented in

Appendix A). The same measure may also be connected to increased intensity of stimulation. The proposed methods for constructing the spatial database do not have the issues related to privacy and ethics that are commonly associated with image-based analysis. The overall approach requires constructing the spatial database only once for each city and uses point-based and text data that can be processed quickly. Another advantage of this method is that it incorporates a fusion of POIs with street network data. The resulting spatial database can, thus, be used for network analysis incorporating any attributes associated with OSM and POI data, such as traffic, presence of traffic lights, elevation, density and intensity of mixed-use, or detailed categories of land use. Data derived from image-based analysis could also be embedded next to the other data if required, as long as the photos are geotagged.

The methods for the construction of the spatial database could also be used for any other project that requires an estimation of spatial concentrations of stimulus complexity. The analysis between POI density and complexity (presented in Appendix A) also showed strong links between POI density and predictors of imageability; therefore, the spatial database could be slightly modified to estimate this variable as well.

10.3.2. CONTRIBUTIONS TO THE THEORETICAL FIELD OF INVESTIGATION

Apart from the methodological and practical contributions stated in section 10.3.1, the presented work also involved constructing a theoretical and conceptual framework for the analysis of physiological responses in the urban environment. The findings of the experiments presented in Chapters 6 and 8 agreed with some variables of the conceptual framework and enriched our current understanding regarding the interplay between different contextual and movement-related factors and physiological responses. Apart from their importance in the context of this research, the presented framework and the findings of the experiments also constitute theoretical and conceptual contributions, as they enrich current research on the links between urban environment, activity and physiological responses. The developed conceptual framework needs undoubtedly more testing and refinement based on research in other environments involving a larger and more diverse population sample. The variables which were not identified as significant in the statistical analysis in Chapter 6 need to be examined in future studies, as mentioned in section 10.2.2. At the same time, its current version managed to capture some aspects of the urban environment and activity that had not been studied until now and situate them under relevant stress and arousal theories.

10.4. LIMITATIONS

While every effort was put towards adhering to the principles of rigorous research, some limitations of the presented work should be mentioned. The technical issues and limitations related to specific parts of the methodology were explained in detail in the respective chapters. This section will thus focus on the limitations related to the overall study design.

First of all, the study could only include some representative contextual features that capture the general conditions of a place. The contextual analysis of the routes is thus based on a limited set of factors which can influence physiological responses. There might be other factors which have a personal meaning for the participant but were not included in this analysis. The uncertainty of urban life cannot be fully described by the designed models, and it would not be possible to get a very detailed description of the actual circumstances and events during a route, without the addition of more hardware or the use of methods that would infringe the privacy of the users. At the same time, the accelerometer data describing the movement of the user are enough for the analysis of any activity-related information in detail.

The inferential part of the research also had some limitations, mostly related to the characteristics of the studied sample. The studied groups were not representative of the diversity that can be found in the whole population. The studied cohort did not involve children or elderly, and the reported results may not reflect the physiological responses of people belonging to these age groups. These limitations also reduce the generalisability of the predictive models described in Chapter 8. Furthermore, the sample size was not big enough to guarantee statistical power for the inferential analysis. At the same time, most studies in this research area have had similar issues, and the research design was in line with typical study setups in terms of sample size, as shown in the literature review presented in Chapter 1.

Another issue was that the research could not include HR data in the inferential analysis, as the instruments which were available for testing had HR sensors that were not on par with high-quality instruments used in clinical research. It was thus decided to focus on the analysis of EDA data, starting from Chapter 6 and onwards, since the EDA sensors of the available instruments were highly reliable. Due to this issue, the proposed methods for analysing physiological responses in Chapter 5 were more rigorously tested using EDA data. The methods proposed for HR data analysis in Chapter 5 are still reliable, as they are based on existing literature. The movement analysis presented in Chapter 5 can be applied without any change for identifying which changes in HR can be attributed to movement effects. Some parameters though need to be refined through rigorous testing, such as the identification of appropriate thresholds for attribution of an increase in HR to stressful events during movement. Some other parts of the research that involve analysis of physiological responses can still be used with HR data, after being modified appropriately and refined through dedicated testing. For instance, the hotspot analysis and cluster identification of physiological responses can still be conducted in the same way as with EDA data. The pathfinding module is also more based on the analysis of spatial attributes, and the inclusion of physiological responses is optional. Physiological responses derived from HR can be again included in the same way as it was demonstrated using EDA data. The only exception is the module for predicting physiological responses, which is currently built exclusively around the prediction of EDA data. In this case, the prediction of HR data is a task that would require a dedicated round of experiments focused on this purpose, leading to a separate machine learning model.

Another limitation is that the benefits of this research might not prove to be of much relevance for vulnerable and underprivileged populations, since resultant interventions that come from aggregated datasets might become alienating for this group unless their perspective is considered. Future research efforts should thus give careful consideration towards becoming more inclusive and pay attention not to amplify inequities.

The final concern that will be discussed here is connected to issues of ethics and privacy. The presented methods for the analysis of physiological data include collecting GPS data, which need to be handled with special care to ensure the protection of privacy of the users. The analysis of the data in the context of this research included anonymisation before processing. Each user was given a unique, randomly generated ID, and all their data were connected to this anonymous identity. The users were also associated with the same organisation, and their paths frequently converged in the data collected during the free-living activities. It was not possible to identify a particular individual through their route, without knowing more personal information of the users. However, while the data collection methods do not include the collection of any private information, the perception of privacy is a factor that should be taken into account in future research. If the proposed models are implemented in the future in a digital platform or any other application that includes a public demonstration of the data, the users should be given the option to remove any data they consider sensitive. Such data could be, for instance, the trajectory points within a buffer around the location of their home or work. In this scenario, the detailed analysis of data from a single user should be an available option primarily for the user that generates the data. Access to this data should be given only after obtaining consent from the user. The data of multiple users should also be only displayed in an aggregated form to the public, as an extra security measure.

10.5. RESEARCH IMPLICATIONS FOR DIFFERENT DOMAINS

10.5.1. IMPLICATIONS FOR URBAN DESIGN AND PLANNING

The presented work involved extensive discussions on the effects of urban parameters such as traffic and density of mixed-use on physiological responses. A question that naturally arises in this context is whether the presented analysis should lead to changes in the way that the urban space is planned and designed.

The literature reviewed in Chapter 3 showed that excessive stimulation levels could act as a psychological stressor for the organism. Some of the urban features that were examined as parameters related to stimulation, such as traffic levels, are generally regarded as factors that affect the experience of space negatively (Aletta et al. 2018). The reduction of exposure to traffic noise is already a part of contemporary strategies towards the promotion of urban health (Giles Corti et al. 2016).

However, other urban features, such as mixed-use, are again connected to increased stimulation, but they are also essential ingredients for creating neighbourhoods with high vitality and walkability, as discussed in Chapter 3. A balance has to be retained so that the environment has enough complexity to attract the attention of the pedestrian and create a satisfying experience, without being overstimulating. The effect of parameters related to activity has also to be considered here. The visual analysis of the data analysed in this research suggested that some highly complex environments in terms of stimuli did not create intense physiological responses when the individual was in the start of their trip, and the general arousal of the organism was low. The most intense responses may occur when the organism is already under stress from an activity of extended duration or other stressors. However, more research is needed in order to solidify these links.

The most appropriate approach would be to consider the different sensitivity to stimulation of different population groups when designing an urban space or deciding on the appropriate level of mixed-use during the design of a masterplan. Measures for moderating stimulation levels and creating less stressful experiences would be more needed in areas such as aged care homes, hospitals and other places with a large concentration of individuals that may be more easily affected by these parameters. Furthermore, these design considerations should involve the transition between environments with different qualities. An abrupt transition from an environment very rich in stimulation to a tranquil space can also act as a stressor; therefore, the seams between spaces should be designed with care.

10.5.2. METHODOLOGICAL CONSIDERATIONS FOR FUTURE STUDIES ON CONTINUOUS PHYSIOLOGICAL DATA MONITORING IN THE URBAN ENVIRONMENT

Another important parameter that was brought forth by this study was the significance of different aspects of the research design in studies on physiological responses in the urban environment.

The organisation of experiments on a predefined route requires special consideration regarding the effect of the duration of activity on physiological responses. The same urban feature might have a different effect on physiological responses based on the general arousal of the organism, affected by this physical stressor. The experiments that are conducted using a predefined outdoor route for data collection should include exposure to the stressors of interest during conditions of both high and low arousal caused by the duration of the activity. Both conditions should be examined in order to have a complete picture of how a stressor affects the body under different circumstances. A selected group of participants should also follow the reversed route to include in the study the presence of any order effects.

The ambient temperature should also be noted for comparison between studies, and if the climate and the sample size allow it, the experiments should be conducted multiple times under different temperatures, to take into account this effect as well.

It may be challenging to cover all these aspects in one study while also having a large enough sample, but these points should be considered during the interpretation of the findings.

10.6. FUTURE WORK

This section discusses the possibilities for future research based on the presented work. Future improvements regarding each component of the methodology have already been discussed in the respective chapters; therefore, this section presents future possibilities related to the broader agenda of this research.

10.6.1. RESEARCH ON THE LINKS BETWEEN URBAN ENVIRONMENT FEATURES, ACTIVITY AND PHYSIOLOGICAL RESPONSES FOR DIFFERENT USER GROUPS

The presented experiments for the identification of the effect of different features on physiological responses were based on two groups of young and middle-aged individuals. The research should be repeated with a larger sample and in different contexts in order to derive more concrete results. Future work should also examine the effects of the features analysed here on elderly and other population groups with a range of lived experiences that could include conditions that affect their perception and sensitivity. The continuation of the presented work in this direction will be highly significant for the advancement of research in environmental psychology and stress theory in the urban environment.

10.6.2. INCORPORATION OF QUALITATIVE DATA RELATED TO USER EXPERIENCE

One part of the research that could be improved in the future involves the analysis of qualitative data describing the experience of the users. The presented work used qualitative data from the participants for the predefined route and the free-living activities in Sydney.

The incorporation of the PANAS scale for the measurement of the affect in the indoor experiment and the predefined route showed the value of the inclusion of tools for a structured measurement of the different dimensions of the perceived experience associated with different events. The analysis of the fluctuations in the positive and negative affect during the predefined route in Sydney was only briefly reported (in section 6.4.3. in Chapter 6, and section 3.1.5. in Appendix B). However, it revealed valuable information regarding the trends in the positive and negative affect in parallel to the trends in the studied EDA measures.

The qualitative data collected during the free-living activities was unstructured, and some participants submitted limited information for some routes or did not submit any qualitative data. The review of the data assisted in understanding how the participants perceived routes with differences in the stimulation levels or the activity pattern. It was also assistive for ruling out the possibility of unexpected events that might influence physiological responses. However, this was only possible in cases where the participants had provided a detailed description of the experience.

The inclusion of structured and unstructured methods for collecting data related to the perceived experience was undoubtedly valuable for understanding how the users perceive the effect of different physical and psychological stressors. The conducted experiments showed that there is value in collecting information at three levels; the overall perceived experience, the experience in segments of the route which have differences in the contextual qualities, and the experience during specific moments of interest (such as recorded physiological responses of increased intensity). However, more research is needed regarding the best approach and tools for collecting this information. Some studies have used applications for self-reporting the user experience (e.g., Zeile et al. 2016) during the route. This method of recording the experience has the advantage that it is conducted in real-time while experiencing the different stressors, and each record is geotagged. At the same time, the participants may have to alter their movement to think and record their response. It would be, therefore, uncertain if the recorded physiological responses are a result of the experience or the actions related to its recording.

An alternative option could be the design of an application for requesting information from the users on different parts of the route shortly after they finish their activity, based on their recollections. This step should first involve analysing their physiological responses so that the users can be asked information regarding the experience during specific responses. The manual review of notes could also be assisted by algorithmic methods that involve text processing, identification of clusters of significant themes and sentiment analysis.

10.6.3. PERSONALISATION OF THE MODELS FOR PREDICTION OF PHYSIOLOGICAL RESPONSES

As mentioned in section 10.3.1.4, one limitation of the models for prediction of physiological responses (described in Chapter 8) is that they lack personalisation and cannot predict the unique responses that a specific user might have to a particular stressor or a sequence of stressors. Future work could involve the exploration of solutions for this issue; for instance, the customisation to each user's traits could be facilitated by training a separate model for each user based on their past physiological responses. This option would only be useful for users that have EDA tracking equipment, but it can be explored in future research in this area.

10.6.4. USE OF THE DEVELOPED METHODS FOR POST-OCCUPANCY EVALUATION

One research direction that could be explored in the future is the utilisation of the developed methods as a tool for post-occupancy evaluation of urban areas. Since the methodology involves the collection of trajectory data, this data could be analysed to understand the patterns of user activity in selected urban open spaces. The analysis of physiological responses, combined with the collected contextual information, could be used on top of the analysis of space usage, to understand how users react to different spatial configurations. Such a tool could also help understand the differences in space usage before and after an urban intervention, or during different stages of an intervention, and compare the physiological reactions elicited during each stage.

10.6.5. USE OF THE SPATIAL DATABASE TO IDENTIFY STRESSOR PATTERNS AT A CITY SCALE

An alternative use of the proposed methods for creating the spatial database could be to use them to identify the distribution of physical and psychological stressors in an area, without adding physiological data from users. This analysis could lead to the development of a ranking tool that identifies differences in the patterns of stressors within one city or between different cities. For instance, the spatial database could be used to identify neighbourhoods where more psychological stressors are prevalent due to the excessive presence of stimuli, or areas with more intense concentrations of physical stressors due to the presence of many obstacles. The identification of differences in temperature as a physical stressor can also be included in the ranking system, after adding functions for the analysis of parameters related to temperature (i.e., green and water) in the methods for building the spatial database. There is much potential in working towards this research direction in the future, as the analysis of this information could help researchers understand which areas in the city could be connected to more physical or psychological stress compared to others.

10.6.6. ENRICHMENT OF THE SPATIAL DATABASE WITH SOCIOECONOMIC AND OTHER STRESSORS

While the methods for building the spatial database described in Chapter 5 were focused on a limited number of parameters that can act as stressors, more information layers can be added if needed. This could involve environmental parameters that might affect physiological responses, such as air pollution, or social, economic and cultural factors that can act as psychological stressors. For instance, if there is available geotagged data regarding the spatiotemporal patterns of crime in a city, this information could be added in the spatial database as another potential psychological stressor. Future work could thus involve demonstrating how the addition of new information layers would work in practice.

10.6.7. ADAPTABILITY AND RESPONSE TO THE CURRENT CIRCUMSTANCES

Finally, another direction that will be considered for future research is the possible need to adapt this work in light of events that changed the global landscape in 2020. In the third year of this study, the world witnessed the development of a public health emergency which brought forth new considerations regarding the relations between people and public space. The social measures which were taken in various countries due to the COVID-19 pandemic included staying at home as much as possible, reducing physical interactions and keeping a physical distance of at least 1.5 metres from others (Zhang et al. 2020). Some early studies (e.g., Maugeri et al. 2020) indicated a significant reduction in physical activity and a negative impact on psychological health and wellbeing for the populations of countries that took strong social distancing measures.

The repercussions of the changes in the normal way of living that we are experiencing now are still unknown, as the global health emergency is still affecting the population. Some aspects of the presented research might acquire a different significance or meaning due to the current circumstances. At an individual level, the proximity to other people becomes an additional stressor, due to the possible danger of contracting the virus. At a city scale, the presence of mixed-use and elements of public space which usually attract human activity has now been associated with unwanted crowding. At the same time, trying to avoid interactions with other people results in reduced physical activity, which has adversary health effects, as it was shown.

Some parts of the presented research could be modified to adapt to these circumstances and assist in providing solutions for enhancing active mobility in a way that responds to the needs of these times. For instance, the module for pathfinding towards reducing exposure to stressors already incorporates methods that are essentially built to avoid crowding, apart from traffic. These methods were initially designed in this way for other reasons, following the context of this research, but they could be used directly to assist people in finding routes that help them exercise while also avoiding increased possibilities of unwanted crowding.

As a closing note, the presented work managed to solve many issues among those identified in the literature review in Chapter 1, but it was only a first step in this research area.

Future work will be devoted to a more in-depth exploration of some of the topics presented in this research. The proposed theoretical and conceptual framework shall be a good start for future studies in this area and inspire new approaches. Hopefully, the presented work will help other practitioners to conduct research more efficiently in this area and enrich our knowledge on how the urban environment influences the body.

APPENDIX A

ANALYSING THE RELATIONSHIP BETWEEN POI DENSITY AND PREDICTORS OF STIMULUS COMPLEXITY IN THE URBAN ENVIRONMENT

This is an original manuscript of an article published by Taylor & Francis in Journal of Urban Design on 9 April 2021, available online: http://www.tandfonline.com/10.1080/13574809.2021.1903306.

The article contains material related to the examination of the relationship between POI density and complexity. The presented analysis was conducted to support the argument that POI density can be used as an indicator of stimulus complexity in the urban environment. The work is presented as it was submitted for publication. Only the figures have been renamed to indicate that they belong to this appendix. The references are included in the reference list in the end of the thesis.

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Author contributions: DD conceived the idea, developed the theory, planned the case studies and performed the data analysis. BN supervised the work and provided critical feedback. DD wrote the manuscript with input from BN.

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ABSTRACT

The complexity of an environment is an important factor related to the quality of urban life, as it affects perception. Existing methods for estimating complexity from images or field visits are helpful but difficult to apply when the area of interest is large. This study identifies alternative ways of estimating the complexity of an environment, by analysing the density of Points of Interest (POI) of an area and using it as an indicator of mixed land use. Two case studies are explored, and spatial regression models are employed to test the association between POI density and complexity, and its predictors.

Keywords: density, complexity, points of interest, mixed-use

1. INTRODUCTION

The urban environment can be seen as a composition of elements which act as stimuli and may attract the attention of humans. Shopfronts, building facades, traffic noises and other elements of the surroundings have visual, auditory, tactile and other properties which are recognised by the human sensory system. Research has shown that the psychological and physiological responses to an environment are influenced by several stimuli and their properties (Berlyne et al. 1963).

One such property which has been associated with psychophysiological effects is complexity. Attributes related to complexity include the number of distinguishable elements, as well as structure and order (Berlyne et al. 1963). The notion of stimulus complexity has been associated with the rate of receiving and analysing information from the environment (Rapoport and Hawkes 1970). When individuals are faced with environments of high complexity, they may require a higher processing time to analyse this information. Studies have shown that the excessive presence or the deprivation of stimuli, known as overstimulation and understimulation respectively, can act as a stressor (Frankenhaeuser et al. 1971). There have also been studies which suggest the existence of a relationship between complexity and appraisal of a scene; Berlyne (1960) indicated the existence of a U-shaped relationship between complexity and appraisal, suggesting that scenes with a medium degree of complexity are preferable in comparison to environments with low or high complexity. However, the work of Berlyne was focused on the relationship between complexity and appraisal as a general phenomenon, and was not related specifically to the urban context.

Understanding complexity in the context of urban space is important for urban planning and design, due to its connections with perception, cognitive load, preference and appraisal. While the work of Berlyne refers to the general effects of complexity, other subsequent studies have situated their research on complexity in the urban context. For instance, Ewing and Clemente (2013) describe complexity in the urban environment as 'the visual richness of a place that depends on the variety of the physical environment, specifically the numbers and kinds of buildings, architectural diversity and ornamentation, landscape elements, street furniture, signage, and human activity' (Ewing and Clemente 2013, 130). Rapoport and Hawkes (1970) suggested that complexity is a desirable property for the urban environment. Their proposal for the definition of optimal complexity is based on the rate of usable information in an environment, as well as personal preferences and cultural differences. According to their definition, while an environment may rank very highly in terms of overall visual variety, it may be so chaotic that it is impossible to decode any useful meaning from it, in which case the complexity is not desirable, and the usable information is low. These ideas are close to the concept of 'overload', discussed by Milgram (1970). His theory was also based on information processing, and involved a critique on modern cities which may contain environments with an excessive input in terms of information available to city dwellers. He suggested that the difficulty to handle the excessive input might affect cognitive functioning and have a negative impact on different facets of urban experience and daily life.

The notion of complexity has also been systematically appearing in the field of environmental psychology, in studies on stress recovery. Ulrich et al. (1991) provide a summary of studies related to arousal, which suggest that a lower complexity is preferred when an individual is under stress. Since the complexity of natural environments tend to be lower than that of urban settings, this argument has been used to support the hypothesis that natural environments may be more helpful for stress restoration, compared to urban environments. However, while a lower degree of complexity may assist in stress restoration, a moderate increase in complexity may be related to higher preference of an environment. Kaplan et al. (1972) showed that natural environments with a higher complexity were preferred over natural environments with lower complexity; the same positive association between complexity and preference was found when analysing urban environments with different degrees of complexity. In their study, the natural environments were also generally preferred over urban environments, regardless of the differences in complexity within each group.

The main points which emerge from these studies are that complexity seems to be positively connected with higher appraisal and preference of an environment, but when it reaches excessive levels it may lead to a stressful or overwhelming experience. For similar reasons, the presence of lower complexity may be a better option compared to excessive stimulation when the objective is the restoration from stress. It is thus evident that stimulus complexity is an important factor which may affect the way that an individual perceives their environment, having the potential to make an interaction with this environment more pleasurable or more stressful. Understanding the complexity of the urban environment is important for multiple research domains, ranging from neuroscience to urban design and planning. There has though not been much effort towards the development of ways to capture the variations of this aspect of the environment and use this information to understand which environments need to be redesigned in order to be more pleasurable for their inhabitants. Previous studies on the identification and analysis of stimulus complexity and its psychophysiological effects, such as the experiments of Berlyne (1963) and Kaplan et al. (1972) have been largely based on images, such as cards or projection of slides. Some researchers in studies on psychophysiological responses in the built environment have incorporated an automated measurement of complexity, by using image processing tools for the extraction of properties such as visual clutter (i.e., Benita and Tunçer 2019). One of the most comprehensive works in this area is the toolkit which was developed recently by

Ewing and Clemente (2013) for the evaluation of urban scenes. This toolkit is based on measurable attributes; it was developed (Ewing and Handy 2009) and tested by rating images, and it was designed to be used as a walking audit instrument. A common element in all these approaches is that they require collecting a sufficient sample of images for the measurement of complexity. Some researchers such as Ewing and Clemente (2013) have made use of web imagery for this purpose, from platforms such as Google Street View, but this approach still required spending time to assess each photo. These obstacles hinder the measurement of this quality of the urban environment in areas larger than a neighbourhood.

In this context, this study focuses on the problem of estimating the complexity of an environment in cases where visual assessment is not feasible. The approach which was investigated in this paper was the analysis of the relationship between complexity and the density of Points of Interest (POI). Points of Interest (POIs) have emerged as a data source which is widely available from providers such as Google and OpenStreetMap (OSM) and conveys information concerning land use characteristics of an area. POIs are a form of spatial data, which are created when a location is identified as interesting, and this information is posted online, accompanied by geographical coordinates. POIs usually represent points where the land use is not residential, and they have been used extensively in the past 10 years in the context of land use analysis (i.e., Jiang et al. 2015). The analysis of POI data can give information with regards to land use density and diversity (i.e., Wang et al. 2019; Yue et al. 2016). POI density is used here as a term which describes the intensity of the spatial distribution of POIs, based on their spatial proximity. A place with high POI density in this context is a place where there are many POIs close to each other, signifying a concentration of points which have been identified as 'of interest' by the inhabitants or visitors of the area.

The reason for selecting POI density as a possible indicator of the degree of complexity was that many of the factors that have been connected with complexity in the urban context seem to be also connected to POIs. The study of Ewing and Clemente (2013), which incorporated an exhaustive analysis of several urban environment characteristics which could be connected to complexity according to the theoretical background, identified the following factors as the most significant predictors of complexity: the number of buildings, building colours and accent colours, the number of people, the presence of outdoor dining and the number of street artworks. As POIs are commonly used as indicators of the presence of retail or mixed land use, it was expected that high POI density would be associated with higher pedestrian activity and a higher presence of signs, diverse colours and other visual elements. The link between pedestrian activity and POI density was expected to be particularly strong, due to the significant association between commercial land use and pedestrian volume. The model of Schneider et al. (2009), for instance, identifies the number of commercial retail properties within proximity of an intersection as a significant predictor of pedestrian volume.

This study makes thus use of POIs as a proxy of mixed and commercial land use and examines the relationship between POI density and complexity. This relationship is tested by extracting the POI density from POI data and comparing it to the overall degree of complexity, as well as separate factors related to it, such as pedestrian volume and number of colours. The aim is to explore this link in order to use this information in future studies, in order to estimate the degree of complexity of a place which can be applied without having to analyse a large volume of images or spend time and resources in field visits. The POIs are retrieved by freely available APIs, and the POI density is estimated by using the nodes of the street network, retrieved from OSM data which are also freely available and have worldwide coverage.

The paper thus has a twofold contribution; firstly, it enriches current research on factors which predict complexity, by analysing the link between POI density (and thus commercial and mixed-use density) and complexity. At the same time, it showcases a novel methodological approach for identifying places where there is a probability of high complexity. This method is easily reproducible, computationally inexpensive and can be applied as a fully automated process wherever there is sufficient documentation of POIs.

The paper starts by elaborating on the methods used for the extraction of POI density, the extraction of the degree of complexity from images, and the statistical methods used for their comparison. The results are then presented for two case studies, followed by a discussion on the findings.

2. MATERIALS AND METHODS

Two case studies were designed in order to provide a sufficient understanding of the relation between POI density, complexity and its predictors. The first test involved the analysis of points sampled randomly from a 20x20 km bounding box, centred at the Central Station of Sydney. The second test involved a more focused analysis on points sampled from a selected 1.8 km walking route.

In the first case study, the points were sampled from various areas with largely different degrees of density, including quiet suburban districts and urban green areas as well as the highly crowded Sydney CBD. The methods of analysis involved an analysis of features related to complexity, based on the study of Ewing and Clemente (2013), and the statistical analysis of the relation between these features and the degree of POI density for the sampled points. The extraction of features related to complexity was conducted by accessing and rating images from Google Street View for the geocoordinates of each of the sampled nodes. The method for calculating POI density is outlined in section 2.1.

A subsection of the first area of examination was selected for the second case study. This experiment aimed to examine the variations in complexity during a 30-minute route within the Sydney CBD. The relations between POI density and factors related to complexity were explored here in a more fine-grained manner, by examining if the variations in complexity would parallel the variations in POI density during the route. Images from Google Street View were accessed again for each point of the route, for the extraction of features related to complexity, and the POI density was calculated with the same method as in the first test. Statistical analysis was then conducted for the examination of the relationship between complexity and POI density. The analysis was complemented by video footage which aimed to enrich the understanding of spatiotemporal variations of complexity; one video was captured at each GPS point, lasting approximately 80 seconds. The videos were captured during one weekday in Spring 2019, with mild weather, between 2 and 4 pm.

2.1. SPATIAL DATA PROCESSING: DATA ANALYSIS AND DATA FUSION

POI data were obtained for free using the Triposo API. Street network data were acquired from the OSM database, using the python library *osmnx*. Two k-d trees were constructed for separate spatial indexing of the POI and the OSM data. The OSM data contained the geocoordinates of the nodes and links of the street network. The POI density was calculated by querying the k-d tree and detecting the number of POIs within 100m of each POI. The resulting metric thus depicted the relationship between the different POIs and reflected the varying densities in their spatial distribution. Figure A1 shows an example of the calculation of POI density for the Sydney CBD.

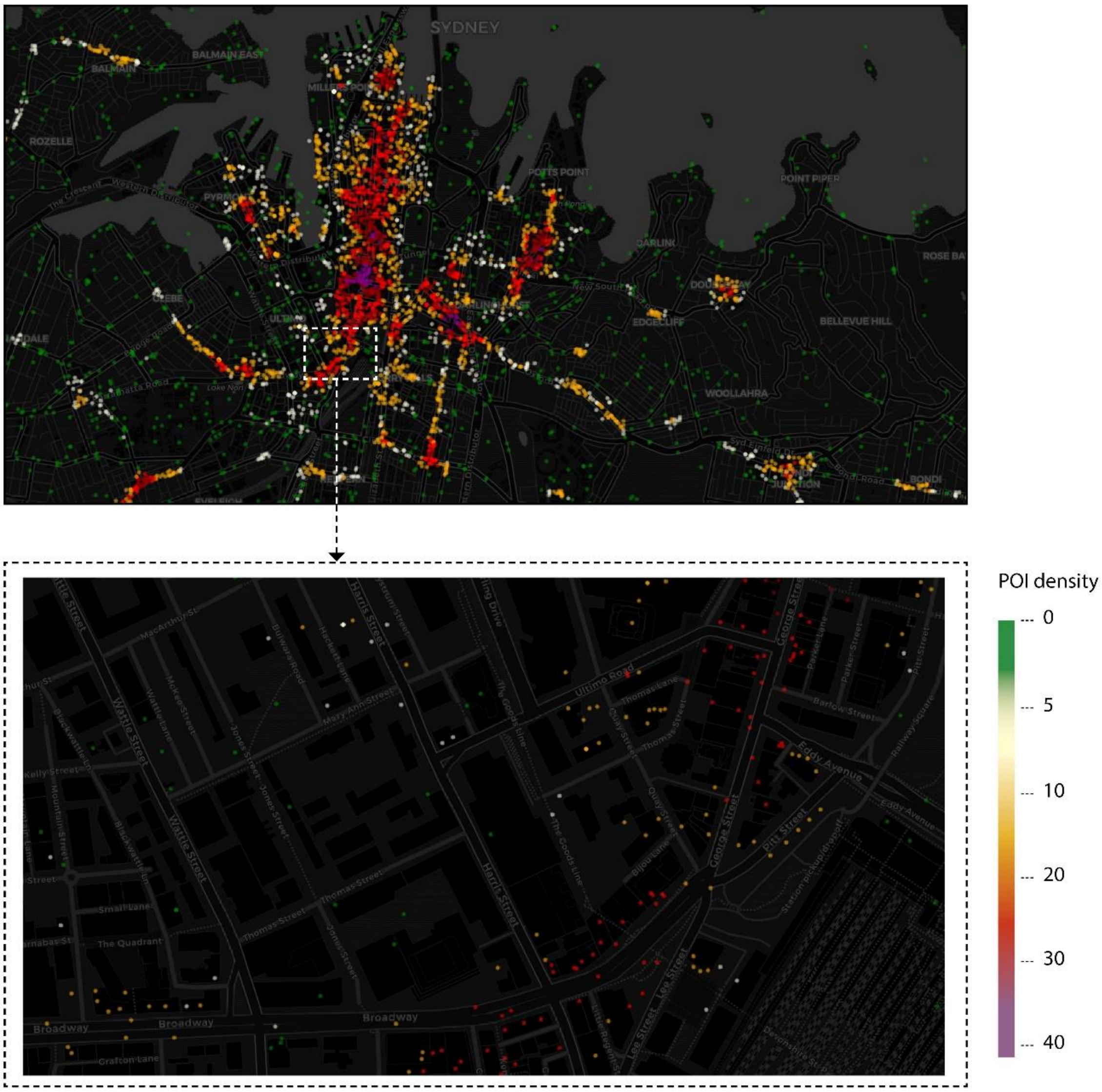

Figure A1. Upper: The outcome of the calculation of POI density for the Sydney CBD. Lower: POI density in the area selected for Case Study 2

The fusion of OSM and POI data then followed by calculating the closest POI for each street network node of the OSM database. The closest POI was found using a nearest neighbor query, using the OSM k-d tree. The fusion of OSM and POI data was conducted in order to provide a representation of the whole street network in terms of variability of complexity, and not only the nodes which were associated with POIs. The nodes which were far from POIs were essentially marked with POI density close to zero.

