Computational models of human response to urban heat

From physiology to behaviour

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Valentin Melnikov
Computational models of human response to urban heat: from physiology to behaviour

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ACADEMISCH PROEFSCHRIFT

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ten overstaan van een door het College voor Promoties ingestelde commissie, in het openbaar te verdedigen in de Agnietenkapel op woensdag 12 mei 2021, te 13.00 uur

door

Valentin MELNIKOV
geboren te Sint-Petersburg
# Promotiecommissie

<table>
<thead>
<tr>
<th>Promotor</th>
<th>prof. dr. P.M.A. Sloot</th>
<th>Universiteit van Amsterdam</th>
</tr>
</thead>
<tbody>
<tr>
<td>Copromotores</td>
<td>dr. V. Krzhizhanovskaya</td>
<td>Universiteit van Amsterdam</td>
</tr>
<tr>
<td></td>
<td>dr. M.H. Lees</td>
<td>Universiteit van Amsterdam</td>
</tr>
<tr>
<td>Overige leden</td>
<td>prof. dr. ir. A.G. Hoekstra</td>
<td>Universiteit van Amsterdam</td>
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<tr>
<td></td>
<td>prof. dr. D. Borsboom</td>
<td>Universiteit van Amsterdam</td>
</tr>
<tr>
<td></td>
<td>prof. dr. ir. L. Bertolini</td>
<td>Universiteit van Amsterdam</td>
</tr>
<tr>
<td></td>
<td>prof. dr. G. Schmitt</td>
<td>ETH Zürich</td>
</tr>
<tr>
<td></td>
<td>prof. dr. A.V. Boukhanovsky</td>
<td>ITMO University</td>
</tr>
</tbody>
</table>

Faculteit der Natuurwetenschappen, Wiskunde en Informatica
Abstract

Understanding human response to the dynamic urban thermal environments is crucial for effective adaptation to a changing climate and the preservation of health and well-being of an ever urbanizing humanity. While there exists extensive research examining urban climates within the city, knowledge of human response to the dynamic microclimate in outdoor spaces is still limited. This thesis takes a multi-level computational modelling approach to develop understanding of the complex phenomenon of outdoor thermal comfort (OTC). Human response to the thermal environment is considered on three interacting levels: physiological, perceptual and behavioural. On the physiological level, an advanced system dynamics model of thermal regulation is built and calibrated for a wide range of dynamic thermal environments. We propose translation of the instantaneous thermophysiological state of a person into thermal perception driving human thermoregulatory behaviour. We report an empirical study of pedestrian walking speeds in Singapore and demonstrate computationally that Singaporeans incur additional heat stress due to elevated pace of life. Our research suggests that behavioural adaptation of walking speed could improve their thermal comfort. To analyse and quantify the behaviour of pedestrian sun avoidance, a controlled experiment with human participants in a natural outdoor environment is considered. We propose a novel hierarchical model of path choices to estimate an individual’s perceived effort of walking under the sun. This model provides the means to study and predict pedestrian behaviour in complex urban environments. This thesis presents a comprehensive set of empirical studies, as well as mathematical and computational models of human response to outdoor thermal environments on the individual level. In addition, we apply these models in the study of heat stress effects on the human innate immune system response. That is, we identify regimes of heat exposure and activity intensity, which can positively or negatively impact the performance of the immune system. A proposed approach of computational modelling of OTC
enables its assessment, prediction and improvement in existing and future urban spaces, ultimately making human activities in these spaces a more pleasant and healthy experience. The approach of multi-level modelling of complex human-environment interaction, demonstrated in this thesis using an example of OTC, can be adopted to comprehensively study human response to other environmental stimuli.
Computationele modellen van menselijke reactie op stedelijke hitte: van fysiologie tot gedrag

Samenvatting

Het begrijpen van de reactie van de mens op de dynamische stedelijke thermische omgevingen is cruciaal voor een effectieve aanpassing aan een veranderend klimaat en het behoud van de gezondheid en het welzijn van een steeds verstedelijkende mensheid. Hoewel er uitgebreid onderzoek is gedaan naar het stedelijke klimaat in de stad, is de kennis van de menselijke reactie op het dynamische microklimaat in buitenruimtes nog steeds beperkt. In deze thesis maken we gebruik van een multi-level computationele modellering om inzicht te krijgen in het complexe fenomeen van thermisch comfort buitenshuis (OTC). De menselijke reactie op de thermische omgeving wordt beschouwd op drie op elkaar inwerkende niveaus: fysiologisch, perceptief en gedragsmatig. Op fysiologisch niveau is een geavanceerd systeemynamisch model van thermische regulering gebouwd en gekalibreerd voor een breed scala aan dynamische thermische omgevingen. We stellen voor om de instantane thermofysiologische toestand van een persoon te vertalen naar thermische perceptie die het thermoregulerende gedrag van de mens aanstuurt. Een empirische studie van de loopsnelheden van voetgangers in Singapore is uitgevoerd. Hierbij is computationeel aangetoond dat Singaporezen extra hittestress oplopen als gevolg van een hoger levensritme. Ons onderzoek suggereert dat gedragsaanpassing van loopsnelheid menselijk thermisch comfort zou kunnen verbeteren. Om het gedrag van voetgangerszonvermijding te analyseren en kwantificeren, wordt een gecontroleerd experiment met menselijke deelnemers in een natuurlijke buitenomgeving overwogen. We stellen een nieuw hiërarchisch model van padkeuzes voor om de waargenomen inspanning van een lopende individu onder de zon in te schatten. Dit model biedt de mogelijkheid om voetgangersgedrag in complexe stedelijke omgevingen te bestuderen en te voorspellen. Deze thesis presenteert een uitgebreide reeks aan empirische studies, evenals wiskundige en computationele modellen van de menselijke reactie op thermische buitenomgevingen op individueel niveau. Bovendien passen we deze modellen toe in de studie van
hittestress-effecten op de menselijke aangeboren immuunsysteemrespons. Dat wil zeggen, we identificeren regimes van blootstelling aan hitte en activiteitsintensiteit, die de prestaties van het immuunsysteem positief of negatief kunnen beïnvloeden. Onze voorgestelde benadering van computationele modellering van OTC maakt het mogelijk om bestaande en toekomstige stedelijke ruimtes te beoordelen, voorspellen en verbeteren. Hierdoor zullen menselijke activiteiten in de stedelijke ruimtes uiteindelijk een aangename en gezondere ervaring beleven. De benadering van multi-level modellering van complexe mens-omgeving interactie, aangetoond in deze thesis aan de hand van een voorbeeld van OTC, kan gebruikt worden om de menselijke reactie op andere omgevingsstimuli uitgebreid te bestuderen.
# Contents

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract</td>
<td>iii</td>
</tr>
<tr>
<td>Samenvatting</td>
<td>v</td>
</tr>
<tr>
<td>1 Introduction</td>
<td>3</td>
</tr>
<tr>
<td>1.1 Motivation</td>
<td>3</td>
</tr>
<tr>
<td>1.2 The context of this thesis</td>
<td>5</td>
</tr>
<tr>
<td>1.2.1 Current state of the research</td>
<td>5</td>
</tr>
<tr>
<td>Urban climate</td>
<td>6</td>
</tr>
<tr>
<td>Outdoor thermal comfort</td>
<td>8</td>
</tr>
<tr>
<td>1.2.2 People in thermal environments</td>
<td>9</td>
</tr>
<tr>
<td>Physiological response: thermal regulation</td>
<td>10</td>
</tr>
<tr>
<td>Psychological response: thermal perception</td>
<td>11</td>
</tr>
<tr>
<td>Behavioural response: thermoregulatory behaviour</td>
<td>13</td>
</tr>
<tr>
<td>1.3 Outline of this thesis</td>
<td>14</td>
</tr>
<tr>
<td>2 System dynamics of human body thermal regulation in outdoor environments</td>
<td>17</td>
</tr>
<tr>
<td>2.1 Introduction</td>
<td>18</td>
</tr>
<tr>
<td>2.2 System dynamics representation of the model</td>
<td>20</td>
</tr>
<tr>
<td>2.3 Formulation of the model</td>
<td>22</td>
</tr>
<tr>
<td>2.3.1 Parameters of the model</td>
<td>22</td>
</tr>
<tr>
<td>2.3.2 Model variables</td>
<td>25</td>
</tr>
<tr>
<td>Thermal signals</td>
<td>25</td>
</tr>
<tr>
<td>Blood flow regulation</td>
<td>25</td>
</tr>
<tr>
<td>Masses of nodes</td>
<td>26</td>
</tr>
<tr>
<td>2.3.3 Flows</td>
<td>26</td>
</tr>
<tr>
<td>Flows to and from the core</td>
<td>26</td>
</tr>
</tbody>
</table>
“Pedestrians just need to be loved.”

Ilya Ilf and Yevgeny Petrov,
*The Little Golden Calf*, 1931
Chapter 1

Introduction

1.1 Motivation

The epigraph I start my thesis with is the first line of The Little Golden Calf – a satiric novel about life in Soviet Union published in 1931. Though joking, authors emphasise an important trend of that epoch: pedestrians being forced out of the streets of the cities by the booming use of automobiles. "Pedestrians comprise the larger part of humanity. More than that: its better part. Pedestrians created the world. It was they who built cities..." state the authors to underline the paradox of the process: those who have built cities, for comfort of whom cities are intended, are degraded to second-class citizens and "lead martyr’s lives in the big city"1.

90 years have passed since the book was published, the urban population of the world has rocketed more than tenfold (from an estimated 0.33 to 4.35 billion living in an urban environment) [1, 2, 3]. With the growth of cities, the number of cars is constantly growing [4]. To complicate things further, it is not only cars, but the whole spectrum of urban stressors, such as crowding [5], pollution [6], noise [7] and climate [8], which are omnipresent in modern cities. The problem of big cities pinpointed almost a century ago was not solved, rather, it was exacerbated.

In fact, the pedestrian behaviour, expressed in attendance of outdoor space, walking rates and walking speeds, was found to be directly associated with the level of crowding, noise [9], properties of urban form [10, 11] and climate [12, 13]. Correlation between average walking speeds in the city and its size

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1Here and before the translation of The Little Golden Calf from the Russian by Anne O. Fisher is used.
Chapter 1. Introduction

[14] has become one of the urban scaling laws [15] and elevated average walking speed was not only suggested to be an indicator of pace-of-life in the city [16], but also hypothesised as withdrawal behaviour from over-stimulating outdoor urban environments [14]. Stressful urban environments are not just a matter of reduced walking, but a matter of everyday comfort, health and well-being of billions of people [17]. The key to enhancement of experience and lives of urban dwellers is understanding the complex interaction of people with urban environments, of people’s response to urban stimuli on all levels and scales. This problem is drawing growing attention across the globe, leading to multi-million dollar research initiatives [18, 19, 20].

Outdoor thermal comfort (OTC) – a result of complex interaction of people and outdoor thermal environments has seen increased research attention in the last decades. With studies spanning Asia [21, 22] and Europe [23, 24, 25], North [26, 27] and South America, Africa [29, 30] and Australia [31], OTC can be called a global concern. This is due to the global processes of climate change [32], urban heat islands (UHI) [33] and rapid urbanisation [34], which result in more people being exposed to excessive urban heat, challenging many aspects of modern society: public health [35], human [36] and economic development [37, 38] and social relations [39].

The current OTC research focuses on understanding the interaction of climate and urban physical environment, to reduce, through design and planning, the amount of excessive heat people are exposed to [40, 41, 42, 43]. This allows for testing and implementation of urban heat mitigation strategies, such as orientation and materials of buildings [44], built [45, 46] and green infrastructure [47, 48, 49] and smart path planning [50, 51]. However, human response to thermal environments, while being an ultimate focus of OTC, is not yet understood in its entirety. Existing OTC studies are usually limited to measurement of subjective sensation and perception through surveys regressing them to properties of thermal environments.

It is the complexity of human response to thermal environments [52] that renders the task of comprehensive understanding of this response a non-trivial one. Humans and their thermal environment form a complex system, with intricate interaction on multiple levels and non-linear dynamics. This
thesis targets at understanding this complex response of humans to their thermal environments through experiments, mathematical modelling and computer simulation. We address the complexity of the problem by decomposing the overall response into different levels (namely physiological, perceptual and behavioural response to urban heat). Based on the existing body of knowledge and our own empirical studies, for each of these levels of human response we propose dedicated models. These computational models enable us to achieve the ultimate goal of this research: to develop an understanding of the complex connection between the urban climate and the human thermoregulatory system and how this in turn triggers adaptive response in humans. The resulting work provides novel computational tools and methods to study the interaction of the human thermoregulatory response and other processes within the human body. We demonstrate the application of these tools to infer the heat stress cost of elevated walking speeds and the regimes of heat exposure and physical activities, which can have a detrimental effect on the performance of the human innate immune system response.

The studies reported in this thesis pave the way towards thinking of outdoor thermal comfort in its most explicit, precise and insightful way: as a result of complex response of humans to dynamic thermal environments on multiple levels from physiology to behaviour.

1.2 The context of this thesis

1.2.1 Current state of the research

Urban climates are produced by a combination of the climate and the built environment as depicted in Figure 1.1. We emphasise the role of the built urban environment in shaping the urban climate. Ultimately, the way human settlements are designed, planned and operated determines both the urban climate and the resulting microclimate people experience on an every-day basis. The phenomenon of outdoor thermal comfort arises as a result of the interaction of people and their microclimate. This interaction can occur at multiple levels:
through a physiological response, a change in perception or a behavioural response. This thesis develops computational methods and tools to help understand how these responses occur and how they help regulate outdoor thermal comfort (see Figure 1.1). In the following subsections we describe the current state of the art research related to urban climate and outdoor thermal comfort modelling, motivate the need to focus on human response to thermal environments and briefly discuss the levels at which we consider this response.

**Figure 1.1:** Conceptual diagram of the OTC process, the levels of human response to thermal environments and interaction with outer environmental domains.

**Urban climate**

Climate is the first component of the complex phenomenon of outdoor thermal experience of people. Climate, and adaptation to it, have shaped, without
1.2. The context of this thesis

Exaggeration, the way humanity has developed. The way our ancestors populated the land [53], the food we eat [54] and clothes we wear [55, 56], the houses we live in [57] and activities we perform [12] – this all is at least partially affected by the climate we live in.

The relation between climate and humanity is not a one-way process, the way we live and perform our activities is now shaping the climate. The process of global climate change [32], characterised by rising temperatures in many parts of the world, has its anthropogenic input [58]. And while it is a matter of ongoing public debates, to what extent climate change is of anthropogenic nature [59], there is no doubt in the nature of notoriously known Urban Heat Island (UHI) effect [60]. UHIs are defined as a difference between air temperatures in urban core and rural surroundings of cities [33], and are due to the intrinsic properties of modern cities: capturing of heat due to increased heat capacity of building materials, anthropogenic heat emission from manufacturing, transportation and indoor air conditioning, obstruction of wind flows and other factors [61].

In fact, if there is anthropogenic input in climate change, then cities and activities in them are the main contributors of it [62]. It was found, however, that parameters of cities such as city size, green cover and albedo of materials are associated with the intensity of UHI [63]. This implies that certain urban planning and policy measures taken on a local scale can reduce the UHI and improve the thermal experience of people in outdoor environments.

To inform climate-aware policy making, urban climate modelling is used. The models range from macro- and meso-scale (such as Weather Research and Forecasting model with a grid resolution from kilometers up to 30 meters [64]) to microscale models, such as EnviMet [65] with resolution of up to 0.5 meters. Being computationally expensive, the models have to compromise either scale, or resolution, or the number of simulated parameters. Specialised models are developed to, for example, simulate the radiative heat in an urban areas [66, 67], effect of heat rejection from the air conditioning systems [68] and effect of trees on street-level cooling [43].

While having some limitations, the models of urban climate are constantly developing. With the growing computational power, it is reasonable to expect
that eventually we will develop models capable of comprehensive simulation of the microclimate with a resolution on the scale of building blocks and neighborhoods if not cities. We argue, however, that while being critically important, climate simulation by itself does not answer the question of how people will experience climate and importantly what will be their response to it. For these questions to be answered, human response to outdoor thermal environments should be understood and explicitly modeled.

**Outdoor thermal comfort**

Outdoor thermal comfort (OTC) is the broad term encompassing human response to outdoor thermal environments. OTC research has developed from indoor thermal comfort studies, which were critical to provide comfortable working and living environments for occupants of buildings [69]. The measures of indoor climate such as predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) [70] were developed to measure the comfort of thermal environments. The thermally neutral indoor environments usually correspond to level of PPD = 5%, which increases as the environment diverges from thermal neutrality. The guidelines for indoor air conditioning systems usually focus on air temperature and relative humidity, under the reasonable assumption that radiation and air velocity are kept low and relatively constant in enclosed indoor environments.

Outdoor environments, however, are more heterogeneous. There radiation and windchill play an important role. Oftentimes, thermal parameters of outdoor environments interact in a complex manner by compensating or amplifying the effect of one another on thermal regulation. To account for that, physiological indices of microclimate are used. Out of them, physiologically equivalent temperature (PET) [71] and universal thermal comfort index (UTCI) [72] are probably the most widely used. These indices measure microclimates by their effect on the thermal state of the human body. Reducing multiple environmental and personal parameters to one number, they allow for comparison between multiple microclimates in terms of their impact on the thermophysiological state of the human body. The index value, defined
1.2. The context of this thesis

in degrees Celsius, corresponds to air temperature in reference indoor environment required to achieve the same steady thermophysiological state as is achieved in the assessed microclimate. This value of an index can be calculated using multiple tools [66, 67], including the micro-scale climate modelling tool EnviMet [65], which allows one to assess simulated microclimate scenarios in terms of a person’s physiological response to them.

The high variability in microclimate parameters in outdoor environments is complemented by high temporal variation of outdoor climate due to its own nature and the nature of human activities in it. Thus, a stable thermophysiological state is almost never achieved in outdoor environments [69]. What is perceived as pleasurable exposure after exiting an air conditioned building can be felt and perceived as stressful by a person, who has already spent considerable time outdoors or is dressed in heavy clothing. Moreover, human activities are not evenly distributed in the outdoor urban spaces and are of a different nature (e.g. transit or leisure). This implies, that modelling space use and human behaviour is important to understand exposure and evaluate the impact of environment on people, who use it. The need for a more comprehensive approach to modelling of OTC was emphasised in a paper dating 2012 [73]. In it, the authors propose an agent-based approach and multi-level modelling of an individual’s response to thermal environments. Since then, several studies have advanced this avenue of research [74, 75, 76], but there is still a need for the development of a comprehensive set of models on all levels of human response to microclimate. The studies of this thesis bring us closer to this goal.

1.2.2 People in thermal environments

Human response to thermal environments (outdoor thermal comfort) is a complex multi-level phenomenon. Figure 1.1 depicts outdoor thermal comfort process showing the levels of response considered within this thesis: physiology, perception and behaviour. We aim at gaining a better understanding of the response on these levels through the creation of a set of computational models. The following subsections will describe the fundamentals of human
response on the three levels depicted in Figure 1.1 to motivate their importance, while deeper insights will be given in the separate chapters of this manuscript.

**Physiological response: thermal regulation**

The human body constantly interacts with its environment, in thermal terms the body can be considered a sink or a source of energy dissipated to or gained from the environment. Heat exchange between the body and its thermal environment is happening by convection, radiation, respiration and evaporation [77]. Additionally, part of internal metabolic energy production is spent on mechanical work (e.g. moving the center of mass and limbs in walking) [78]. These processes are graphically presented in Figure 1.2.

**Figure 1.2:** The process, components and parameters of thermal regulation of human body and heat exchange between it and the surrounding environment. Reproduced from: [https://www.thermoanalytics.com/](https://www.thermoanalytics.com/)

The goal of the thermoregulatory system is to maintain this heat exchange in balance with the internal heat production to ensure the core temperature
remains close to set temperature of 36.8°C vital for proper functioning of biological processes of a human body. Thermoregulatory system employs autonomous mechanisms such as vaso-dilation and constriction, shivering and sweating to maintain core temperature close to the set point of 36.8°C [77]. This system is sensitive to even small deviations of core and skin temperature from the set point, resulting in a thermal sensation (on a scale from cold to hot) that will drive human response on the higher levels of adaptation to thermal environment (discussed in the following subsections).

Failing to maintain heat balance, due to the limited capacity of a thermoregulatory system, results in hypo- or hyperthermia. Prolonged exposure to these conditions has detrimental effects on human health [79] and can be lethal [80]. While being a sophisticated first response to heat stress, the physiological system of thermal regulation has its limits and the adaptation and response at higher levels is crucial for efficient thermal regulation.

Multiple models of the human thermoregulatory system exist [81]. Most differ in terms of the granularity of body parts and the layers of body tissue considered [82, 83]. In Chapter 2 we describe, using a system dynamics representation, an enhanced version of a classical two-node model and compare it to the performance of other existing models. This model serves a cornerstone for the subsequent studies of this thesis, due to the fact that the physiological state of the human body is the main driver of human response at all levels.

Psychological response: thermal perception

Human psychological perception is the next level on which thermal sensation is felt and is typically evaluated on the scale comfortable-to-uncomfortable [84] or acceptable-to-unacceptable. This mapping might appear straightforward, but as will be shown later, it is as complex as any perceptual process in humans. Remarkably, humans are probably the only animals that voluntarily compromise their thermal regulation to a life-threatening extent for other, non-vital, purposes such as religion and fun [85]. The role of perception in this behaviour is pivotal.

In a study of outdoor thermal comfort in Cambridge, UK the predicted percentage of dissatisfied people (see Section 1.2.1) was calculated for a set
of observed microclimatic conditions [86]. Occupants of a public space were asked to give their evaluation of the thermal environment. The observed percentage of dissatisfied people was dramatically lower than expected (13% observed vs. 91% predicted). It turned out that, having been developed for indoor environment, PMV and PPD indices are not able to predict thermal satisfaction in outdoor environments. Factors such as perceived control, naturalness, expectations and past experiences should be considered, when predicting perception of the thermal environment [87]. While gaining more insights into factors influencing human thermal perception, "Yet in the case of thermoregulatory behaviour, the interface between physiology and psychology remains largely terra incognita", Cabanac (2010) [85].

The myriad of existing studies of OTC resorts to measurement of perception of thermal environment through surveys and questionnaires [88]. Measuring the thermal environment and calculating physiological indices of microclimate (see Section 1.2.1) allows to map thermal conditions to average perception. This mapping is not universal, the same values of physiological index are perceived differently in different parts of the world, which makes it necessary to recalibrate the perception scale for particular regions [89]. Even within the same city, these scales are adjusted for land use (residential, natural, etc.), type of activity (leisure, work, commute) and age group [90]. These hardly generalisable developments, while being of practical value for local policy and planning, unfortunately add little to common understanding of climate perception.

Motivated by the discussed complexity of the perception process and little existing knowledge, we do not approach development of computational models of microclimate perception. Our approach rather relies on the locally calibrated mapping of values of physiological index (and thus physiological state in given climate) to average perception. This estimated level of perception will then serve as an interface between physiological and behavioural models.

To tackle this issue of environmental conditions and perception, part of the research of this thesis involves a real-world experiment on pedestrian behaviour in outdoor environments. The data collected within the behavioural experiment presents a unique combination of precise measurement of climate,
exposure, physiology, perception and behaviour. We discuss its potential to advance the understanding of thermal perception in conclusions to this thesis.

**Behavioural response: thermoregulatory behaviour**

In Section 1.2.1 we have discussed the different ways climate has shaped humanity. All the examples of adaptation to climate are nothing but thermoregulatory behavioural response of people. As alluded to in Section 1.2.2, autonomous (physiological) response to thermal environment is limited and behavioural adaptation is the only means of thermal regulation in the long run [91]. Understanding this behaviour is critical to assess, predict and improve the experience of people in outdoor thermal environments.

Behavioural responses can be classified as either reactive (adaptation to environment) or proactive (adaptation of environment) [86]. In this thesis we focus on the former. The latter is considered outside the scope of our research. In animal and human behaviour, postural, activity and displacement behavioural adaptations to thermal stimulation are probably the most pronounced [85].

The empirical studies of activity intensity adaptation and displacement response in outdoor thermal environments are reported in the two chapters of this manuscript. The intensity of activity determines the rate of internal heat production. Thus, by adjusting activity intensity one can minimise heat stress [92]. It was previously shown in laboratory studies that people are capable of efficiently avoiding both hypo- and hyperthermia through regulation of activity [93]. We investigate the presence of this adaptation to the natural outdoor thermal environments in the context of urban pace of life (see Section 1.1) in Chapter 4. When exposed to a thermal gradient in laboratory environments, animals move to a location with a more comfortable temperature, a process called thermopreferendum [85]. In Chapter 5 we study this behaviour in people in natural environments to quantitatively investigate the additional perceived effort of walking under the sun.

While there are existing studies of thermal behaviour in outdoor spaces, they mostly observe the outcome of this behaviour at an aggregate level (e.g. clothing level [55, 56] or attendance and activities in public spaces [12] or walking rates [13]). Our studies, however, investigate momentary behavioural
response of individuals to dynamic thermal environment, providing a new perspective on human thermal behaviour in natural environments.

1.3 Outline of this thesis

This thesis is composed of five studies performed in the concept of multi-level human response to thermal environment presented in Figure 1.1. Each of these chapters is based on the manuscripts published in or submitted to peer-reviewed proceedings and journals. Below we describe how these chapters come together and constitute the achievement of the goal of current thesis: building a comprehensive understanding of multi-level response of people to dynamic thermal environments.

Chapter 2 describes the model of a physiological response to thermal environments. It provides the full definition of the classical two-node model of human body thermal regulation. We do it with a system dynamics approach: mapping out all the components in stocks-and-flows diagram allows for understanding of complex causal relations and feedback loops in interaction of body energy stocks and parameters with environment. We validate the model on available data on dynamic response of core and skin temperature and propose adjustments to model parameters which significantly improve the accuracy of predicted dynamics of the thermoregulatory system, attaining comparable or even better accuracy than more sophisticated models. This combination of high accuracy in dynamic scenarios and relatively low computational complexity makes the model a good candidate for use in agent-based modelling of OTC. This model is used in our later studies and provides a reliable and comprehensive representation of thermophysiological response to a wide range of thermal environments.

Chapter 3 describes the state-of-the-art of pedestrian behaviour modelling in the context of response to dynamic environments. This study proposes the proxy to perceptional response to thermal environment. Behavioural models are formulated as functions of deviation of an instantaneous value of a physiological index (such as PET, which can be calculated with a physiological model described in Chapter 2) from the acceptable range. We hypothesise four different behaviours and formulate the models for them. Two of these
behaviours, namely speed adaptation and adaptive path choice, have become the focus of two consequent studies, reported in Chapters 4 and 5. The agent-based modelling approach to pedestrian behaviour as a process of human interaction with physical and thermal environment on several levels constitutes the practical guide to implementation of human-centered simulation of OTC.

We investigate the walking speed adaptation as behavioural thermoregulatory response to thermal environments in Chapter 4. Based on existing literature and physiological underpinnings of thermal regulation, we hypothesise that walkers alter their walking speed to adjust the rate of metabolic heat production and to improve their thermal comfort. We have performed this study in the context of elevated urban pace of life – a counteracting motive of walking speed behaviour. We use physiological model to formulate the heat-stress-optimal walking speed and calculate its values for a broad range of thermal environments. We test the predicted values of heat-stress-optimal walking speeds against those empirically observed in a natural experiment in Singapore. We find that the values of average walking speed are systematically higher than heat-stress-optimal speed. We then analyse the implication of elevated walking speeds on additional heat stress due to pace of life in Singapore. The experiment in this study investigated the behavioural response to different shaded thermal environments (i.e. having no apparent visual and radiative stimulation), the behaviour under pronounced presence of the sun has become a focus of the Chapter 5.

Chapter 5 presents the results of investigation of path choice behaviour of people in stressful outdoor environments. We describe the design of experiment with human participants in natural outdoor environment, which is in contrast to reported human behaviour studies performed in lab environments. Observing people taking longer, but less sunny paths, allowed us to measure the burden or effort associated with walking under the stressful exposure to the sun. We use video recordings and computational models of a space and sun movement to precisely characterise, in terms of sun-shade composition, the path options provided to participants. This allows us to quantitatively estimate a distance-inflating coefficient of the sun – a proxy to associated effort of walking under the sun. The results provide quantitative understanding of human perception of the effort of walking under the sun,
tree shade and building shade and its implications for the path choices one might expect to observe in urban environments.

While in the first four chapters the reader is guided through the three levels of human response to thermal environments and the proposed models for them, Chapter 6 demonstrates the use of these models to address important questions beyond thermal comfort. We first investigate through computational modelling the performance of the human innate immune system (HIIS) under the elevated core temperatures. We estimate the range of core temperatures, at which the performance of the HIIS is compromised. We employ a physiological model of human thermal regulation to identify heat exposure and exercise intensity regimes, which causes body core temperatures to reach a level undermining the performance of the HIIS response. Our study demonstrates that, apart from apparent thermal discomfort, heat stress affects the basic biological mechanisms of human body beyond thermal regulation, and behavioural thermoregulatory response is crucial to preserve the proper functioning of these vital systems of human body.

Chapter 7 concludes the contribution of this research and discusses the directions for its further development and integration into agent-based OTC simulation framework.
Chapter 2

System dynamics of human body thermal regulation in outdoor environments

Thermal regulation serves a need of human body to maintain the stable core temperature to ensure the proper functioning of all the biological systems. Heat exchange between the human body and the environment is regulated by the physiological thermoregulatory system, which is the first line of response to thermal stimulation. It is the thermophysiological state, determined by both the environment and the system of thermal regulation, which drives the human response on other levels considered in this thesis, which in turn are employed to bring this state as close as possible to a neutral one. Understanding and being able to accurately reproduce the physiological response is central to the study of response on other levels. This chapter covers the system dynamics model of human body thermal regulation, which along with providing the model of human response on the physiological level also serves as a supporting model for the studies in the next chapters.

Abstract

Thermal comfort of people in outdoor urban spaces is a growing concern in cities due to climate change and urbanisation. In outdoor settings the climate

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and behaviour of people are more dynamic than in indoor situations, therefore a steady state of the thermoregulatory system is rarely reached. Understanding the dynamics of outdoor thermal comfort requires accurate predictive models. In this chapter we extend a classical two-node model of human body thermal regulation. We give a detailed description and interpretation of all the components and parameter values and test the dynamics of the model against experimental data. We propose a modification of the skin blood flow model which, while keeping realistic values and responsiveness, improves skin temperature prediction nearly fourfold. We further analyse the sensitivity of the model with respect to climatic and personal parameters. This analysis reveals the relative importance of, for instance, air temperature, wind speed and clothing, in thermoregulatory processes of the human body in various climatic settings. We conclude, that our model realistically reproduces the dynamics of aggregate measures of human body thermal regulation. Validated for cool, warm and hot environments, the model is shown to be accurate in terms of its dynamics and it is conceptually and computationally far more efficient than any existing multi-node and multi-part model.

2.1 Introduction

Thermal comfort of people in outdoor urban spaces is a growing issue for many of the world’s cities due to the global processes of climate change and urbanisation. Heat is not only related to physiological and psychological stress, but also to population morbidity and mortality [94]. The physiological thermal regulation system is one of the key means of adaptation of human beings to heat in outdoor environments. The state of this system, typically described with parameters such as core-, skin- temperature or sweating rate, defines stress and to a large extent determines an individual’s level of comfort. In outdoor environments, due to the large variability of the outdoor climate, and people’s activity in urban settings, the thermoregulatory system is highly dynamic. To model outdoor thermal comfort (OTC) of people, one should be able to accurately reproduce individual dynamics of the thermoregulatory system. Such OTC models could be applied to understand
2.1. Introduction

how to design urban environments and maximise the comfort of individuals. For example, how to design spaces that reduce radiance, increase airflow or promote heat reduction due to evapotranspiration. Ideally these models should be applied to whole populations of individuals in order to understand how an environment impacts those individuals. It is therefore important to minimise the complexity of the model while retaining accurate dynamics.

Multiple models have been proposed to predict the state of human body thermal regulation. Probably the most influential is the 25-node model proposed by Stolwijk [95][96], consisting of one central blood "node" and 24 body "nodes" (six body segments, each with four compartments). Several improvements have been introduced to the model since then, in order to better predict the dynamics of local response of body parts, for instance increasing the number of body compartments and body parts [97][98][99]. A model that simplified the original model for prediction of the overall thermophysiological state was proposed by Gagge in 1972 [100]. Gagge’s model has since been used intensively in studies of thermal comfort. It was adopted by the ASHRAE standard for indoor thermal environments [101] and used to define the Physiologically Equivalent Temperature (PET) [71], which is the most commonly used thermal comfort index. Properties of both Stolwijk’s and Gagge’s model were analysed for steady state values predictability in indoor environments [96][102]. These studies however were lacking evaluation of the dynamic behaviour. Munir et al. [103] reevaluated the model of Stolwijk in terms of its dynamical properties and analysed several adjustments to the model, the authors demonstrated that the dynamics can closely reproduce empirical data. Based on this data Foda et al. [104] evaluated three other models: multi-node multi-part Fiala’s model [97], the UCB model [99] and a two-node multi-part MS-Pierce model [105]. The results demonstrate significant discrepancy in the dynamics of the models. The authors of the study do not propose a measure for quantitative evaluation of the model’s accuracy in terms of its dynamic behaviour. Gagge’s two-node model has been used to model the dynamics of thermal regulation of pedestrians in outdoor environments [106][107], but has not been extensively analysed for its dynamical properties. A comprehensive review of existing models, their evaluation and application can be found in [108].
The absence of analysis of the simplified two-node model, as well as weak results of dynamic performance of the other, much more sophisticated, models suggest the evaluation and reconsideration of the two-node model. In this study we implement the classical two-node model of Gagge based on descriptions found in [102, 109, 105]. We rethink the representation of the model by applying concepts from system dynamics: namely stock-and-flow diagrams. System dynamics uses energy stocks and flows to define the dynamics of the system and the causal relationships between parameters. We then analyse the performance of the model in a dynamic environment and use root mean square error for its quantitative evaluation. We demonstrate how the system dynamics approach can help to identify parameters responsible for the poor dynamics and show significantly improved model dynamics by parameter calibration against Munir’s data [103]. We demonstrate the validation of the model for cool, warm and hot environments. Global sensitivity analysis adds another dimension to the model, allowing for the identification of the most important environmental and individual parameters in different climates.

The remainder of this chapter is organised as follows: we provide a system dynamics representation of the model in Section 2.2 and its exhaustive formulation in Section 2.3. We then investigate the performance of the model and report results of model calibration and sensitivity analysis in Section 2.4. We discuss the results in Section 2.5 and conclude the chapter with Section 2.6.

### 2.2 System dynamics representation of the model

Two nodes of the model of Gagge [100], core and skin, are represented in our system dynamics model as two stocks storing the energy within the body, where the energy is translated into temperatures of two nodes: $T_{\text{core}}$ and $T_{\text{skin}}$, see Figure 2.1.