The resulting database contained 109117 nodes in total. The following features were extracted from the POI database and transferred to the OSM database: *closest POI density, closest POI distance.* The two metrics were then combined in the following manner, in order to take into account the effect of distance:

$$\text{Node POI density} = \text{closest POI density} / [\ln(\text{closest POI distance} + 1)]^2 \qquad (1)$$

This formula (Equation 1) was constructed after conducting several experiments and fine-tuning the parameters so that the result would be as representative as possible of the real spatial relationship between a node and the spatial distribution of its closest POIs.

2.2 MEASURING COMPLEXITY FROM THE SITE CHARACTERISTICS

The measurement on complexity was based on the visual analysis of different environments, using street imagery from web pages (Google Street View) for the first case study, and a combination of web page imagery and videos taken in the field for the second case study. Each environment was analysed for the extraction of attributes which were identified as significant with respect to complexity in Ewing and Clemente (2013). The Google Street View images were assessed manually, while for the video analysis, an algorithm was built for the automatic extraction of frames, and the identification of pedestrians. The algorithm makes use of state of the art techniques for object recognition and computer vision using deep learning models, implemented in the Python library ImageAI. This analysis was conducted in order to extract additional information regarding the degree of change in pedestrian activity and traffic.

The following attributes were extracted: number of buildings, number of people, number of dominant building colours, number of accent colours, presence of outdoor dining, number of public artworks. The variable extraction followed the guidelines of Ewing and Clemente (2013, 104-135). The variable ‘complexity’ was then calculated, using the coefficients which were found in Table 3.9 in Ewing and Clemente (2013, 50.).

The images displayed in Figure A2 are examples of the environments which were assessed in terms of complexity. The degree of complexity, according to the ranked variables, increases progressively: the upper images have very low complexity and POI density, being typical examples of environments of low residential density. All the factors which contribute to the complexity ranking are very low for these two streets (Dunoon Avenue and Elizabeth Parade), as shown in Figure A3 there were no signs of pedestrian activity in the images which were assessed around these points, and there was a high homogeneity in terms of visual elements. The images in the middle have a medium degree of complexity and POI density, and represent typical suburban scenarios with low to medium presence of mixed-use, usually found in the centre of the suburb. There is some pedestrian activity in The Seven Ways, but much fewer compared to York Street and George Street. The images in the bottom of Figure A2 rank highly in terms of complexity and POI density; there is a significant presence of skyscrapers and commercial activity, accompanied by intense pedestrian activity. The high ranking in these factors is also visible in Figure A3, where it is shown that the number of pedestrians and buildings is much higher for York Street and George Street in comparison to the other cases.

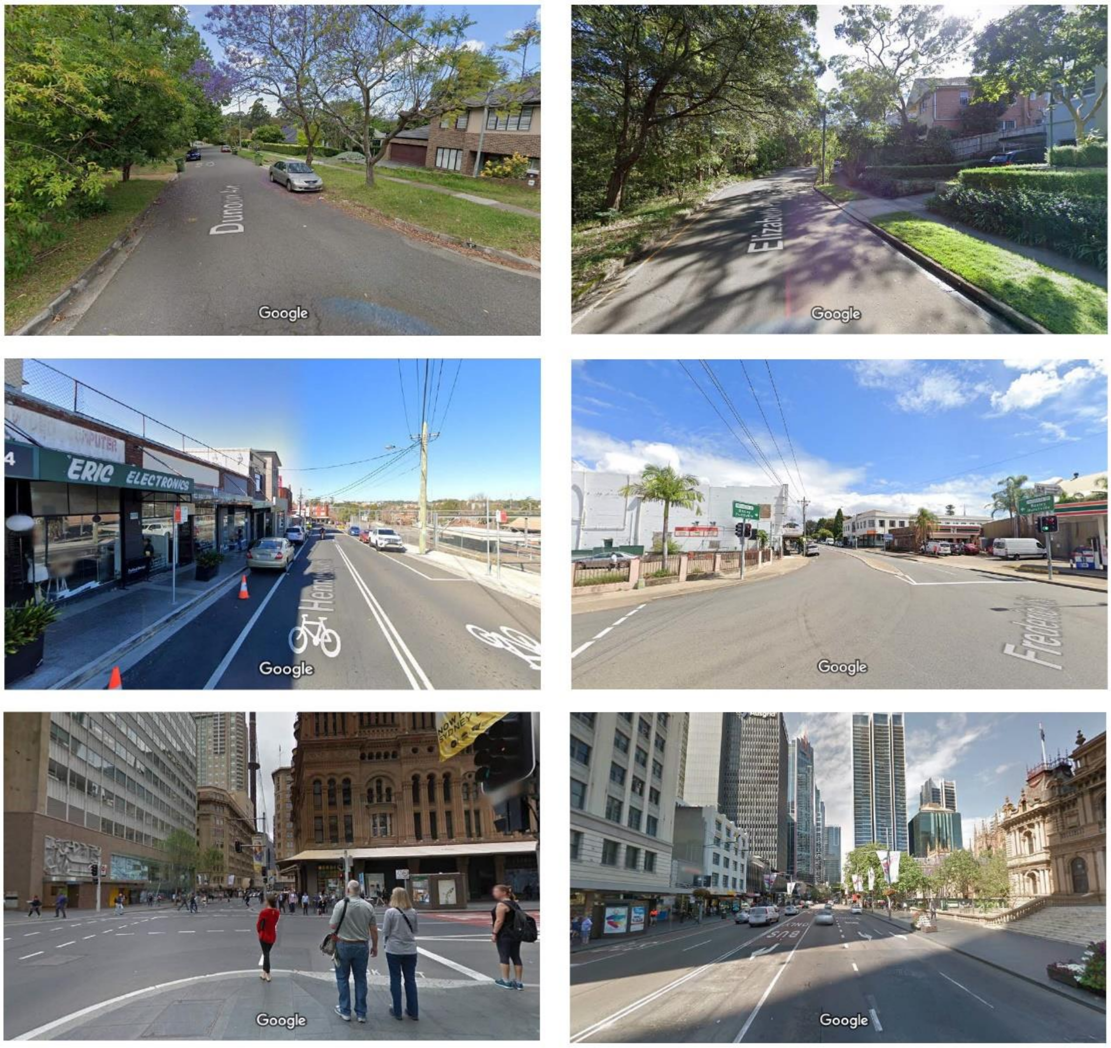

Figure A2. Examples of the locations which were assessed in terms of complexity. Upper left: Dunoon Av. Upper right: Elizabeth Parade. Middle left: Hennesy St. Middle Right: The Seven Ways. Bottom Left: York St. Bottom Right: George St. Source: Google Street View

Address	FACTORS RELATED TO COMPLEXITY						Complexity	POI density
	Number of accent colours	Number of building colours	Number of buildings	Outdoor dining	Pedestrians	Public art		
York St, City of Sydney	6	4	24	0	140	0	8.4	35
George St, City of Sydney	9	4	22	1	126	2	9.3	34
The Seven Ways, Rockdale	7	2	9	0	8	0	3.3	13
Hennessy St, Croydon	5	3	4	1	0	0	3.3	9
Dunoon Avenue, West Pymble	0	1	2	0	0	0	1.7	0
Elizabeth Parade, Lane Cove West	1	1	2	0	0	0	1.8	1

Figure A3. An example of the attributes extracted from the images in relation to complexity. The resulting degree of complexity is also displayed for each location, as well as the corresponding POI density.

2.3. STATISTICAL ANALYSIS

The first test involved the random selection of 600 nodes from the OSM street network data. Special attention was paid to ensure that the randomly selected points would represent all the different density levels of the studied area. The database was split into four bands according to the density levels of each point, and 150 points were then selected randomly from each band. The final dataset contained 512 points.

The statistical analysis involved correlation analysis for the examination of the relationship between POI density and complexity. There was also interest in understanding the relationship between the parameters which were combined to construct the ‘complexity’ variable, and POI density; or in other words, to see which properties of a space related to complexity were most related to POI density in the studied site. The results of the Moran’s I test showed significant autocorrelation in the distribution of both variables, which would violate the assumptions of independence of the variables needed for Ordinary Least Squares (OLS) regression. Spatial autocorrelation was also identified in the residuals when an OLS regression test was conducted, suggesting that the resulting coefficients of this test would not be valid.

For this reason, the main statistical analysis was conducted with a spatial regression model, which takes into account the spatial dependency of the variables. The data points were processed in the GEODA software, and a matrix of weights was extracted for weights based on contiguity as well as distance, describing the spatial relationship of the variables. The Lagrange Multiplier test diagnostics of the OLS regression produced very similar values for the spatial error and the spatial lag model; it was thus decided to proceed with both spatial error and spatial lag models, and compare the results to see which variables would emerge as significant in both versions. The models which are presented in section 3 were first checked to confirm that there was no spatial autocorrelation in the residuals.

The second test examined a set of 27 GPS points obtained from the selected outdoor route close to the Central Station. The statistical analysis here involved correlation analysis between POI density and complexity and visual examination of the graphs of the different variables.

3. RESULTS

3.1. CASE STUDY 1

The correlation analysis between POI density and complexity suggested that there is a moderate to strong positive association between the two variables (Spearman's r_s=0.64, p<0.00001). A spatial regression model was also run for the examination of the association between POI density and complexity, with complexity as the dependent variable and POI density as the predictor. The model also showed that there was a moderate but statistically significant association between the two variables (r squared = 0.43, p<0.00001), also showing that there was a significant presence of spatial error (p<0.00001).

The results of the spatial regression models with POI density as the dependent variable and the other factors related to complexity as predictors showed that there was a statistically significant association (p<0.00001) between POI density and the number of pedestrians, as well as the presence of outdoor dining. This finding was consistent in all models (apart from one model where the association with the number of pedestrians was again significant but with a higher p-value). The most successful model, according to the Akaike Information Criterion (AIC) of the different models, had r^2 = 0.70; the results were similar for the other models. The models are presented in Figure A4.

	Spatial error model					*Spatial lag model*			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Predictors	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
Intercept	6.54***	6.7**	6.71***	7.84*****	6.87****	-0.39	-0.40	0.13	-1.01
Number of buildings	0.23	0.24	0.23ᴵ	0.30**	-	0.20	0.20		0.17
Number of building colours	0.11	-	-	-	0.43	0.005	-		0.09
Number of accent colours	0.42	0.44	0.46	-	0.82**	0.56	0.59ᴵ	0.82***	0.46
Number of pedestrians	0.17*****	0.17*****	0.17*****	0.17*****	0.19*****	0.15*****	0.15*****	0.16*****	0.05**
Public art	1.1	1.09	-	-	-	1.11	-		0.49
Outdoor dining	2.1****	2.1****	2.18****	2.34*****	-	1.96****	2.02****	2****	1.74*****
Spatial lag	-	-	-	-	-	0.57*****	0.57*****	0.59*****	0.74*****
Spatial error lambda	0.69*****	0.69*****	0.69*****	0.69*****	0.70*****	-	-		

p <0.1	ᴵ
p <0.05	*
p <0.01	**
p <0.001	***
p <0.0001	****
p <0.00001	*****

Figure A4. The results of the spatial regression models.

The fact that the coefficient was smaller for the number of pedestrians compared to other variables was expected due to the much higher range in this variable in comparison to the others; for instance, in some of the points with a high degree of complexity and POI density, there were more than 100 pedestrians, while in other areas there were none. The number of accent colours was also identified as statistically significant (p<0.01) in two models, and the number of buildings in one model.

3.2. CASE STUDY 2

The correlation between POI density and complexity for the planned route was again moderate to strong, and statistically significant at $p<0.05$ ($r_s = 0.66$, $p=0.0001$). In this case, though, the variables were not completely independent, as the points have spatial proximity. The result of the correlation analysis here is thus reported as an indication that the relation between POI density and complexity which was observed before is also holding true in this case, but it is significantly affected by the spatial distribution of the points. This spatial relationship is also visible in the graphs of POI density and complexity (Figure A5), where there is a tendency of parallel increases and decreases in the two variables.

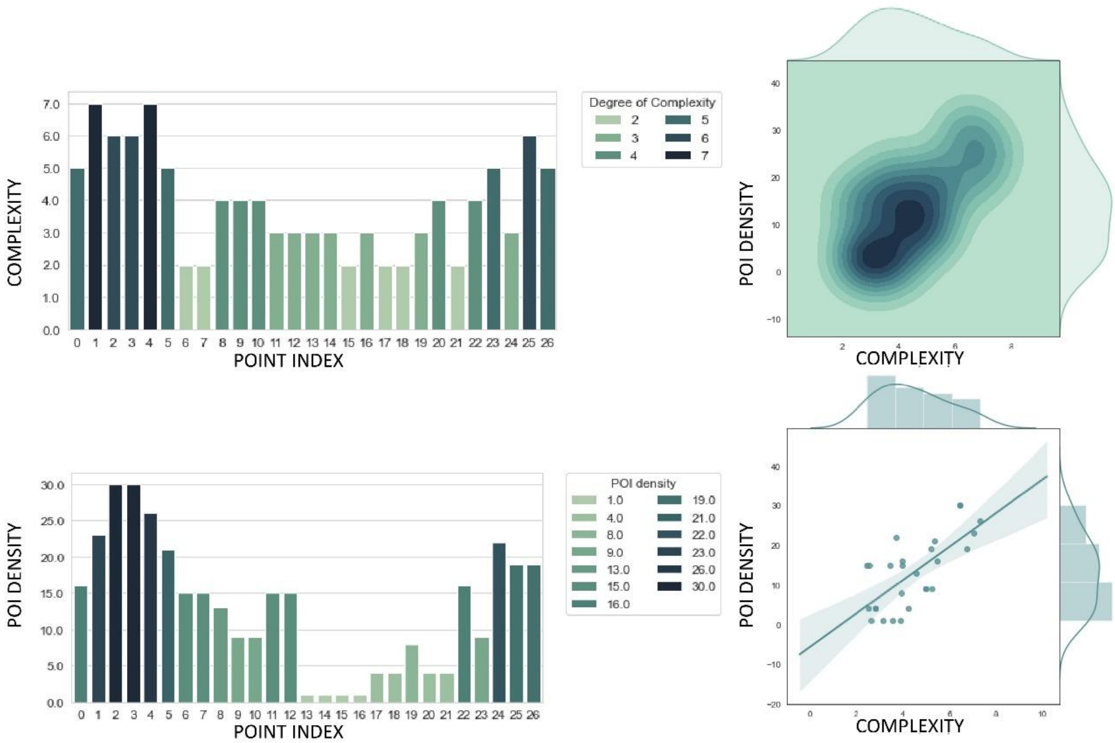

Figure A5. Left: Graphs presenting the calculated degree of complexity and POI density for each point. Right: A kernel density plot and a regression plot showing the two-dimensional relationship between the two variables.

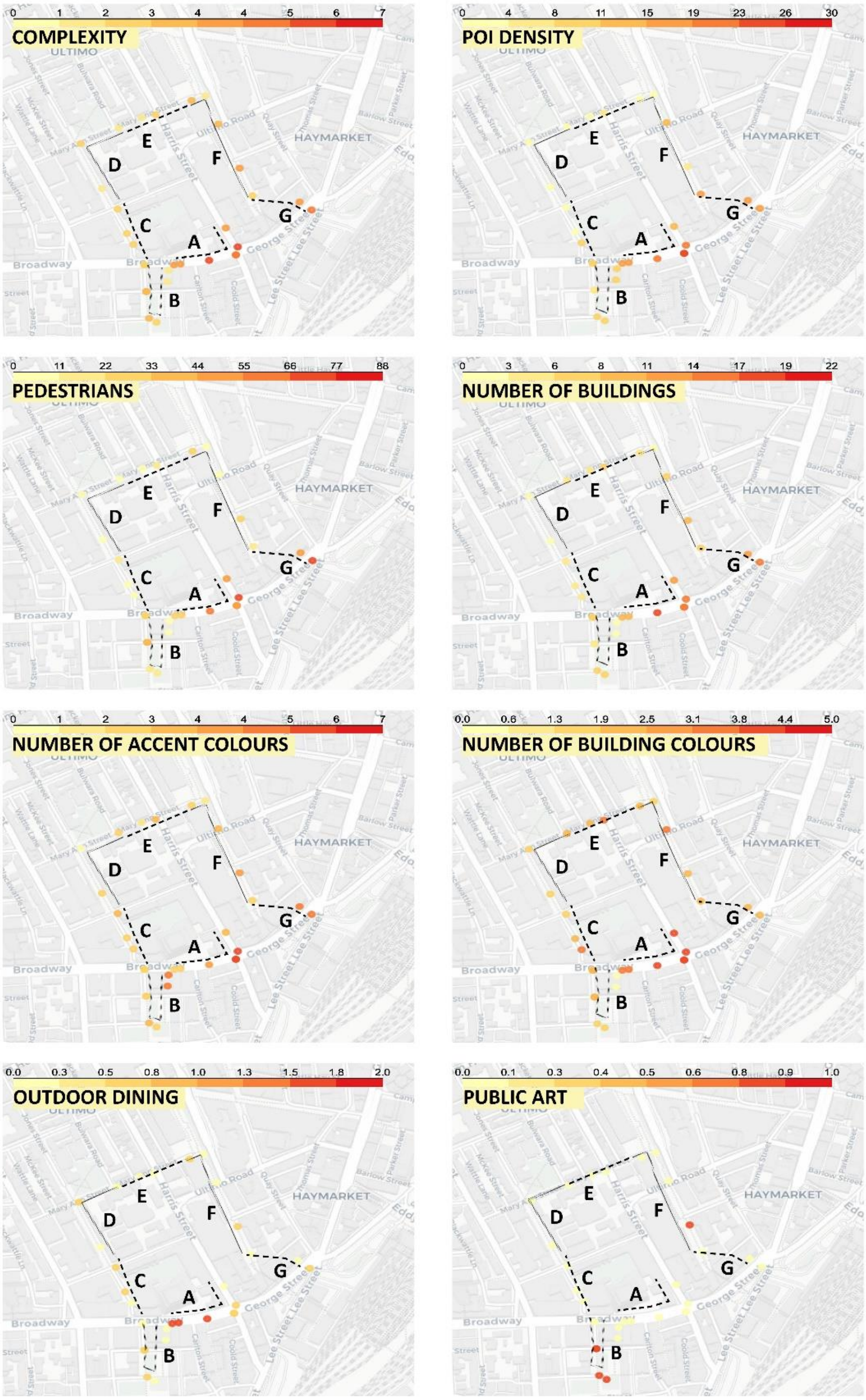

Figure A6. Maps showing the spatial distribution of complexity, POI density and the separate predictors of complexity

The maps shown in Figure A6 incorporate a fragmentation of the route points in segments from A to G; this segmentation was applied to allow a comparison of the variations in the studied variables, and it was conducted by splitting the route into parts which had similar length in terms of walking distance, and similar contextual qualities according to the authors' knowledge of the area.

The visual inspection of the maps (Figure A6) also confirms the similarity between the degree of POI density and complexity. Segments A and G appear to have the highest complexity and density, as well as a high number of pedestrians, buildings and accent colours. Segment A has also points with a larger number of building colours. There were generally very few points with outdoor dining and public art in the selected sample; these characteristics were also found relatively less frequently in the first case study. The few points with outdoor dining were found in segment A, and public art appeared in segments B and C.

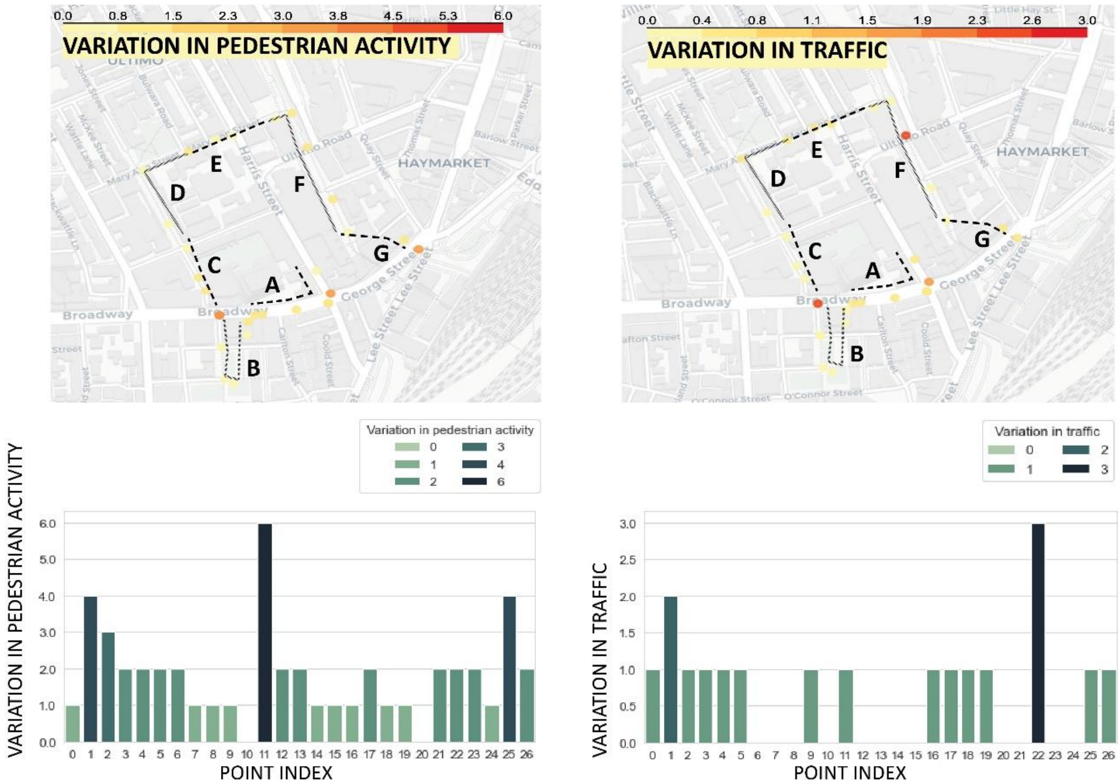

Figure A7. Maps showing the variation in pedestrian activity and traffic. The points with highest variation are depicted with red colour, while low variations are depicted with light yellow.

The analysis of the video segments showed that the most intense variations in pedestrian activity were in three points; one in the middle of segment A, one at the end of segment B and one in the middle of segment F (Figure A7). These points are very close to traffic lights, on one of the busiest streets of the Sydney CBD. The pedestrian volume is also high at these points; this means that there is intense crowding but also a rapid change of moving stimuli at these points. Figure A8 shows one of these points, contrasted with one point where there is low pedestrian volume, as well as low change in the number of pedestrians. The analysis of variations in traffic showed that there is a small degree of variation in the majority of the route, apart from two points, where there was an intense change in the volume of passing cars when the videos were taken.

Figure A8. Variations in the number of pedestrians in two selected spots.

The visual inspection of photos from Google Street View and field visits also showed that while some places had similar values in terms of POI density and complexity, they had a very different character. For instance, segment D contained a residential street segment and a small urban park. Segment B also contained an urban park, which attracted much higher activity as it was very close to a shopping mall. Both segments had similar POI density and complexity values, and a field visit showed that both places were generally calmer compared to other segments which had higher values in terms of POI density and complexity. At the same time, the two urban parks had a much higher presence of natural elements compared to the residential street segment, and were able to host a wide range of activities due to their design, while the residential street had a more transitional character. The two parks also differed in terms of factors such as the sense of enclosure due to the surroundings, or the degree of presence of water.

These qualitative differences may be related to other parameters connected to the way that a place is perceived aside from the complexity factor.

4. DISCUSSION

The results of both case studies suggest that there is a positive association between POI density and complexity. Among the different predictors of complexity which were tested, the presence of people and outdoor dining were identified as the variables with the most significant association with POI density. This finding was also expected, especially concerning the link between POI density and presence of people: a denser concentration of POIs indicated a higher presence of mixed or commercial use and thus a higher degree of pedestrian activity. The significant association between POI density, pedestrian activity and outdoor dining also suggests that the same metric could be used as an indicator of the imageability of a place, as these variables were identified as important with respect to imageability in the models of Ewing and Clemente (2013).

The inspection of the predicted and actual values in the models suggested a moderately good fit. The practical implications of the identification of this link between POI density and complexity are that street network nodes which have a high degree of POI density have a higher probability of being more complex environments in comparison to nodes with low POI density. Urban designers or planners could thus use maps which show the distribution of POI density as a tool for the rough identification of spatial variations of complexity, in combination with other modes of urban analysis. This information can be then used to find places which may need to become richer in terms of stimuli in order to provide a more satisfying sensorial experience. The same strategy could be followed to find areas where there is a lack of places that allow restoration from stress. This could happen in areas which have a very intense concentration of POIs may be too rich in stimuli of high intensity, to such an extent that the experience may become stressful for the pedestrians, according to the concept of sensory overload (Milgram 1970).

Apart from confirming the relationship between POI density and complexity in the studied context of Sydney, this research also has an important contribution in terms of the methodological approach which was adopted here; due to the proposed fusion of POI data with street network data, the POI density, as well as the degree of complexity which can be inferred from it, can be studied in the future in relation to other metrics related to urban network analysis, such as node centrality measures (Jiang and Claramunt 2004).

Another novelty was the employment of state of the art methods for object recognition, for the extraction of variation in the human activity. This method, which was employed in the second case study, proved particularly useful for the identification of an additional dimension with respect to complexity: the degree of variation in the movement of people, or in other words the variation in surrounding circumstances and stimuli which have to be analysed during interactions with the surroundings. This method can be adopted in future field studies where image-based techniques are applied for understanding and analysing complexity. Its applicability is currently constrained on small scale studies, as it requires the use of videos or images captured at the same place with a high frequency.

The analysis presented in section 3 showed that the variations in the spatial distribution of POIs, measured by POI density, could be used as an indicator of complexity. However, there are some theoretical issues, as well as methodological and practical limitations which need to be addressed in future studies.

The main issue which needs to be studied to strengthen the theoretical foundations of this research area is: how much complexity is necessary to stimulate pleasureable urban life without becoming overwhelming?. If we use POI density as a measure of complexity, this needs to be identified. Existing literature only contains general guidelines regarding the relationship between complexity and its effects on pedestrians. More evidence-based research is needed in order to support and refine such guidelines.

The literature review presented in the introduction indicated a relationship between complexity and two other factors: appraisal or preference of an environment, and stress restoration. It was suggested that very high levels of complexity could have a negative effect for both factors. However, there is lack of quantitative and qualitative research that can help us define these limits. Future studies should thus be conducted to address this issue, involving mapping psychophysiological responses during exposure to environments with different degrees of complexity, coupled with a qualitative analysis of perceived experience.

Another issue that should be considered is that user experience is also affected by other factors apart from complexity, such as imageability. This has to be kept in mind in the analysis of the qualities of the urban environment. The identified relation between POI density and complexity should also not be interpreted as an indication that the number of POIs and the resulting degree of complexity are the only factors that automatically guarantee the successful design of an environment. Multiple factors such as the functional program, context, the needs of the local residents and the size of the local economy at the urban planning level should be always be considered to make informed urban design decisions.

The quality, structure and character of stimuli also affect other facets of the resulting experience, such as comfort and walkability. The links between the different parameters are also evident in the analysis of Ewing and Clemente (2013), which showed that some of the parameters that affect complexity, such as pedestrian volume and outdoor dining, also affect imageability. A high presence of these elements, and a sufficient integration of mixed-use which is related to them, is necessary in order to stimulate urban life and achieve a successful and vibrant urban environment (Jacobs 1961; Montgomery 1998). It is thus difficult to identify an ideal level of complexity in a way that ensures a good balance between complexity, imageability and other factors.

It should also be noted that the absence of any 'points of interest' in an environment does not necessarily suggest the lack of ingredients that can capture the attention of the pedestrian. The personal experiences and preferences of each individual also play a role in the way that they analyse and interpret their surroundings. The actual response to the different levels of stimulation may vary from person to person. An individual who is used to living in an environment of very high density, for instance, may perceive differently an urban environment rich in stimulation in comparison to another person who is used to living in the countryside. The context and the history of encounters with the stimuli, as well as the intent of the visit also plays a role. The degree of novelty of an environment is a critical factor, as prior exposure to the same environment may affect the way that it is perceived. The surrounding stimuli may not attract the attention of people who are already familiar with them, compared to people that visit the same areas for the first time. For instance, the experience of encountering a landmark in a city from the perspective of a tourist may not be the same as a similar encounter from the perspective of a resident, despite the fact that the overall degree of information is the same.

A lower presence of stimuli is also not a necessarily negative quality, as it could assist the pedestrian in having a more reflective experience. Urban green areas are good examples of such places. Similarly, the exposure to excessive stimulation levels in cases where the complexity of the environment is very high may be interpreted as an exciting and memorable event for some people. This depends on their sensitivity in terms of sensory processing and their personal preferences. The urban fabric should thus be designed in a way that allows vibrant as well as restorative environments to coexist.

One methodological limitation of this study was that all the material was reviewed by the same researcher, but another reviewer might have rated some variables slightly differently. This concern would be more applicable for two variables (number of building colours and accent colours), as the study of Ewing and Clemente (2013) showed that there was moderate inter-rater reliability for them, despite the adoption of common guidelines. Additionally, the images which were used for the assessment of pedestrian activity are only an indication of the gross variations in this variable, and cannot represent all the possible diurnal variations of pedestrian volume.

Another limitation was that the route which was chosen for the second case study was not based on an entirely random selection of points. The points were sampled from the local area based on the presence of different degrees of complexity. The analysis showed that the extrapolated values of complexity and POI density had similar trends in the second case study. However, this finding may be affected by particular characteristics of the chosen route. The choice of another route might have yielded different results. At the same time, this part of the study was exploratory and the emphasis was on acquiring a better understanding of the differences between places with different degrees of complexity. The aim was to collect evidence regarding the way that the emerging similarities and differences between places with a different degree of complexity would be reflected in the analysis of the POI density. The findings of the second case study were certainly illustrative from this perspective. They showed the need to complement the analysis of complexity with other data which can enrich our understanding of spatial qualities. This data could be provided by a combination of semantic analysis of POI data, street images and other material collected during field visits.

To conclude, the analysis of POI density as was conducted in this research is more helpful as a tool which suggests areas that could need interventions, but this is only a first step which has to be followed by a more focused analysis, taking into account the input of local residents. The conducted analysis showed that POI density can be used as an indicator of complexity. The identified association between POI density and complexity should, however, be interpreted as a tendency rather than a rule. The findings of this study are representative of the context of Sydney, and more research is needed before generalising these findings in environments with another cultural background or other factors which may affect the perception of the environment. Future research in this area will be largely beneficial for understanding the multitude of urban planning and design elements which affect the quality of urban life.

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DECLARATION OF INTEREST

No potential conflict of interest was reported by the authors.

APPENDIX B

ANALYSIS OF THE OUTDOOR EXPERIMENT CONDUCTED IN SYDNEY ON A PREDEFINED ROUTE

This section presents a detailed analysis of the outdoor experiment conducted in Sydney on a predefined route. This analysis enriches the material presented in Chapter 7. The work is presented as it was submitted for publication in the Journal of Urban Technology. Only the figures have been renamed to indicate that they belong to this appendix. The references are included in the reference list in the end of the thesis. There is some overlap between some parts of this paper and the material presented in the main body of this thesis.

Submitted as: Dritsa, D. & Biloria, N. (n.d.), 'Measuring the impact of movement and contextual parameters on physiological responses in the urban environment with wearable sensors', *Journal of Urban Technology* (under review).

Author contributions: DD conceived the idea, developed the theory, planned the case studies and performed the data analysis. BN supervised the work and provided critical feedback. DD wrote the manuscript with input from BN.

Author signatures:

Dimitra Dritsa: Production Note: Signature removed prior to publication.

Nimish Biloria: Production Note: Signature removed prior to publication.

ABSTRACT

Understanding the way that the urban environment affects the human body is important for the advancement of health and wellbeing. Electrodermal activity (EDA) has been extensively used as an indicator of stress. The aim of this study is the analysis of urban features that can act as stressors by using wearable technologies that measure EDA. We analyze the physiological responses of walkers while navigating an outdoor route in Sydney, Australia. The analyzed parameters include contextual and movement-related features. The results suggest that the duration and intensity of activity, as well as the density of mixed-use affect physiological responses significantly.

KEYWORDS

Wearable sensors, Physiological responses, Urban environment, Electrodermal activity, stressors

1. INTRODUCTION

Electrodermal activity (EDA) is a physiological measure that reflects the changes in skin resistance due to the activity of the sweat gland. It is one of the most widely used measures of the activity of the sympathetic nervous system (Boucsein, 2012), a branch of the autonomic nervous system which mobilizes the body to prepare it for action. EDA measures are widely used as indicators of stress, due to the connection between stress and the sympathetic nervous system.

According to the concept of allostasis (Sterling and Eyer, 1988), stress mechanisms are activated when there is a change from a stable body state ("steady state") to another. These states may be associated with different conditions, such as a change from a sitting position to moving position, or a sudden drop in temperature. This model is an evolution of early conceptualizations of stress such as the "fight or flight" concept (Cannon, 1929). The situations which may activate the stress response are called "stressors". There is evidence that at least two types of stressors are recognized by the brain (Dayas et al., 2001): physical and psychological stressors. While stress is commonly used in studies as a term describing a condition that is negatively perceived by the individual that experiences it (Boucsein and Backs, 2009), some conditions may generate physiological stress responses without being associated with a negative experience. For instance, physical activity has been extensively studied as a physical stressor (Hackney 2006), which is usually associated with a positive emotion (Sanchis-Gomar et al., 2012).

While there is a large body of research on physiological responses to stressors in the laboratory, there is much less evidence of the impact of these stressors in the urban environment. The urban fabric incorporates factors such as temperature and noise, which can act as stressors. One such factor is the complexity and intensity of sensorial input; there has been evidence that overstimulation can act as a psychological stressor (Frankenhaeuser et al., 1971). Milgram (1970) referred to the phenomenon of sensory overload in connection to urban life.

According to the Psycho-Evolutionary Theory of Stress Reduction (Ulrich et al., 1991), environments with a high presence and intensity of stimuli may require a higher time of information processing, thus slowing down restoration from stress. Another psychological stressor with a high presence in urban life is noise; there is plenty of evidence that exposure to noise can generate stress responses (i.e., Babisch, 2011). Traffic is associated with this stressor, as it is one of the significant sources of noise in the urban fabric.

In the past ten years, there have been several studies that use wearable sensors for the study of physiological responses in urban or natural environments. Most studies had as an objective the analysis of the effect of green areas on physiological responses; the examination of electroencephalography (EEG) data has been employed for this purpose, in studies which compare green with urban zones (Aspinall et al., 2015; Neale et al., 2017). The findings of Aspinall et al. (2015) showed physiological patterns closer to meditation and with less frustration, engagement, and arousal, in the green areas compared to the urban setting.

The effect of urban form on physiological responses has also been the focus of a few studies, where the analyzed parameters were isovist properties, and the physiological responses were further classified as emotions. An isovist is the area which is visible from a given point in space. This factor is, thus, related to the visual field of the pedestrian. The parameters of an isovist include properties such as the occlusivity (the amount of open edges) or the compactness of the visual field (Hijazi et al., 2016). The experiments of Hijazi et al. (2016) showed a relation between some of these properties and negative emotion arousal. Environmental parameters have also been included in a few studies. Benita and Tunçer (2019), for instance, studied the effect of environmental parameters and urban conditions on stress responses in Singapore. Their analysis indicated that the strongest relationship was between physiological responses and ambient temperature.

Some recent studies have also used parameters related to traffic in their analysis of physiological responses during walking. The analysis of Chrisinger and King (2018), which involved 14 participants and was conducted during a 20-minute walk, showed that the EDA was significantly lower in streets with high traffic levels when compared to local streets, contrary to the expectations. Saitis and Kalimeri (2018) studied 12 visually impaired pedestrians, and found that the blind participants had higher heart rate while crossing an intersection, compared to individuals with severely impaired vision. The study of Birenboim et al. (2019), which involved 15 participants, also showed an increase in EDA responses when crossing a main street without a traffic light, compared to a neutral environment.

A gap that has been identified in previous studies is the lack of research on the effect of movement on physiological responses. The mapping of physiological responses in the studies which were mentioned above was conducted while the participants were walking or cycling. While movement was included in the setup, it was not a part of the studied factors in the inferential analysis. The incorporation of this aspect currently lacks in studies in this research area. Studies that mention this gap typically consider the effects of movement as artefacts. This holds true for spontaneous movements which dislocate the equipment and produce sharp peaks and drops in EDA which cannot be attributed to physiological changes (Boucsein, 2012). However, the fact that physical activity is a stressor, creates a new angle to this problem. The possibility that there are effects related to activity on physiological responses (which are not artefacts, based on the shape of the signal), requires study. This is of value in the context of research on stress and physiological arousal in the urban environment.

In this context, the focus of this study is on the analysis of the relation between physical and psychological stressors related to movement and urban conditions, and physiological responses during walking in the urban environment. The study of physical stressors primarily involves parameters related to movement which could be related to an increase in stress levels. One such parameter is the change in activity state. Following the concept of allostasis by Sterling and Eyer (1988), a change from a state to another, such as a change from walking to standing, could act as a physical stressor. Two other parameters that could act as stressors are the duration of activity, and the activity intensity (Acevedo et al., 2007). Temperature is also considered as a physical stressor that can affect physiological responses (Benita and Tunçer, 2019).

In terms of psychological stressors, the parameters studied are traffic, the presence of traffic lights and the density of mixed-use. The focus here is on parameters which affect stimulation, having the potential to cause information overload. Traffic is included as a parameter since other studies have shown a link between this factor and physiological responses. This parameter is related to stimulation levels as it is connected to noise. The presence of traffic lights is also studied for the same reason, and due to their potential ability to affect movement. The density of mixed-use, has not been studied adequately before in relation to physiological responses. In urban environments with a high presence of mixed-use, there is typically an increased diversity of colors and visual elements, as well as a higher presence of people, due to the higher presence of functions that attract human activity. These elements act as stimuli which attract the attention of the pedestrians. Points of Interest (POIs) are typically utilized to support this analysis. POIs have emerged in the past ten years as a source of information on land use characteristics, such as the density or diversity of land use types. Several studies have used POIs for the representation of variations in these parameters; Zeng and Lin (2016), for instance, used POIs to study the land use density, entropy and degree of concentration along an urban rail line. Following these studies, POI density will be used as a representation of the density of mixed-use.

This paper acts as a pilot project addressing the following objectives: (1) test a methodology for collecting and mapping physiological responses in parallel to contextual and activity data, and (2) examine the relationship between the collected data. The effect of parameters related to the context and the movement of the participant on physiological responses are investigated after describing the methodology for data collection and analysis. The combination of these two objectives enhance current research on the impact of urban features on physiological responses. The main research question of the paper is the following: *Do the selected contextual parameters (traffic, density of mixed-use, and traffic lights) and the studied characteristics of movement (duration of activity, activity intensity, change in activity state) affect physiological responses?* This question is investigated by collecting physiological, contextual and movement-related data from 18 participants during an outdoor predefined walking route in Sydney.

The paper is organized as follows; section 2 elaborates on the study design, the methods used for data collection and analysis, and the statistical approach. Section 3 reports the results of the outdoor experiment. Section 4 discusses the findings and their implications and elaborates on limitations and future research directions. The conclusions are presented in section 5.

2. MATERIALS AND METHODS

2.1. STUDY DESIGN

The studied parameters are examined by conducting an outdoor experiment where the participants are asked to walk on a predefined route. Before the outdoor experiment, all the participants completed a 10-minute sequence of activities (sitting, standing, walking) in an indoor environment with a temperature between 18-20°C. This ensured that they were exposed to the same circumstances before the outdoor experiment, and allowed them to familiarize with the equipment.

In terms of physiological data monitoring, this study focuses on changes in EDA and measures stemming from it.

Eighteen participants were recruited for this test (age = 31.3 ± 5.3 yrs.). The research project was advertised using posters at the university [name redacted for double-blind review] of the authors. The prospective participants had to be affiliated with the university to take part in the research. This requirement ensured that they would be somewhat familiar with the facilities of the university and the areas in which the outdoor route traversed. This familiarity helps in controlling the parameter of novelty, which can affect the physiological responses (Berlyne, 1960). The protocol for the study design was approved by the University's Human Research Ethics Committee (*University name redacted for double-blind review* HREC REF NO. ETH19-3752). All the participants provided informed written consent before the commencement of the experiment. One participant exhibited very low EDA and EDR responses during the indoor and outdoor experiments. This means that they had generally very low levels of EDA data, without any visible responses in the presence of stimulation or movement changes. The data from this participant was excluded. The final sample was, therefore, n=17 (nine females and eight males).

The tests were conducted at an outdoor temperature of 21 ± 4 °C during the afternoon. The time needed for completing the route was approximately 40 minutes. The outdoor route was designed to include exposure to conditions of high and low mixed-use (represented by POI density), noise, traffic, and crowding, within a walkable distance from the starting point of the route.

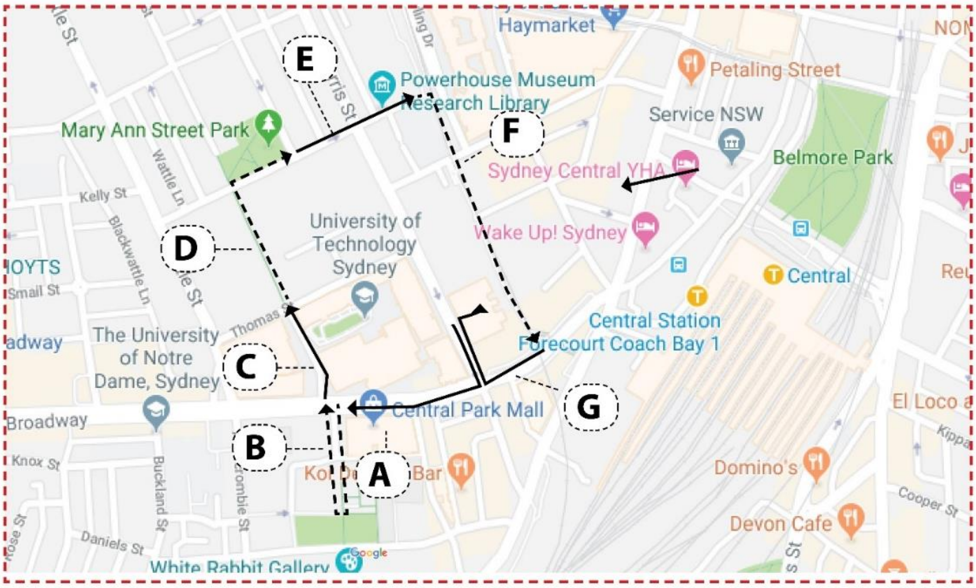


Figure B1. The outdoor route. The image is based on a screenshot taken from Google maps (Google Maps, 2020).

The statistical analysis of the data involved two types of analysis: the comparison of differences in the physiological responses during transitions between different segments of the route, and regression analysis. The first analysis involved splitting the route into seven segments that represented different contextual qualities. Figure B1 presents a map of the route; The qualities of the segments are as follows:

- Segment A is on Broadway Street, one of the busiest roads of Sydney in terms of pedestrian and car traffic, with a high presence of restaurants and retail stores.
- Segment B starts at the entrance of the One Central Park tower, an iconic mixed-use building; the participants are asked to go through the part of the building which is open to pedestrians, towards a small lively park in the back of the building, and sit in the park for 5 minutes. After this, they return to Broadway Street through the park, completing segment B. At the end of segment B, there is a traffic light, which the participants have to cross to reach segment C; at this spot, there is an intense transition from a place with high presence of natural characteristics and human recreational activity, to intense noise, crowding and traffic conditions.
- Segment C has low traffic levels and is characterized by medium to high levels of pedestrian activity, as it is positioned between two buildings of one of the local universities.
- Segment D has lower pedestrian activity, very low traffic, and high levels of green, including a tree canopy which is covering the majority of the street, and a park.
- Segment E marks a transition to higher levels of traffic and noise and a traffic light.
- Segment F includes walking on an elevated urban park with high pedestrian activity. Towards the end of Segment F, the presence of mixed-use becomes much higher.

- Segment G involves walking in the Central Station tunnel. The tunnel includes some retail shops and cafes, and is characterized by high levels of crowding; finally, the participants finish the walk by visiting briefly the very noisy and crowded Broadway street.

In addition to the measurements using the hardware, participants were asked to fill the PANAS scale questionnaire for each segment. The typical PANAS test includes twenty adjectives that describe different moods (Watson et al., 1988); ten moods are connected to the positive affect and the rest to the negative affect. The participants are usually asked to describe the extent to which they experienced each state by rating it on a scale of 1-5. In this study, it was important to understand the experience of the participants in different parts of the route, and track how it changed in parallel to the contextual changes. Therefore, the participants were asked to complete the test for each of the seven segments presented in Figure B1, and were asked to note the intensity with which they experienced each of the provided ten positive and ten negative states, by rating them on a scale of 1-5. The overall procedure was thus the same as in the typical PANAS questionnaire, with the only difference being the administration of the questionnaire seven times, one for each segment.

The participants were also asked to note down anything that they considered significant during the outdoor route, in the form of an open question or comment. The inclusion of this observation allowed noting any unexpected factors that could have affected their experience during the measurements. The questionnaire for the outdoor route was given approximately 15 minutes after the participants returned from the outdoor route.

2.2. DATA COLLECTION AND DATA FUSION

2.2.1. PHYSIOLOGICAL DATA

The participants were given an Empatica E4 wristband for the measurement of EDA and accelerometer data. This wristband has the size of a typical wrist watch. It has been used extensively in similar studies and provides a highly accurate measurement of EDA. The sampling rate was 4 Hz. In addition to this, GPS data was collected using smartphones of the participants, with a sampling rate of 1Hz.

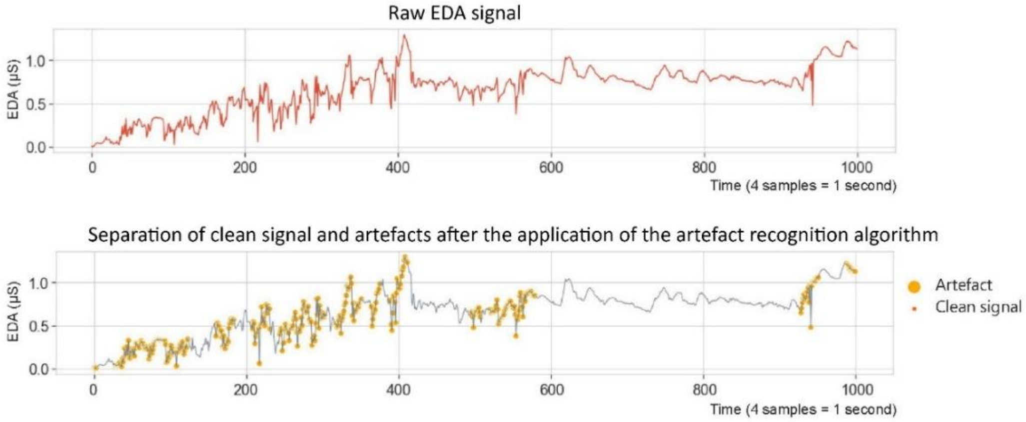


Figure B2. Demonstration of the application of the artefact recognition algorithm

The EDA data were cleaned from artifacts using an algorithm for artefact recognition (Figure B2), similar to that of Taylor et al. (2015). The EDA signal is typically processed for the extraction of tonic and phasic components. The tonic component (tonic EDA) is a smooth curve representing the slow changes in EDA over time. The phasic component (phasic EDA, or electrodermal responses, EDR) is connected to the immediate reaction to external stimuli. These reactions have the shape of a peak and are superposed on the slowly changing component (tonic EDA).

The extraction of EDRs was conducted with a peak recognition algorithm based on the derivative of the signal.

The measures that were extracted from the EDA data were the following: *tonic EDA, mean EDR amplitude, EDR frequency,* and *sum of EDR amplitudes*. The tonic EDA is the tonic component of the signal. The mean EDR amplitude is related to the amplitude of the peaks (the EDRs). It represents the intensity of physiological responses and the way that it changes based on the external input. The EDR frequency is the rate of appearance of physiological responses. The sum of EDR amplitudes is the result of the addition of the amplitudes of all the EDRs in a predefined time window. The resulting variable is thus a measure that reflects both the intensity and rate of appearance of physiological responses.

The steps followed for the calculation of the variables are outlined below:

- The calculation of *tonic EDA* involved interpolating the starting and ending point of each peak and connecting the rest of the signal with these interpolated segments. The signal was, then, smoothed by down-sampling it at 20 seconds.
- The calculation of the *mean EDR amplitude* involved finding the mean value of the amplitudes of EDRs in 1-minute data segments.
- The calculation of *EDR frequency* involved finding the number of EDRs in 1-minute data segments.
- The variable *sum of EDR amplitudes* was extracted by finding the sum of the amplitudes of the EDRs in 1-minute data segments.
- The tonic EDA was normalized for each participant based on their maximum EDA (Boucsein, 2012). The EDR amplitude was also normalized for the calculation of the *mean EDR amplitude*.

The main feature which was used as the dependent variable in the regression analysis was the sum of EDR amplitudes since it indicates both the number and intensity of the responses, as mentioned above. However, it was decided to include an analysis of the other EDA features (*EDA frequency, tonic EDA, mean EDR amplitude*) at least in the segment analysis. This analysis helps in understanding the fluctuations of each feature during the analyzed route in detail. Figure B3 presents an example of the extraction of the different features from the raw EDA signal.

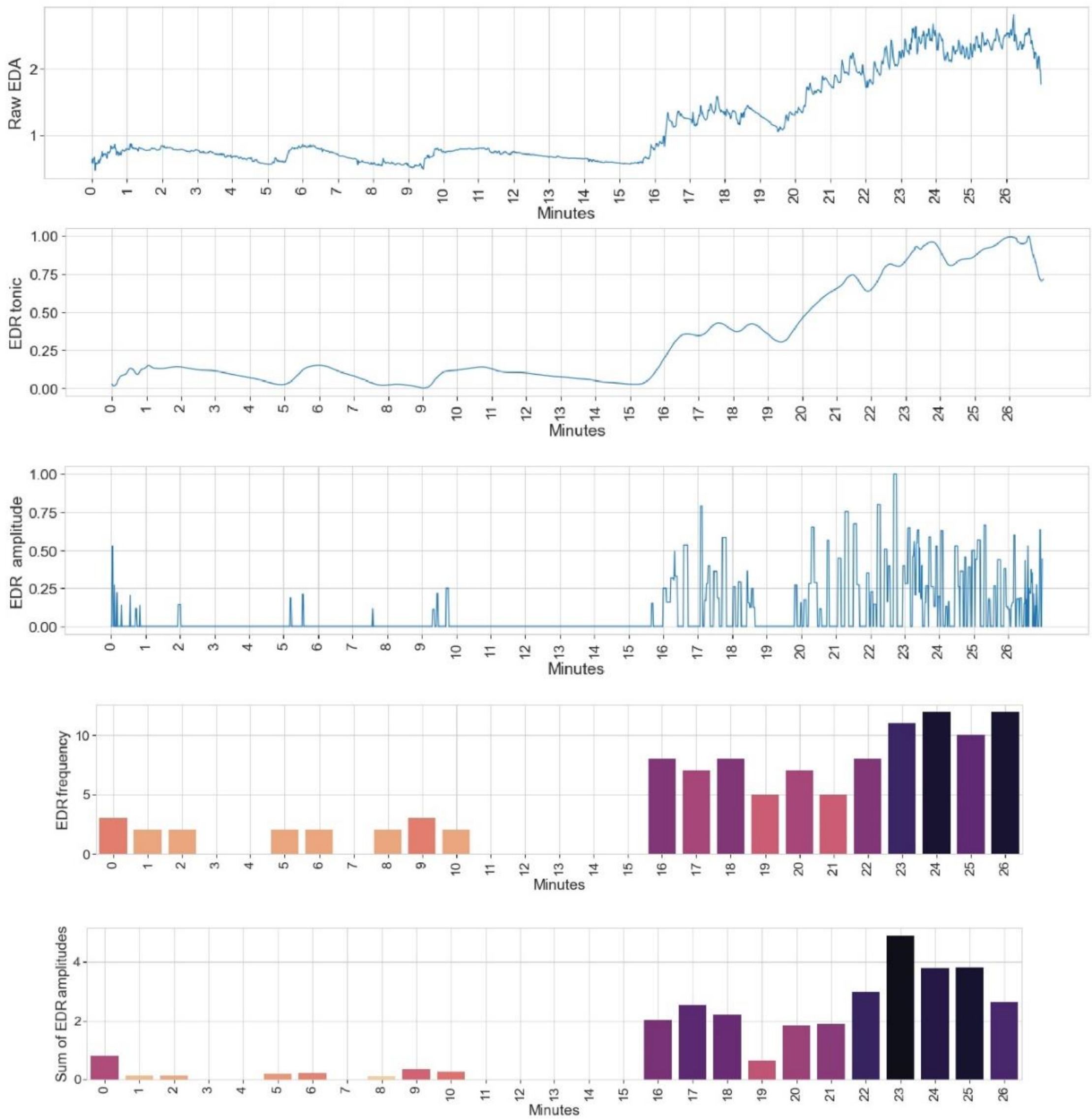


Figure B3. An example of extraction of different features from EDA data.

2.2.2. MOVEMENT-RELATED DATA

An activity recognition algorithm was used for the analysis of accelerometer data and the identification of three conditions related to activity intensity: *Still, Walking* and *Intense movement.* The algorithm involved the application of a machine learning model, trained using the data collected during the indoor activities. The data was split into segments following the application of the algorithm. The features retrieved from this analysis were the following: *activity intensity, steady-state walking* (being in the "walking" state for more than 2 minutes), *duration of activity* (minutes since the beginning of the walk), and *change in activity state*.

- The "activity intensity" feature was created using a numerical scale (1-3) which represents the activity intensity. Level 1 corresponds to sitting or standing; level 2 to walking, and level 3 to more intense movements. Consecutive points which had the same activity intensity were grouped and labelled accordingly.

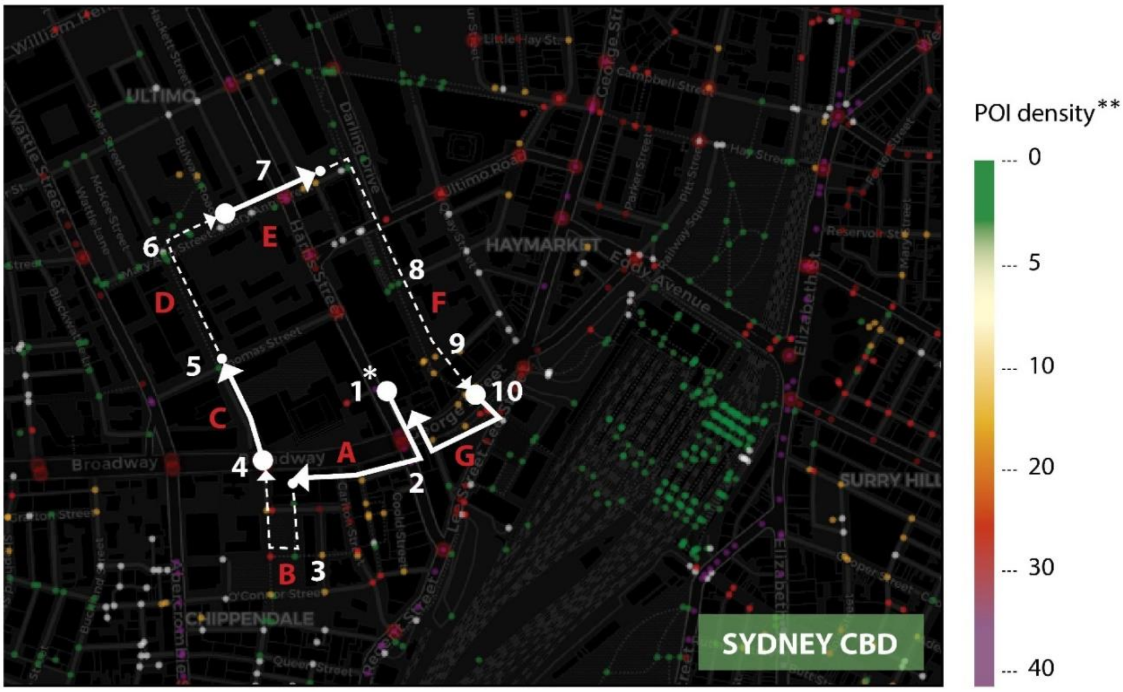
- The “duration of activity“ variable represented the time since the beginning of the outdoor walk, and it was calculated for each data point (initially in seconds and then transformed to minutes since the beginning).
- The “change in activity state“ feature was calculated by processing the “activity intensity“ variable, and finding points where there was a change in activity intensity after the analysis of the first-order derivative of this feature. Binary coding was used to indicate the presence of a change in activity intensity (0=no change, 1=change). The focus for this analysis was on the changes from a steady-state to another (i.e., a change from walking for at least 2 minutes, to standing). Only these changes were coded with 1.
- The “steady-state walking“ feature was calculated by measuring the duration of each group of points with similar activity intensity. Binary coding was used for this feature. If the activity was “walking“for at least two minutes, the “steady-state walking“ variable was given the value of 1, and the rest of the points were given the value of 0.