Flows of the model represent energy fluxes within, to and from the human body: metabolic rate $M$, generation of heat through shivering $Sh$, heating and humidification of inhaled air $Re$, mechanical work rate $W$, core-skin heat transfer $CS$, convection $C$, latent heat flux through evaporation of sweat $E$.
Figure 2.1: Stock-and-flow diagram of a two-node model of the thermoregulatory system. Rectangles with solid stroke represent two energy stocks: core and skin, black-headed arrows are energy flows within, to and from the human body, blue arrows represent causal relationships between parameters of the model.
and radiative heat exchange $R$ (note that all the fluxes are defined with respect to the unit of body surface area).

Heat storage rate $St$ is then defined as the sum of all fluxes coming to and from the body, corresponding to cooling of the body when negative and to heating when positive:

$$St = M + Sh - Re - W - C - E - R \left[ \frac{W}{m^2} \right]$$ (2.1)

The steady state of the system is then defined as the state where energy balance is found, thus $St = 0$. The dynamics of the system is always moving towards steady state and individual and microclimate parameters determine whether and when the system will converge to this state.

Figure 2.1 shows the stocks-and-flows diagram traditionally used in system dynamics modelling. It depicts the two cores as rectangles with solid stroke connected between each other and thermal environment through flows – fluxes as described above, shown as arrows with ‘valves’. Arrows identify causal relationships between the parameters, variables, stocks and flows of the model, with polarity signs on their heads revealing the influence of their change in the dependent variable, assuming other determining parameters are fixed.

We further define all the fluxes through the parameters of the model and then give the final equations of the nodes dynamics expressed as fluxes.

### 2.3 Formulation of the model

#### 2.3.1 Parameters of the model

We define the constants used in the derivation below by the values indicated in the first section of Table 2.1. The model considers the individual parameters of a person listed in the second section of Table 2.1. Many variables of the model are defined with respect to surface area of human body, which is estimated by Dubois formula.
2.3. Formulation of the model

Table 2.1: Parameters of the model

<table>
<thead>
<tr>
<th>Param.</th>
<th>Value</th>
<th>Units</th>
<th>Range</th>
<th>Description</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Constant</td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>$5.67 \cdot 10^{-8}$</td>
<td>$\frac{W}{m^2 \cdot K^4}$</td>
<td>–</td>
<td>Stefan-Boltzmann constant</td>
<td>–</td>
</tr>
<tr>
<td>$c_b$</td>
<td>3492</td>
<td>$\frac{J}{kg \cdot K}$</td>
<td>–</td>
<td>Specific heat of human body</td>
<td>[102, 109]</td>
</tr>
<tr>
<td>$c_{bl}$</td>
<td>1.163</td>
<td>$\frac{W \cdot hr}{l \cdot K}$</td>
<td>–</td>
<td>Thermal capacity of blood</td>
<td>[102, 109]</td>
</tr>
<tr>
<td>$c_{sw}$</td>
<td>2426</td>
<td>$\frac{J}{gr}$</td>
<td>–</td>
<td>Evaporation heat of sweat</td>
<td>[110]</td>
</tr>
<tr>
<td>$k_b$</td>
<td>5.28</td>
<td>$\frac{W}{m^2}$</td>
<td>–</td>
<td>Conductance of body tissues</td>
<td>[102, 109]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Individual parameters</td>
<td></td>
</tr>
<tr>
<td>$m_{body}$</td>
<td>75.0</td>
<td>$kg$</td>
<td>–</td>
<td>Weight</td>
<td>–</td>
</tr>
<tr>
<td>$h_{body}$</td>
<td>1.8</td>
<td>$m$</td>
<td>–</td>
<td>Height</td>
<td>–</td>
</tr>
<tr>
<td>$M$</td>
<td>80</td>
<td>$\frac{W}{m^2}$</td>
<td>–</td>
<td>Metabolic rate</td>
<td>[101]</td>
</tr>
<tr>
<td>$\mu W$</td>
<td>[0;1]</td>
<td>–</td>
<td>–</td>
<td>Mechanical work efficiency</td>
<td>[111, 112, 113]</td>
</tr>
<tr>
<td>$I_{cl}$</td>
<td>0.155</td>
<td>$\frac{K \cdot m^2}{W}$</td>
<td>–</td>
<td>Clothing level</td>
<td>[101]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Climatic parameters</td>
<td></td>
</tr>
<tr>
<td>$T_{air}$</td>
<td>–</td>
<td>$^\circ C$</td>
<td>–</td>
<td>Air temperature</td>
<td>–</td>
</tr>
<tr>
<td>$T_{mrt}$</td>
<td>–</td>
<td>$^\circ C$</td>
<td>–</td>
<td>Mean radiant temp.</td>
<td>[114]</td>
</tr>
<tr>
<td>$v$</td>
<td>–</td>
<td>$m \cdot s^{-1}$</td>
<td>–</td>
<td>Rel. air speed</td>
<td>–</td>
</tr>
<tr>
<td>$p_a$</td>
<td>–</td>
<td>$mmHg$</td>
<td>–</td>
<td>Atmospheric pressure</td>
<td>–</td>
</tr>
<tr>
<td>$RH$</td>
<td>–</td>
<td>$%$</td>
<td>–</td>
<td>Relative humidity</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Static parameters</td>
<td></td>
</tr>
<tr>
<td>$T_{body}^*$</td>
<td>36.49</td>
<td>$^\circ C$</td>
<td>–</td>
<td>Neutral temp. of the body</td>
<td>[102, 109]</td>
</tr>
<tr>
<td>$T_{core}^*$</td>
<td>36.8</td>
<td>$^\circ C$</td>
<td>36.6–36.8</td>
<td>Neutral temp. of the core</td>
<td>[109]</td>
</tr>
<tr>
<td>$T_{skin}^*$</td>
<td>33.7</td>
<td>$^\circ C$</td>
<td>33.7–34.0</td>
<td>Neutral temp. of the skin</td>
<td>[109]</td>
</tr>
<tr>
<td>$q_{bl}^*$</td>
<td>6.3</td>
<td>$\frac{l}{hr \cdot m^2}$</td>
<td>–</td>
<td>Neutral skin blood flow</td>
<td>[100]</td>
</tr>
<tr>
<td>$\alpha_{rad}$</td>
<td>0.72</td>
<td>–</td>
<td>0.61–0.79</td>
<td>Ratio of effective radiative area</td>
<td>[115]</td>
</tr>
<tr>
<td>$c_{con}$</td>
<td>0.5</td>
<td>$^\circ C^{-1}$</td>
<td>0.1–0.5</td>
<td>Coef. for vasoconstriction</td>
<td>[109]</td>
</tr>
<tr>
<td>$c_{dil}$</td>
<td>200</td>
<td>$\frac{l}{hr \cdot m^2 \cdot ^\circ C}$</td>
<td>50–240</td>
<td>Coef. for vasodilation</td>
<td>[109]</td>
</tr>
<tr>
<td>$c_{rswe}$</td>
<td>170</td>
<td>$\frac{gr}{m^2 \cdot ^\circ C \cdot hr}$</td>
<td>±50%</td>
<td>Coef. for sweating rate</td>
<td>[102]</td>
</tr>
<tr>
<td>$c_{shiv}$</td>
<td>19.4</td>
<td>$\frac{W}{m^2 \cdot ^\circ C^2}$</td>
<td>–</td>
<td>Coef. for shivering</td>
<td>[102, 109]</td>
</tr>
<tr>
<td>$\epsilon_{cl}$</td>
<td>0.97</td>
<td>–</td>
<td>0.92–1.0</td>
<td>Emissivity of clothed body</td>
<td>[102, 109]</td>
</tr>
</tbody>
</table>
The level of clothing of a person determines the increase in body surface area reported in [105] as follows:

\[
f_{cl} = \begin{cases} 
1 + 1.290 \cdot I_{cl} & \text{if } I_{cl} < 0.072, \\
1.05 + 0.645 \cdot I_{cl} & \text{otherwise.}
\end{cases}
\]  

(2.3)

Clothed body surface area then can be calculated as follows:

\[
A_{cl} = f_{cl} \cdot A_{Du} \quad [m^2]
\]  

(2.4)

The microclimate parameters considered in the model are listed in the third section of the Table 2.1. Other important parameters are derived from these values. Saturation vapour pressure is estimated according to [102]:

\[
p_{sat} = \exp \left( 18.67 - \frac{4030.18}{T_{air} + 235} \right) \quad [mmHg]
\]  

(2.5)

From which the ambient vapour pressure is derived:

\[
p_{va} = p_{sat} \frac{RH}{100} \quad [mmHg]
\]  

(2.6)

Certain parameters of the model are usually set to a fixed value, however different authors have estimated different values for the parameters and in some cases parameters vary between individuals. The last section of the Table 2.1 lists these parameters. Conventional values of these parameters and a range of possible values are shown where appropriate.
2.3. Formulation of the model

2.3.2 Model variables

Thermal signals

There are three thermal signals, which are regulating the system, derived from temperatures of core, skin and the whole body.

\[ S_{\text{core}} = T_{\text{core}} - T^*_{\text{core}} \quad [\degree C], \]  
\[ S_{\text{skin}} = T_{\text{skin}} - T^*_{\text{skin}} \quad [\degree C], \]  
\[ S_{\text{body}} = T_{\text{body}} - T^*_{\text{body}} \quad [\degree C]. \]  

Where \( T_{\text{body}} \) is the average weighted body temperature as defined in eq. 2.20.

The signal of the whole body \( S_{\text{body}} \) is regulating the sweating response. The respective cold and warm signals are defined as follow:

\[ S^+_{\text{core}} = \max(0, S_{\text{core}}) \quad [\degree C], \]  
\[ S^-_{\text{core}} = \min(S_{\text{core}}, 0) \quad [\degree C], \]  
\[ S^+_{\text{skin}} = \max(0, S_{\text{skin}}) \quad [\degree C], \]  
\[ S^-_{\text{skin}} = \min(S_{\text{skin}}, 0) \quad [\degree C], \]  
\[ S^+_{\text{body}} = \max(0, S_{\text{body}}) \quad [\degree C], \]  
\[ S^-_{\text{body}} = \min(S_{\text{body}}, 0) \quad [\degree C]. \]  

Blood flow regulation

Thermal signals of core and skin define the blood flow thermal regulation through vasoconstriction and vasodilation. The warm signal of the core being multiplied with the coefficient of vasodilation increases the blood flow from core to skin, whereas the cold signal of the skin, multiplied with coefficient of vasoconstriction, reduces it. For core-to-skin blood flow this relationship is:

\[ q_{\text{bl}} = \frac{q^{*}_{\text{bl}} + c_{\text{dil}} \cdot S^+_{\text{core}}}{1 - c_{\text{con}} \cdot S^-_{\text{skin}}} \left[ \frac{l}{hr \cdot m^2} \right] \]  

(2.16)
Masses of nodes

Blood flow regulation determines how much blood is exchanged between the nodes, implying that the boundary between nodes moves with changes in the blood flow between the nodes. The higher this blood flow – the less the fraction of the skin compartment in the total mass of the body. The fraction of skin in the body mass is then defined as follows:

\[
\alpha_{\text{skin}} = 0.0418 + \frac{0.7425 \left[ l/(hr \cdot m^2) \right]}{q_{bl} + 0.5854 \left[ l/(hr \cdot m^2) \right]} \tag{2.17}
\]

Then the masses of the skin and core compartments are:

\[
m_{\text{skin}} = \alpha_{\text{skin}} \cdot m_{\text{body}} \quad [kg], \tag{2.18}
\]

\[
m_{\text{core}} = m_{\text{body}} - m_{\text{skin}} \quad [kg]. \tag{2.19}
\]

And the average weighted body temperature:

\[
T_{\text{body}} = \alpha_{\text{skin}} \cdot T_{\text{skin}} + (1 - \alpha_{\text{skin}}) \cdot T_{\text{core}} \quad [^\circ C] \tag{2.20}
\]

2.3.3 Flows

Flows to and from the core

The metabolic rate \( M \) represents the internal heat production due to food digestion. This rate is highly dependent on the type of activity performed by an individual and it is usually estimated through reference tables, for example in Table 2.1 the value for \( M \) is given for sedentary light office work activity.

The rate of mechanical work \( W \) represents the amount of energy spent to perform some physical activity (i.e. not for heating the body). For sitting in the office, it is usually assumed to be zero. For walking, these values are calculated through the mechanical work efficiency \( \mu_W \) (see eq. 2.21), which is maximised at the optimal walking speed of approximately 1.2 m/s. \( \mu_W \in [0.21; 0.23] \) if defined relative to the total metabolic rate [111]. Some authors define this efficiency relative to the total minus standing or basal metabolic rate, which results in a higher estimated value of \( \mu_W \) [112, 113]. In case of running, unlike for walking, the efficiency grows with increasing
2.3. Formulation of the model

speed, reaching the value of $\mu_W = 0.8$. This is due to the difference in physics of the two types of activity.

$$W = \mu_W \cdot M \left[ \frac{W}{m^2} \right] \quad (2.21)$$

Having cold signals from both core and skin nodes implies that the additional heat is produced by the body through shivering, defined as follows [102, 109]:

$$Sh = c_{shiv} \cdot S_{core}^{-} \cdot S_{skin}^{-} \left[ \frac{W}{m^2} \right] \quad (2.22)$$

The inhaled air is humidified and heated within the respiratory system, which results in energy expenditure. The amount of inhaled air is proportional to the metabolic rate. Respiration heat flux is then estimated by:

$$Re = \frac{M}{10^4} \cdot \left[ 14 \cdot (34 - T_{air}) + 23 \cdot (44 - p_{va}) \right] \left[ \frac{W}{m^2} \right] \quad (2.23)$$

where $p_{va}$ is ambient vapour pressure defined by eq. 2.6

Core-to-skin heat transfer

The core exchanges heat with the outer compartment of the body – skin. This exchange depends on the difference in temperature of these nodes and blood flow between them:

$$CS = (k_b + c_b \cdot q_{bl})(T_{core} - T_{skin}) \left[ \frac{W}{m^2} \right] \quad (2.24)$$

Flows to and from the skin

Being an outer compartment of the body, the skin is the major source of energy exchange between the body and its environment. This energy exchange happens through three major fluxes: convection, evaporation and radiation. Conduction is usually considered not significant in the range of models that we consider.
Convection is highly dependent on the airflow speed and for different environments different coefficients for convection are estimated:

\[ h_{c1} = 3 \left( \frac{p_a}{760} \right)^{0.53} \left[ \frac{W}{m^2 \circ C} \right], \quad (2.25) \]
\[ h_{c2} = 8.6 \left( v \cdot \frac{p_a}{760} \right)^{0.53} \left[ \frac{W}{m^2 \circ C} \right], \quad (2.26) \]
\[ h_{c3} = 5.66 \left( \frac{M}{58.2} - 0.85 \right)^{0.39} \left[ \frac{W}{m^2 \circ C} \right], \quad (2.27) \]
\[ h_{c4} = 2.38 (T_{clo} - T_{air})^{0.25} \left[ \frac{W}{m^2 \circ C} \right], \quad (2.28) \]
\[ h_{c5} = 12.1 \sqrt{v} \left[ \frac{W}{m^2 \circ C} \right]. \quad (2.29) \]

Where \( T_{clo} \) is the clothing temperature defined in eq. 2.34. The largest \( h_c \) value is used to estimate the convective flux:

\[ h_c = \max(h_{c1}, h_{c2}, h_{c3}, h_{c4}, h_{c5}) \left[ \frac{W}{m^2 \circ C} \right] \quad (2.30) \]

Finally the convective flux is defined as follows:

\[ C = h_c \cdot f_{cl} \cdot (T_{clo} - T_{air}) \left[ \frac{W}{m^2} \right] \quad (2.31) \]

Radiative heat exchange between human body and environment is mainly determined by the difference in clothing temperature and mean radiant temperature.

\[ R = f_{cl} \cdot \alpha_{rad} \cdot \epsilon_{cl} \cdot \sigma \cdot (T_{clo,K}^4 - T_{MRT,K}^4) \left[ \frac{W}{m^2} \right] \quad (2.32) \]

where \( T_{clo,K} \) and \( T_{MRT,K} \) are clothing and mean radiant temperature in Kelvin.

Once the expressions for \( C \) and \( R \) are introduced, the clothing temperature can be found as the one under which the heat transfer from skin through clothing on the surface of the clothes is equal to the sum of convective and radiative heat exchange between clothing and environment:

\[ \frac{(T_{clo} - T_{skin})}{J_{cl}} = C + R \left[ \frac{W}{m^2} \right] \quad (2.33) \]
2.3. Formulation of the model

The $C$ and $R$ terms can be substituted into the equation to allow it to be solved for $T_{clo}$ in closed form, however in practice the value is easier to find computationally using numerical optimisation:

$$T_{clo} = \arg \min_{T_{clo}} \left( |(T_{clo} - T_{skin})/I_{cl} - C - R| \right) \ [\degree C] \ (2.34)$$

Latent heat removal through evaporation of sweat on the skin surface depends on the convection potential of the environment and clothing level, which is reflected in the coefficient for evaporation:

$$h_e = \frac{L \cdot h_c}{1 + 0.92 \cdot I_{cl} \cdot h_c} \left[ \frac{W}{m^2 \cdot mm Hg} \right] \ (2.35)$$

Where $L$ is the Lewis’ relation and is set to $L = 2.2$ for sea level altitude.