Speed was also computed from the GPS data as an alternative representation of activity intensity. This feature captures small fluctuations in walking speed that are not included in the other “activity intensity“ feature computed from the accelerometer data. At the same time, the “activity intensity“ feature from the accelerometer data includes hand movements that cannot be captured with the speed data. It was, thus, decided to test both in this pilot project.

2.2.3. CONTEXTUAL DATA

One methodological issue that this study attempts to address is the heavy reliance of previous studies on the use of video and photos as sources of contextual data. The collection of this type of data requires additional effort and hardware, while also raising questions of privacy. Furthermore, while the data collected from these sources is invaluable, most studies that used these data sources examined the footage manually, which delays the process of analysis significantly. This study thus investigates other options for understanding the context, based on the collection of freely available OpenStreetMap (OSM) data.

The contextual data that were included in the analysis were the following: POI density, traffic levels, and the presence of traffic signals. The *osmnx* Python library was used for the collection of the street network and POI data for the studied area. POI density was computed as the number of POIs within 100m from each street network node (Figure B4). The traffic levels were calculated from the collected OSM data by analyzing the tags of each street network node and link. The information relevant to traffic was extracted and sorted in 5 zones, reflecting the gradual increase in the intensity of traffic levels. The lowest level was used for streets which only hosted pedestrian activity and the highest level was used for motorways.



*The numbers refer to the photos displayed in Figure 6.
The letters A to G, displayed with red, refer to the route segments displayed in Figure 1.
** The number of POIs within 100m of each node.

Figure B4. Map displaying the POI density in the studied area, following the analysis of the contextual data.

The presence of traffic lights was identified by parsing the tags of the nodes of the OSM data and finding the tag "traffic_signals. A binary coding scheme was used, marking the nodes that contained this tag with "1" and the rest with "0".

Environmental data (ambient temperature) were also collected and included in the data fusion scheme. The data was collected by accessing historical data from local governmental sources (Australian Government Bureau of Meteorology 2020) at an hourly resolution for each session, for a nearby location (one km away). This data does not reflect the local variations in microclimate, but it is adequate for understanding coarse differences in the temperature.

The data fusion model included first the fusion of physiological data with the movement features based on the timestamps, and then with the contextual features based on the GPS data. For each GPS point, the traffic, POI density, and traffic light data were computed by retrieving these features from the closest street network node. In this way, all data were able to be analyzed as synchronized time-series data. All features were resampled at 1Hz (1 value per second). Figure B5 presents some of the extracted features after their synchronization, corresponding to the route of one participant. The contextual characteristics of different parts of the route are displayed in Figure B6.

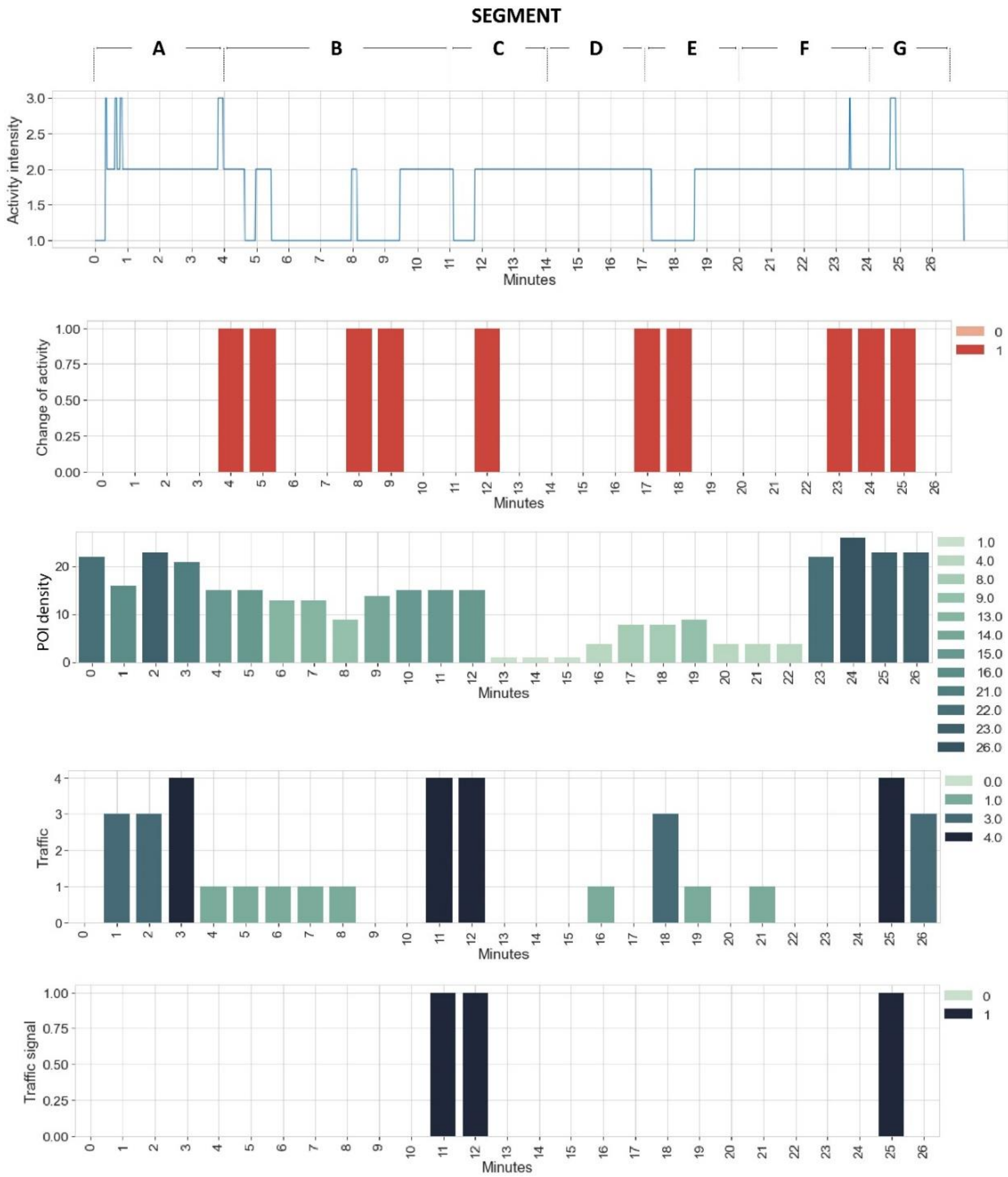


Figure B5. An example of the extraction and analysis of movement-related and contextual features for one route.

Figure B6. Photos from the route. The photos were obtained from Google Street View (Google Maps, 2020), apart from points 8 and 9, for which there were no available data in Google Street View and images taken by the author were used.

2.3. STATISTICAL ANALYSIS

2.3.1. ANALYSIS OF PHYSIOLOGICAL DATA

The statistical analysis for the outdoor activity included the following tests for comparison of EDA measures along with movement and contextual features: Wilcoxon signed-rank tests on data aggregated at the segment level; Linear mixed model analysis with the sum of EDR amplitudes as the dependent variable; hotspot analysis on the changes in the EDA measures. A description of each stage follows below.

As explained in section 2.1, the segment analysis included splitting the route into seven parts according to differences in the contextual characteristics. For each participant, the mean for each of the following parameters was calculated: *sum of EDA amplitudes, tonic EDA, EDA frequency, mean EDA amplitude, density, traffic, activity intensity* (based on the accelerometer data), *steady-state walking, change in activity state, duration of activity,* and *traffic light*. All the variables were continuous after the calculation of the means. Only the "change in activity state" was kept as a categorical variable, as it resulted in a model with a better fit compared to the same variable in its continuous form. The portions of the data where there was any spontaneous movement (an intense movement lasting less than 2 seconds) were excluded. The Wilcoxon signed-rank test was then applied on each pair of segments (A-B, B-C and so on) to identify if there were significant differences in the physiological measures for each pair.

The linear mixed model analysis was selected for the regression analysis to handle the dependencies between the multiple data points from the same participants. A linear mixed model was fitted for the dependent variable ("sum of EDR amplitudes"). A square root transformation was applied to the variable to improve the distribution of the residuals. The Moran's I test was also conducted using the GeoDa software, to check for spatial autocorrelation. The results suggested significant presence of spatial autocorrelation in the data as well as in the residuals of the linear mixed model. Therefore, it was decided to include a spatially lagged variable to account for the spatial dependencies in the distribution of the dependent variable. This variable described the spatial relations between points based on their proximity. It was created after constructing a matrix with spatial weights (Anselin 2009).

As for the features which were used as independent variables, all the features presented in Figure B7 were initially considered as possible candidates. Different combinations and interactions were tested after ensuring that there was no issue of multicollinearity. The full model had the following form:

$$Yi = \beta_0 + \beta_1 X_1 + \ldots + \beta_i X_i + \gamma_1 + \gamma_2 + \gamma_3 + \varepsilon_{i,}$$

where the variables X_1 to X_i represent the independent variables presented in Figure B7. The variables γ_{01}, γ_{02} and γ_{03} correspond to random intercepts for each subject, age and sex.

For this analysis, the data were resampled at 120 seconds. The variables were analyzed as continuous (apart from the "change in activity state"), after the calculation of the mean values in data segments of 120 seconds.

Hotspot analysis was also conducted, for which the data were resampled at 10 seconds. This analysis used as input the *sum of EDR amplitudes* variable. A separate analysis was also conducted for the change in this measure, calculated between each minute and its previous one. The result thus reflected the spatial concentrations of the studied measure and the changes in it. The analysis was accompanied by the presentation of the spatial concentration of the contextual and movement-related features.

Finally, a stress score was calculated for each participant, based on the rules outlined in Kyriakou et al. (2019). After calculating the stress score, correlation analysis was applied for the change in the Sum of EDR amplitudes and the stress scores.

FEATURES		Details	*Mean*	*Min*	*Max*	*STD*	*Use in the statistical analysis*
Physiological measures	**Tonic EDA**	Tonic EDA (normalized in [0-1] scale)	0.33	0	1	0.29	Only included in the segment (pairwise) analysis
	Mean EDR amplitude	Mean EDR amplitude for the examined minute (normalized in [0-1] scale)	0.07	0	1	0.14	Only included in the segment (pairwise) analysis
	EDR frequency	Number of EDRs (peaks) for the examined minute (measured in number of peaks/minute)	8	1	43	7	Only included in the segment (pairwise) analysis
	Sum of EDR amplitudes	Sum of the EDR amplitudes for the examined minute (measured in µS/minute)	0.9	0	4.6	1	**Primary focus of analysis. Dependent variable in the linear mixed model**, and also included in the segment analysis
Movement-related variables	**Activity intensity**	activity intensity (measured in [1-3] scale : 1=standing/sitting,2=walking, 3 = more intense movement)	1.8	1	3	0.4	Independent variable
	Duration of activity (Time since the beginning)	minutes	40	31	53	7	Independent variable
	Change in activity state	categorical variable: 0=no change, 1 = presence of a change in the activity state	NA	0	1	NA	Independent variable
	Speed	m/s	3	0	6	2.1	Independent variable
	Steady state walking	if the performed activity during the examined minute is a part of 'steady state' and the activity intensity is 2, corresponding to 'walking' state. (measured in [0-1] scale)	0.5	0	1	0.4	Independent variable
Contextual variables	**Mean (POI) density**	number of POIs within 100m	13	1	30	7	Independent variable
	Traffic	traffic intensity (measured in [0-4] scale)	1.3	0	4	1.2	Independent variable
	Traffic light	presence of traffic light (measured in [0-1] scale)	0.1	0	1	0.2	Independent variable
	Temperature	°C	21	15	30	4	Independent variable

Figure B7. A description of the features used in the analysis.

2.3.2. QUESTIONNAIRE ANALYSIS

The questionnaire was used to collect data regarding the perceived experience of the participants in each segment. The Wilcoxon signed-rank test was used for the statistical analysis of the results. The test was conducted by analyzing the transition from each segment to the next. The comparison was thus pairwise, and it was conducted separately for the positive and negative affect. The results aimed to show which transitions affected the positive and the negative affect significantly.

All the statistical tests were conducted in R.

3. RESULTS

3.1. ANALYSIS OF MEASURES DURING THE OUTDOOR ROUTE

3.1.1. SEGMENT-BASED ANALYSIS

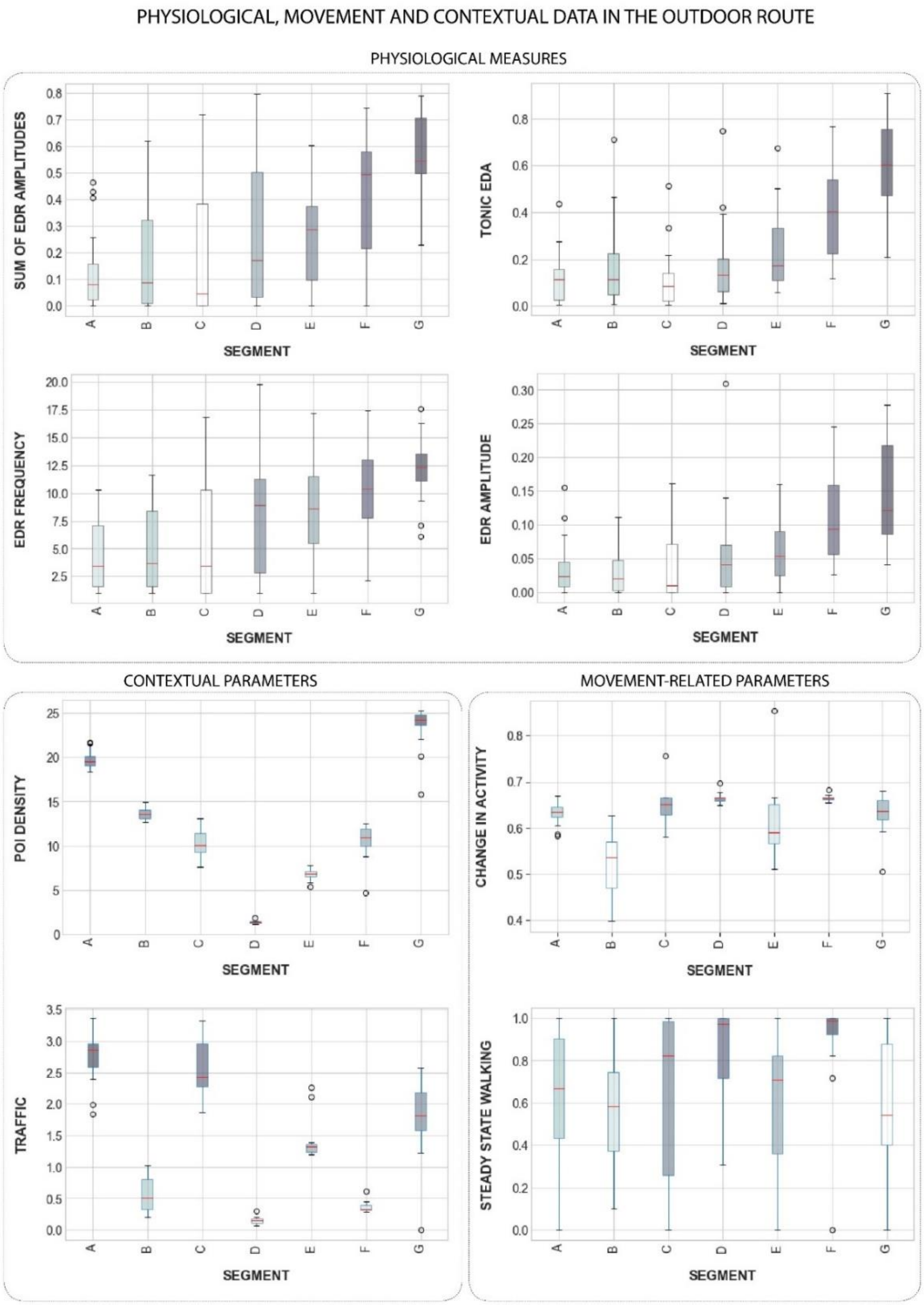


Figure B8. Graphs describing the EDA measures and the contextual and movement variables at each segment, for all participants.

In the segment-based analysis of the outdoor route, there is a trend of small fluctuations in the first three segments (A-C). As the participants walk from segment D to segment G, they interface an increase in POI density, accompanied by a gradual increase in the EDA measures. The increase from C to D is most intense for EDR frequency (statistically significant at $p=0.017$). This is the point that the participants start a bout of steady-state walking (Figure B8). The presence of steady-state walking can be related to the increase in EDR frequency. For the other measures, the steepest increases are from E to F and from F to G. Segment E includes waiting at a traffic light, which created a change in activity for some participants; there is also a gradual increase in density. The increase of EDA measures for these transitions (E-F and F-G) is statistically significant ($p<0.05$) for all measures apart from EDR frequency for the transition E-F ($p=0.12$) and mean EDR amplitude for F-G ($p=0.32$). There were no other statistically significant transitions.

3.1.2. HOTSPOT ANALYSIS

The identified clusters of EDA measures were attained by calculating the Local Moran's I values. This type of hotspot analysis shows places where there are points of high values of the studied measure, next to other high values. The analysis from this section and onwards was focused on the sum of EDR amplitudes. The hotspot analysis also involved the study of changes in the signal. Only the points where the results had statistical significance ($p<.05$) are shown in the maps.

The visual inspection of the clusters (Figure B9) suggests that there is a spatial relation between POI density, traffic, and the clusters of the studied physiological measure (sum of EDR amplitudes). This relation is most visible in Segments F and G.

The clusters of change in the studied physiological measure (sum of EDR amplitudes) are again at places of high POI density, in Segment F. A cluster of intense change is also found in segment E, coinciding with traffic, the presence of a traffic light and a cluster of changes in activity. Another cluster is found in Segment D, where there are only changes in activity.

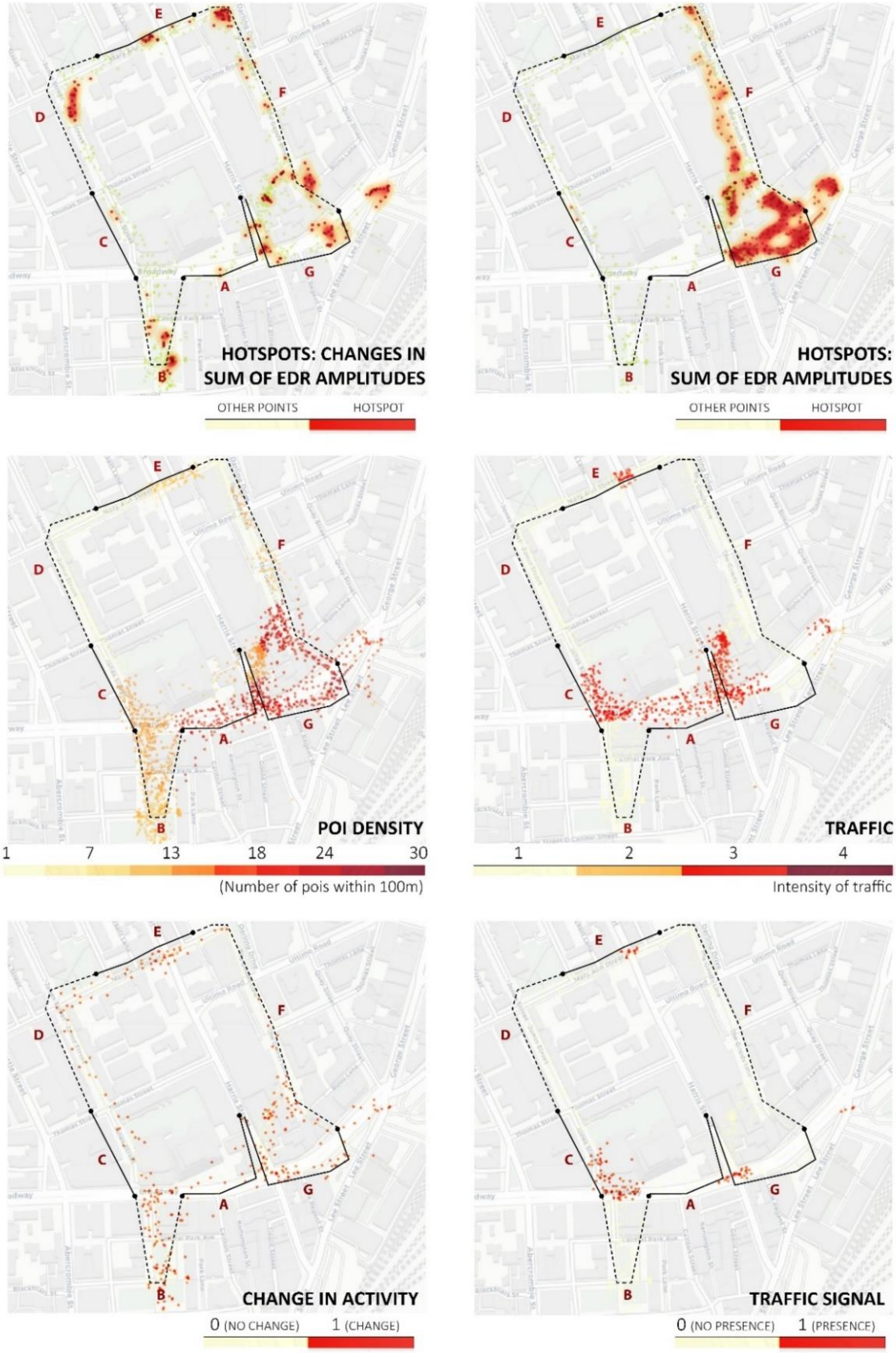


Figure B9. The results of the hotspot analysis for the sum of EDR amplitudes and the changes in this measure, in parallel to contextual and movement-related parameters.

3.1.3. STRESS SCORE ANALYSIS

The comparison of the stress scores for each participant with the change in the Sum of EDR amplitudes showed a moderate but significant correlation ($r_s = 0.49$, $p<0.00001$).

This effect was prominent (ρ = 0.61, p<0.00001) for a subgroup of 11 participants who conducted the activities in lower temperatures (< 21^{o}C) in comparison to the others.

3.1.4. LINEAR MIXED MODELS

LMM model for the predefined outdoor route in Sydney

	Coef.+++	p-value+	95% CI (lower)+++	95% CI (upper)+++	Unit
Intercept	-0.543	0.1279	-1.242	0.157	
Sum of EDR amplitudes_lag	0.008	0.8672	-0.081	0.096	
Duration of activity	0.022	<0.00001***	0.019	0.025	effect of 1 minute increase in duration of activity
POI Density	0.011	0.0005***	0.005	0.017	effect of presence of 1 more POI per 100m
Traffic	-0.002	0.9279	-0.036	0.033	effect of 1 level increase in the traffic intensity scheme [0-4]
Speed	0.029	0.0082**	0.008	0.050	effect of increase by 1 m/s
Change in activity state(1)++	0.006	0.8921	-0.077	0.088	0 (no change) or 1(change)
Temperature	0.030	0.0851	-0.005	0.064	effect of 1 °C increase in temperature

+ *P-values coded as follows: p<0.05: *; p<0.01: **; p<0.001: ****

++ *The coefficient corresponding to 'Change in activity state =1', signifying the presence of a change in activity state*

+++ *The coefficients and confidence intervals show the effect of each parameter on the variable with the square root transform*

Figure B10. The results of the linear mixed model analysis, with the sum of EDR amplitudes as the dependent variable.

The results of the linear mixed model for the outdoor activity showed a significant association (β=0.022; p <0.00001) between the parameter "duration of activity", signifying the minutes passed since the start of the outdoor activity, and the dependent variable (sum of EDR amplitudes) which represented the intensity of physiological responses. The parameters POI density (representing the density of mixed-use; β=0.011, p=0.0005) and speed (β=0.029; p=0.0082) also had a significant influence on the studied measure.

The coefficients reported in Figure B10 show the effect of each variable on the transformed dependent variable. The resulting model was also used to create predictions for low, medium and high values of each parameter, and the square root transformation was reversed for each predicted value, to better understand the effect of each parameter on the actual dependent variable. This experimentation showed that the increase from 1 to 15 minutes in terms of duration of activity had a small to medium effect on the sum of EDR amplitudes (an increase of 0.21 ± 0.13μS). The increase from 15 to 30 minutes had a medium to strong effect (0.62 ± 0.27μS/minute increase in sum of EDR amplitudes). An increase from 0 to 15 units in POI density had a small effect on the dependent variable (0.08 ± 0.07 μS/minute increase). This increase represented the transition from an environment without any POI to one with 15 POIs within 100m. An increase from 15 to 30 units in POI density had a more considerable effect (0.23 ± 0.14 μS/minute increase). Finally, an increase from 1 m/s to 3.5m/s in terms of speed resulted to a very small increase in the sum of EDR amplitudes (0.02 ± 0.03μS increase). An increase from 3.5 to 6m/s had again a small effect (0.05 ± 0.06μS/minute increase).

3.1.5. ANALYSIS OF PERCEIVED EXPERIENCE

The Wilcoxon signed-rank test showed that the positive affect was considerably lower after the outdoor test ($p=0.0048$), while the negative affect was not impacted. A few participants noted in the open comments section that the traffic noises were identified as annoying or surprising.

The questionnaire analysis for the outdoor walk showed that the rating of the positive affect did not have significant differences in the pairwise comparison of the segments. The results are displayed in Figure B11. The negative affect shows a decreasing trend between segments A and D, a steep increase from D to E, and then an increasing trend until the end of the route. The mean values though remained very low. All transitions after segment B (B-C etc.) were statistically significant at $p<0.05$.

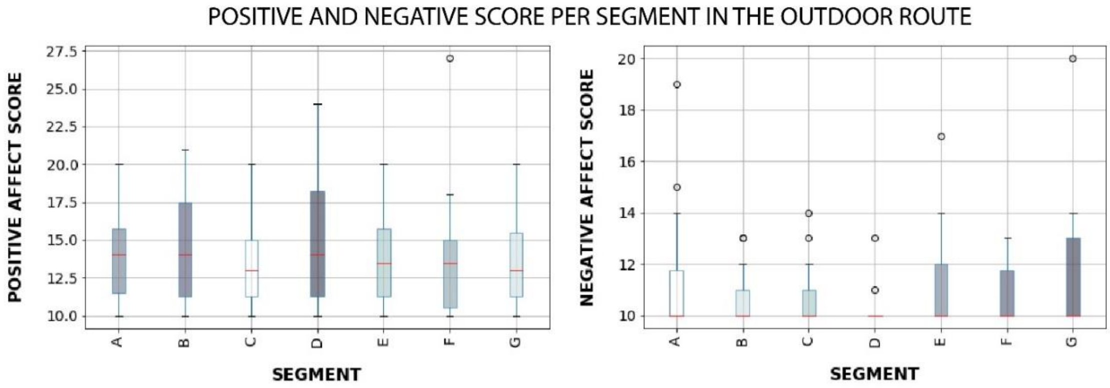


Figure B11. Graphs showing the positive and negative affect score of all participants for each segment.

4. DISCUSSION

4.1. ELABORATION ON THE PRESENTED METHODOLOGY AND ANALYSIS OF THE FINDINGS

This study presented a methodology for collection and analysis of physiological responses based on contextual and movement-related data. The methodological approach followed for the identification of contextual changes is a significant contribution to this research field. As POI and OSM data are freely available for many parts of the world, this method allows the automatic estimation of gross contextual changes. It only requires the addition of physiological and movement data in the case of replication. The calculation of all features related to movement and context, including those that were not statistically significant, gave valuable information that helped in understanding the underlying circumstances.

Apart from testing the methodology, the study also involved the analysis of the relationship between physiological responses and the extracted features related to movement and context. The identified links between movement and physiological responses were among the most important findings of this research. The first significant aspect of the movement was the overall time of exercise and its effect on the physiological responses. The inspection of the data showed a gradual increase in EDA and in the amplitude of the EDA responses in parallel to the time passed since the beginning of the activity. The statistical analysis presented in section 3.1.4 confirmed that the duration of activity was significantly related to the studied physiological measure (the sum of EDR amplitudes). The overall increase in EDA can be interpreted as the effect of sympathetic activation due to exercise acting as a stressor.

The analysis also showed that speed was related to an increase in physiological responses. This feature is related to activity intensity, as a higher walking speed is connected to higher energy expenditure. The other features computed from the accelerometer data were not statistically significant in this study. Future studies will involve further investigation of these features.

The analysis of the outdoor walk also showed that the density of mixed-use, represented by POI density, was a factor that had a significant effect on physiological responses. Some of the other factors which were studied were not identified as statistically significant in the linear mixed model analysis. However, the hotspot analysis showed that areas with an increased presence of the studied contextual parameters, sometimes combined with a change in activity state, were connected to a significant increase in the sum of EDR amplitudes. The links between these factors and the physiological responses might be based on complex interactions or patterns which might be more evident in the spatial analysis of the different factors.

The visual inspection of the graphs also showed that the effect of the different parameters was more prominent towards the end of the activity for some participants. There is a large body of literature supporting the argument that the interaction of stressors may cause an amplification of the response which would follow the application of each separate stressor (i.e., Webb et al., 2017). The inclusion of interactions between the duration of activity and the different parameters did not bring any improvement in the linear mixed model analysis in this study. However, this possibility should be more researched in the future.

The identified increases in physiological responses could be associated with physical stress, psychological distress or an attention shift. Increases in the tonic and phasic EDA measures which were included in this analysis are generally regarded as signs of psychological distress. From this perspective, the increase which was observed in these measures in the last segments of the route could indicate distress. The extraction of stress scores based on analytical methods used in other studies also showed a moderate correlation between the sum of EDR amplitudes and the stress scores. These combined findings suggested that a considerable portion of the physiological responses would be interpreted as signs of distress, using the metrics of other similar studies.