The sweating rate is determined by the body and core warm signal:

$$r_{sw} = \frac{c_{rsw}}{3600} \cdot S_{body}^+ \exp \left( \frac{S_{skin}^+}{10.7} \right) \left[ \frac{gramm}{m^2 \cdot s} \right] \ (2.36)$$

The difference between saturation vapour pressure $p_{clo}$ at clothing temperature $T_{clo}$ (calculated similar to eq. 2.5) and ambient vapour pressure, determine the maximum evaporative capacity of the environment (assuming skin wettedness $w_{skin} = 1$):

$$p_{diff} = p_{clo} - p_{va} \ [mm Hg], \quad E_{max} = 1 \cdot h_e \cdot p_{diff} \left[ \frac{W}{m^2} \right]. \ (2.37, 2.38)$$

Skin wettedness level due to sweating:

$$w_{sw} = \min \left( \frac{r_{sw} \cdot c_{sw}}{E_{max}}, 1 \right) \ (2.39)$$

Wettedness of the skin due to sweating is $w_{sw} \in [0; 1]$, excessive sweat which cannot be evaporated is dripping. Natural wetteness of the skin due to the
vapour diffusion through it and total skin wettedness are then defined as:

\[ w_{\text{dif}} = 0.06 \cdot (1 - w_{\text{sw}}), \]
\[ w_{\text{sk}} = w_{\text{dif}} + w_{\text{sw}}. \]  

Finally, the expression for the evaporative heat flux is:

\[ E = w_{\text{sk}} \cdot h_{\text{e}} \cdot p_{\text{diff}} \left[ \frac{W}{m^2} \right] \]  

**Governing equations for system dynamics of thermal regulation**

After the flows are calculated for the model at time \( t \) seconds the value of stocks at time \( t + \Delta t \) are calculated as follows:

\[ T_{\text{core}}(t + \Delta t) = T_{\text{core}}(t) + \frac{A_{\text{Du}}[M - W - Re - CS]}{c_b \cdot m_{\text{core}}} \Delta t, \]  
\[ T_{\text{skin}}(t + \Delta t) = T_{\text{skin}}(t) + \frac{A_{\text{Du}}[CS - C - E - R]}{c_b \cdot m_{\text{skin}}} \Delta t. \]  

### 2.4 Model analysis and results

#### 2.4.1 Initial validation

For validation of the model’s static and dynamic performance we simulated the dynamics of skin and core temperatures for the experimental schedule reported in Munir et al. \[103\]. In the experiment subjects were moving between climatic chambers with different microclimates according to a neutral-cool-neutral-warm-neutral schedule (see Figure 2.2 for duration and climate parameters of stages of the schedule).

The model was initialised with climatic parameters from the first scenario and average personal characteristics (height, weight and clothing) and simulated with one-second time steps, for which model has shown numerical stability.

As can be seen from Figure 2.2 the general dynamics and absolute values of the skin and core temperatures are well captured by the model. However,
the growth of skin temperature at the third stage of the schedule is significantly slower than the growth observed in the experiments. While this is acceptable behaviour for a model of thermoregulation in static indoor thermal environments, for modeling dynamic thermal sensation in transient outdoor environments this can become a reason for inaccurate estimation of people’s physiological state and their overall thermal sensation. Further in this chapter we are focusing on the dynamics of skin temperature, as it is In the next section we show how the system dynamics approach helps to identify the component of the model responsible for these inaccurate dynamics and demonstrate how parameter tuning can improve the model’s dynamics.

**Figure 2.2:** Comparison of the system dynamics simulation results with empirical data [103] (top) and simulated energy fluxes of heat exchange with the environment (below), where positive flux has heating effect on body and negative flux has cooling effect.
2.4.2 Model calibration

The difference in dynamics of the skin temperature between experimental data and simulation suggests that the skin temperature is not changing fast enough for certain physiological states and varying environmental conditions (third stage in Figure 2.2). To investigate the factors that influence skin temperature dynamics, we construct a causal tree for the skin temperature node stock-and-flow diagram (see Figure 2.3).

![Image of causal tree of skin temperature of depth 3.]

We find that parameters influencing skin temperature are radiation, convection, evaporation flows and core-skin heat transfer. The first three flows, however, do not have a sufficient gradient between the skin temperature and the environment to transfer heat from the environment to the body. The only source of heat significantly influencing the heating process is the core-skin heat transfer. This term depends on multiple parameters, only one of which is available for adjustment: core-skin blood flow. Other parameters are either constants or have valid values according to observations (core and skin temperature before the change in the microclimate conditions). The equation for core-skin blood flow is estimated in the original model from empirical data, that is, it is based on data, but not on the underlying physical process. The parameters influencing it are $c_{\text{conv}}$, $c_{\text{dil}}$, $T_{\text{core}}^*$, $T_{\text{skin}}^*$, which can be chosen arbitrarily from the ranges mentioned in Table 2.1. We ran global optimisation procedures for these parameters minimizing the difference between experimental and simulated dynamics of skin temperature, where the difference is expressed in terms of root mean square error (RMSE).
Table 2.2 lists three sets of parameters for which model was simulated. The first parameter set represents the most commonly used in literature; the second is the result of parameters optimisation procedure, where parameters were allowed to vary within the ranges found in literature and listed in Table 2.1. The third set of parameters is a result of optimisation procedure, where we allow tuning of the neutral core-skin blood flow $q^{*}_{bl}$ (with a reported value of $q^{*}_{bl} = 6.3 \text{ l.hr}^{-1}\cdot\text{m}^{-2}$ [102, 109]). We allow $q^{*}_{bl}$ to vary within the range of $[4;12] \text{ l.hr}^{-1}\cdot\text{m}^{-2}$ (established experimentally after several runs of optimisation procedure), taking into account that all the other parameters also have wide ranges reported in literature [102, 109]. The results are shown in Figure 2.4a, where the curve number represents the simulated dynamics of $T_{skin}$ using the corresponding set of core-skin blood flow parameters listed in Table 2.2, i.e. $T_{skin1}$ corresponds to skin temperature dynamics in model with original set of parameters. We can conclude that tuning parameters within reported ranges does not give a significant improvement of skin dynamics $T_{skin2}$. The tuned value of $q^{*}_{bl} = 10.7 \text{ l.hr}^{-1}\cdot\text{m}^{-2}$ does significantly improve the dynamics of skin temperature $T_{skin3}$, resulting in a nearly four-fold reduction in RMSE.

Adjustment of $q^{*}_{bl}$ requires the validation of the resulting $q_{bl}$ against the values generated with the conventional set of parameters. Figure 2.4b shows the dynamics of $q_{bl}$ for each of the parameter sets from Table 2.2. Comparing the values of the core-skin blood flow obtained by the calibrated models ($q_{bl2}$ and $q_{bl3}$) to the model with the original set of parameters ($q_{bl1}$), we expect that:

1. the flow values during the neutral stage (stage 1) to be close to those of $q_{bl1}$;
2. a reduced response to cooling stage 2: a too big drop in $q_{bl}$ during this stage would lead to the inability of $T_{skin}$ to restore fast enough during the subsequent stage;
3. a reduced response to the warming stage 4, since it is unrealistically high and leads to overestimation of $T_{skin}$.

From Figure 2.4b it follows that $q_{bl3}$ meets all the listed expectations. Therefore, from here on wards we will use set 3 in our simulations, this will result
in significantly improved dynamics of $T_{\text{skin}}$.

<table>
<thead>
<tr>
<th>Set no.</th>
<th>$q^{*}_{bl}$</th>
<th>$T^{*}_{\text{core}}$</th>
<th>$T^{*}_{\text{skin}}$</th>
<th>$c_{\text{dil}}$</th>
<th>$c_{\text{con}}$</th>
<th>$T_{\text{skin}}$ RMSE, °C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.3</td>
<td>36.8</td>
<td>33.7</td>
<td>200</td>
<td>0.5</td>
<td>0.665</td>
</tr>
<tr>
<td>2</td>
<td>6.3</td>
<td>36.6</td>
<td>33.7</td>
<td>50</td>
<td>0.1</td>
<td>0.549</td>
</tr>
<tr>
<td>3</td>
<td>10.7</td>
<td>36.7</td>
<td>33.7</td>
<td>50</td>
<td>0.1</td>
<td>0.182</td>
</tr>
</tbody>
</table>

**Table 2.2: Model parameters used in simulations shown in Figure 2.4a**

![Figure 2.4](image)

(A) Skin temperature $T_{\text{skin}}$  
(b) Skin blood flow $q_{bl}$

**Figure 2.4**: The dynamics of skin temperature and skin blood flow for Munir’s schedule simulated for three sets of parameters of skin blood flow (see Table 2.2) compared to empirical data.

### 2.4.3 Performance of the calibrated model

We compared the results of our calibrated model with other models reported in the literature for the first schedule of Munir et al. The data for other models was obtained through digitisation of plots from the original sources: Stolwijk’s (multi-node, multi-segment) model [103], Fiala’s (multi-node multi-segment) model and MS-Pierce (two-node, multi-segment) model [104]. The performance of the models was evaluated with measure of RMSE. Figure 2.5 demonstrates the dynamics of the existing models and the current model compared with empirical data. The dynamics of the current model is significantly
better than Fiala’s model and MS-Pierce’s model and is more or less equivalent to Stolwijk’s multi-node multi-segment model in terms of RMSE. In summary we can conclude that the tuned model outperforms some of the existing, more sophisticated models, and performs similarly to Stolwijk’s more complex model.

![Image](image.png)

**Figure 2.5:** The comparison of current model with the dynamics of other found in literature.

Munir et al. also reported the second schedule with prolonged stages 2, 4 and 5. We simulated original model of Gagge’s and our model for this scenario and compared it with the experimental data and Stolwijk’s model simulation reported by Munir et al [103]. The results are provided in Figure 2.6 and demonstrate good consistency of the model, especially when compared with the original one.

### 2.4.4 Sensitivity analysis

Sensitivity analysis allows for understanding the sensitivity of the model’s output to variations in the model’s inputs. Performing the analysis helps to uncover the relative influence of parameters on the model’s output. Knowing which parameters the model is sensitive or insensitive to can help to identify which parameter must be estimated more accurately through data or experimentation. We performed variance-based global sensitivity analysis [117] of the model for 8 parameters: 4 climatic parameters ($T_{air}$, $T_{MRT}$, $RH$ and $v$),
and 4 individual parameters ($M$, $I_{cl}$, $m_{body}$ and $h_{body}$). Sensitivity analysis of the model was performed for two sets of parameters, representing a moderate summer climate (e.g. Europe or North America) and a hot and humid climate representing hot and humid (sub-) tropical climates (e.g. Singapore or Thailand). The ranges of parameters were chosen within reasonable values and are not intended to set strict definition of these climates. For each type of climate the parameters of the model were sampled from the space defined by the respective ranges using Saltelli extension of Sobol’s sequence [119], with total number of parameter samples $N = 1800$ ensuring sufficient and uniform coverage of the sample space. We analysed the sensitivity of the model in terms of the temperatures of two compartments: core and skin.

The results shown in Figure 2.7 demonstrate that the sensitivity of the parameters is different for the two different climates. In the moderate climate the skin temperature is shown to be most sensitive to the level of clothing followed by air temperature. Interestingly, in hot and humid climates the sensitivity of these parameters flip: air temperature becomes more sensitive parameter than clothing level. The third most important parameter for skin temperature in both climates is wind speed. For core temperature sensitivity in moderate climates, metabolic rate is the most important parameter, followed by wind speed and air temperature. In hot and humid climate sensitivity to

\footnote{Using the Python library SALib 1.1.0 [118]}

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure2_6.png}
\caption{The comparison of current model with the dynamics of Gagge’s original model, Stolwijk’s model and empirical data from second scenario of Munir et al. [103].}
\end{figure}
these parameters is in the following order: air temperature, wind speed and metabolic rate. This analysis allows to identify the most critical parameters influencing thermal regulation in different climates. For example, in Singapore, a country with hot and humid climate, the most critical factors affecting skin temperature dynamics are air temperature, clothing insulation and wind speed. It is therefore crucial that these parameters are measured or estimated with maximum precision in order to make the most accurate estimation of physiological response, which in turn defines sensation and perception of climate and comfort.

![Figure 2.7](image)

**Figure 2.7:** Results of sensitivity analysis for summer seasons in two different climate zones. Colours indicate the sensitivity of the model to a parameter (sensitivity increases from blue to red colour).

### 2.5 Discussion

In this study, we validated our model against mean skin temperature dynamics as was done by other studies [103][104]. Multiple studies suggest that this is the most responsive, precisely measurable and representative component of the whole thermophysiological system [120][121], whereas core temperature is kept by thermoregulatory processes very close to neutral value of around 36.8°C. So far we demonstrated model performance only in terms of mean skin temperature dynamics in two scenarios found in Munir et al. [103] that consist of stages of neutral, cool and warm environments. In outdoor environments a broader range of parameters is expected and other thermoregulatory aspects become crucial for correct estimation of OTC. For example, in extremely hot environments sweating will play key role in heat dissipation from
the body as well as individual sensation of heat. Calculation of the sweating rate is not a trivial task and no data on sweating rate dynamics has been reported in literature to the best of our knowledge. Sweating rate dynamics can be inferred through evaporation heat loss from the body for which data can be found in the work of Fiala et al. [83]. They report data for an experimental temperature schedule with an extreme hot stage. We simulated this schedule with our new thermoregulatory model and were able to show an excellent correspondence between the simulated and reported data (Figure 2.8). It also demonstrates, that our model is valid for other environments to which it was not particularly calibrated, thus supporting the general validity of the proposed $q_{bl}^*$.

\[ T_{\text{core}} - T_{\text{skin}} \]

**Figure 2.8:** The performance of the model during the schedule with extremely hot stage (reported in Fiala et al. [83]) demonstrated in skin temperature (top) and evaporation heat loss (bottom) dynamics. Values if evaporation heat loss can considered as direct proxy for sweating rate.

To investigate the performance of the model in cold environments, additional data is required since shivering will play a significant role for thermal sensation and comfort in such cases. Shivering is described by eq. 2.22. Unfortunately this equation has counter intuitive implications if any or both of signals $S_{\text{core}}^-$ and $S_{\text{skin}}^-$ fall into the range $(-1; 0)$. Alternatively we could use
the shivering description used by Fiala et al. [83]. This however falls outside the scope of this study.

It is worth discussing core-skin blood flow values as they have proven to be crucial for the dynamics of the model. For thermally neutral environments the absolute values of $q_{bl}$, calculated in the current model (see Figure 2.4b), are 2.8 times larger than those reported in [103, 97, 95] (12.22, 13.49 and 10.6 $l \cdot hr^{-1}$ respectively). A possible explanation for this can be that the first stage in Munir’s temperature schedule is not a thermally neutral environment (as is required by the model and its parameters). In fact the core temperature slightly exceeds the level of the core signal $T^*_{core}$ and once this is multiplied by $c_{dil}$, we see a significant increases in the level of $q_{bl}$.

The two-node model, which was developed initially for uniform and steady indoor thermal environments, can be applied to dynamic outdoor thermal environments. Even if aspects of the outdoor environment, such as localised direct solar radiation or variable wind flow patterns creating non-uniform heating or cooling of the body, can be taken into account by the currently existing models, then still we are faced with significant experimental uncertainties in obtaining those parameters. The required accurate reproducible measurements needed do not exist at this point in time. This is part of ongoing research in many laboratories.

2.6 Conclusions

Studies of outdoor thermal comfort (OTC) must account for the dynamic nature of the urban microclimate and the physical activity of the subjects. The accuracy of physiological models used for OTC studies should be evaluated not only in equilibrium steady-state conditions, but also in dynamical situations. In this chapter we evaluated and extended the dynamical properties of Gagge’s classical model to understand whether the model is appropriate for dynamic assessment of OTC, or whether more sophisticated and computationally expensive models are required.

We provided a detailed specifications of the model parameter values and variable ranges found in literature. A system dynamics representation of the
model, in terms of stocks and flows of energy, gives a highly intuitive understanding of the principles of thermal regulation in the human body and causal relations between climatic, individual and physiological parameters. Implementation of the system dynamics model allows for further exploration of feedback loops and dynamic behaviour of parameters in various scenarios.

Comparing the two-node model with the standard set of parameters and dynamics reported in an empirical study [103] demonstrates discrepancies in the dynamical behaviour of skin temperature. After analysing the model structure, the skin blood flow of the model is identified as the most probable cause of this discrepancy. Optimising the model with parameters of skin blood flow varying within ranges found in literature improves the dynamics. This improvement shows a reduction in RMSE between simulation and empirical data by 17%. The maximum absolute error remains $> 1.3^\circ C$ (Figure 2.4a). Allowing variation in the neutral blood flow results in a new equation for the core-skin blood flow shown in eq. 2.45, RMSE reduction of 73% and the maximum absolute error reduced to $0.63^\circ C$, which is nearly a fourfold improvement in the dynamic behaviour.

$$q_{bl} = \frac{10.7 + 50 \cdot S_{core}^+}{1 - 0.1 \cdot S_{skin}^-} \left[ \frac{l}{hr \cdot m^2} \right]$$

(2.45)

The resulting values of core-skin blood flow are within the standard ranges, this suggests that the modification of neutral skin blood flow is appropriate. Comparing the result of the presented two-node model to results of other multi-node and multi-part models for the same scenario, indicates that highly improved dynamics of skin temperature can be achieved. Due to the unavailability of data the model still requires validation for cold environments.