These findings were enriched by the analysis of the perceived experience, based on the questionnaire. The ratings of the participants showed a trend of increase in the negative affect in parallel to the increase in EDA towards the end of the route. The trend was not very intense, possibly because the situations which the participants encountered are a part of daily activity in the outdoor environment. The combined analysis of the questionnaire and the physiological measures indicates a combination of physical and psychological stress, considering that there was also a presence of physical activity.

4.2. IMPLICATIONS FOR URBAN DESIGN AND PLANNING

The findings of this study, concerning the contextual parameters, suggest that the density of mixed-use (represented by POI density) may be associated with a higher presence of physiological reactions, which could be related to increased distress. However, the presence of mixed-use is integral for achieving a lively urban environment (Jacobs, 1961; Montgomery, 1998). The parameters that could create a state of overstimulation when found at high intensities are the same parameters that create a rich sensorial experience while walking. Gehl (2010) also emphasizes on the need to create streetscapes that allow the observation of human activities at close range, to create welcoming and stimulating environments. Large-scale buildings next to streets without human activity are, in contrast, impersonal and unwelcoming spaces.

The findings of this study should not be read as a suggestion to limit the presence of these positive characteristics in the streetscape. They could be used to stimulate a discussion on the possible links between mixed-use and stress but focused on cases where the mixed-use density is particularly high. Future research could involve the study of populations that might be more affected by intense stimulation levels, such as the elderly.

4.3. LIMITATIONS

One limitation of the study was the sample size and characteristics. The participants in this study were mostly university students between 20-40 years old. There was a lack of representation of other demographic categories. Future research in this area should involve extension of the adopted methods in a way that is more representative of the demographic and cultural differences. As for the sample size, the findings should be reviewed considering that this limitation has been an issue in most studies in this field. The findings are still valuable for suggesting the potential importance of some parameters that were ignored until now.

Some other factors that could have influenced the results are related to the naturalistic setting of the study. For instance, not all participants had to wait in the traffic lights. Due to this difference, some participants might have experienced more changes in activity. The levels of crowding and the number of cars might also be slightly different in each measurement session. However, it would be impossible to control these parameters while retaining the naturalistic setting. Some participants might also find specific sounds or circumstances more stressful. This parameter could be investigated in future studies by creating different groups according to personal traits.

5. CONCLUSION

This paper presented the results of an outdoor experiment conducted in Sydney, where the physiological data of the participants was measured while they were walking on a predefined route. Variables related to movement and context were considered as factors that could affect physiological responses. The following conclusions were derived from the analysis:

(1) The duration of activity, and the speed affected the physiological responses significantly.
(2) The density of mixed-use (analyzed as the POI density) was also significantly associated with an increase in the intensity of physiological responses. This was attributed to the increase in the complexity and intensity of stimuli.

A vital contribution of this research is the presentation of the identified relationships between the examined urban and movement-related features, and physiological responses. The research also presents a replicable methodology for collection and analysis of physiological responses in the urban space, which does not rely on image-based sources for analysis of the context, while also incorporating movement analysis. Future research by the authors shall build on the presented findings by applying the presented methodology for data collection and analysis in different designs of outdoor activities in Sydney as well as in other contexts.

DISCLOSURE STATEMENT

No potential competing interest was reported by the authors.

APPENDIX C

STATISTICAL ANALYSIS OF THE DATA COLLECTED IN THE INDOOR EXPERIMENTS IN SYDNEY

This appendix presents the results of statistical tests conducted using the data collected during the indoor experiment. These tests were conducted to understand the relationship between parameters related to movement (duration of activity, activity intensity, change in activity), stimulation and physiological responses in a controlled experiment. The analysis of these parameters was a critical step for ensuring that the theoretical and conceptual framework described in Chapter 3 is in the right direction.

C.1. PROTOCOL AND STUDY DESIGN

A standardised protocol was designed for the indoor test in Phase A (see Section 2.4.2 in Chapter 2), simulating series of actions which are commonly performed in the urban environment (sitting, standing, moving, carrying a bag). Some activities also included intense hand movements to provoke the generation of artefacts in the EDA measurement.

18 participants took part in this test. These were the same participants that also completed the other part of Phase A (the predefined outdoor route in Sydney). Each participant completed the indoor test two times. The second application of the indoor test was conducted after the predefined outdoor route around UTS, aiming to capture a condition where the user has already high levels of sympathetic arousal due to the physical activity. The main aim of this test was to collect a ground truth dataset for calibrating the algorithms for activity classification (described in Appendix E). The secondary aim was to examine the effects of the physical and psychological stressor (noise and activity change) on physiological responses. The test was conducted two times to investigate if there would be any difference in the responses during the second time that the participants conducted the test. The hypothesis was that the sympathetic activity of the participants would be already elevated after the outdoor activity, and this might affect the responses.

During the indoor test, the participants were also exposed to sudden traffic noise using a video source. The presentation of the traffic noises was predesigned in terms of its time of appearance. The noise stimulus was applied two times in each round of activities. It started as background traffic noise of continuous intensity, and then some loud honks were added. The first application of the noise stimulus was after the first 4 minutes, and its duration was one minute without the honks, and another minute with the honks; then, the same stimulation pattern was repeated once towards the end of the activity.

Code	Name	Activity	Duration	Stimulus
1	sit	sit	1 minute	0
2	walk_0	walk	3 minutes	0
3	walk_0 + noise	walk	1 minute	1
4	stand_0 + noise	stand	15 seconds	2
5	walk_1 + noise	walk	45 seconds	2
6	stand_1	stand	15 seconds	0
7	stand + wear coat	stand	45 seconds	0
8	walk + wear coat	walk	45 seconds	0
9	walk + bag	walk	45 seconds	0
10	walk + talk	walk	30 seconds	0
11	walk + talk + noise	walk	30 seconds	2
12	stand_2	stand	30 seconds	0

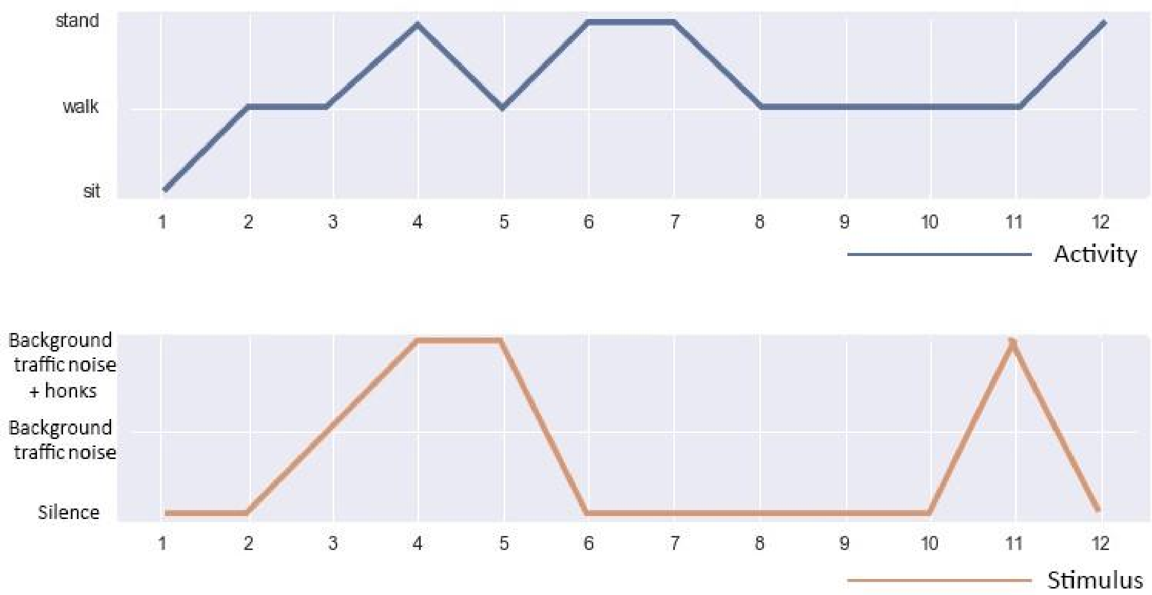


Figure C1. Description of the indoor activities.

The activities were designed as a sequence of states (sitting, standing, walking), with each state having a predetermined duration. Two activities of higher intensity and concentration (standing while putting a coat on and off for 45 seconds, and then walking while putting the coat again on and off) were only used for training the movement recognition algorithm for the identification of movements of higher intensity, which can cause artefacts. The participants were verbally notified each time they had to change their activity. The sequence of activities and the pattern of application of the noise stressor is described in Figure C1. The ‘walk + bag’ and ‘walk + talk’ activities in the figure refer to walking while holding a bag and then walking while talking. The codes 0, 1 and 2 in the ‘Stimulus’ column refer to the silent state (0), the application of background traffic noise (1) and the combination of background traffic noise and honks (2).

The overall duration of the indoor test was 10 minutes each time (before and after the outdoor walk). After completing each round, the participants were asked to report their experience using the PANAS questionnaire for the measurement of the affect. This report was a part of a more extensive questionnaire, as described in Chapter 2.

One threat in terms of validity here was that the outcome of the comparison of physiological responses before and after the outdoor route could be affected by the repeated exposure to the same sequence of stressors. The effect of novelty could play a role, resulting in more intense responses in the first time that the participants conducted the indoor experiment. However, the indoor activities comprised only a small part of the collected data. The study also collected measurements that describe the reactions to similar stressors in outdoor circumstances, where there are no order effects. This threat was thus diminished since the evaluation of the results would not be based only on the indoor tests.

The indoor tests were conducted in a quiet room, with a temperature between 18-20°C.

C.2. STATISTICAL ANALYSIS APPROACH

The data collected from the indoor activities were analysed with the Wilcoxon signed-rank test. This analysis was conducted to compare responses obtained before and after the outdoor activity. After that, it was used for the pairwise comparison of the consecutive stages of activities. The first comparison aimed to show the overall effect of the activity on the responses to the same stimuli and changes of activity. The second comparison aimed to identify if any of the movement changes and other transitions had a significant effect on the EDA measures. The EDA measures that were analysed with the Wilcoxon signed-rank test included the tonic EDA, the EDR frequency, the mean EDR amplitude and the sum of EDR amplitudes. The tonic EDA and the EDR amplitude values were normalised per participant, following the recommendations of Boucsein (2012).

For the Wilcoxon signed-rank tests, the EDR frequency was calculated by dividing the number of EDR peaks with the duration of the activity in minutes. The resulting number thus reflected the number of EDR peaks per minute. The sum of EDR amplitudes was calculated in the same way, by adding the EDR amplitudes for each activity and dividing the result with the duration of the activity.

Two segments (putting a coat on and off for 45 seconds, and then walking while putting the coat again on and off) were excluded from this analysis since they contained many artefacts. These segments are noted as ‘stand + wear coat’ and ‘walk + wear coat’ in Figure C1. These segments were only included in the sequence of activities for training the artefact recognition and the movement recognition algorithm.

A mixed linear model was then fitted for the variable 'sum of EDR amplitudes', with the parameters related to activity and stimulation as fixed effects. A random intercept was included for each subject and the subject's age, sex, and ambient outdoor temperature in the time when the activities were conducted. The input data for the linear mixed model were first resampled at 60 seconds. EDA artefacts had already been excluded from the analysis. For the linear mixed model analysis, the EDR frequency was calculated by extracting the number of EDR peaks per minute. The sum of EDR amplitudes was also calculated by finding the sum of EDR amplitudes per minute.

The full formula which was used in the linear mixed model had the following form:

$$Yi = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \gamma_{01} + \gamma_{02} + \gamma_{03} + \gamma_{04} + \varepsilon_i$$

where *X_1 = time, X_2 = activity intensity, X_3 = change in stimulation, X_4 = change in activity, X_5 = time: change in activity,* and γ_{01}, γ_{02}, γ_{03}, γ_{04} correspond to random intercepts for each subject, age, ambient outdoor temperature and sex. The ambient outdoor temperature referred to the outdoor temperature during the time of the experiment. The variables were coded as categorical variables in the following way: the '*time*' variable was coded with [0] and [1], corresponding to 'before the outdoor activity' and 'after the outdoor activity', respectively. The '*activity intensity*' variable had three levels; [0] represented the lowest intensity ('sit/stand'), [1] represented the intensity of walking and [2] represented higher intensities ('intense move'). The '*change in stimulation*' was coded with [0] representing the absence of any change in stimulation, and [1] representing the presence of a change. The 'change in activity' was coded with [0] representing the absence of a change in activity intensity and [1] representing the presence of a change. The 'time: change in activity' was a variable representing the interaction between the two variables that it contained. The subject and sex variables were also coded as categorical.

Variations of this model were also used, where the interaction of two or more variables was included, or the following variables were added: *stimulation, talk*. Only the combinations of variables that did not create any multicollinearity issues according to the variance inflation factor were tested. The experimentation also involved coding the variables as ordinal, resulting in very small differences.

For the analysis of the questionnaire, the Wilcoxon signed-rank test was conducted to compare the participants' experience in the first and second indoor test. The aim was to identify how the outdoor activity affected the perceived experience in the indoor activity. The test was conducted separately for the positive and negative affect.

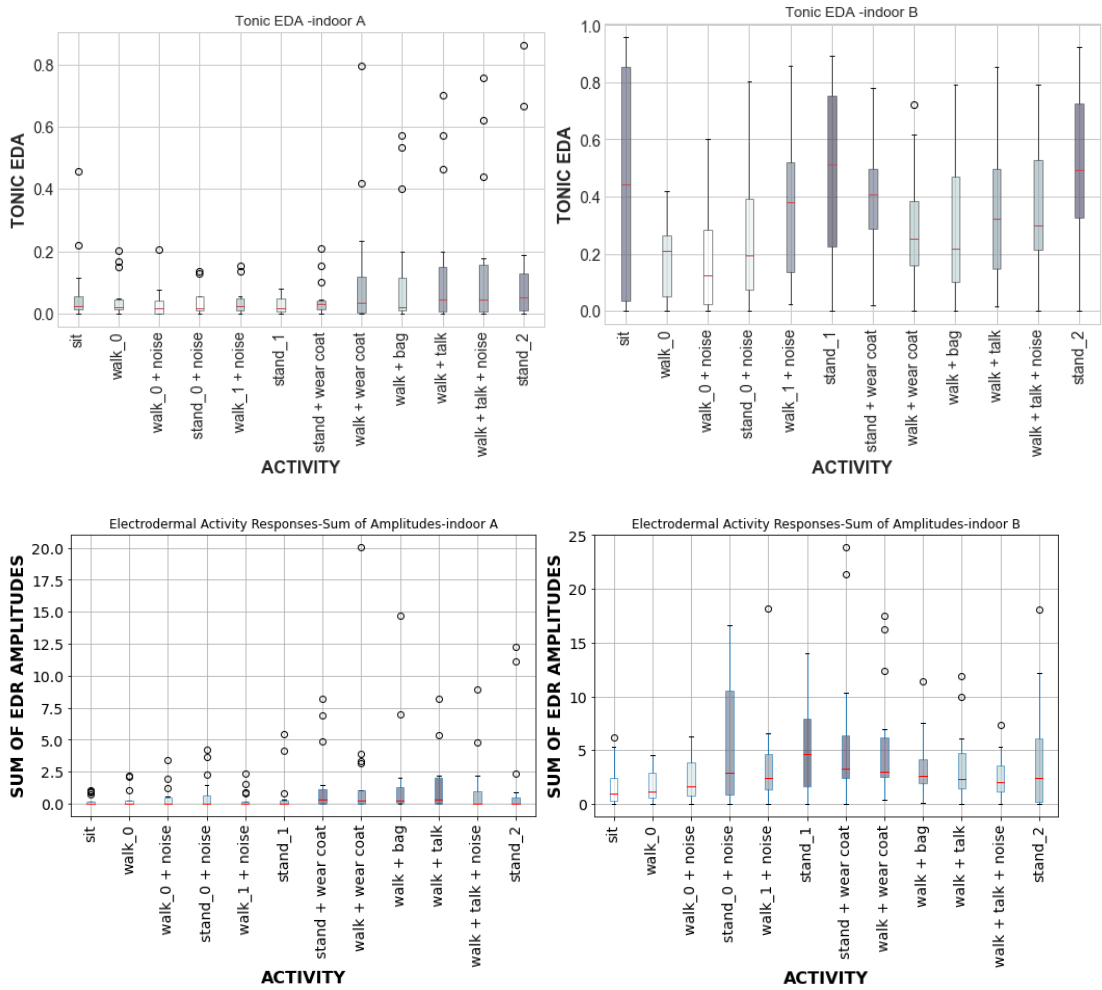


Figure C2. Boxplots showing the tonic EDA and sum of EDR amplitudes for the indoor activities, before the outdoor activity ('indoor A') and after it ('indoor B').

As shown in Figure C2, all EDA measures exhibit elevated values in the activities performed after the outdoor route ('Indoor B'), compared to the same activities performed before it ('Indoor A'). The increase is statistically significant or marginally statistically significant ($p<0.05$ and $p<0.085$, respectively) for almost all activities for all measures. Similar graphs for EDR frequency and amplitude, as well as for other physiological signals tracked during the experiment (HR and skin temperature) can be found in section C.1.5. (Figure C4).

As the graphs show, in the first round of activities ('Indoor A') there is a small increase in all EDA measures when the participants start engaging in an activity which requires more coordination and intensity of movements (for instance 'walk + wear coat'); this increase is retained until the end of this round of activities. In the second round of activities ('Indoor B'), the values in almost all measures exhibit an increasing trend until the participants start engaging in more demanding movement and attention-related activities (such as 'stand + wear coat'). This trend starts decreasing for mean EDR amplitude and tonic EDA. The values of tonic EDA are initially high when the participants return from the outdoor activity. These values decrease when the participants are in the steady-state walking state without any stimulation. Then they follow the same increasing trend as in the other measures, each time the activity state changes. The only significant transitions in the pairwise comparison of activities are found in the transition from walking to standing, with the application of noise stimulation (statistically significant at p=0.015 for EDA tonic, and marginally statistically significant at p=0.084 for the sum of EDR amplitudes), and from standing to walking, again with noise stimulation (marginally statistically significant at p=0.052 for EDA tonic).

RESULTS OF THE LINEAR MIXED MODEL ANALYSIS FOR THE INDOOR EXPERIMENT
Dependent variable: Sum of EDR amplitudes

Predictors	Coef.	Std.Err.	P	95% CI: bottom limit	95% CI: upper limit	Variable explanation
Intercept	-0.083	0.899	0.926	-1.844	1.678	
Time [1]	1.062	0.092	<0.00001	0.883	1.242	Time (effect of overall duration of activity) *[0]: before the outdoor activity* *[1]: after the outdoor activity*
Activity intensity [2]	0.086	0.098	0.379	-0.106	0.278	***Activity intensity levels:*** *[1]: 'sit/stand'* *[2]: 'walk'* *[3]: 'intense move'*
Activity intensity [3]	1.313	0.158	<0.00001	1.004	1.622	
Change in activity [1]	0.133	0.106	0.21	-0.075	0.341	***Change in activity (intensity):*** *[0]: No change* *[1]: Change*
Change in stimulation [1]	0.119	0.081	0.144	-0.041	0.278	***Change in (noise) stimulation:*** *[0]: No change* *[1]: Change*
Time[1] : Change in activity [1]	0.618	0.136	<0.00001	0.351	0.884	***Interaction*** *between* ***time*** *and* ***change in activity*** *(intensity)*

Figure C3. The results of the linear mixed model with the best performance.

The results of the linear mixed model also confirmed that the outdoor activity (marked as 'Time' in Figure C3) had a substantial impact on the EDA responses. This variable expresses the effect of the overall duration of the activity. The model shows a significant association between the sum of EDR amplitudes and this parameter (β=1.062, p<0.00001). This result shows that the sum of EDR amplitudes was significantly higher when the participants repeated the test after the outdoor activity.

The activity intensity had a significant impact on the sum of EDR amplitudes (β=1.313, p<0.00001) when it was at the third level of intensity (corresponding to intense movement). The presence of a change in activity intensity also caused a significant increase (β=0.618, p<0.00001) in the sum of EDR amplitudes, but only after the outdoor activity. This parameter is expressed in the model with the interaction variable ('Time

[1]: Change in activity [1]'). The parameters related to stimulation did not have any significant impact on the EDA responses.

As for the results of the analysis of the questionnaire, the Wilcoxon signed-rank test showed that the positive affect was considerably lower after the outdoor test (p=0.0048), while the negative affect was not impacted. A few participants noted in the open comments section that the traffic noises were identified as annoying or surprising.

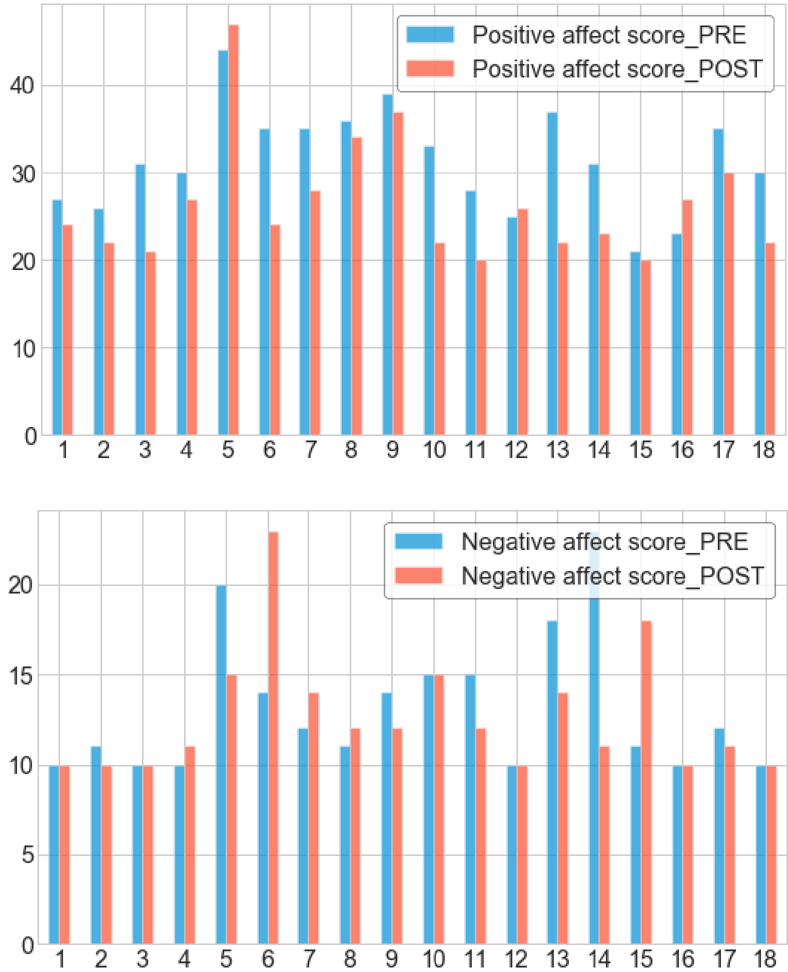


Figure C4. The results of the PANAS questionnaire for each participant for the indoor test, before ('_PRE') and after ('_POST') the outdoor route.

C.4. GRAPHS OF THE OTHER PHYSIOLOGICAL MEASURES DURING THE INDOOR EXPERIMENTS

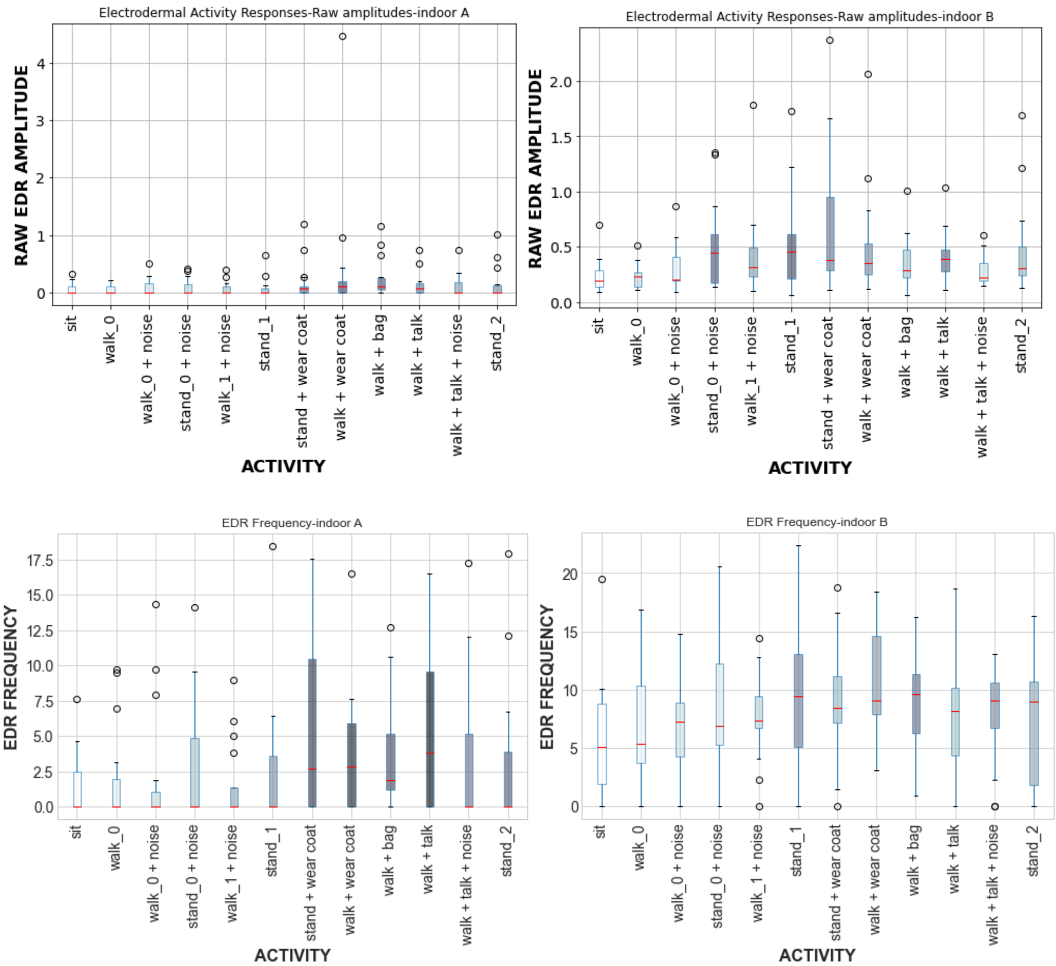


Figure C5. The distribution of other physiological measures related to EDA (EDR frequency measured in peaks/minute; mean EDR amplitude before normalisation, measured in µS) during each activity stage in the indoor experiments

The distribution of the other measures related to EDA and physiological signals which were measured is presented in Figures C5 and C6. The median and standard deviation values for each measure are also displayed in Figure C7. The separate presentation of the amplitude and frequency of EDRs helps understand how each of these measures contributed to the measure that was statistically analysed (the sum of EDR amplitudes).

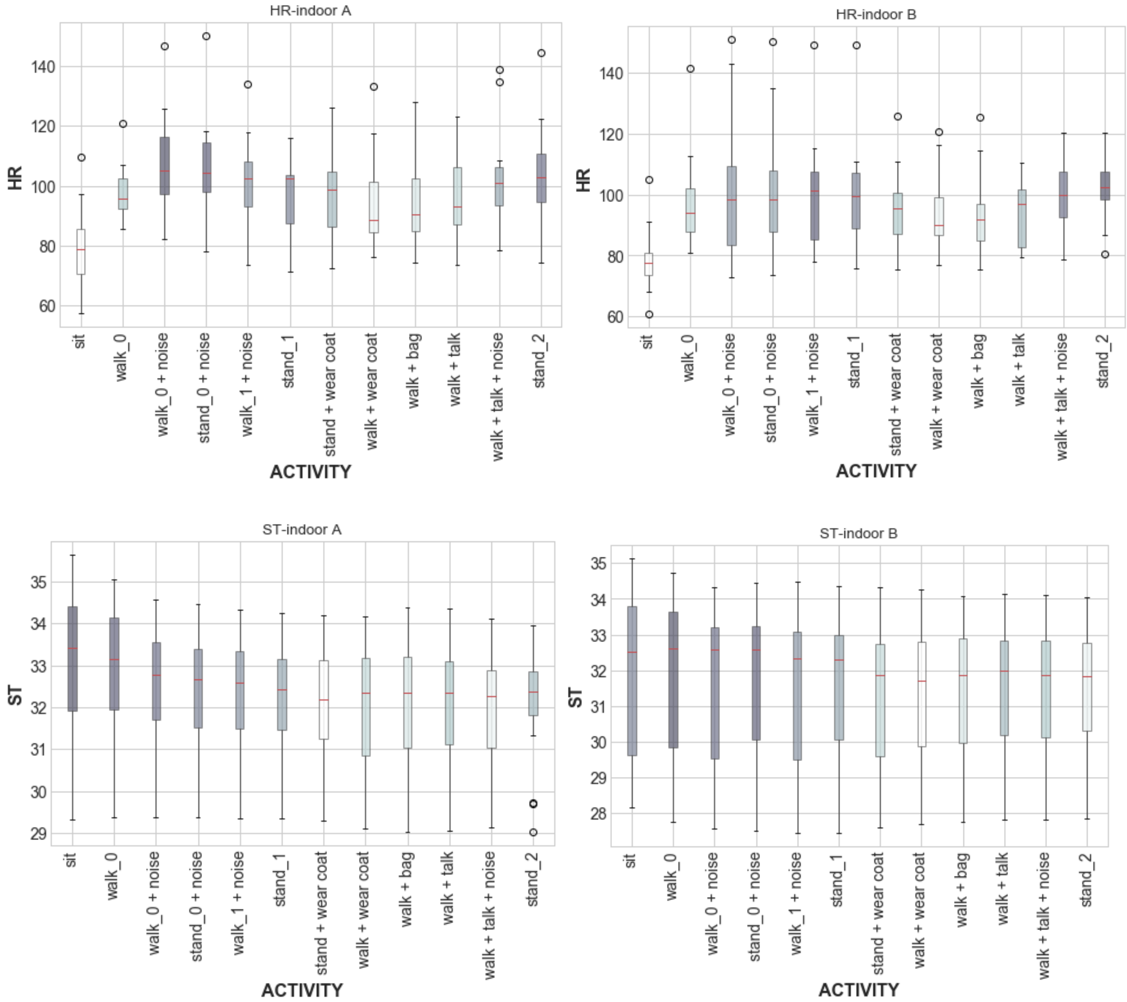


Figure C6. The distribution of other physiological signals (heart rate (HR), skin temperature (ST)) during each activity stage in the indoor experiments

Measure	ACTIVITY NAME												
	sit	walk_0	walk_0 + noise	stand_0 + noise	walk_1 + noise	stand_1	stand + wear coat	walk + wear coat	walk + bag	walk + talk	walk + talk + noise	stand_2	
Indoor A - EDR amplitude	0.0±0.02	0.0±0.02	0.0±0.04	0.0±0.02	0.0±0.02	0.0±0.04	0.0±0.05	0.01±0.17	0.03±0.1	0.0±0.07	0.0±0.06	0.0±0.06	*Normalised value of the mean EDR amplitude per activity (initially in µS)*
Indoor B - EDR amplitude	0.2±0.15	0.23±0.11	0.22±0.21	0.48±0.41	0.33±0.39	0.45±0.46	0.37±0.63	0.35±0.48	0.29±0.22	0.37±0.23	0.22±0.14	0.3±0.46	
Indoor A - EDR frequency	0.0±2.25	0.0±3.4	0.0±4.24	0.0±4.15	0.0±2.76	0.0±4.74	2.68±5.92	2.82±4.3	1.88±3.98	3.81±5.95	0.0±5.0	0.0±5.17	*number of peaks/duration of activity (in minutes)*
Indoor B - EDR frequency	5.11±4.88	5.32±5.17	7.27±4.31	6.86±6.63	7.36±3.61	9.41±6.16	8.42±4.61	9.03±4.64	9.6±3.94	8.14±5.03	9.06±4.1	8.97±5.42	
Indoor A - EDA tonic	0.03±0.11	0.02±0.06	0.02±0.05	0.02±0.04	0.02±0.04	0.02±0.03	0.03±0.06	0.04±0.21	0.02±0.19	0.05±0.22	0.04±0.23	0.05±0.24	*Normalised value of the mean tonic EDA per activity (initially in µS)*
Indoor B - EDA tonic	0.44±0.4	0.21±0.13	0.13±0.19	0.19±0.24	0.38±0.28	0.51±0.31	0.41±0.2	0.25±0.2	0.22±0.26	0.32±0.24	0.3±0.26	0.49±0.29	
Indoor A - Sum of EDR amplitudes	0.0±0.41	0.0±0.72	0.0±0.93	0.0±1.36	0.0±0.69	0.0±1.58	0.3±2.58	0.23±4.82	0.28±3.75	0.34±2.25	0.0±2.36	0.0±3.85	*sum of the amplitude of peaks (in µS)/duration of activity (in minutes)*
Indoor B - Sum of EDR amplitudes	1.01±1.86	1.13±1.46	1.63±1.96	2.91±6.1	2.44±4.22	4.64±4.47	3.33±6.84	3.05±5.18	2.61±2.77	2.34±3.22	2.08±1.94	2.44±4.87	
Indoor A - HR	78±13	95±8	105±15	104±16	102±13	102±11	98±13	88±15	90±15	93±13	101±15	102±16	*mean bpm per activity*
Indoor B - HR	77±9	94±14	98±22	98±20	101±18	99±17	95±11	90±11	91±13	96±9	100±11	102±9	
Indoor A - ST	33.41±1.81	33.15±1.71	32.77±1.52	32.66±1.48	32.59±1.45	32.43±1.42	32.2±1.43	32.34±1.51	32.34±1.6	32.34±1.63	32.26±1.44	32.38±1.38	*mean skin temperature per activity (°C)*
Indoor B - ST	32.52±2.27	32.6±2.23	32.58±2.13	32.58±2.03	32.32±2.1	32.31±1.91	31.86±1.96	31.7±1.88	31.86±1.82	31.99±1.73	31.87±1.68	31.85±1.87	

Figure C7. The median and standard deviation values for each measure during each activity

APPENDIX D

ETHICS APPLICATIONS

This appendix contains material related to the two ethics applications connected to this project.

Section D1 contains the approval letter for the ethics application ETH19-3752. This application was lodged to obtain approval for conducting the experiments for data collection in Sydney (Phase A and B in Section 2.4.2 of Chapter 2). Section D2 contains the approval letter for the ethics application ETH20-5253. This application was lodged to obtain approval for using the publicly available data from the ESUM repository (ESUM 2018). Section D3 contains the participant information sheet which was used to inform participants regarding the overall procedure followed in the data collection experiment in Sydney. The consent form which the participants were asked to sign if they wished to participate in this experiment is also included in this section.

Section D4 presents the template of the questionnaire given to the participants that took part in Phase A of the data collection experiment in Sydney.

Section D5 contains the guide which was given to the participants in the data collection experiment in Sydney. The guide outlines the following:

- which devices are being used,
- what happens with the collected data,
- the protocol followed in Phase A of the experiment (see Section 2.4.2 of Chapter 2),
- the main duties of the participants regarding the data collection during the free-living activities,
- a guideline for keeping notes regarding the experience in each route in the data collection during the free-living activities.

D.1. ETHICS APPROVAL LETTER: ETH19-3752

HREC Approval Granted - ETH19-3752

Research.Ethics@uts.edu.au <Research.Ethics@uts.edu.au>
Thu 7/4/2019 9:54 AM

To: Dimitra Dritsa <Dimitra.Dritsa@uts.edu.au>; Nimish Biloria <Nimish.Biloria@uts.edu.au>; Dimitra Dritsa <Dimitra.Dritsa@student.uts.edu.au>; Research Ethics <research.ethics@uts.edu.au>

Dear Applicant

Thank you for your response to the Committee's comments for your project titled, "Collection and analysis of physiological, movement and environmental data in the context of different daily activities". The Committee agreed that this application now meets the requirements of the National Statement on Ethical Conduct in Human Research (2007) and has been approved on that basis. You are therefore authorised to commence activities as outlined in your application.

You are reminded that this letter constitutes ethics approval only. This research project must also be undertaken in accordance with all UTS policies and guidelines including the Research Management Policy (http://www.gsu.uts.edu.au/policies/research-management-policy.html).

Your approval number is UTS HREC REF NO. ETH19-3752.

Approval will be for a period of five (5) years from the date of this correspondence subject to the submission of annual progress reports.

The following standard conditions apply to your approval:

- Your approval number must be included in all participant material and advertisements. Any advertisements on Staff Connect without an approval number will be removed.

- The Principal Investigator will immediately report anything that might warrant review of ethical approval of the project to the Ethics Secretariat (Research.Ethics@uts.edu.au).

- The Principal Investigator will notify the UTS HREC of any event that requires a modification to the protocol or other project documents, and submit any required amendments prior to implementation. Instructions can be found at https://staff.uts.edu.au/topichub/Pages/Researching/Research%20Ethics%20and%20Integrity/Human%20research%20ethics/Post-approval/post-approval.aspx#tab2.

- The Principal Investigator will promptly report adverse events to the Ethics Secretariat (Research.Ethics@uts.edu.au). An adverse event is any event (anticipated or otherwise) that has a negative impact on participants, researchers or the reputation of the University. Adverse events can also include privacy breaches, loss of data and damage to property.

- The Principal Investigator will report to the UTS HREC annually and notify the HREC when the project is completed at all sites. The Principal Investigator will notify the UTS HREC of any plan to extend the duration of the project past the approval period listed above through the progress report.

- The Principal Investigator will obtain any additional approvals or authorisations as required (e.g. from other ethics committees, collaborating institutions, supporting organisations).

- The Principal Investigator will notify the UTS HREC of his or her inability to continue as Principal Investigator including the name of and contact information for a replacement.

I also refer you to the AVCC guidelines relating to the storage of data, which require that data be kept for a minimum of 5 years after publication of research. However, in NSW, longer retention requirements are required for research on human subjects with potential long-term effects, research with long-term environmental effects, or research considered of national or international significance, importance, or controversy. If the data from this research project falls into one of these categories, contact University Records for advice on long-term retention.

You should consider this your official letter of approval. If you require a hardcopy please contact Research.Ethics@uts.edu.au.

If you have any queries about your ethics approval, or require any amendments to your research in the future, please do not hesitate to contact Research.Ethics@uts.edu.au.

Yours sincerely,

A/Prof Beata Bajorek
Chairperson
UTS Human Research Ethics Committee
C/- Research Office
University of Technology Sydney
E: Research.Ethics@uts.edu.au

REF: E38

D.2. ETHICS APPROVAL LETTER: ETH20-5253

Neg Risk approval - ETH20-5253

research.ethics@uts.edu.au <research.ethics@uts.edu.au>

Thu 7/30/2020 9:17 PM

To: Research Ethics <research.ethics@uts.edu.au>; Dimitra Dritsa <Dimitra.Dritsa@uts.edu.au>; Nimish Biloria <Nimish.Biloria@uts.edu.au>

1 attachments (175 KB)

Ethics Application.pdf;

This is an automated email

Dear Applicant

Re: ETH20-5253 - "Analysis of common factors and differences in physiological data collected in the urban environment in different contexts"

You have declared your research as Negligible Risk and that it **DOES NOT** involve any of the following:

- Establishment of a register or databank for possible use in future research projects
- Collection, transfer and/or banking of human biospecimens[(1)]
- Any significant alteration to routine care or health service provided to participants
- Interventions and therapies, including clinical and non-clinical trials, and innovations
- Targeted recruitment or analysis of data from any of the participant groups listed in Chapter 4 of the National Statement (or where any of these participants are likely to be significantly over-represented in the group being studied) including:
  - Women who are pregnant and the human fetus
  - Children and young people (under 18 years)
  - People in dependent or unequal relationships
  - People highly dependent on medical care who may be unable to give consent
  - People with a cognitive impairment, an intellectual disability, or a mental illness
  - People who may be involved in illegal activities (including those affected)
  - Aboriginal and Torres Strait Islander Peoples
- Collection, use or disclosure of personal information (except where expert opinion is being canvased with full disclosure, consent and identification for use in the public domain)
- Collection, use or disclosure of health information[(2)]
- Collection, use or disclosure of sensitive information[(3)]
- Covert observation, active concealment, or planned deception of participants
- Activity that potentially infringes the privacy or professional reputation of participants, providers or organisations (except where expert opinion is being canvased with full disclosure, consent and identification for use in the public domain)
- Potential for participants to experience harm (e.g. physical, psychological, social, economic and/or legal)
- Direct contact with UTS staff/students, patients, consumers or members of the public (except where expert opinion is being canvased with full disclosure, consent and identification for use in the public domain)
- Participants who have a pre-existing relationship with the researcher (except where expert opinion is being canvased with full disclosure, consent and identification for use in the public domain)

- People unable to give free informed consent due to difficulties in understanding the Information Sheet or Consent Form
- People in other countries

The UTS HRECs consider the following to be of negligible risk:
(1) use of commercial cell lines and/or supply of blood or blood products from Australian Red Cross Lifeblood
(2) consensus methods (i.e. Delphi)
(3) use of existing collections of data or records that contain only non-identifiable data about human beings (i.e. no codes)

I declare that I believe this research to be of negligible risk in accordance with the National Statement on Ethical Conduct in Human Research (Chapter 2.1)

I will notify the UTS Human Research Ethics Committees of any variation to this research that may alter the level of risk associated with it. This research will be undertaken in compliance with the UTS Research Ethics and Integrity Policy or any replacement or amendment thereof.

This research will be undertaken in compliance with the Australian Code for the Responsible Conduct of Research and National Statement on Ethical Conduct in Human Research.

Please keep a copy of your ethics application form and approval letter on file to show you have considered the risks associated with your research. You should consider this your official letter of approval.

To access this application, please click here. A copy of your application form has been attached to this email.

If you have any queries about this approval, please do not hesitate to contact your local research office or Research.Ethics@uts.edu.au.

Kind regards,
UTS HREC Ethics Secretariat

C/- Research Office
University of Technology Sydney
Research.Ethics@uts.edu.au | Website
PO Box 123 Broadway NSW 2007

Ref: Ethics 2 -Neg Risk approved (c)

D.3. PARTICIPANT INFORMATION SHEET AND CONSENT FORM FOR THE EXPERIMENTS IN SYDNEY

UTS UNIVERSITY OF TECHNOLOGY SYDNEY

PARTICIPANT INFORMATION SHEET

COLLECTION AND ANALYSIS OF PHYSIOLOGICAL, MOVEMENT AND ENVIRONMENTAL DATA IN THE CONTEXT OF DIFFERENT DAILY ACTIVITIES (UTS HREC REF NO. ETH19-3752)

WHO IS DOING THE RESEARCH?

My name is Dimitra Dritsa and I am a student at UTS. My supervisor is Nimish Biloria (nimish.biloria@uts.edu.au).

WHAT IS THIS RESEARCH ABOUT?

The purpose of the study is to collect and analyse data related to health and wellbeing that can be captured with wristbands and smartphones (noise, movement, heart rate, skin conductance). The research is conducted in order to find ways to easily analyse how the urban environment influences physical activity, stress and other parameters related to health and wellbeing.

WHY HAVE I BEEN ASKED?

You have been invited to participate in this study because you are a student/employee of UTS, or you are an adult friend/family member of a student/employee of UTS.

IF I SAY YES, WHAT WILL IT INVOLVE?

If you decide to participate, we will arrange a convenient time for briefing and conducting the first data collection experiment.
In this session you will first be briefed about how your data shall be treated with utmost security, and you will get familiar with the hardware that will be used during the experiment. Then we will proceed with the data collection which will involve indoor and outdoor walking tests. The overall time needed for this session will not exceed 2 hours.

- In the **indoor walking test**, you will be asked to perform a series of common daily activities (sitting, standing, walking) while wearing two wristbands. This test will not last more than 10 minutes and will be performed twice.
- We will be giving you instructions in terms of how many minutes you have to devote to each activity.
- During this test you might be exposed to continuous or sudden sounds (traffic, police car, ambulance).
- In the **outdoor walking test**, you will be asked to walk on a predefined route in the urban environment (within the vicinity of UTS), which will take approximately 30 minutes. During this test, you will be wearing two wristbands (measuring heart rate, body temperature, skin conductivity) while your smartphone will be used to measure location and noise). The route does not pose any challenges regarding accessibility.
- After this, you will be asked to fill a quick 10-minute **questionnaire** regarding your overall wellbeing and your experience during the experiment.

Then, you will be given instructions for the next phase:

- *The next phase will involve your participation for a period of 7 days*
- During this phase, you can follow your daily activities without any alteration. You will be asked to monitor your activities at least during commuting times.
- You will be asked to use wearable sensors and your smartphone for data collection. You will receive detailed instructions regarding how to use the equipment, as well as a visual guide which you will be able to keep during the experiment.
- You might need to charge some of the sensing equipment overnight (if needed).

- You will also need to download 3 free apps on your mobile devices to monitor environmental conditions and you shall be provided with anonymous logins and asked to create your own passwords for the same.
- At the end of each day, you will be asked to make some short notes regarding significant moments and places during your routes or activities. This shall take no more than 15 minutes per day.
- You shall need to be particularly careful of not losing any of the hardware provided to you since the kit provided to you is customized and is expensive.

After the end of the experiment, you shall meet the research team at the University of Technology Sydney to return the equipment. This will not take more than 15 minutes.

ARE THERE ANY RISKS/INCONVENIENCE?

The following are considered as potential risks that could occur during the project:
- Concern for privacy
- Inconvenience caused in cases requiring battery change and charging of wearable devices
- Time investment for the first data collection and briefing session at the beginning of the experiment (2 hours), for the completion of the daily journal (15 minutes every day) and for returning the equipment after the data collection period (15 minutes).
- Accident during the outdoor walking test if you fail to follow road safety rules and regulations
- Need to repeat the data collection if there is any malfunctioning in the equipment

In case of injury or safety concerns, you can contact the UTS Security Control Room at **9514 1192.** Security staff will be able to escort you back to UTS and offer their assistance.

You can also use the following contact numbers:
UTS security for emergencies (free call): **1800 249 559**
Campus security offices at Broadway (Building 1): **9514 1192/3**
Campus security offices at Haymarket (Building 5): **9514 3399**

DO I HAVE TO SAY YES?

Participation in this study is voluntary. It is completely up to you whether or not you decide to take part.
If you know personally any of the involved researchers, please note that there is no benefit to you from your participation in this study, and your agreement or refusal of participation will not alter your relationship in any manner. We will treat all the prospective participants in the same way, while operating under the ethical code of conduct.

WHAT WILL HAPPEN IF I SAY NO?

If you decide not to participate, it will not affect your relationship with the researchers or the University of Technology Sydney.

If you wish to withdraw from the study once it has started, you can do so at any time without having to give a reason, by contacting me or my supervisor. If you know personally any of the involved researchers, do not feel obligated to continue the study if you wish to withdraw.

If you decide to leave the research project, we will not collect additional personal information from you, although personal information already collected will be retained to ensure that the results of the research project can be measured properly and to comply with law. You should be aware that data collected up to the time you withdraw will form part of the research project results.

CONFIDENTIALITY

By signing the consent form you consent to the research team collecting and using personal information about you for the research project. All this information will be treated confidentially by providing access only to the research staff, encrypting all digital datasets, keeping all physical data securely locked and anonymising personal information. Your information will only be used for the purpose of this research and it will only be disclosed with your permission, except as required by law. With your permission, we would like to store your information for future use in research projects that are an extension of this research. In all instances your information will be treated confidentially.

We plan to publish the results in various Conference Proceedings, Scientific Journals and Books. In all circumstances information will be provided in such a way that you cannot be identified.

WHAT IF I HAVE CONCERNS OR A COMPLAINT?

If you have concerns about the research that you think we can help you with, please feel free to contact dimitra.dritsa@student.uts.edu.au or nimish.biloria@uts.edu.au.

You will be given a copy of this form to keep.

NOTE:
This study has been approved by the University of Technology Sydney Human Research Ethics Committee [UTS HREC]. If you have any concerns or complaints about any aspect of the conduct of this research, please contact the Ethics Secretariat on ph.: +61 2 9514 2478 or email: Research.Ethics@uts.edu.au], and quote the UTS HREC reference number. Any matter raised will be treated confidentially, investigated and you will be informed of the outcome.

CONSENT FORM

Collection and analysis of physiological, movement and environmental data in the context of different daily activities
(UTS HREC REF NO. ETH19-3752)

I ____________________ agree to participate in the research project *Collection and analysis of physiological, movement and environmental data in the context of different daily activities –UTS HREC REF NO. ETH19-3752* being conducted by Dimitra Dritsa, Faculty of Design Architecture and Building, University of Technology Sydney, City Campus, Broadway, Post Box 123, NSW 2007 Australia, Tel: +61295148848.

I have read the Participant Information Sheet or someone has read it to me in a language that I understand.

I understand the purposes, procedures and risks of the research as described in the Participant Information Sheet.

I have had an opportunity to ask questions and I am satisfied with the answers I have received.

I freely agree to participate in this research project as described and understand that I am free to withdraw at any time without affecting my relationship with the researchers or the University of Technology Sydney.

I understand that I will be given a signed copy of this document to keep.

I understand that the collected data will be individually re-identifiable, until the end of the data collection period. I understand that this will happen because I will need to be notified if there is any malfunctioning in the equipment that I will be using, in order to arrange their fix or replacement, and that after the data collection ends, my data will not be individually identifiable any more.

I agree to:

UTS UNIVERSITY OF TECHNOLOGY SYDNEY

☐ Use the provided Wearable Sensors
☐ Be careful with safeguarding all the equipment
☐ Be certain to charge any of the devices as and when needed

I agree that the research data gathered from this project may be published in a form that:
☐ Does not identify me in any way
☐ May be used for future research purposes

I am aware that I can contact Dimitra Dritsa or Dr. Nimish Biloria from UTS if I have any concerns about the research.

______________________________________ ____/____/____
Name and Signature [participant] Date

______________________________________ ____/____/____
Name and Signature [researcher or delegate] Date

D.4. QUESTIONNAIRE

The typical PANAS test includes twenty adjectives that describe different moods; ten moods are connected to the positive affect and the rest to the negative affect. The participants are usually asked to describe the extent to which they felt each state by rating it on a scale of 1-5. In this study, the participants were asked to complete this test for each of the three parts of Phase A of data collection. They were asked to complete sections 1 and 2 of the questionnaire directly after finishing the first indoor test. Sections 3 and 4 of the questionnaire were completed directly after finishing the second indoor test.

UTS UNIVERSITY OF TECHNOLOGY SYDNEY

QUESTIONNAIRE

COLLECTION AND ANALYSIS OF PHYSIOLOGICAL, MOVEMENT AND ENVIRONMENTAL DATA IN THE CONTEXT OF DIFFERENT DAILY ACTIVITIES (UTS HREC REF NO. ETH19-3752)

SECTION 1- PERSONAL BACKGROUND

1. What is your age?

……………………………………………………

2. What is your gender?

……………………………………………………

SECTION 2- 1st INDOOR TEST

1. Please rate your experience during the test by putting a score from 1 to 5 in the following sections.

1 Very slightly or not at all	2 A little	3 Moderately	4 Quite a bit	5 Extremely

c	Score	Feelings/Emotions	#	Score	Feelings/Emotions
1		Interested	1		Irritable
2		Distressed	2		Alert
3		Excited	3		Ashamed
4		Upset	4		Inspired
5		Strong	5		Nervous
6		Guilty	6		Determined
7		Scared	7		Attentive
8		Hostile	8		Jittery
9		Enthusiastic	9		Active
10		Proud	10		Afraid

2. Were there any specific moments during the test which caused a notable difference in your experience? If yes, please describe shortly.

……………………………………………………

SECTION 3- EXPERIENCE DURING THE OUTDOOR WALKING TEST

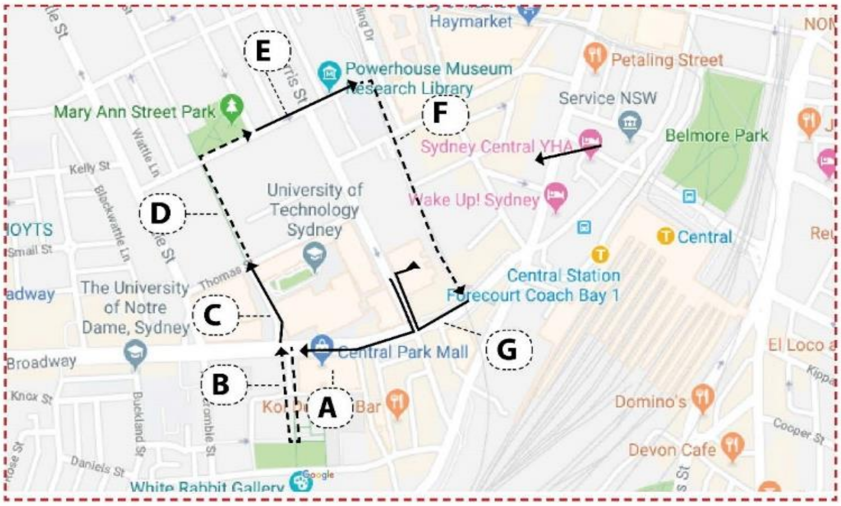
1. For each part of the route (part A to G), please rate your experience during the test by using the following guide:

   -Below each route section, note down only the adjectives where your score would be more than 1 (>1). Next to each adjective, note down also the score.

Example:
Part A
Interested (3), Active (2) …………………………………………………………………………………………

……

c	Feelings/Emotions	#	Feelings/Emotions
1	Interested	1	Irritable
2	Distressed	2	Alert
3	Excited	3	Ashamed
4	Upset	4	Inspired
5	Strong	5	Nervous
6	Guilty	6	Determined
7	Scared	7	Attentive
8	Hostile	8	Jittery
9	Enthusiastic	9	Active
10	Proud	10	Afraid



1 Very slightly or not at all	2 A little	3 Moderately	4 Quite a bit	5 Extremely

c	Feelings/Emotions	#	Feelings/Emotions
1	Interested	1	Irritable
2	Distressed	2	Alert
3	Excited	3	Ashamed
4	Upset	4	Inspired
5	Strong	5	Nervous
6	Guilty	6	Determined
7	Scared	7	Attentive
8	Hostile	8	Jittery
9	Enthusiastic	9	Active
10	Proud	10	Afraid

Part A
……………………………………………………………………………………………………
……………………………………………………………………………………………………

Part B
……………………………………………………………………………………………………
……………………………………………………………………………………………………

Part C
……………………………………………………………………………………………………
……………………………………………………………………………………………………

Part D
……………………………………………………………………………………………………
……………………………………………………………………………………………………

Part E
……………………………………………………………………………………………………
……………………………………………………………………………………………………

Part F
……………………………………………………………………………………………………
……………………………………………………………………………………………………

Part G
……………………………………………………………………………………………………
……………………………………………………………………………………………………

2. Do you recall any specific moments during the test where your experience suddenly changed (i.e. a moment where you felt especially excited, or nervous)? If yes, please describe shortly, by mentioning the part of the route, the experience and the reason.

   (**Example**: "Part X: sudden stress, due to an ambulance passing by)

…………………………………………………

3. Please rate how comfortable was your experience of using the sensing equipment

1 Not comfortable at all	2 A little uncomfortable	3 Moderately comfortable	4 Quite comfortable	5 Extremely comfortable

…………………………………………………

SECTION 4- 2nd INDOOR TEST

4. Please rate your experience during the test by putting a score from 1 to 5 in the following sections.

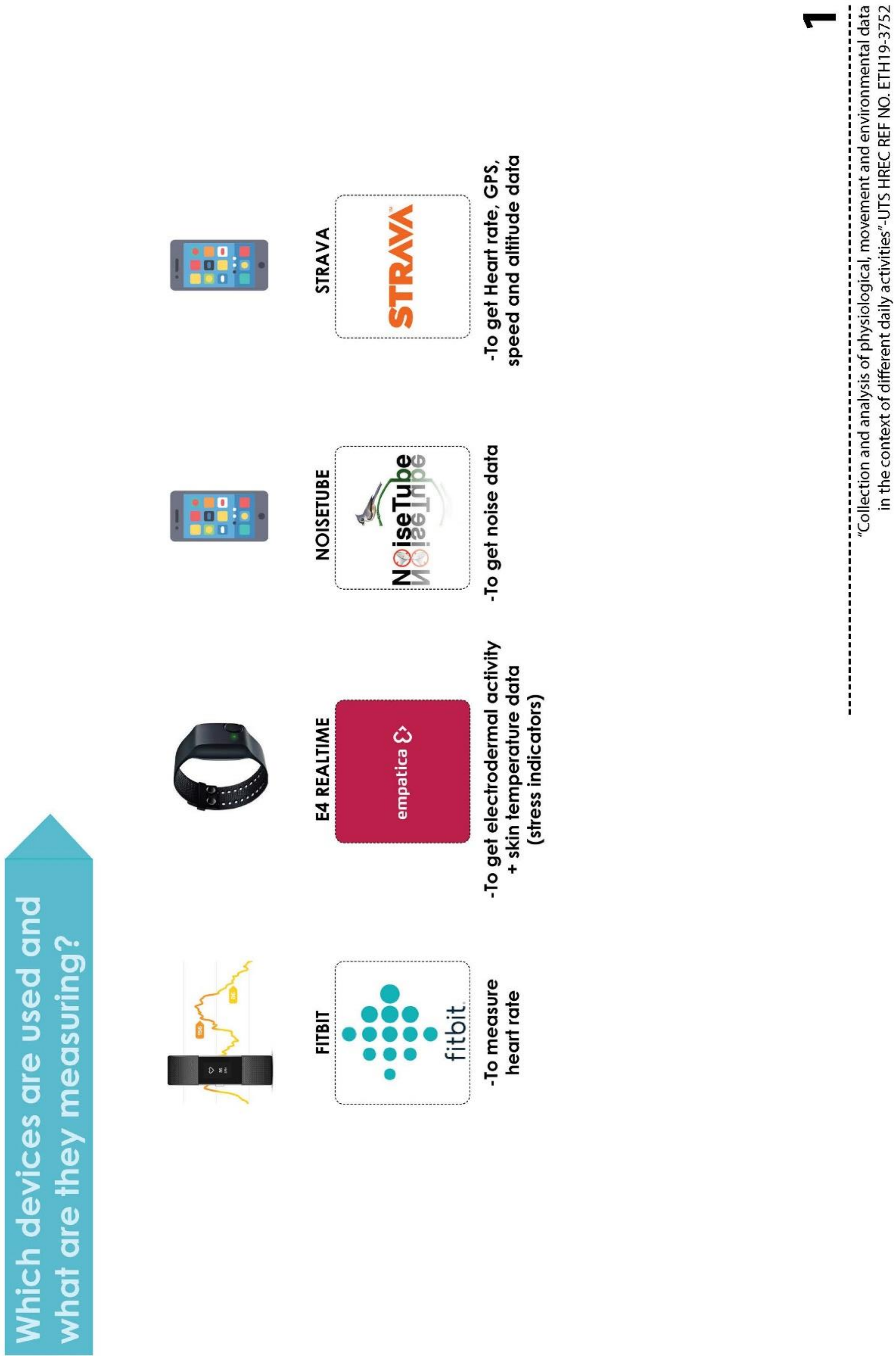
1 Very slightly or not at all	2 A little	3 Moderately	4 Quite a bit	5 Extremely

#	Score	Feelings/Emotions	#	Score	Feelings/Emotions
1		Interested	1		Irritable
2		Distressed	2		Alert
3		Excited	3		Ashamed
4		Upset	4		Inspired
5		Strong	5		Nervous
6		Guilty	6		Determined
7		Scared	7		Attentive
8		Hostile	8		Jittery
9		Enthusiastic	9		Active
10		Proud	10		Afraid

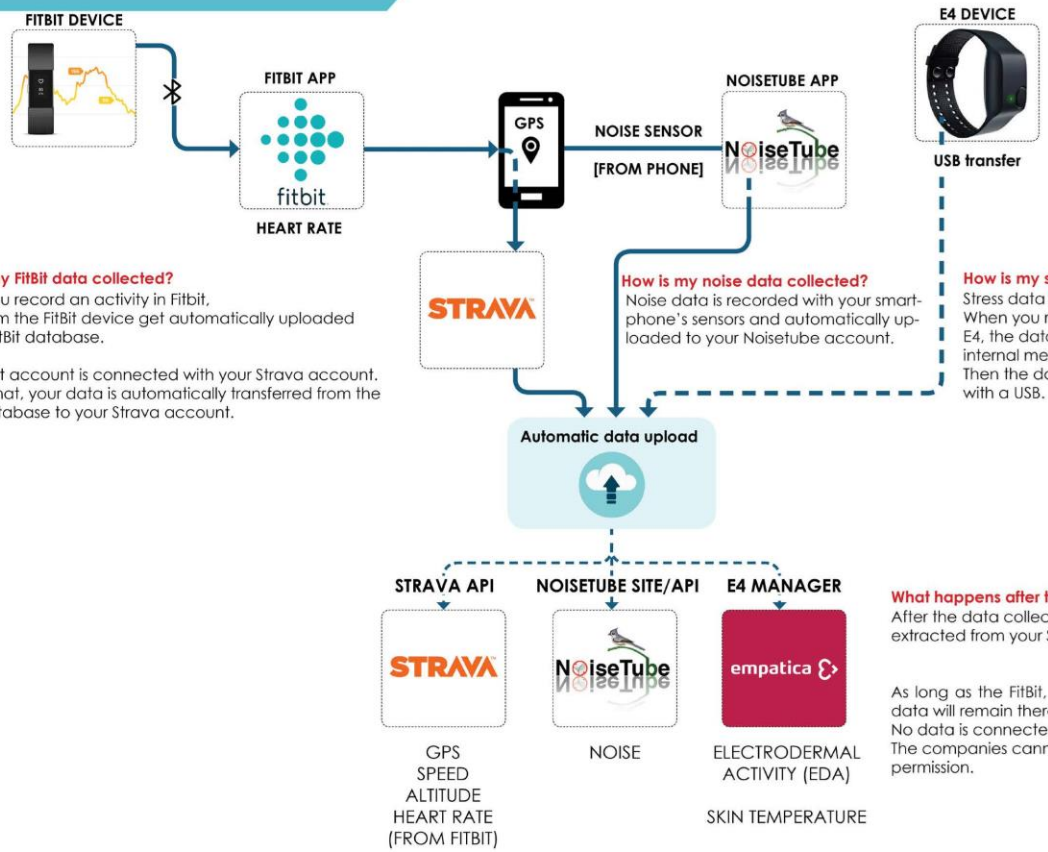
5. Were there any specific moments during the test where there was a notable difference in your experience (i.e. a moment where you felt especially excited, or nervous)? If yes, please describe shortly.