We have shown that optimised core-skin blood flow allows to accurately reproduce the dynamics, which makes the model amenable for OTC studies, such as: implementation of dynamic Physiologically Equivalent Temperature calculation, investigation of adaptation strategies efficiency and agent-based modelling discussed in Chapter 3, implementation of accumulated heat stress measure used in Chapter 4. The developed system dynamics model can be easily modified to improve, for example, the prediction of individual thermophysiological response, by including parameters of body composition, fitness,
gender and age [122].
Chapter 3

Models of pedestrian adaptive behaviour in hot outdoor spaces

Thermal perception is the level of human response in-between physiology and behaviour. It plays the central role in the process of OTC, as comfort is a perceptual concept. It also drives the response at the behavioural level and in the end, overall human response to thermal environments is determined by the level of perceived thermal comfort. Influenced by physiology, but also by environmental and personal psychological parameters, thermal perception is a complex and currently poorly understood process. In this chapter we suggest the use of an instantaneous thermophysiological index, which can be calculated with our physiological model, to approximate the level of comfort. The deviation of this dynamic index from comfortable range is then proposed as a driver of behavioural adaptation. We use this driver to formulate several models of pedestrian adaptive behaviour. Two of these behaviours are experimentally and computationally studied in subsequent chapters. This chapter plays an important role in connecting individual levels of human response to thermal environments into coordinated multi-level response.

This chapter is based on Melnikov, V., Krzhizhanovskaya, V. V., & Sloot, P. M. A. (2017). Models of pedestrian adaptive behaviour in hot outdoor public spaces. Procedia Computer Science, 108, 185-194.
Abstract

Current studies of outdoor thermal comfort are limited to calculating thermal indices or interviewing people. The first method does not take into account the way people use the urban space, whereas the second one is limited to one particular study area. Simulating people’s thermal perception along with their activities in public urban spaces will help architects and city planners to test their concepts and to design smarter and more liveable cities. In this chapter, we propose an agent-based modelling approach to simulate people’s adaptive behaviour in space. Two levels of pedestrian behaviour are considered: reactive and proactive, and three types of thermal adaptive behaviour of pedestrians are modelled with single-agent scenarios: speed adaptation, thermal attraction/repulsion and vision-motivated route alternation. An "accumulated heat stress" parameter of the agent is calculated during the simulation, and pedestrian behaviour is analysed in terms of its ability to reduce the accumulated heat stress. This work is the first step towards the "human component" in urban microclimate simulation systems. We used simulations to drive the design of real-life experiments, which will help calibrating model parameters, such as the heat-speed response, thermal sensitivity and perceived cost of walking under the sun.

3.1 Introduction

Two thirds of the world population are predicted to live in urban areas by 2050, adding more than 2.5 billion people living in cities. 90% of this growth is projected to be in Africa and Asia with tropical and subtropical (hot and humid) climate \[3\]. Outdoor thermal comfort is therefore critically important for urban studies. A prolonged exposure to the stressful heat is not just an uncomfortable experience, but a severe threat to human health and even life. One of the sad examples is the heat wave in Europe in 2003, which caused more than 70,000 deaths due to the heat-related causes like a stroke or acute hypertension \[123\]. This makes the governments and scientists all over the world to work on mitigation of the difference in temperatures between urban and surrounding rural areas, also known as "urban heat island" (UHI)
3.1. Introduction

This difference can reach 15 °C (degree Celsius) in extreme weather and geographical locations like Athens [124].

Singapore is a highly-urbanised city-state situated in South East Asia, with very high annual average temperature of 27 °C and humidity of 84% [125]. According to [126], the UHI in Singapore reaches 7 °C in the season of south-west monsoons. Such an enormous amount of extra heat produced and captured by the city is a challenge in protecting people’s health and lives, as well as in sustainable city development. People’s thermal comfort is more vulnerable in outdoor spaces, where they are exposed to solar and reflected radiation and have very few opportunities for cooling. Current research in Outdoor Thermal Comfort (OTC) investigates public spaces as an interaction of two components: climate and built environment. This is usually done by calculating the distribution of thermal comfort indices, such as PET (Physiologically Equivalent Temperature) [71] or UTCI (Universal Thermal Comfort Index) [72]. These indices use air temperature, humidity, wind speed and mean radiant temperature to calculate the OTC as a "feels-like" temperature in a reference indoor environment. Software packages such as RayMan [67] or Solweig [66] allow to perform simulations of urban spaces and calculation of these indices. There are very few studies though that analysed the influence of anthropogenic heat and urban design on microclimate and individual perception of thermal comfort, with the goal of developing the guidelines for designing more thermally comfortable urban spaces.

Some projects studied thermal comfort in urban spaces in different climates, including a Nordic city [127], hot and humid Taiwan [128], and Mediterranean [129]. Combining the measurements of climate parameters with interviews of people, these studies gained a good insight into the factors influencing thermal perception and behaviour. They analysed space use and human behaviour based on discrete choice of actions, but did not create a generic simulation framework for modelling other places and testing different scenarios. Several studies took into account real pedestrian flows, for example the authors of [130] proposed a data-driven navigation application for minimisation of pedestrian exposure to stressful heat. It however does not model the climate or pedestrian behaviour in urban areas. In [131] the authors modelled pedestrian flows in Switzerland and Singapore, and investigated the impact
of pollution on pedestrian health. However, thermal environmental parameters were not considered. This chapter aims to formulate human component of the design-simulation framework for assessing existing urban spaces and new urban designs in terms of outdoor thermal comfort. The ultimate goal of such framework is to assist architects and urban planners in formulating the principles of thermally comfortable urban design. The OTC simulation platform would include three components: City, Climate, and People (see Figure 3.1). The detailed City and Climate models \cite{68} take into account heat exhaust from air conditioners and vehicles, and calculate precise distribution of all climatic parameters in space and time. The third critical component, modelling human response, is the topic of our research. This component will allow us to analyse urban space as a place used, perceived and experienced by people. This modelling component takes into account the space function (e.g. sports, dining, or transit), travel demand, people movement, thermal physiology, perception and behaviour in space. Finally, we will be able to formulate a measure of outdoor thermal comfort for public spaces as perceived by people. This builds a connection between physiological and behavioural levels of response to thermal environments through thermal perception. Here we consider perception of instantaneous thermophysiological state (i.e. level of thermal comfort) as a driver of thermoregulatory behaviour of pedestrians. We hypothesise several types of such behaviour and use the thermal perception driver to formulate the models for these behaviours, and demonstrate the
first simulation results in three single-agent scenarios. The chapter is organised as follows: Section 3.2 reviews the basic principles of thermal adaptation and levels of human behaviour, Section 3.3 describes our models of thermal adaptive human behaviour, Section 3.4 demonstrates simulation results, and Section 3.5 concludes the chapter.

### 3.2 Adaptive behaviour overview

An adaptation of people to the environment is found everywhere. The most obvious is navigation in space: obstacles and collision avoidance. Other examples of people’s adaptive behaviour are hiding from the rain under the trees or going to the green parks on a sunny day. In this chapter, we consider thermal adaptation of people in hot and wet climate, i.e. adjustments made by the people in their normal outdoors behaviour to reduce exposure to heat.

#### 3.2.1 Thermal adaptation

People can adapt to the thermal environment in many different ways, which are usually classified into physical adaptation (implying change in behaviour) and physiological adaptation (implying change in physiological thermoregulation [86]). Adaptive behaviour is therefore a physical adaptation, which can be reactive (adapting to the environment) and interactive (adaptation of the environment). Interactive adaptation is almost absent in outdoor environments, unlike indoors, because urban environment rarely allows modification. Clothing and physiological metabolic adaptation to heat are not considered here, because these types of adaptation are inherent to the climate and are restricted in variation while people perform their activities in a particular space. The remaining type of physical adaptation is spatial variation, which therefore is the main objective of this study.

Authors of [86, 87] demonstrate that psychological adaptation of people to outdoor spaces influences significantly their thermal perception of space and is governed by such factors as naturalness, expectations, time of exposure and perceived control. In the studies of outdoor spaces in Cambridge, it was found that the percentage of dissatisfied people was 7 times less than predicted by
the Predicted Mean Vote technique (13% found versus 91% predicted). That tells that psychological factors shall be taken into account in assessing thermal comfort in outdoor environments.

3.2.2 Levels and models of pedestrian behaviour

Pedestrian behaviour is usually classified in 3 levels: strategic, tactical and operational [132]. In the strategic level, pedestrians decide on their goals and activities. In the tactical level, they plan locations and schedule activities. In the operational level, they perform the actual transition between locations. According to this classification, our study is considering pedestrian behaviour on operational level, assuming that the selected goals and schedules bring pedestrians into the studied urban areas. Assessment of public spaces in terms of their thermal comfort for activities different from walking, i.e. implementation of strategic and tactical behaviour levels is the topic of our future work.

We distinguish between two sub-levels within the operational level: the reactive and proactive level, similar to those from the general classification of animal behaviour [133]. Reactive behaviour (also known as steering behaviour [134]) responds to the movement in space, while complying with a set of rules, such as path following, collision avoidance, cohesion, alignment, etc. The proactive level is responsible for planning and motivated travel decisions. In this chapter, it is restricted to the route choice. Table 3.1 describes the levels of pedestrian behaviour we consider and the models traditionally used to simulate this behaviour.

3.3 Models of pedestrian thermal adaptive behaviour

We model three hypothesised ways of pedestrian thermal adaptation: speed adaptation, thermal attraction/repulsion and vision-motivated route alternation. These models are based on general knowledge of human behaviour and on experimentally observed effects. Here we assume that instantaneous value of the thermophysiolocal index (such as PET [71]) is calculated (e.g. with physiological model reported in Chapter 2) for an agent. We then model the
Table 3.1: Levels of pedestrian behaviour and corresponding models.

<table>
<thead>
<tr>
<th>Behaviour level</th>
<th>Behaviour activities</th>
<th>Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proactive</td>
<td>Route choice and dynamic update (negotiating obstacles, cost minimisation)</td>
<td>Path finding algorithms (Dijkstra, A*) with custom cost functions and heuristics Vision models</td>
</tr>
<tr>
<td>Reactive</td>
<td>Path following</td>
<td>Rule based [134], Social Force Model [136], Reciprocal Velocity Obstacles (RVO) [137]</td>
</tr>
<tr>
<td></td>
<td>Collision avoidance</td>
<td></td>
</tr>
</tbody>
</table>

perceptual response to thermophysiological state as a deviation of this index from the range of values perceived as comfortable by a particular agent. We leave the determination of individualised comfortable ranges of thermophysiological index outside the scope of this thesis due to inability of currently limited knowledge of thermal perception to inform the computational models. Our perceptual model reflects the amount of thermal discomfort, which is driving the behaviour proposed in the following subsections. These behavioural models are then incorporated into the agent-based simulations, where we used the Reciprocal Velocity Obstacles (RVO) model for agent navigation and collision avoidance [137]. The RVO2 library was employed, as it allows velocity vector updates at every time step. The behavioural model rules are therefore used to re-calculate the agent’s velocity vector, which is then passed on to the RVO simulation engine.

3.3.1 Speed adaptation model

Walking speed is affected by several factors of the environment, such as crowd density, surface slope, gender, age and even music playing in the person’s earphones [138]. According to an extensive study of walking speed factors [139], an increase of speed was observed not only while people go down the slope but also up the slope, which brings us to conclusion that people speed up to pass the stressing/disrupting areas faster. This conclusion is supported by a study performed in Canada [140], where significantly higher walking speeds
were observed at -15ºC, compared to those observed at 15ºC (1.43 m/s versus 1.23 m/s). For temperatures above 15ºC, the speed slightly increased again, to 1.28 m/s at 25ºC. People walk faster at temperatures outside their comfortable range, to escape the uncomfortable area as soon as possible. The exact values of mean and variance of walking speeds in Singapore are reported in Chapter 4. Here we assume the following values: $V_{\text{conf}} = 1.2 \text{ m/s (4.3 km/hour)}$, $V_{\text{max}} = 1.65 \text{ m/s (5.9 km/hour)}$. The upper bound of comfortable feels-like temperature $\text{PET}_{\text{conf}} = 28ºC$.

We define an adaptive walking speed as a function of experienced PET, where the speed linearly grows from $V_{\text{conf}}$ to $V_{\text{max}}$ as PET exceeds the comfortable value $\text{PET}_{\text{conf}}$. In this study, only hot climate is modelled, therefore cold temperatures are not considered. To avoid unrealistically high accelerations, the acceleration/deceleration rates are restricted to 0.1 $m/s^2$ per time step.

$$V_{\text{adapt}}(\text{PET}) = V_{\text{conf}} + \delta_{\text{PET}}(V_{\text{max}} - V_{\text{conf}}), \text{ where}$$

$$\delta_{\text{PET}} = \begin{cases} 
\frac{\text{PET} - \text{PET}_{\text{conf}}}{\text{PET}_{\text{max}} - \text{PET}_{\text{conf}}}, & \text{if PET > PET}_{\text{conf}} \\
0, & \text{otherwise}
\end{cases} \quad (3.1)$$

### 3.3.2 Reactive thermal attraction model

Perceived air temperature can vary in space with no obvious visual signals, such as shade, trees or water bodies. It may be due to the winds, drafts or air-conditioning (both cool air and hot exhausts from the cooling units). People sense temperature by their skin receptors and accurately estimate spatial gradients (e.g. it is cooler to the left). This ability to perceive temperature difference is surprisingly precise: as shown in [141], humans can sense a difference of 0.005ºC by arm, and even smaller difference by forehead. This perceived difference can motivate pedestrians to deviate from a straight pathway towards a cooler area. This will result in a curved path, different from the shortest line. The shape of this curve is governed by 4 parameters: sensitivity for thermal stimulus, current thermal comfort, admissible deviation angle, and sensation radius (approximately a half of the shoulder width). To implement
this reactive thermal attraction, we assume that pedestrians can sense PET by their arms at the side of the body, or 0.4 m to the left and to the right from the agent movement direction (PET_{left} and PET_{right}). The agent then compares it to the currently experienced PET in the centre and deviates from the direct trajectory by an angle \( \alpha(t) \) according to a stimulus value \( \beta_{PET}(t) \) and sensitivity to the thermal stimulus \( \theta \):

\[
\alpha(t) = \alpha_{\max} \frac{\beta_{PET}(t)}{\theta}, \quad \text{where}
\]

\[
\beta_{PET}(t) = \begin{cases} 
-\beta_{right}, & \text{if } \beta_{right} > \beta_{left} \text{ and } \beta_{PET}(t) \leq \theta \\
\beta_{left}, & \text{otherwise}
\end{cases}
\]

\[
\beta_{left} = \begin{cases} 
PET(t) - PET_{left}, & \text{if } PET(t) > PET_{comf} \text{ and } PET(t) \geq PET_{left} \\
0, & \text{otherwise}
\end{cases}
\]

\[
\beta_{right} = \begin{cases} 
PET(t) - PET_{right}, & \text{if } PET(t) > PET_{comf} \text{ and } PET(t) \geq PET_{right} \\
0, & \text{otherwise}
\end{cases}
\]

(3.2)

### 3.3.3 Proactive vision-motivated route planning model

At the proactive level, pedestrians may recalculate the cost of possible future paths based on the new factors encountered \(^{142}\). These factors influencing the travel cost are obstacles, crowdedness or even attractive shops \(^{143}\). From different studies \(^{144}\) it follows that visible thermal properties of space, such as sun/shade or greenery, are factors taken into account by pedestrians while evaluating the path attractiveness. Parameters governing the choice of a modified route are the current thermal comfort, expected thermal stress costs of travelling along the shortest but hot path, and expected travel time/distance cost of a detour from the shortest path along a more attractive route. We model this type of behaviour as vision-based cost estimation. Given the current goal, an agent looks to the left and right within a certain angle \( \omega \) (see Figure 3.2). This angle depends on the current thermal comfort (or how urgent it is to cool down). Then the region of possible paths is processed by the agent and alternative paths are weighted according to the personal cost function. This function depends on path length, ratios of route parts of certain
type (e.g. sun, shade, grass) and coefficients relating the cost of walking in this type of environment to the cost of walking in some reference conditions (e.g. shade). In case of only two types of visible thermal zones, e.g. sun and shade, we define $g$ to be the cost function dependent on path length $l$, ratio of a shady path $\alpha_{\text{shade}}$, and the cost multiplier of travelling a unit distance in the sun compared to travelling in shade, $c_{\text{sun}}$. Finally, an alternative path minimising the cost is selected and a new trajectory is planned.

$$g(\alpha_{\text{shade}}, c_{\text{sun}}, l) = l \cdot [\alpha_{\text{shade}} + c_{\text{sun}}(1 - \alpha_{\text{shade}})]$$  \hspace{1cm} (3.3)

![Figure 3.2: Proactive path planning: regions of searching for an optimal path at two different angles of vision $\omega$.](image)

### 3.3.4 Experience-motivated route alternation model

In our daily life, we are continuously gaining experience that helps us avoiding discomfort in the future. In addition to the simple vision-motivated decisions, people are building more complex decision chains based on their intelligence and memory. For example, if we need to go around a half of a building in a sunny day then we can easily predict which side of the building is shady before we actually see it. Or we may remember that one side can offer a nice tree canopy above the pathway. Or in the end of the day, after the sunset, we can calculate which side has been shady for the past few hours and is therefore cooler. To model this in the future, we will need also extra agent properties
3.4 Simulation results

To test the implementation of thermal adaptive behaviour rules integrated into the general walking behaviour, we designed 3 simple scenarios: reactive speed adaptation and thermal attraction, and proactive vision-motivated route planning.