……………………………………………………

D.5. GUIDE GIVEN TO THE PARTICIPANTS EXPLAINING THE USE OF THE EQUIPMENT



What happens with my data?



How is my FitBit data collected?
When you record an activity in Fitbit, data from the FitBit device get automatically uploaded to the FitBit database.

Your FitBit account is connected with your Strava account. Due to that, your data is automatically transferred from the FitBit database to your Strava account.

How is my noise data collected?
Noise data is recorded with your smart-phone's sensors and automatically up-loaded to your Noisetube account.

How is my stress data collected?
Stress data is collected with the Empatica E4. When you record an activity in Empatica E4, the data is stored in the wristband's internal memory.
Then the data is transferred to the computer with a USB.

What happens after the data collection finishes?
After the data collection finishes, your data will be automatically extracted from your Strava and Noisetube account.

As long as the FitBit, Strava and NoiseTube account is active, the data will remain there.
No data is connected with your official name in these accounts.
The companies cannot use it for other reasons without your permission.

BEFORE THE EXPERIMENT

3

"Collection and analysis of physiological, movement and environmental data in the context of different daily activities"-UTS HREC REF NO. ETH19-3752

Your main duties during the 7 day experiment

1

RECORD YOUR ACTIVITIES WHEN YOU MOVE OUTSIDE THE HOUSE

-WEAR Activity + Stress Tracker
-Activate the apps + start an activity

FOR INSTRUCTIONS see page 5 and 6

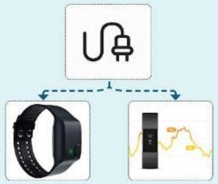
You only need to record your activities during the trip towards your destination

(i.e. when you go from the house to the university, or when you go for a walk)

- Avoid interaction with water
- If you record activities for more than 60 hours (8 hours per day), please contact us to extract the collected data so that you can continue the experiment (the memory of the watch is capable of storing only 60 hours of data)

2

CHARGE THE EQUIPMENT every 3 days



The 2 wristbands
FitBit + Empatica E4

Each wristband needs 1-2 hours for charging.

3

KEEP SHORT NOTES after each trip

FOR INSTRUCTIONS see page 7

How to start recording your activities
when you START your trip

1 WEAR FitBit + Empatica E4

2 Activate in your phone:
GPS + BLUETOOTH + DATA

3 Start the following APPS:
fitbit + NoiseTube
Start a new "activity" in FitBit
(see the next page)

4 Activate Empatica E4
empatica
how?
On the E4 watch,
Press the button for 2 secs so that it becomes green

How to stop recording your activities
when you FINISH your trip

1 TAKE OFF FitBit + Empatica E4
[You can keep wearing the FitBit, since we will not be able to get any data when the phone is not on "activity" mode]

2 Deactivate in your phone:
GPS + BLUETOOTH + DATA
[optional]

3 STOP the following APPS:
fitbit + NoiseTube
Press "Pause" and then "Finish"
Press "Stop" and then "Ok"

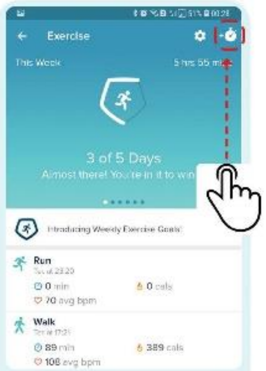
4 Deactivate Empatica E4
empatica
how?
On the E4 watch,
Press the button for 2-5 secs (until the green light below the watch stops blinking)

Starting an activity in FitBit

1

Press the "Exercise " icon

2



Press the clock icon

3

Select "Walk" and then press Play

4

If that appears, press Continue

5

Hold repeatedly the green button to finish

6

"Collection and analysis of physiological, movement and environmental data in the context of different daily activities"-UTS HREC REF NO. ETH19-3752

Guideline for keeping notes

-You can do this activity at the end of each trip, or at the end of the day.
-You can keep notes using a paper or electronic format (i.e. in a Word document)

What sort of notes are expected?

A. what was the purpose of the trip (commuting or leisure)
"example: trip purpose: commuting")

B. if you had any general feelings of stress or anxiety for other reasons (i.e. work related) during that trip.
(example: "felt anxious in general")

C. Notes regarding the **qualities** of places that you encounter during your trips, such as:

-stressful places
-places where you feel that your stress is reduced
-stimulating places
(example: "intersection at Jones and Jenkins street: noisy,crowded, slightly stressful")
You do not need to do this for every place that you visit- only for the memorable ones.

D. If you were holding the smartphone at hand or in your clothes/bag/pocket etc.
(example: "smartphone kept at hand")

E. If you were alone or with company during the trip, and if you talked at all during the trip (i.e. with friends, customer service, over the phone)
(example: "was talking with friends during the whole route")

GUIDELINES FOR LISTING QUALITIES OF PLACES
You can use one or more from the following list:

noise

temperature

number of pedestrians*(crowded/not crowded),*

pace of pedestrians *(fast/slow)*

humidity*(high/low)*

presence of obstacles
(i.e. traffic lights, surface conditions)

presence of natural characteristics
(i.e. green, water),

presence of interesting architecture

feeling of safety *(yes/no)*

overall comfort *(comfortable/uncomfortable)*

APPENDIX E

CONSTRUCTION OF THE ALGORITHMS FOR THE ANALYSIS OF ACTIVITY AND ARTEFACT RECOGNITION

The algorithms presented in this appendix are used in the data fusion model presented in Chapter 5 (sections 5.2.3. and 5.2.4).

E.1. ACCELEROMETER DATA ANALYSIS: ACTIVITY CLASSIFICATION

An essential part of the data fusion scheme presented in Chapter 5 for the analysis of physiological responses is the analysis of activity. Spontaneous, intense movements can generate false peaks in the EDA signal and should, therefore, be identified. The overall duration of the activity and the changes in activity intensity may also affect HR and EDA responses. Chapter 4 showed that both speed and accelerometer data could be used to analyse physical activity intensity. However, it was chosen to use only accelerometer data for this task, based on its higher resolution and accuracy compared to speed data from GPS sensors. This section will describe the tests which were conducted for activity classification.

Two approaches were followed for the construction of the activity classification algorithm, based on relevant literature from Chapter 4 (section 4.3.1.2). The first approach (presented in section E.1.2.) involved a threshold-based algorithm for classification. The second approach (presented in section E.1.3.) involved testing different supervised ML algorithms for the same task. In the end, the best performing ML algorithm was compared with the threshold-based algorithm. Section E.1.4. presents the results.

E.1.1. DESCRIPTION OF THE DATASET AND ASSIGNMENT OF THE GROUND TRUTH LABELS

The dataset that was used for activity classification contained the labelled activity data from the indoor experiment (Figure E1; the experiment is a part of the Phase A described in Chapter 2, section 2.4.2.). In this experiment, the participants (n=18) performed a series of timed activities in an indoor environment for 10 minutes. The activities are displayed in Appendix C (Figure C1). They were performed as a continuous, uninterrupted sequence. The accelerometer data from all participants were inspected, and no erroneous data were identified.

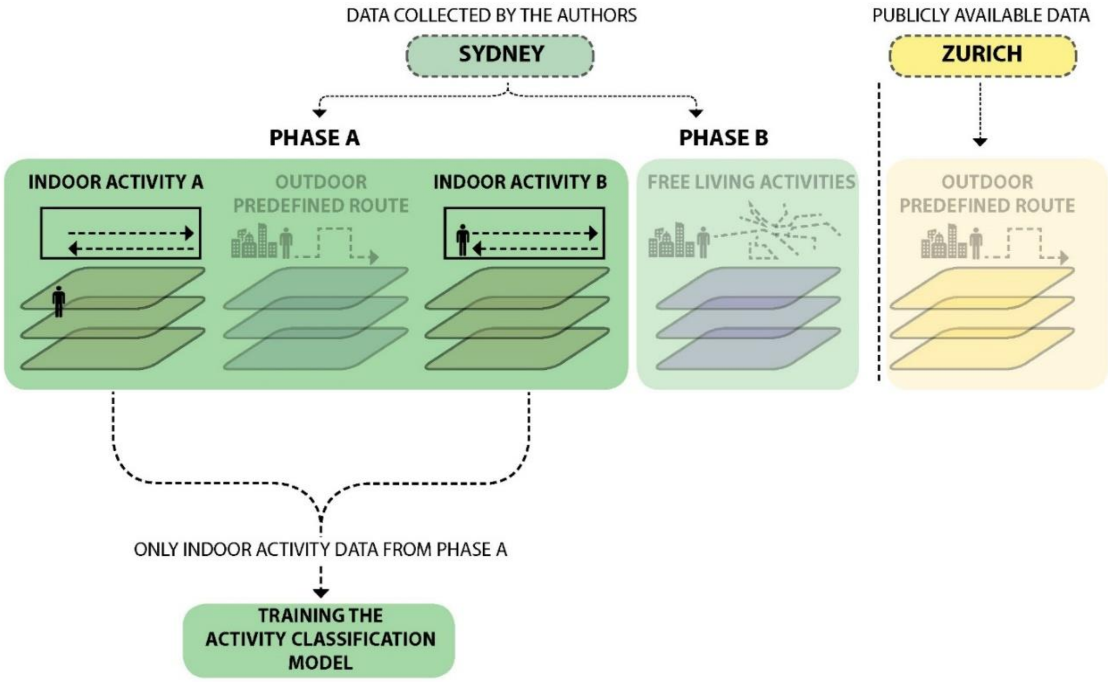


Figure E1. The data used for the construction of the activity classification model

The obtained data were labelled manually by partitioning the dataset according to the time log of the activities. Visual inspection of the graphs was performed to confirm the exact time of change from one activity to another.

The performed activities were grouped into three categories in terms of activity intensity. The lowest intensity level (1) contained the state of sitting and standing; the medium intensity level (2) contained the state of walking, and the high intensity level (3) contained states where there was more intense movement than walking with normal pace. Some examples of this included running, climbing stairs, or a short-lasting hand movement.

The task was framed as a multi-class classification problem for the detection of 3 classes. An example of the three classes, using data of one participant collected during the indoor activity, is provided in Figure E2.

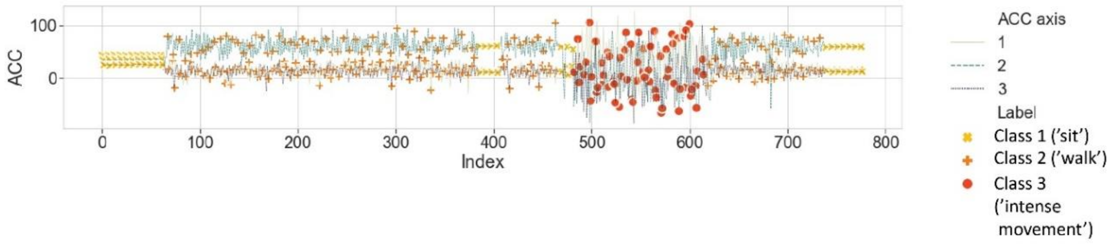


Figure E2. An example of labelled accelerometer data.

The dataset contained 92088 samples before the segmentation in windows. The classes were not balanced, as most of the data points (64%) belonged to the second class (walking). The other two classes contained approximately equal data (17% in each class).

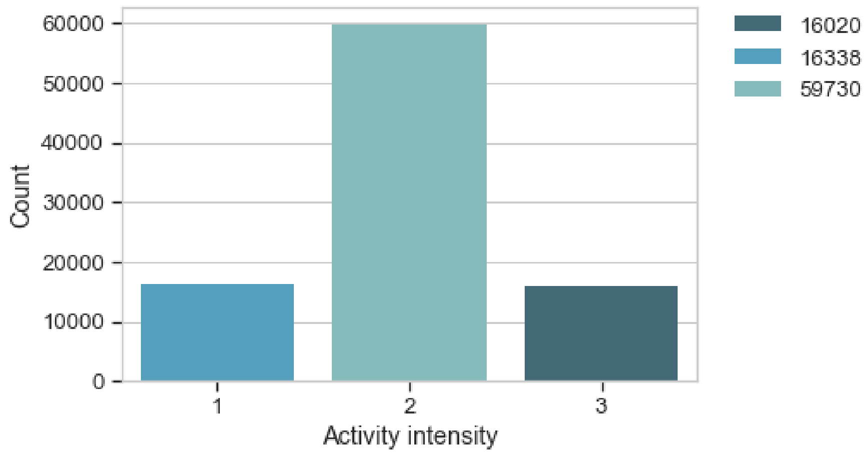


Figure E3. The number of data belonging to each level of activity intensity

E.1.2. A THRESHOLD-BASED METHOD FOR ACTIVITY CLASSIFICATION

The threshold-based approach involved segmentation of the data based on filters. The filters (thresholds) were empirically defined after iterative experimentation.

In the threshold-based approach, the processing of the accelerometer data involved the following steps. First, the standard deviation (STD) of accelerometer values was calculated after resampling a copied instance of the data at 600ms. These values reflected the degree of change in activity intensity. Then, the first order derivative of the resampled STD dataset was calculated, followed by the extraction of its mean values using a window of 1000ms.

These features were used for classifying the accelerometer data points in the three levels (classes) of activity intensity ('still', 'walking' and 'intense movement'). Data points with high mean STD and high absolute derivative of STD are classified as 'intense movement', as these characteristics reflect intense changes in the movement pattern. Data points which have medium mean STD and low absolute derivative of STD are classified as 'walking', as they reflect a movement pattern which may contain small changes in intensity but is steady in overall. Finally, data points with low mean STD and low absolute first grade difference of STD are classified in the 'still' category, as they reflect a movement pattern with very low intensity and no changes.

The classification process is based on averaging the changes in movement over 600ms and 1000ms, and the labels are only applied if at least 2 consecutive data points have the same label. This procedure is applied for each of the 3 axes; therefore, a vector of 3 possible labels is generated for each timestamp. Then, the dominant label is extracted for each timestamp. This process is overridden if there is at least one 'intense movement' label; then, this label becomes dominant. If this process ends and some data points still do not have a label (as they may not fall in any of the filters used for data partitioning), then the statistical features of these data points are compared to the features of neighbouring data, and the label of the most similar neighbouring points is adopted. An example of the outcome of this process can be seen in Figure E4.

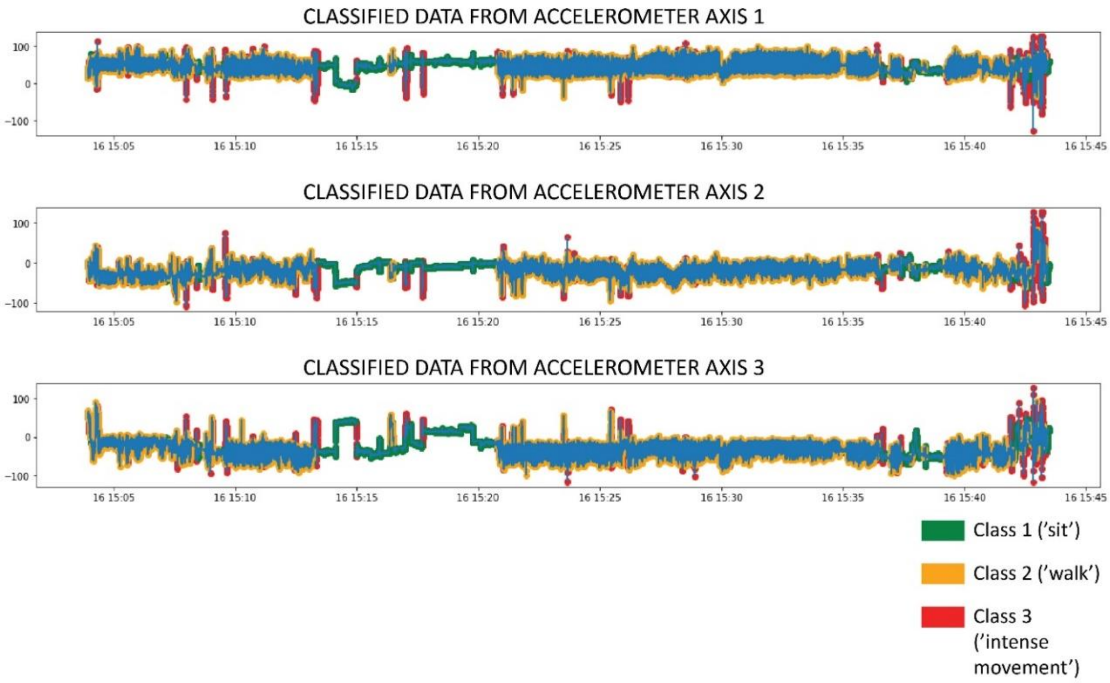


Figure E4. Application of the threshold-based algorithm for activity recognition.

E.1.3. SUPERVISED ML METHODS FOR ACTIVITY CLASSIFICATION

E.1.3.1. CLASSIFICATION APPROACH AND ML ALGORITHMS

The experimentation with supervised ML algorithms involved testing different algorithms for the identification of the best performing one. The data was randomised and partitioned using a 60/20/20% split to create training, validation and testing sets. The ML algorithms which were tested were the following: decision tree (DT), random forests (RF), k-nearest neighbors (k-NN), support vector machine (SVM), and deep neural networks (DNN).

E.1.3.2. FEATURE EXTRACTION

For this task, the data was resampled at 4 Hz (4 values per second). The data from each axis was normalised and split using a non-overlapping window. Different window sizes were tested. The sizes ranged from 4 to 40 values (equal to 1 to 10 seconds). The following features were extracted in each window from each axis: the normalised accelerometer values, as well as their STD and the first order derivative values in this window. 9 features were included in total.

E.1.3.3. CLASSIFICATION APPROACH AND ML ALGORITHMS

Figure E5 shows the results of the experimentation with the different models using various window sizes.

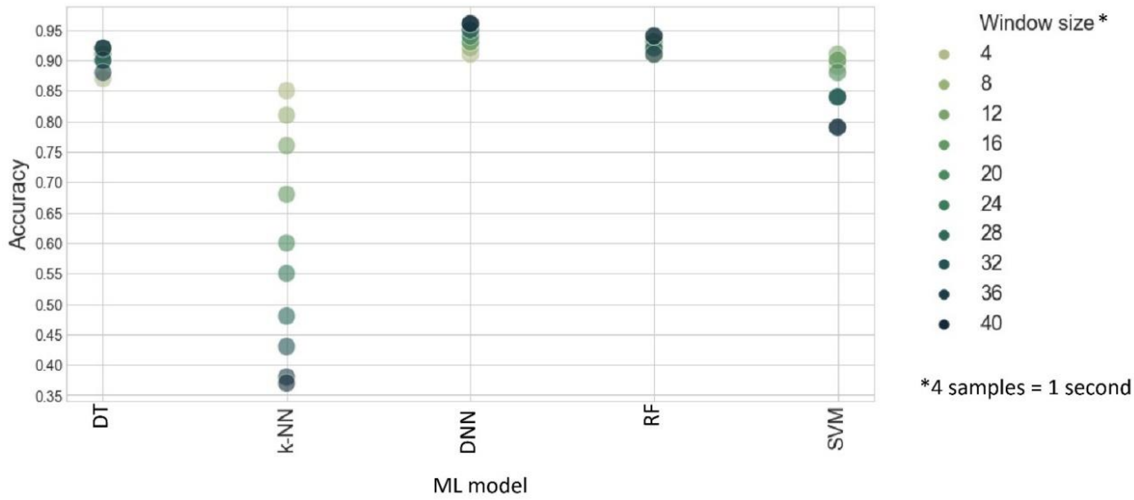


Figure E5. Accuracy scores for each model for the activity classification task

As Figure E5 shows, most of the models have good performance (above 85% accuracy) for all the tested window sizes, apart from the k-NN model, which has very low scores in larger window sizes. Figure E6 also shows that there is high inconsistency in the recall, precision and f1 metrics for the SVM and the k-NN models. These results suggest that the SVM and the k-NN models were not so successful in identifying all the relevant members of each label correctly.

The best results from the first round of experiments were obtained using the DNN model, with a window size of 40 values (10 seconds). The accuracy score for this configuration was 96%.

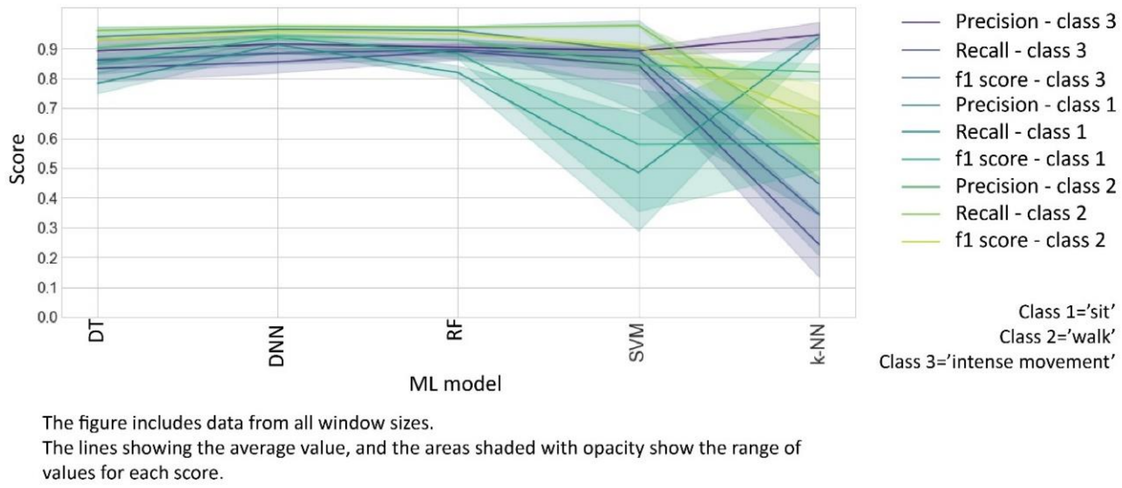


Figure E6. Performance metrics for each activity classification model

After identifying the DNN model as the best candidate of the first round, more experimentations were conducted with this model, with different configurations in terms of the number of hidden layers. The number of nodes in each layer was set to 128. The ADAM (adaptive moment estimation) algorithm was used for optimisation, and the categorical cross-entropy function was used as the loss function. The mini-batch training method was used, with a batch size of 250.

Hidden layers	*Class*	*Precision*	*Recall*	*F1*
3	**3**	0.97	0.93	0.95
	1	0.96	0.96	0.96
	2	0.97	0.98	0.98
	Accuracy	0.97		
*5**	**3**	1.00	0.85	0.92
	1	0.98	0.92	0.95
	2	0.94	1.00	0.97
	Accuracy	0.96		
6	**3**	0.96	0.94	0.95
	1	0.97	0.96	0.97
	2	0.98	0.98	0.98
	Accuracy	0.97		
7	**3**	0.97	0.97	0.94
	1	0.95	0.96	0.96
	2	0.96	0.98	0.99
	Accuracy	0.97		
8	**3**	0.88	0.99	0.93
	1	0.98	0.93	0.96
	2	0.99	0.97	0.98
	Accuracy	0.97		
9	**3**	0.95	0.96	0.95
	1	0.96	0.94	0.95
	2	0.98	0.98	0.98
	Accuracy	0.97		

Window size : 40 samples (10 seconds)
*The model with 4 hidden layers was omitted from the table, as it had the same results as the model with 3 layers

Figure E7. Comparison of DNN models with different layers for the activity classification task

The experimentation with different structures of the DNN model brought a slight improvement in the performance (Figure E7). The recall metric scores are consistently high, showing that the models have very good performance in terms of identifying the actual label for all classes, without many false negatives. The best score was obtained from the DNN model with the 6 layers (97.3% accuracy). This model also had the best results in the F1 score. An example of activity classification using the selected DNN model with a 10-second window is presented in Figure E8.

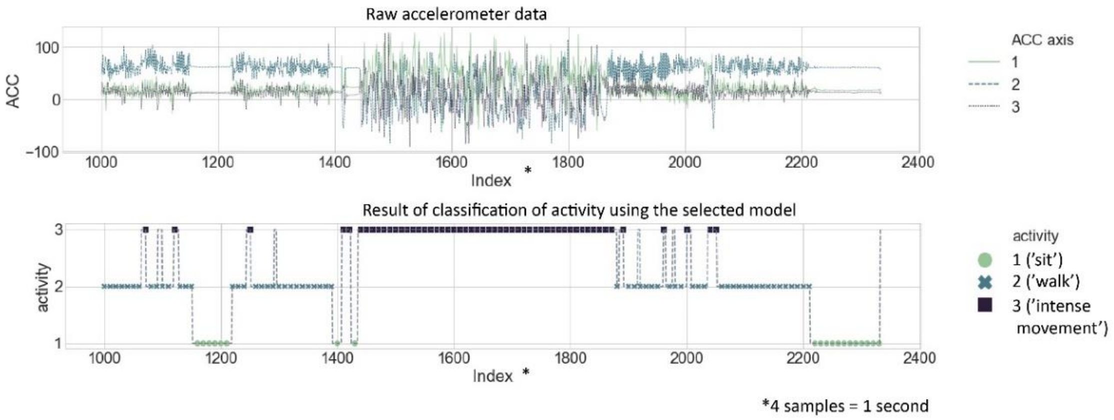


Figure E8. An example of activity classification using the selected DNN model.

E.1.4. COMPARISON OF THE THRESHOLD-BASED APPROACH WITH THE ML MODEL FOR ACTIVITY CLASSIFICATION

Hidden layers	*Window size (seconds)*	*Class (0:'intense move', 1:'sit', 2:'walk')*	*Precision*	*Recall*	*F1*
ML model (DNN, 6 hidden layers)	*10*	**0**	0.96	0.94	0.95
		1	0.97	0.96	0.97
		2	0.98	0.98	0.98
		Accuracy		0.97	
Threshold-based approach	*10*	**0**	0.63	0.97	0.96
		1	0.97	0.95	0.96
		2	0.98	0.85	0.91
		Accuracy		0.89	
ML model (DNN, 6 hidden layers)	*2*	**0**	0.87	0.78	0.82
		1	0.98	0.89	0.93
		2	0.92	0.97	0.95
		Accuracy		0.92	
Threshold-based approach	*2*	**0**	0.99	0.91	0.95
		1	0.96	0.78	0.86
		2	0.52	0.93	0.66
		Accuracy		0.83	

Figure E9. Comparison between the threshold-based approach and the ML model for activity classification, using the test data

The final step of this experimentation was the comparison between the selected ML model and the threshold-based approach. As shown in Figure E9, the threshold-based approach had a worse performance than the ML model. The best performance for the threshold-based approach (89% accuracy, compared to 97% accuracy for the ML model) was achieved using a 10-second window.

The DNN model with the 6 hidden layers was thus chosen as the model that will be further used in this research (starting from Chapter 5) for activity recognition. The supervised ML model is more powerful in terms of accuracy, especially concerning its ability to identify intense movements. This ability is essential for identifying physiological responses which might be related to spontaneous movements. The threshold-based approach is still a good alternative option with acceptable accuracy and could be used by other researchers who do not have data for training the ML model.

E.2. ARTEFACT RECOGNITION

After identifying the best performing activity classification model, the second task of this phase was to test different algorithms for artefact recognition. This task is necessary for processing EDA data and removing erroneous data portions.

E.2.1. DATASET

The dataset that was used as input for the artefact recognition model (Figure E10) contained all data from Phase A of the experiment in Sydney (see section 2.4.2. in Chapter 2). The design of the indoor experiments involved some activities that included intense hand movements to create artefacts (Figure C1, Appendix C). The data from all participants (n=18) of this phase was used to construct the model for artefact recognition.

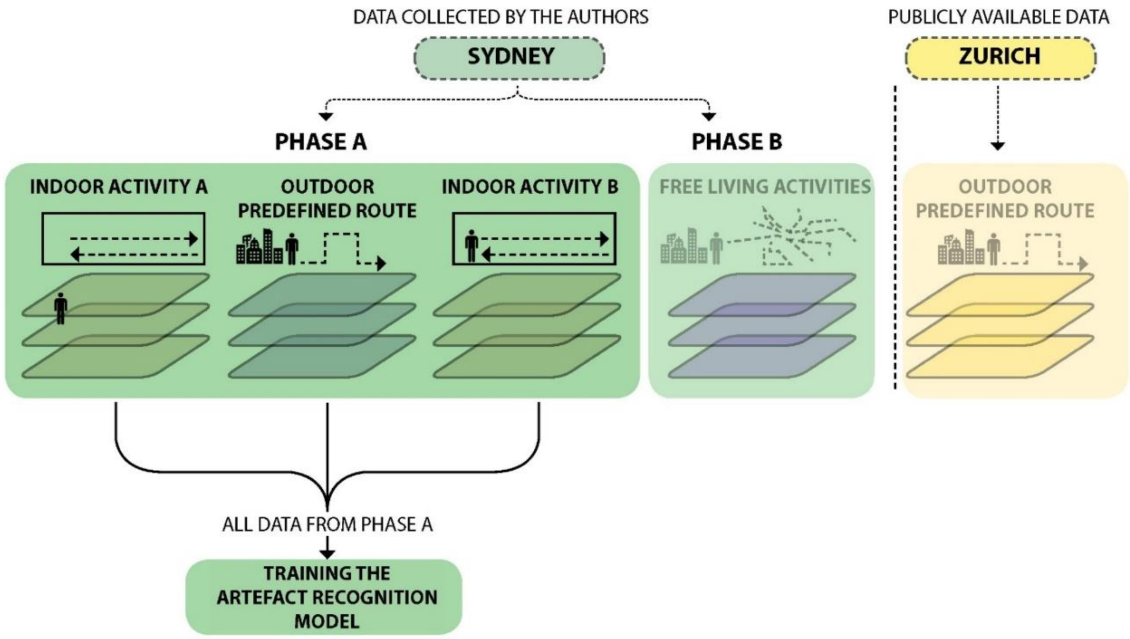


Figure E10. The data used in the EDA artefact recognition model.

The dataset was then inspected visually and labelled. The labels were assigned after splitting the data into segments using non-overlapping 5-second windows. An algorithm was built in Python for interactive labelling of the data segments. The process involved visualising each window separately and within its neighbouring data points, and then assigning a label (Figure E12). A similar approach was followed in the website that was built for artefact classification in Taylor et al. (2015). The ML task was framed as a binary classification problem, where class 0 indicated the absence of an artefact and class 1 indicated its presence.

The dataset contained 256,703 samples before the segmentation in windows and was unbalanced (Figure E11). After segmenting the data in windows, approximately 10% were marked as artefacts belonging to class 1. The baseline accuracy was, therefore, relatively high (90%).

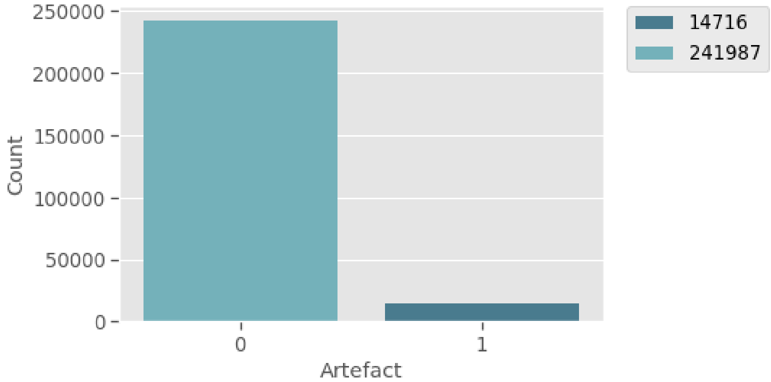


Figure E11. The distribution of the data used for training the artefact recognition algorithm

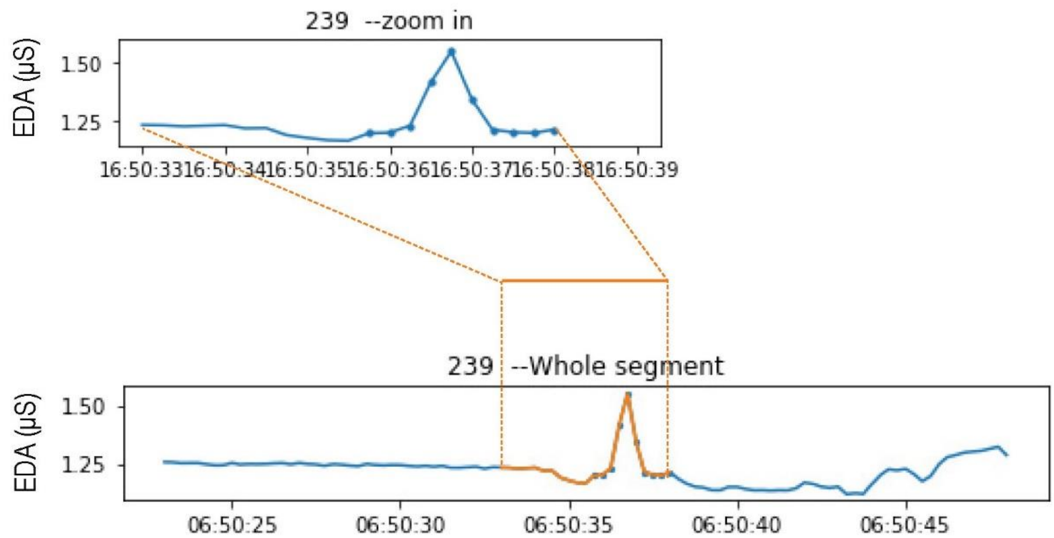


Figure E12. The method used for visualising the data in segments and labelling them as artefacts or clean data

E.2.2. FEATURE EXTRACTION

The data was resampled at 4 Hz (4 values per second) for the artefact recognition task, following the original frequency of the EDA sensor of the Empatica E4 wristband. The data was then split to non-overlapping windows for feature extraction. The different window sizes that were tested here ranged from 4 to 20 samples (corresponding to 1-5 seconds). The experimentation showed that there was no improvement when using windows with a size larger than 5 seconds.

Seven features were extracted from the EDA signal in each window: mean, first order derivative, second order derivative, mean of the first order derivative, mean of the second order derivative, STD, and STD of the first order derivative.

E.2.3. CLASSIFICATION APPROACH AND ML ALGORITHMS

The experimentation with different ML algorithms for artefact recognition involved the same strategy followed in the activity classification task. The same ML algorithms were tested here as well. Figure E13 shows the results.

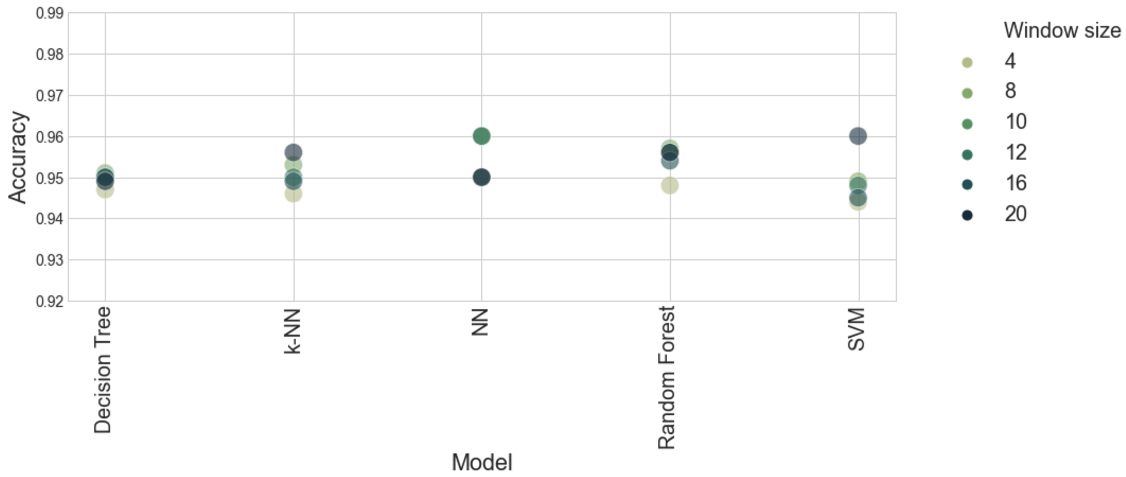


Figure E13. Accuracy scores for each model for the artefact recognition task.

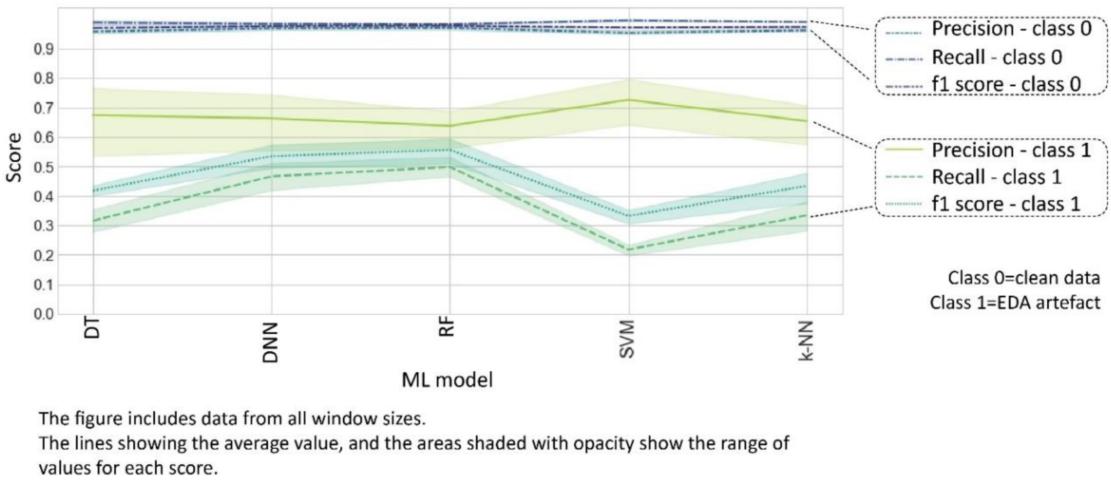


Figure E14. Performance metrics for each artefact recognition model

As shown in Figure E13, all the algorithms achieved very high accuracy, ranging between 94% and 96%. The highest accuracy (96%) was achieved by the DNN model (using a window size between 2-3 seconds) and the SVM model (5-second window). However, Figure E14 shows that while the performance metrics are very high for the dominant class, they are much lower for the class representing the artefacts (Class 1). A possible reason for this difference in the performance is the imbalance between the classes. The SVM model had particularly low metrics for Class 1; the recall metric and the F1 score were the lowest among all models. The DNN and the RF model had the best metrics regarding the overall performance.

The only similar work that involves ML methods for artefact recognition is the study of Taylor et al. (2015). In their study, the best performing model was the SVM classifier, which had similar accuracy (95.6%) in the binary classification task. However, in this study, the SVM model had the poorest performance in the detailed analysis of the metrics (Figure E14).

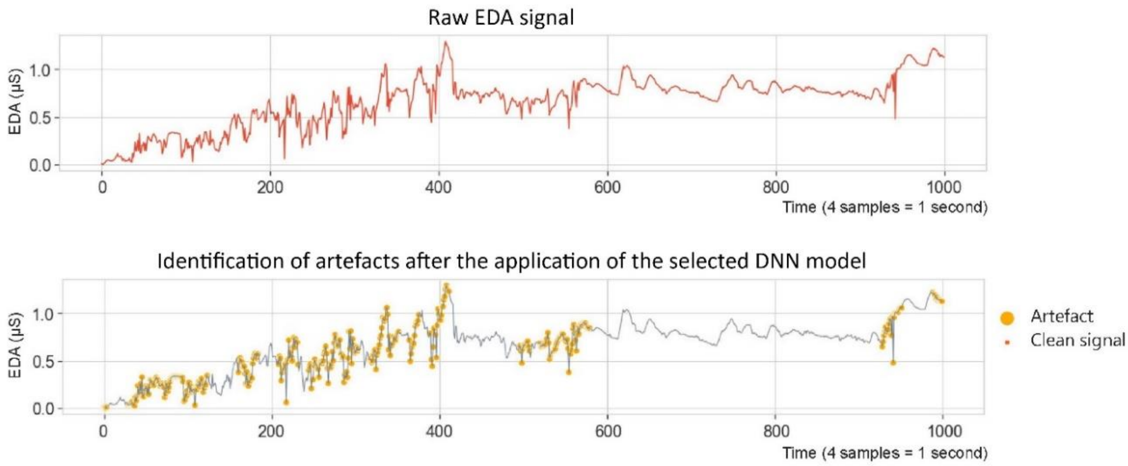


Figure E15. Example of the application of the constructed DNN model for artefact recognition

Based on the findings of the experiments presented above, the DNN model was selected as the best candidate for artefact recognition, using a 3-second window. An example of the application of the model on the EDA data of one user from the test sample is presented in Figure E15. The performance of the model was also checked by applying it to the free-living activities dataset. The visual inspection of the results showed that the model identified correctly most of the artefacts, especially in cases where there were many erroneous data points grouped together, as in Figure E15. Some occasional misclassifications were still observed. The model, thus, does not guarantee the complete elimination of artefacts. However, it is an overall well-performing solution, considering that the only alternative would be the manual inspection of the data, which is extremely time consuming in very large datasets.

APPENDIX F

PHYSIOLOGICAL MEASURES AND EMOTIONS

This section contains a brief review of the relationship between physiological measures and emotions. The content is primarily related to Chapter 3.

The relationship between physiological changes and emotions is a complex one. Emotions are often generated from the perception of the physiological functions; for instance, the perceived effort during an activity can generate negative feelings, or the autonomic arousal caused by a threatening situation can elicit an anxious or fearful behaviour. At the same time, emotions can be generated from other subjective or objective factors and may influence the physiological state in return (Boucsein & Backs 2009).

According to emotion theory, the majority of mood states and emotions can be positioned within ranges spread across two dimensions. The first dimension depicts the intensity of the emotion, or degree of activation and is connected to arousal. The second is referred to as affect or valence and depicts the degree of pleasantness (Boucsein 2012). Studies on the physiological effects of mood and emotions often use these dimensions to describe the emotional state (Jacob et al. 1999). There have also been suggestions (Shapiro et al. 2001) that emotional states should not be evaluated as discrete reactions, but as multifaceted experiences which may be composed of contrasting feelings (such as anxious and happy).

In terms of the relation between emotions and bodily responses, research has shown that emotional states affect the autonomic nervous system, especially in the case of emotions grouped under the negative dimension of the affect. This activation is manifested with various measures: blood pressure, blood volume, EDA and HR (Cacioppo et al. 1993).

In terms of HR, the usually examined variables are the rise of HR and the duration of this increase. The findings have been somewhat inconsistent; for example, while Jacob et al. (1999) found that negative and positive emotions sometimes elicit similar reactions in terms of the magnitude of HR response, Shapiro et al. (2001) found that only the negative moods were associated with an increase in HR. Anttonen and Surakka (2005) observed a small decrease in HR as a response to both negative and positive stimuli. In all cases, if the subject's mood affected HR, that was a slight change of 3 to 5 bpm. These differences may be due to methodological issues, such as differences in stimuli used to induce the emotion (Stemmler 2010). The meta-analysis of Kreibig (2010) showed that the HR increase was not distinctively associated with positive or negative emotions, but more related to the degree of activity. In terms of duration of response, Brosschot and Thayer (2003), as well as Anttonen and Surakka (2005) found that it was more prolonged in the case of negative emotion in daily situations. It should also be noted that while these studies investigated emotions as spontaneous changes in mood, triggered after stimuli such as the display of pleasant or unpleasant pictures, these changes (or emotions and moods elicited from other subjective circumstances) can have a long-lasting effect (i.e., Shapiro et al. 2001).

As for EDA as a measure of emotional state, some studies showed a connection between anger and a higher frequency in NS.SCRs, while fear elicited more NS.SCRs and a smaller increase of tonic EDA in comparison to sadness. Happiness produced a milder rise in tonic EDA compared to disgust, which did not elicit any specific changes in autonomic activity. In the meta-analysis of Cacioppo et al. (1993), when the discrete emotions were grouped to positive and negative ones, there was no significant difference in EDA between the two states (Cacioppo et al. 1993). In the more recent meta-analysis of Kreibig (2010), most emotions were accompanied by an increase in EDA, apart from sadness, contentment and relief. Kreibig suggests that this could be attributed to the degree of preparation for motor activity, which is more related to the other emotions, while the ones with decreased EDA might reflect a state of passivity or lack of tendency for action.

In his review of studies on the connection between emotions and their psychophysiological measures, Boucsein (2009) states that it is difficult to distinguish discrete emotions from their bodily effects, without accompanying them with subjective reports from the studied individuals, as different emotions might elicit similar changes in autonomic arousal. The EDA appears to be a better measure of the intensity of emotion, and HR more appropriate for measuring valence. Boucsein though points out that some of the responses might influence the autonomic nervous system not because of the elicited emotion, but due to the stimulus properties (for instance, using moving instead of still images as the stimulus).

As HR and EDA are also related to other variables, such as movement, it is difficult to identify how these variables interact (Shapiro et al. 2001). Position, activity, location, social activity, consumption (caffeine, alcohol, smoke) can also influence cardiovascular activity and override the effect of mood. In emotion studies, variables related to movement, posture, information processing and environmental parameters such as temperature, are called context effects. The psychophysiological effect of one emotion can be altered when the context effects change, as this creates situations with very different combinations of physical and mental processes Stemmler (2010). Some of the studies mentioned earlier in this section were conducted only with sitting subjects (e.g., Brosschot & Thayer 2003) which suggests that the effects they identified might not be equally visible when the subject is engaged in any activity more intense than sitting. Jacob et al. (1999) confirmed this by analysing the contribution of different variables to changes in cardiovascular activity and showing that the most significant changes are associated with the activity of the subject.

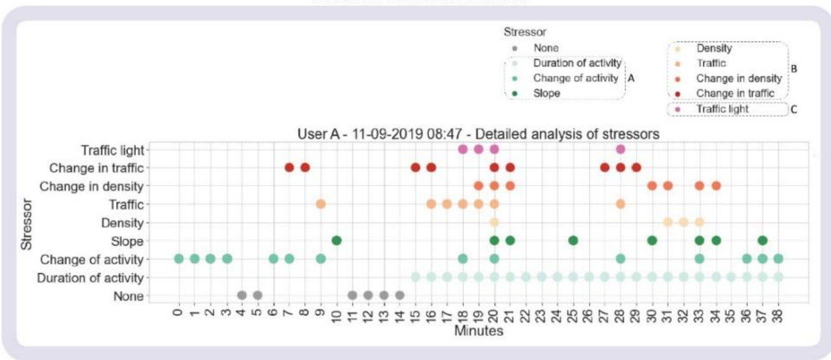
APPENDIX G

ANALYSIS OF CHANGES IN HR FOR THE ROUTES OF SELECTED USERS

This appendix contains material related to Chapter 5 (section 5.3). For each of the routes studied in section 5.3, the results of the HR data analysis are presented here, complementing the results of the analysis of the EDA data.

USER A - ROUTE 2

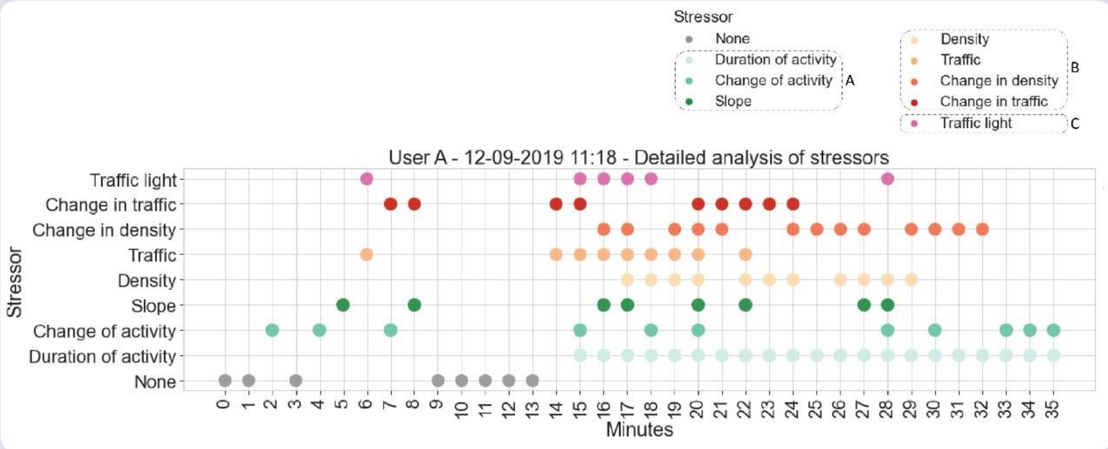
DETAILED CONTEXT ANALYSIS



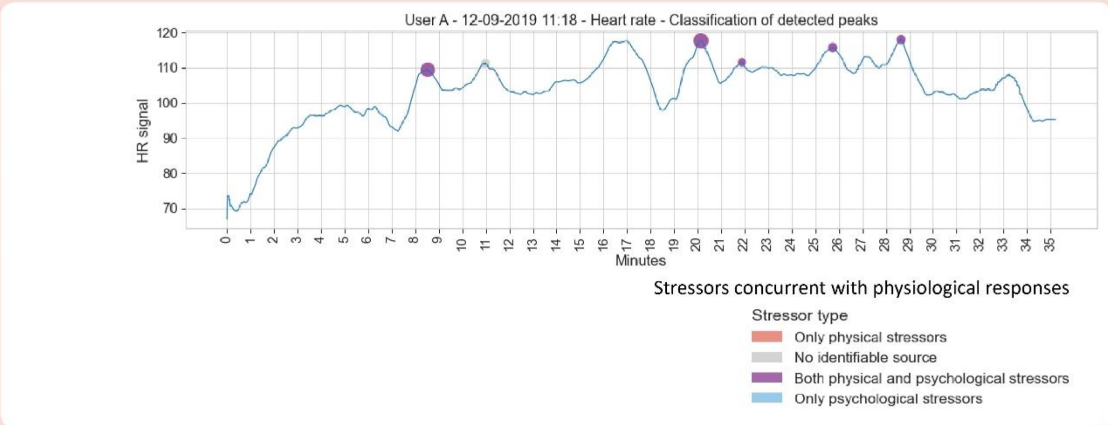
HR ANALYSIS

USER A - ROUTE 5

DETAILED CONTEXT ANALYSIS

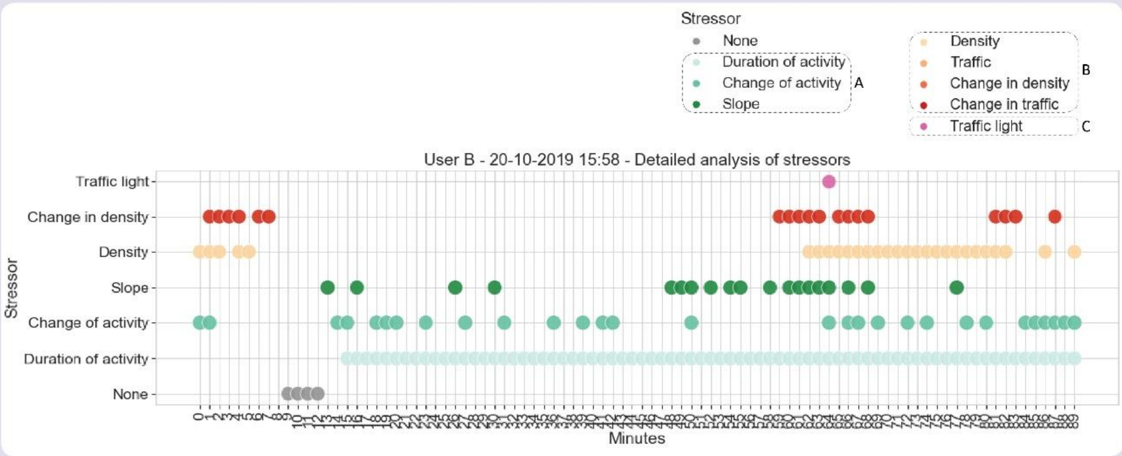


HR ANALYSIS

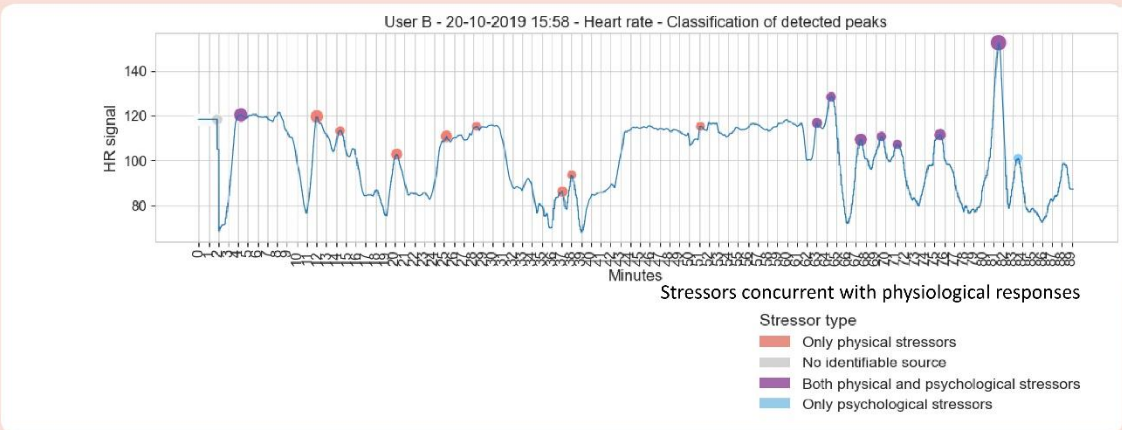


USER B - ROUTE 9

DETAILED CONTEXT ANALYSIS



HR ANALYSIS



APPENDIX H
OTHER MATERIAL

This appendix contains figures related to the statistical analysis presented in Chapter 6.

The frequencies for each level of the categorical/ordinal variables
(at a 1-second frequency, before their resampling)

FEATURES		SYDNEY									
		DATASET 1: PREDEFINED ROUTE					DATASET 2: FREE LIVING ACTIVITIES				
		0	*1*	*2*	*3*	*4*	*0*	*1*	*2*	*3*	*4*
Change in activity	0 = no change 1 = change	24548	11766	-	-	-	239982	179757	-	-	-
Steady state activity	0 = no steady state 1 = steady state	16284	20030	-	-	-	237247	182492	-	-	-
Traffic	0-4: From lowest to highest traffic intensity	14131	9711	398	6885	5189	144725	134452	23891	66248	50423
Traffic light	0 = no traffic light 1 = presence of traffic light	32493	3821	-	-	-	361401	58338	-	-	-
Change in activity state	0 = no change 1 = change	31326	4988	-	-	-	373809	45930	-	-	-
activity intensity	1 = stand/stop 2 = walk 3 = more intense movement	-	9091	25792	1431	-	-	128869	230087	60783	-

Figure H1. Frequency table for the categorical variables in the data collected in Zürich and the combined dataset

FEATURES		DATASET 3: ZURICH					DATASET 4: ALL COMBINED				
		0	*1*	*2*	*3*	*4*	*0*	*1*	*2*	*3*	*4*
Change in activity	0 = no change 1 = change	19550	15108	-	-	-	284080	206631	-	-	-
Steady state activity	0 = no steady state 1 = steady state	27668	6990	-	-	-	281199	209512	-	-	-
Traffic	0-4: From lowest to highest traffic intensity	20303	12175	2180	0	0	179159	156338	26469	73133	55612
Traffic light	0 = no traffic light 1 = presence of traffic light	33658	1000	-	-	-	427552	63159	-	-	-
Change in activity state	0 = no change 1 = change	31839	2819	-	-	-	436974	53737	-	-	-
activity intensity	1 = stand/stop 2 = walk 3 = more intense movement	-	12353	22195	110	-	-	150313	278074	62324	-

Figure H2. Frequency table for the categorical variables in the data collected in Sydney

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