3.4.1 Speed adaptation simulation results

For demonstration of the speed variation behaviour, we used a quasi-one-dimensional strip of 200 meters with 5 zones of different length with a varying value of PET. The agent is travelling from left to right, crossing these different thermal zones (see Figure 3.3). Agent’s PET thermal perception is updated to a new value instantaneously, i.e. the change from one value of PET to another is a step function. The results of speed adaptation are shown in Figure 3.3. The table inset shows that speed adaptation reduced the amount of accumulated heat stress by 20%, and the average is reduced only by 8% (because travel time reduced with the speed increase in hot areas).
Chapter 3. Models of pedestrian adaptive behaviour

3.4.2 Reactive thermal attraction simulation results

To demonstrate reactive adaptive behaviour, the following simulation setup is used: a two-dimensional area 200 m by 50 m, where PET increases linearly from 26 °C to 36 °C along the Y-direction (see Figure 3.4). Several agents are travelling from left to right from the same origin to the same destination (the shortest path would be parallel to X-axis). Agents feel the temperature 0.4 metre to the left and to the right and adjust their direction towards a cooler area. Parameters governing the resulting trajectory of agents are the maximum angle of deviation from direct path (\( \alpha_{\text{max}} \), degrees) and sensitivity to the cooling stimuli (\( \theta \)). Figure 3.4 shows how these parameters affect the curvature of the path. The longest path is taken by the agent with the largest deviation angle and highest sensitivity (smallest \( \theta \)). The table inset in Figure 3.4 shows that the accumulated heat stress of the agent with \( \alpha_{\text{max}} = 14^\circ \) and \( \theta = 0.05^\circ \text{C} \), is 83% lower than that of walking straight through the hot area. Adding speed adaptation to the direction change, further reduce the heat stress. As the agent deviates to a cooler place it uses less speed adaptation, thus contribution of speed adaptation in heat stress reduction is much less while combining two adaptive behaviours. Agents are responsive to cool stimulus only when they are experiencing temperature higher than comfortable; we can see that the red trajectory becomes parallel to X-axis once the agent reaches a comfortable PET\(_{\text{comf}} = 28^\circ \text{C} \). This trajectory also demonstrates the agent’s perception of heat: he is not returning to the destination until the very last moment, to minimise the heat stress.
3.4. Simulation results

3.4.3 Proactive route planning simulation results

Simulation of vision-motivated proactive path planning was performed in a rectangular environment of 200m by 100m. There are 3 shaded regions. For simplicity we assume that these shades are produced by sun screens installed in many pedestrian zones in Singapore. The rest is heated by the scorching sun. There are no obstacles, so the agents are free to choose any trajectory they consider optimal. Figure 3.5 demonstrates the pathways of agents with a plan to go from side to side (Figure 3.5, left) and from corner to corner (right). The smartest tactics is to go directly to the shade and move in it for as long as possible (that is, while it still lies within the region of possible paths). While building alternative paths, the agents consider each shaded region in their vision and calculate an optimal path within this shade. Then all possible combinations of up to 3 shades are evaluated by minimising the cost function. Finally, a path with the minimal cost is selected. Figure 3.5 demonstrates that for different origin-destination pairs as well as cost functions, different alternatives will be chosen. People in real life tend to keep some clearance from the edge of shade. This is taken into account in the model, and all alternative paths go with a 3-meter margin from the edge of shade. This parameter can be set different for individual pedestrians to create more variation in paths and to make them more realistic.
Chapter 3. Models of pedestrian adaptive behaviour

3.5 Conclusions and future work

Thermal comfort of outdoor environments should be analysed from the perspective of individual users of space, able to perceive environment thermally and to adapt to it both reactively and proactively. In this chapter we proposed four models of thermal adaptive behaviour of pedestrians driven by the instantaneous value of a thermophysiological index, which approximates thermal perception. Three of these adaptive strategies with various model parameters have been studied and evaluated in terms of the accumulated and average heat stresses. These numerical studies helped to design real-life experiments of human behaviour reported in Chapters 4 and 5.

The usage of the dynamic value of the thermophysiological index for each individual agent allows to obtain more realistic measure of thermal (dis)comfort (i.e. perception) of people, which in turn drives behavioural response. This measure accounts for individual characteristics like height, weight, metabolic rate, time of exposure and thermal history of that person. Integration of the thermophysiological model allows to formulate measure of accumulated heat stress and helps developing more precise behavioural models, e.g. taking into account the fact that speeding up increases internal heat production due to the higher metabolic energy production (see Chapter 4).

After coupling the pedestrian simulation engine with the other components of the design-simulation-loop tool, city planners can evaluate urban
spaces in terms of thermal comfort of people using those environments.
Chapter 4

The impact of pace of life on pedestrian heat stress

In the previous chapter several modes of behavioural adaptation to thermal environments were hypothesised. Adaptation of activity intensity, for example of speed of walking, can serve as an efficient form of thermal regulation through regulation of internal heat production. This chapter first investigates, computationally, the interaction of walking speed and thermal regulation with the use of the thermophysiological model reported in Chapter 2. Based on this investigation, we propose a concept of heat-stress-optimal walking speed. Secondly, we report an empirical study of walking speeds in Singapore, which reveals elevated average walking speed that does not change in response to variation in thermal conditions. This chapter demonstrates that a lack of behavioural adaptation leads to additional heat stress experienced by people in urban environments at a physiological level. This underlines the importance of studying OTC as a multi-level process describing the interaction between people and their thermal environment.

Abstract

Elevated walking speed is an indicator of increased pace of life in cities, caused by environmental pressures inherent to urban environments, which lead to

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This chapter is based on Melnikov, V. R., Krzhizhanovskaya, V. V., Lees, M. H., & Sloot, P. M. A. (2020). The impact of pace of life on pedestrian heat stress: A computational modelling approach. Environmental research, 109397.
short- and long-term consequences for health and well-being. In this chapter we investigate the effect of walking speed on heat stress. We define the heat-stress-optimal walking speed and estimate its values for a wide range of air temperatures with the use of computational modelling of metabolic heat production and thermal regulation. The heat-stress-optimal walking speed shows three distinct phases in relation to air temperature, determined by different modes of interaction between the environment and physiology. Simulation results suggest that different temperature regimes require walking speed adaptation to preserve heat balance. Empirical data collected for Singapore reveals elevated average walking speed, which is not responsive to slight changes in microclimate (4-5 °C). The proposed computational model predicts the amount of additional heat produced by an individual due to the high pace of life. We conclude that there are direct implications of the high pace of life in cities on the immediate heat stress of people, and we show how a lower walking speed significantly reduces self-overheating and improves thermal comfort.

4.1 Introduction

The ongoing process of global urbanisation [145] is the manifestation of cities as a pinnacle of social, economic and political organisation. The complex interaction of millions of people in the city results in economies of scale for more efficient wealth and innovation creation, use of infrastructure and provision of social services such as education and health care [15]. Urbanisation, however, also results in more people being exposed to urban environment stressors such as noise, pollution and crowdedness. As a result, human behaviour, being a function of the environment [146], changes to adapt to the urban pressures and pace of life [147]. The study of Bornstein & Bornstein [14] demonstrated that the logarithm of walking speed is linearly dependent on the logarithm of population size of 15 considered cities. This finding is now commonly considered as one of the urban scaling laws [15]. Later studies of the pace of life by Levine [16] confirmed high variation of average walking speed around the globe. Bornstein & Bornstein suggest that this phenomenon could
be the evidence of avoidance and withdrawal behaviour: “increased walking speeds serve to minimise environmental stimulation”. A recent study [9] has shown that urban noise causes significantly higher walking speeds in the same urban environment. Other personal [148] and environmental [149, 139, 150] parameters were found to also affect the walking speed. In this study we focus on the urban heat – a stressor of a growing concern due to the phenomena of climate change and urban heat island, which pose high risk to human health and well-being [151, 152]. We consider immediate physiological implications of walking speed variation — its effect on metabolic rate and thus internal heat production. In hot urban environments, the increased walking speed would imply that people are producing extra heat amplifying their heat stress. Similar effects have been shown in other research, for example, in the study of the effect of urban pollution on walking speed [153]. In that paper lower-than-usual walking speeds were suggested for walkers to minimise the uptake of pollutants in the body. Previous studies (e.g., [154] in Florida, US) have found a significant difference in walking speeds in between cool air-conditioned and warm outdoor environments, as well as in outdoor environments between cool and hot seasons. Remarkably, the difference in the thermal environment was reflected in the participants’ evaluation of sensation, but did not result in a difference in psychological arousal. The authors suggest that: "pedestrian tempo is ideally suited for identifying conditions under which individuals show little or no awareness of their actions". They also state that it is still necessary to determine why these differences in tempo are observed. In this chapter we study whether thermoregulatory processes of the human body, and behavioural adaptation to the thermal environment [155], can be the determinants of these walking speed variations.

Here we investigate walking speed and climate interaction by means of computational modelling. We combine our model of thermal regulation (see Chapter 2) with the model of energy cost of walking [156] to simulate a wide range of scenarios. We describe the complex interaction of walking speed, internal heat production and its dissipation to the environment. The simulations enable us to approach the phenomenon from two perspectives: to estimate the heat-stress-optimal walking speed for given climatic conditions; and
to evaluate heat stress implications of the pace-of-life in cities. We first demonstrate the dependency of heat-stress-optimal walking speed on thermal conditions and walking distance. We then present the results of our empirical study of walking speeds in Singapore and test them against the model predictions. Using the described models, we calculate the additional heat stress incurred by Singaporeans due to their urban lifestyle. We further discuss the empirical findings such as the effect of usage of smartphone or walking in a group on walking speed. We conclude the discussion with the analysis of simulation of self-overheating due to pace-of-life in 31 cities reported in Levine’s study.

The chapter is organised as follows: we describe the models in Section 4.2, we describe and analyse the computational study in Section 4.3, in Section 4.3.2 we describe the procedure and results of the walking speed experiment performed in Singapore. We discuss the results and implications of the computational and empirical studies in Section 4.4 and provide the conclusions in Section 4.5.

4.2 Methods

In this section we describe the models used to perform the simulations and analysis of optimal walking speeds in terms of heat balance: a model of heat production due to walking and a model of thermal regulation of the human body.

4.2.1 Model of human body thermal regulation

Our model of human body thermal regulation is based on the Gagge’s two-node model [100], with optimised parameters of core-skin blood flow we performed earlier [157]. This model with modified parameters reproduced accurately the dynamics of skin temperature and sweating in warm and hot microclimates. Figure 4.1 demonstrates how walking speed affects the components of the model.

Below we briefly describe key parameters affected by the phenomenon in the current study: walking in outdoor environments. A complete model can be found in [157].
4.2. Methods

The ratio of effective radiative area $\alpha_{rad}$ describes the fraction of body surface directly exposed to the environment and thus exchanging radiative energy with it. This parameter depends on the posture of a person [115], with values varying from 0.61 while sitting to 0.79 while standing with hands up. In our study, the value of $\alpha_{rad} = 0.72$ for a standing person is used.

Speed of walking directly affects the relative air velocity. In our simulations we assume a zero wind speed $v_w = 0 \text{ m/s}$, allowing the relative air velocity $v_a$ to be equal to walking speed ($v_a = V$). Relative air velocity determines the efficiency of convective and evaporative heat removal from the body. These dependencies are expressed in terms of convection and evaporation coefficients for respective heat flows. From several existing formulations of the convection coefficient [158, 159, 160], we chose the one based on experimental data [159]:

$$ h_c = 12.1 \cdot v_a^{0.404} \left[ \frac{W}{m^2 \cdot ^\circ C} \right]. \quad (4.1) $$

The convection coefficient influences evaporation coefficient as follows:

$$ h_e = \frac{L \cdot h_c}{1 + 0.92 \cdot I_{cl} \cdot h_c} \left[ \frac{W}{m^2 \cdot mmHg} \right], \quad (4.2) $$

where $L = 2.2$ is the Lewis relation and $I_{cl}$ is the level of clothing insulation described below.

Clothing plays an important role in regulation of heat exchange between the body and the environment. In our simulation scenarios we use the level
of clothing $I_{cl}$ appropriate for the climate, but not lower than 0.3 clo, which corresponds to a T-shirt, shorts and sandals [161]. Figure 4.2 demonstrates the appropriate level of clothing as a piecewise linear function of outdoor air temperature, which is adopted from an empirical study of Mediterranean climate in Rome [56].

![Figure 4.2: Linear function of appropriate to climate level of clothing used in simulation scenarios, adopted from [56].](image)

Internal heat production is a vital process of human body. The levels of heat production are often taken from reference tables for different types of activity (e.g. sitting, standing, walking). It is appropriate for approximate evaluation of thermal comfort, but not sufficiently accurate for the purpose of our study. An accurate model of internal heat production is described in the following section.

### 4.2.2 Model of internal heat production

The thermoregulatory model considers metabolic rate $M$ being transferred into mechanical work $W$ and heat, which is stored in the core of the body. For activities like sitting or standing the positive work is considered to be zero. However, a considerable amount of energy is spent on moving limbs and the core of the body while walking. It is important to mention that the ratio of positive work to metabolic rate is not constant for different walking speeds, thus models for both $M(V)$ and $W(V)$ are required to infer the amount of energy transferred into heating while walking. We derive the model of metabolic rate
4.2. Methods

$M(V)$ as polynomial fit of data reported for young adults of average age of 24 years, $n=6$ [162]. In that study, the metabolic energy production was estimated from oxygen consumption and carbon dioxide production measured with a portable telemetric system. The corresponding data and quadratic fit are shown in Figure 4.3.

![Figure 4.3: Dependency of total energy expenditure $M$, mechanical work $W$, and energy transferred into heat $H = M - W$ on walking speed $V$. Dots represent data points from [163] used to build models (shown by solid lines).](image)

We then define the metabolic rate $M(V)$ with the following expression:

$$M(V) = 3.16V^2 - 4.08V + 4.65 \quad [\text{W kg}^{-1}] \quad \forall \ V \in [0.5; 2.5] \text{ m/s} \quad (4.3)$$

We use the data reported in [163] to infer the rate of positive work performed during walking. The calculations were done for young adults (n=6) and include positive work of moving the center of body mass and mechanical work of moving limbs relative to the body measured with a force platform and cinematography. The data and resulting fit is shown in Figure 4.3. The model for $W$ is defined as follows:

$$W(V) = 0.57V^2 + 0.00V - 0.04 \quad [\text{W kg}^{-1}] \quad \forall \ V \in [0.5; 2.5] \text{ m/s} \quad (4.4)$$
By definition of energy transferred into heat we derive expression for $H$ as follows:

$$H(V) = M(V) - W(V) = 2.59V^2 - 4.08V + 4.69 \quad \forall \quad V \in [0.5; 2.5] \text{m/s}$$  \hfill (4.5)

### 4.2.3 Optimal walking speed

From the energy and mechanical work expressions (3)-(5), two values for optimal speed can be derived: First, the speed at which total energy expenditure per distance $M(V)/V$ is minimised and second, the speed maximising efficiency of mechanical work. Figure 4.4 presents the $M(V)/V$ plot, which takes its minimum at $V^*_E = 1.21 \text{m/s}$. This fact suggests that people are optimising the amount of energy spent per unit of distance walked, resulting in average speeds that are commonly observed. The efficiency of mechanical work during walking is defined as

$$\eta(V) = \frac{W(V)}{M(V) - M_{stand}} \quad [-] \quad \forall \quad V \in [0.5; 2.5] \text{m/s},$$  \hfill (4.6)

where $M_{stand} = 1.94\text{W/kg}$ is the metabolic rate while standing. This efficiency $\eta$ reflects the ratio of positive work to energy expenditure associated with walking activity. The resulting value of optimal walking speed $V^*_\eta = 1.40 \text{m/s}$ is higher than $V^*_E$, but is still within the range of reported values. However, the reference energy expenditure $M_{stand}$, on which efficiency depends, is chosen arbitrarily, therefore in our future analysis we will use a different value, given by the energy-expenditure-optimal walking speed $V^*_E = 1.21 \text{m/s}$.

### 4.2.4 Heat-stress-optimal walking speed

We introduce heat storage rate $S(t)$ as the left-hand side of a heat balance equation (eq. 4.7) which is equal to sum of all the energy fluxes coming to and from the human body: metabolic rate $M$, mechanical work $W$, shivering $Sh$, respiratory heating and humidification of inhaled air $Re$, convection $C$, evaporation $E$ and radiation $R$. The reader is referred to for a detailed
4.2. Methods

Figure 4.4: Optimal speeds defined as minimising the amount of energy spent per 1 meter walked $\frac{E_{\text{tot}}}{V}$ and as maximising the efficiency $\eta = \frac{W}{M(V) - M_{\text{stand}}}$. 

A description of these fluxes. At a given point in time the body may experience a particular heat storage rate, which leads to a positive heat gain. Our definition of heat storage (joules) considers the total heat gain over a fixed time period, so the integral of heat storage rate (watts) over some fixed time. The role of thermoregulatory system of the human body is to attain heat balance, i.e. reach the state of $S = 0$.

\[
S = M + Sh + Re + W + C + E + R \quad [W] \tag{4.7}
\]

Here the energy fluxes are not normalised to the body surface area, unlike presented in [157], to avoid confusion with the weight-normalised models of metabolic rate, mechanical work and heat production. Instead we calculate these components for a person with height of 1.8 meters, weight of 75 kilograms, and body surface area of 1.95 $m^2$.

We adopt the classical definition of stress as proposed by Selye [164]: "Stress is the nonspecific response of the body to any demand". We define heat stress as thermoregulatory response of the human body to a specific stimulus: this happens when the body experiences a non-zero heat storage for some period
Chapter 4. The impact of pace of life on pedestrian heat stress

of time (a non-zero integral). This definition implies that heat stress is proportional to heat storage, has polarity and magnitude. Thus, our definition differs from the standard definition of heat stress used in occupational health and safety literature, which considers heat stress as amount of heat storage that leads to disorders and disabilities in functioning of human body.

We then define heat-stress-optimal speed $V_{HS}^*$ as the one at which the absolute value of heat storage $|S_{d,V}|$ over distance $d$ is minimised, as this corresponds to the minimal thermal stress of a person. Thus:

$$V_{HS}^* = \arg\min_V |S_{d,V}| \left[ \frac{m}{s} \right],$$

where

$$S_{d,V} = \int_0^{t_V} S(t) dt \ [J]$$

$$t_V = \frac{d}{V} \ [s]$$

Figure 4.5 demonstrates the contributions of different terms into the total heat storage over a stretch of one kilometer in typical conditions of shaded outdoor area of Singapore for two walking speeds. As can be seen, previously found $V_E^* = 1.21 \ m/s$ promises a higher heat gain than $V = 1.0 \ m/s$ in this microclimate. In fact we later show that this walking speed corresponds to our definition of heat-stress-optimal walking speed $V_{HS}^*$ in this microclimate.

4.3 Results

4.3.1 Simulation results

Climate and heat-stress-optimal walking speed

In this subsection we investigate the behaviour of $V_{HS}^*$ as a function of microclimate.

We start with three scenarios of walking along a stretch of 1 kilometer in cool, neutral and warm thermal environments at $T_{air} = T_{MRT} = \{15, 22, 30\} ^\circ C$, where $T_{MRT}$ is mean radiant temperature. Here arbitrary microclimate conditions $T_{air} = T_{MRT}$ are used and can be regarded as a clouded or evening-time condition, when the temperature of surrounding surfaces is equal to air
4.3. Results

Figure 4.5: Simulated energy fluxes from and to human body at two different walking speeds. Heat storage rate $S(t)$ and total heat storage over the course of walking $S_{d,V}$ are shown.

We will investigate the impact of sun radiation and mean radiant temperature $T_{MRT}$ in the subsequent set of simulations. For each of the three microclimates, an appropriate level of clothing was assigned (see Section 4.2.1). Relative humidity (RH) was assumed 60%. Here and in the following simulations, we assume that people start walking with a thermoregulatory system in a steady state of $T_{core} = 36.85^\circ C$ and $T_{skin} = 33.89^\circ C$ achieved in static indoor environment ($T_{air} = T_{MRT} = 22^\circ C$, relative humidity 50%, wind speed 0.05 m/s, $I_{cl} = 1.0 \text{ clo}, M = 80 \text{ W/m}^2$).

The results are shown in Figure 4.6. For the cool environment, heat gain $S_{d,V}$ decreases with the decrease of walking speed, eventually crossing 0. This means that for walking speeds lower than optimal a loss of heat is expected. Recall that $V_{HS}^*$ is defined as the speed that produces the minimum absolute heat gain/loss, so in the left most plot of Figure 4.6 $V_{HS}^*$ is set to 1.28 m/s i.e., where $S_{d,V} = 0$.

We also observe an intuitive increase in $V_{HS}^*$ as the environment is changed from neutral to cool, this can be explained by a higher metabolic rate needed to compensate for higher rate of energy dissipation in the cold environment. A similar tendency is observed when switching to a warmer environment.
typical for Singapore. Here zero storage rate is not achievable: any walking speed will result in a heat gain. Walking speed minimising this gain is \( V_{HS}^* = 0.98 \, m/s \), which is higher than the value found for the neutral environment. This value of \( V_{HS}^* \) can be explained by the need to move slightly faster in the warm environment to enhance convection and reduce the time of exposure to heat.

![Figure 4.6: Dependency of heat gain \( S_{d,V} \) over the distance of 1 km on walking speed \( V \) in cool, neutral and warm thermal environments. \( V_{HS}^* \) is the heat-stress-optimal speed that provides heat balance or minimises heat gain (\( RH = 60\% \)).](image)

We continue our investigation of thermally comfortable optimal speeds with varying another important parameter of outdoor environments: radiation. This parameter is usually expressed in terms of mean radiant temperature (MRT) \( T_{MRT} \). Figure 4.7 demonstrates the results for three simulated scenarios corresponding to different levels of radiation: dense clouds (no sun), light clouds, and sunny day. The thermally comfortable walking speed \( V_{HS}^* \) grows with increasing sun radiation \( T_{MRT} \), reaching the value of 1.19 \( m/s \) for the scenario of exposure to a direct solar radiation. This is explained by the fact that as \( T_{MRT} \) increases there is an additional source of heating, which is not mitigated, but instead is worsened by lowering the walking speed. This is why the prevailing strategy for minimising the heat stress becomes minimisation of time of exposure by walking faster.

Figure 4.8 demonstrates the results of the computation of values of \( V_{HS}^* \) along a 1 kilometer stretch in a wide range of environmental conditions: from cool to very hot (\( T_{air} = T_{MRT}, RH = 60\% \)). It reveals that the minimum walking speed prescribed by minimal heat gain \( V_{HS}^* = 0.88 \, m/s \) is achieved at \( T_{air} = 20^\circ C \), suggesting that these microclimate conditions are the most
neutral in terms of human body thermal regulation, requiring no walking speed adaptation. As the environment shifts from $T_{air} = 20^\circ C$ to the colder or hotter temperatures, the walking speed adaptation is required to preserve the heat balance or minimise heat gain or heat loss. This agrees with the previous observations reported in \cite{154}. There the authors registered the minimum walking speed of 1.24 m/s at $T_{air} = 23.3^\circ C$ and higher walking speed of 1.52 m/s in cooler season with $T_{air} = 17.2^\circ C$ and in hotter season with $T_{air} \approx 29^\circ C$ (no exact value of walking speed is provided). The absolute values of walking speeds predicted by our physiological model and with our formulation of heat-stress-optimal walking speed, are however systematically lower. Energy-expenditure-optimal walking speed shown in Section 4.2.3, $V_{E^*} = 1.21 m/s$ corresponds to $V_{HS^*}$ for conditions of $T_{air} = 16^\circ C$.

Three segments of the curve can be distinguished in Figure 4.8a, each explained by a different regime of heat gain/loss regulation:

- $T_{air} < 20^\circ C$, where the $V_{HS^*}$ increases fast for colder air temperatures. This increase in walking speed is dictated by the need to produce additional energy to compensate for the heat loss in the environments cooler than $20^\circ C$. The form of this segment can be explained by the form of heat production curve $H(V)$ shown in Figure 4.3, it is a quadratic function of walking speed. This implies that at higher walking speeds a smaller increase of walking speed is required to attain heat gain, which

![Figure 4.7: Dependency of heat gain $S_{d,V}$ on walking speed $V$ and thermally comfortable optimal speed $V_{HS}$ in different levels of thermal radiation. $T_{air} = 30^\circ C, RH = 60\%, I_{cl} = 0.35 clo$](image)
Chapter 4. The impact of pace of life on pedestrian heat stress

Figure 4.8: (a) The dependency of heat-stress-optimal walking speed on the microclimate. (b) The heat gain curves for considered microclimates. Here the minimums of the curves correspond to the value of heat-stress-optimal walking speed in a given microclimate.

results in a higher growth rate of walking speed close to the transition point of 20°C.

- $T_{air} \in [20, 42]^\circ C$, where $V_{HS}^*$ increases almost linearly at the rate of $\approx 0.015 \frac{m \cdot s^{-1}}{K}$. In this range of microclimates the thermoregulatory system has the means to counterbalance the heat gain (primarily through sweating and evaporation of sweat), so the increase of walking speed (to enhance convection and evaporation and minimise time of exposure) is relatively slow.

- $T_{air} > 42^\circ C$, where the growth rate of $V_{HS}^*$ becomes nearly 4 times faster (\(\approx 0.06 \frac{m \cdot s^{-1}}{K}\)). At $T_{air} = 42^\circ C$, the value of skin wettedness reaches 1, so there is no more capacity for the thermoregulatory system to compensate for overheating through evaporation of sweat, therefore minimisation of time of exposure becomes the only way to reduce overheating.

The dashed lines in Figure 4.8a represent the levels of walking speed $V$ that would result in a certain amount of heat gain (lines above $V_{HS}^*$) or heat loss (lines below $V_{HS}^*$). We define several heat gain/loss bands in terms of kilojoules. For interpretability purposes, we also provide a rough estimate of skin temperature change $\Delta T_{skin}$ caused by this heat gain/loss, assuming that all the heat is gained/lost through the skin. Humans are very sensitive to skin temperature stimulation, and can feel the slightest change in skin temperature
of as low as $0.005^\circ C$ [165]. The bands shown in in Figure 4.8a correspond to those from almost undetectable to significant changes in $T_{\text{skin}}$.

Figure 4.8b demonstrates the curves of $S_{d,V}$ for the considered values of air temperature. It also shows how the bands are defined and corresponding range of $V$ is determined. In Figure 4.8a, we can see that the bands result in wider ranges of $V$ in the middle segment of the considered climate ($T_{\text{air}} \in [20, 42]^\circ C$). This is due to the fact that the left and right segments correspond to more thermally stressful conditions and thus less deviation of $V$ is needed for the considered heat gain/loss compared to the central segment. This implies that one should expect greater variation in walking speeds in more moderate climatic conditions (i.e. $T_{\text{air}} \in [20, 42]^\circ C$).

**Distance and heat-stress-optimal walking speed**

In this section we analyse whether the difference in walking distance in the same thermal environment suggests a different level of heat-stress-optimal walking speed. In all our scenarios a one kilometer walking distance is used, however, most of the walks performed in urban environments are significantly shorter. For example, the average walking distance in Singapore is 259 meters [166]. This, however, depends on the purpose of walking, and much longer walks are also possible. This is why we simulated the thermally comfortable walking speed for distances from 100 to 3000 meters for thermal environments ranging from cool ($15^\circ C$) to severely hot ($45^\circ C$), assuming $T_{MRT} = T_{\text{air}}$ for a clear comparison. The level of clothing appropriate to each thermal environment was used.

The results are shown in Figure 4.9. Figure 4.9a shows that the lowest walking speed of $V_{\text{HS}}^*$ is observed at temperature $T_{\text{air}} = 20^\circ C$, which is in agreement with Figure 4.4. As the environment diverges from neutral on both the cooler and hotter side, the level of thermally comfortable walking speed increases. As the walking distance increases, the optimal walking speed level tends to decrease. The optimal speed for 1 km distance in $T_{\text{air}} = 30^\circ C$ (found in Section 4.3.1) is 11% lower than the walking speed for a distance of 0.25 km (0.96 versus 1.08 m/s).
There is a difference in the shape between the curves for the $T_{\text{air}} = 40^\circ C$ and $T_{\text{air}} = 45^\circ C$, which requires further investigation. We provide simulation results performed for the range $T_{\text{air}} \in [40, 45]^\circ C$ with a step of one degree Celsius. The results shown in Figure 4.9b shows the relationship between heat-stress-optimal walking speed and distance. For all air temperatures two regimes can be observed, for short distances the optimal speed decreases rapidly (e.g., for $T_{\text{air}} = 45^\circ C$ going from 1.65 m/s to 1.4 m/s between 100 meters and 500 meters) then at some distance the speed decrease begins to happen more slowly (e.g., for $T_{\text{air}} = 45^\circ C$ at 500 meters the optimal speed is 1.4 m/s and 1.25 m/s at 3000 meters). Interestingly, the distance at which this change occurs varies for different air temperatures, for $T_{\text{air}} = 45^\circ C$ this happens at 500 meters whereas for $T_{\text{air}} = 42^\circ C$ this happens at 1500 meters. Interpreting this observation: walking speed reduction (i.e. reduction of internal heat production) is more efficient for shorter walking distances and more moderate thermal conditions as compared to longer distances and hotter environments.

4.3.2 Empirical results

We have performed an empirical study of walking speeds in Singapore, a city-state with hot and humid tropical climate and population exceeding 5
4.3. Results

millions. Singapore’s climate is characterised by low variation of air temperature with an annual mean of 27.5 °C, and high relative humidity with annual mean of 83.5%. Previous studies of walking speed in this city performed in 1984 estimated average walking speed to be 1.23 m/s. This result is in agreement with the 1999 Levine’s study of pace-of-life, which reported a value of 1.24 m/s.

Unlike in the previous studies, we have not studied a downtown area of the city, where other urban factors could impact thermal stimulation and could not be singled out. Instead, we chose a walk path leading to Lakeside MRT (subway) station situated in mostly residential area of the city. It is characterised by a straight clearly observable walking path of 30 meters long and 2 meters wide, so we consider movement is happening in 1 dimension along the pathway. The pedestrians were recorded on a video camera from a distance, so that their entrance and exit from the measurement region could be clearly identified.

All the recordings were taken for a duration of 30-40 minutes and started at around 17:00, so that the effect of diurnal variation of properties of pedestrian flows can be ruled out. Collecting data in the evening ensures that the samples representative of population are less affected by the time constraints people typically have in the morning. We took videos on three days characterised by different air temperatures, spanning a good range of temperatures typical for Singapore. Microclimate parameters were measured by a portable weather station Kestrel 5400 mounted on a tripod near the point of camera installation.

The entrance and exit events were later labeled manually by two researchers to derive the traversing time. The event of entrance and exit were defined as walker crossing the mark on the screen. The entrance time and exit time (in precision of second) of each participant were recorded, their difference was considered the traversing time. Walking speed was calculated by dividing the distance of 30 meters by the traversal time. All the pedestrians were labeled with the following attributes: direction (to or from the station), gender, age group by appearance (younger than 12, 12 to 18, 18 to 45, older than 45), level of clothing (short top and bottom, either of top or bottom is long, both top and
Figure 4.10: A frame from the video recording of experimental area. Red crosssections indicate the boundaries of the measured walking path. The distance between the two entrances is 30 meters.

bottom are long), usage of smartphone (binary), carrying excessive load (binary) and walking in a group (number of co-walkers, only one characteristic person from a group was considered). All the recorded walkers were considered, i.e. no subjective inclusion criteria were applied. Exclusion criteria were: people appearing performing activity other than walking (e.g. standing and looking around), people entering the area not from the defined ends of a stretch, people walking in a group (of which only one representative walker was recorded).

In our primary analysis we have included only those walkers appearing 12 to 45 years old, not carrying excessive load, not using smartphones, and not walking in a group. The results reported in Table 4.1 reveal that there is no significant difference in average walking speed between the days (here and hereafter we assume the statistical significance level of 0.05). Thus, we could not find a reactivity of the average walking speed to the change in microclimate conditions typical for Singapore’s climate in the range of \( T_{air} \in [27.5, 32.2] °C \), i.e. the change of up to \( \Delta T_{air} = 4.7 °C \).

A detailed analysis of experimental data is summarised in Table 4.2. Here we evaluate the influence of other factors on the variation of walking speed. We found no significant difference in walking speeds of people walking in two opposite directions, which suggests that people were experiencing comparable time pressure while going to and from the station. Walking speeds of walkers of different genders were significantly different considering all three
4.3. Results

Table 4.1: The results of measurement of average walking speeds on three days with different air temperatures. The results of pair-wise Welch’s t-test of samples demonstrate no significant difference in average walking speed on three considered dates.

<table>
<thead>
<tr>
<th>Date</th>
<th>( T_{\text{air}}, ^\circ \text{C} )</th>
<th>( \bar{V}, \text{m/s} )</th>
<th>N</th>
<th>Welch’s t-test, p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>22 Oct 2019</td>
<td>27.5</td>
<td>1.37</td>
<td>69</td>
<td>1</td>
</tr>
<tr>
<td>23 Oct 2019</td>
<td>29.8</td>
<td>1.32</td>
<td>60</td>
<td>1</td>
</tr>
<tr>
<td>7 Nov 2019</td>
<td>32.3</td>
<td>1.32</td>
<td>63</td>
<td>1</td>
</tr>
</tbody>
</table>

The results combined, but not each day individually. This observation agrees with the commonly observed higher walking speeds of males compared to females [167, 150, 139]. The use of smartphones and walking in groups significantly decreased the walking speed.

In the next section we discuss these empirical results in relation to the computational study reported earlier in this chapter.

Table 4.2: Results of statistical testing of several control parameters. Significantly lower average walking speeds are observed for pedestrians using smartphone or walking in groups, as well as for females compared to males.

<table>
<thead>
<tr>
<th>Date</th>
<th>( \bar{V}_A (N_A) )</th>
<th>( \bar{V}_B (N_B) )</th>
<th>p-value</th>
<th>( \bar{V}_A (N_A) )</th>
<th>( \bar{V}_B (N_B) )</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direction</td>
<td>Using smartphone</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>22 Oct 2019</td>
<td>1.45 (17)</td>
<td>1.35 (52)</td>
<td>0.061</td>
<td>1.25 (34)</td>
<td>1.37 (69)</td>
<td><strong>0.006</strong></td>
</tr>
<tr>
<td>23 Oct 2019</td>
<td>1.34 (22)</td>
<td>1.31 (38)</td>
<td>0.585</td>
<td>1.22 (20)</td>
<td>1.32 (60)</td>
<td><strong>0.021</strong></td>
</tr>
<tr>
<td>7 Nov 2019</td>
<td>1.37 (15)</td>
<td>1.31 (48)</td>
<td>0.222</td>
<td>1.18 (34)</td>
<td>1.32 (63)</td>
<td><strong>0.000</strong></td>
</tr>
<tr>
<td>All</td>
<td>1.38 (54)</td>
<td>1.33 (138)</td>
<td>0.054</td>
<td>1.21 (88)</td>
<td>1.34 (192)</td>
<td><strong>0.000</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>In a group</th>
<th>Gender</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>22 Oct 2019</td>
<td>1.05 (22)</td>
<td>1.37 (69)</td>
<td><strong>0.000</strong></td>
<td>1.42 (51)</td>
<td>1.25 (18)</td>
<td><strong>0.004</strong></td>
</tr>
<tr>
<td>23 Oct 2019</td>
<td>0.88 (11)</td>
<td>1.32 (60)</td>
<td><strong>0.047</strong></td>
<td>1.35 (37)</td>
<td>1.29 (23)</td>
<td>0.217</td>
</tr>
<tr>
<td>7 Nov 2019</td>
<td>1.17 (11)</td>
<td>1.32 (63)</td>
<td><strong>0.049</strong></td>
<td>1.33 (32)</td>
<td>1.32 (31)</td>
<td>0.738</td>
</tr>
<tr>
<td>All</td>
<td>1.04 (44)</td>
<td>1.34 (192)</td>
<td><strong>0.000</strong></td>
<td>1.37 (120)</td>
<td>1.29 (72)</td>
<td><strong>0.004</strong></td>
</tr>
</tbody>
</table>
4.4 Discussion

The computational study reported in Section 4.3 has the following implications:

1. Energy-expenditure-optimal walking speed is estimated to be $V_E^* = 1.21 \, \text{m/s}$ and is essentially independent of the environmental conditions.

2. Heat-stress-optimal walking speed is predicted to be dependent on climate and walking distance.

4.4.1 Heat stress implications of observed walking speeds

The results of our empirical studies demonstrated that in the range of air temperatures between 27.5 and 32.2 $\degree C$ average walking speeds do not differ significantly, averaging to 1.34 m/s, with a 95% confidence interval of [1.315, 1.368] m/s. This observation contradicts the expectation that walking speed is determined by process of optimisation for certain parameters:

1. The observed walking speed is considerably (10%) higher than the one found to be energy-expenditure-optimal. This finding can serve as a proof of increased pace-of-life in Singapore: the urban environment dictates parameters, other than internal energy expenditure, for people to optimise for. Thus the Singaporeans pay some energy costs in order to maintain the city’s pace of life. Remarkably, the value of average walking speed in our experimental study in a mostly residential area of Singapore are considerably higher (by nearly 10%) than those obtained in a busy downtown area in studies dating 1986 and 1999 [167, 16]. Thus, we can see an increase in the pace of life in Singapore in the 21st century.

2. It is unlikely that the microclimate parameter of the urban environment is the one optimised for by Singaporeans. Not only are the observed values much higher than the ones predicted by heat-stress-optimal walking speed, but they also do not demonstrate the responsiveness to variation in microclimate, contrary to the prediction of our computational models.
The latter implies that there is a considerable amount of additional heat stress taken by each person individually. The computational models described earlier in this chapter can quantitatively estimate the amount of this additional heat stress for the observed environmental parameters. The results are provided in Table 4.3. We see that indeed the observed average walking speeds are higher than the heat-stress-optimal walking speeds, but for the hottest conditions (on 7 November 2019) $V_{HS}^* = 1.23 \text{ m/s}$:

- is much higher than for the other two days;
- is closer to our observed experimental value of $V = 1.34 \text{ m/s}$;
- is close to values found for average walking speeds of Singapore reported in 1986 and 1999;
- is very close to energy-expenditure-optimal walking speed ($V_{E}^* = 1.21 \text{ m/s}$).

The consequences of these elevated average walking speeds in terms of additional increase of skin temperature $\Delta T_{skin}$ are also provided in Table 4.3. We see that on the hottest day they were the lowest and relatively neglectable, whereas on two cooler days they can be considered as significant overheating. Another, seemingly counter-intuitive, observation is that hotter weather leads to less heat gained additionally due to the high walking speed. This is due to the fact that at the higher temperatures higher walking speeds are prescribed as heat-stress-optimal, so while absolute heat gains rise with the temperature, they become more influenced by exposure to the environment, rather than overheating due to selected walking speed. In other words, the hotter the environment is, the smaller is the contribution of the pace of life to the heat stress.

### 4.4.2 Walking speed variation and factors affecting it

The fact that we did not observe the sensitivity of walking speed to the changes in air temperatures can be explained by the very tight range of considered temperatures. We can suggest that the behavioural adaptation of walking speed does not have a linear response curve (as follows from simulation of our physiological model), but rather has a step or sigmoidal form found in other
Chapter 4. The impact of pace of life on pedestrian heat stress

Table 4.3: Comparison of experimentally observed average walking speeds $V$ and heat-stress-optimal $V_{HS}^{*}$. The computationally estimated quantities (5 right-most columns) assume walking distance $d = 500$ meters (approximate distance between subway station and surrounding residential buildings) and outer body compartment (skin) mass of 7.5 kg.

<table>
<thead>
<tr>
<th>Date</th>
<th>$T_{\text{air}}$</th>
<th>$T_{\text{MRT}}$</th>
<th>RH</th>
<th>$V$</th>
<th>$V_{HS}^{*}$</th>
<th>$S_{d,V}$</th>
<th>$S_{d,V_{HS}^{*}}$</th>
<th>$\Delta S_{d,V}$</th>
<th>$\Delta T_{\text{skin}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>22 Oct 2019</td>
<td>27.5</td>
<td>35.7</td>
<td>81.6</td>
<td>1.37</td>
<td>1.07</td>
<td>48.52</td>
<td>43.55</td>
<td>4.98</td>
<td>0.191</td>
</tr>
<tr>
<td>23 Oct 2019</td>
<td>29.8</td>
<td>34.7</td>
<td>74.3</td>
<td>1.32</td>
<td>1.08</td>
<td>52.39</td>
<td>49.27</td>
<td>3.12</td>
<td>0.120</td>
</tr>
<tr>
<td>7 Nov 2019</td>
<td>32.3</td>
<td>49.0</td>
<td>62.3</td>
<td>1.32</td>
<td>1.23</td>
<td>76.97</td>
<td>76.54</td>
<td>0.43</td>
<td>0.017</td>
</tr>
</tbody>
</table>

Studies [168, 169]. This implies that should a certain threshold be reached, a critical transition may happen, leading to the behavioural adaptation by means of changing the walking speed. We hypothesise that in Singapore the difference could be observed when comparing sun and shade conditions. We plan to test this hypothesis in the upcoming experimental study.

In this chapter, we observed the adaptation of walking speed to rather discrete conditions: usage of a smartphone and walking in a group (see Table 4.2). Average walking speed of those using smartphone was found to be $V_{SP} = 1.21 \ m/s$ – strikingly equal to the energy-expenditure-optimal walking speed $V_{E}^{*} = 1.21 \ m/s$. We can hypothesise that the extra cognitive load of being engaged in interaction with smartphone leads to a cutoff of the environmental stimulation and, as a consequence, to the physiologically optimal walking speed unaffected by the pace of life. Analogously, interaction with others while walking in a group brings average walking speed even lower to the level of $V_{G} = 1.04 \ m/s$. As our physiological simulations predict heat-stress-optimal walking speed to be in general lower than usually observed for normal walkers (see Figure 4.8b), we can speculate that, for a wide range of warm microclimates, external cognitive load, such as phone usage or walking in a group, may compensate for the pace-of-life pressures and result in an improved thermophysiological experience.
4.4.3 Heat stress due to the high pace of life

We have performed the simulation of heat gain during walking for the 31 countries reported in the pace-of-life study of Levine [16]. We considered the typical walking distance for all the countries to be 500 meters. We assigned air temperature of a city equal to the annual average high temperature reported on the Wikipedia pages of the cities. We assumed $T_{MRT} = T_{air}$, relative humidity of 60%, and clothing level appropriate to the air temperature. The data of temperature and walking speed is presented in Figure 4.11a.

For each of the city we calculated the heat-stress-optimal walking speed $V_{HS}^*$ and corresponding heat gain $S_{d,V_{HS}^*}$. Additionally we calculated the pace-of-life heat gain $S_{d,V_{PoL}}$ resulting from walking with a speed observed by Levine for a given city. The difference $\Delta S = S_{d,V_{PoL}} - S_{d,V_{HS}^*}$ can then be considered a heat stress of citizens of a particular city attributable to the pace of life in this city. The results are presented in Figure 4.11b. It follows from simulation that Austria’s and Brazil’s pace of life has no effect on heat stress; countries like Romania or Bulgaria have relatively low walking speeds, resulting in a cold stress; whereas the pace of life in Japan has the most pronounced effect on additional heat stress resulting in almost $0.8^\circ C$ of additional increase in skin temperature.

The computational model used in our study has been shown to accurately reproduce the dynamics of skin temperature and evaporation of sweat in a wide range of air temperatures of $[20, 48]^\circ C$. Exact values of quantities reported in this study are bound to a model-specific assumptions and simplifications (such as average person assumption). This implies that while comparative analysis of scenarios using the model is a valid approach, the estimated absolute quantities can have a discrepancy with the real-life measurements of individual people or scenarios.

4.5 Conclusions

Increased pace of life is an intrinsic characteristic of big cities. It contributes to the city efficiency in economic and social development. On the other hand, it causes a constant stress in our experience of urban environments. One of
the main evidences of increased pace of life is the increased average walking speed in cities, which was shown to scale with the city size.

In this work we studied the heat stress implications of increased walking speeds – a critical issue in conditions of global urbanisation and climate change. We described the computational model of complex interaction between the thermal environment, human physiology and walking speed. We defined the heat-stress-optimal walking speed $V_{HS}^*$ as the one minimising heat gain or loss in a given thermal environment on a given distance. Simulating walking scenarios for a wide range of air temperatures, we found that one should employ behavioural adaptation of walking speed if optimising for thermal comfort (see Figure 4.8a). Heat-stress-optimal walking speed takes its minimum of 0.88 m/s in most thermally neutral environment of air temperature around $20^\circ C$. It rises rapidly as the environment becomes colder, because the increased internal heat production due to faster walking is the only mechanism of compensation for the heat loss. Heat-stress-optimal walking speed increases more moderately in warmer environments, as there are thermoregulatory mechanisms to cope with heat load that make minimisation of time of exposure due to faster walking a secondary heat mitigation mechanism. Minimisation of time of exposure becomes the primary means of the heat gain minimisation, and $V_{HS}^*$ grows fast in air temperatures above $42^\circ C$, because the thermoregulatory mechanisms (evaporation of sweat) reach their capacity.

**Figure 4.11:** Results of simulation of 31 country of pace-of-life study [16].
4.5. Conclusions

We then applied the developed models to investigate the implications of Singaporean pace of life for the thermal experience of its citizens. The results of empirical measurements showed stable average walking speed of 1.34 m/s, which is not responsive to the change of air temperature in a range typical for Singapore [27.5; 32.2] °C. This observation brings us to the conclusion that:

1. Citizens of Singapore do not employ walking speed adaptation as the means of behavioural response to slight change in thermal environment.

2. Singapore has an increased pace of life in terms of walking speed, which grew by approximately 10% since the studies reported in 1986 and 1999.

Modelling results for heat gain in measured conditions of Singapore show that the increased walking speed results in a significant additional heat load in relatively cooler conditions (27.5 and 29.8 °C). As environment becomes hotter, less and less heat stress can be attributed to the increased pace of life, since heat-stress-optimal speed for hotter environment is higher and closer to the empirically observed values of walking speed in Singapore.

For the example of Singapore, we have shown with the computational model, that the urban pace of life has an important implication for people’s well-being in hot climates: extra heat stress. Our study suggests that people should slow down to improve thermal comfort in warm and hot climates – a suggestion seemingly contradicting the ever growing pace of life. We have observed, however, that the use of smartphones or walking in a group slows down the walking speed to a level close to the thermally optimal – a remarkable example of how the overstimulating urban environment can be compensated for by social interaction.

In this chapter we find that behavioural adaptation of walking speed can help to reduce heat stress. Singapore citizens, however, do not exhibit this behaviour in response to air temperatures changing in the narrow range of Singapore’s climate and incur additional heat stress. In Chapter 5 we demonstrate how presence of another thermal parameter, sun exposure, induces a pronounced sun-avoidance behaviour through path choice.
Chapter 5

Empirical study and choice modelling of pedestrian sun avoidance behaviour

This chapter continues the investigation of behavioural response to thermal environments. While in the previous chapter we conducted and analysed an observational study, in this chapter we report results from our experiment with recruited participants aimed at confirming and measuring the sun-avoidance behaviour of people in outdoor thermal environments. This study confirms that pedestrians use behavioural adaptation to mitigate heat stress and are willing to take extra effort in terms of walking distance in order to avoid exposure to the sun. The chapter demonstrates the use of hierarchical probabilistic models to characterise path choices of people and to reveal their preferences towards shade. The model developed in this chapter and its estimated parameters can be directly used in prediction of human behaviour in response to outdoor heat. Moreover, the demonstrated experimental approach, novel to studies of pedestrian behaviour, can be translated into studies of human interaction with other environmental factors.

Abstract

Behavioural adaptation is the only strategy to adapt to the climate in a long run. Understanding human behavioural adaptation in outdoor environments is crucial when planning for climate mitigation strategies. We tested the hypothesis of additional effort associated with heat stress in controlled path choice behaviour experiment in urban environment in hot climate. We observed sun-avoidance behaviour manifested by longer, but less sunny paths chosen. We built the model of study area and sun movement to precisely characterise the path options in terms of sun-shade composition. Using hierarchical model of decisions, we estimate the individual preferences of participants. Our findings indicate, that on average people are willing to walk 16% longer distance to avoid the sun, for some participants this number is close to 80%. Tree shade is not considered as intense as building shade. Our findings suggest that shading infrastructure is crucial to facilitate behavioural adaptation to urban heat.

5.1 Introduction

Behavioural adaptation to climate, i.e. changing behaviour as a response to environmental demands, has shaped the way humanity has developed. How our ancestors have populated the land [53], what we eat [54] and wear [170, 55], where we live [57] and even the way we rest [171] are intricately driven by the need to adapt to cold and heat. For instance, minimisation of exposure to the sun is hypothesised to be one of the possible reasons that drove development of bipedalism in hominids whom had to move from shaded forest environments into prairies exposed to the sun [172]. While human beings are equipped with a complex physiological system of thermal regulation [100], this autonomic response to thermal environments cannot be sustained for long. Thus, behavioural adaptation is the only means of thermal regulation in the long run [91].

The ability to adapt to our climate is challenged by many mega-trends, especially the dramatic increase in urban population and density and the effects of climate change [32]. The population growth, happening mostly in the cities
the areas mainly contributing to the climate change and strongly affected by higher temperatures – results into an increasing number of people being exposed to excessive heat. This in turn will challenge many aspects of modern society: public health, human development, mental health and social relations.

In light of these challenges, outdoor thermal comfort of people in urban areas has seen booming research attention. Computational modelling of urban climate at the pedestrian level allows to predict the thermal environment. For instance, thermal perception and acceptance studies conducted through surveys throughout the world (e.g. in Asia, Europe, North and South America, Africa and Australia) allow to connect the microclimate and comfort of people in it. These developments allow to evaluate and introduce the design and planning measures to improve thermal comfort on pedestrians through green and built shading infrastructure, orientation of buildings and smart path planning. The behavioural response of people to dynamic outdoor thermal environments, however, is under-investigated in existing studies. To evaluate the benefits of the design and planning decisions to provide thermally comfortable urban environments it is critically important to gain quantitative understanding of human behaviour in dynamic microclimate environments.

Behavioural adaptation is a pronounced mechanism of thermal regulation both in animals and humans. Among others, posture adaptation, adaptation of activity intensity and displacement have been found to be manifestations of thermal adaptive behaviour. Walking rates in different cities, attendance of the urban areas and occupation of sun and shade were found to be associated with the climate. In a recent study in China it was found that the attendance, time spent and type of activity performed at the urban park were correlated with the climate seasonality. Analysis of pedestrian counts in New York found that preference for a sunny side of street is changing over year and less people take it during the summer. Though qualitative, this observation indicates that people optimise for their anticipated thermal experience of walking rather than solely for physical distance while making path choices.
Disparity between (objective) urban geometry and (subjective) (mis-)representation of the urban spaces is not a new problem. This disparity between mental and physical space has been early on highlighted as a critical problem in cognitive science, geography and urban science [176, 177, 178]. As with a multitude of other physical parameters, such as time, money or effort, objective distance to be walked is weighted by other factors – including infrastructure [179] aesthetics [10, 11], climatic or social parameters [180]. In such cases, absolute topological metrics are distorted: for instance, a shaded and longer pathway is preferred to a shorter but exposed to the sun one. It is thus critical to systematically examine how human pedestrian behaviour integrates distance and temperature to make route choices.

There is need to develop formal, stylised choice models of pedestrian decisions – i.e. to develop a more precise representation of the underlying computational properties of human thermally-weighted pedestrian choices. Choice modelling, ”the dominant [field] to study choice” [181], recently advanced by significant progress in computational modelling [182], has been successfully employed to uncover the decision processes in many domains – from finance and behavioural economics to transportation, marketing, food preferences and animal behaviour [183, 184], many of them being so successful to form the basis of Nobel-prize research [185, 186]. In these paradigms, preferences are revealed (as opposed to stated, which is what happens in surveys [187]) ensuring a delicate balance between lab-based, controlled environments (suffering from lack of ecological validity) and real-life observed behaviour (suffering from lower control of independent variables). Participants make binary choices that force them to evaluate the effect of, usually antithetical, decision parameters (in our case distance vs. temperature). This so-called two-alternative forced choice (2AFC) methodology is based on established work in psychophysics [188], translated in economic and financial decision models and recently readily adopted by cognitive neuroscience to even model neuronal responses during choice. Critically, this paradigm allows for the development and testing of increasingly precise computational models that can parametrically model and predict behaviour at the individual and aggregate level.

The present study uses theoretical and methodological tools from decision
Results

5.2.1 Description of experiment and resulting dataset

The experiments have been performed in the courtyard of the National Institute of Education, at the campus of Nanyang Technological University in Singapore during the period from June 6th to December 26th in 2019. The experimental area is characterised by two wide walking paths next to buildings which frame a triangular shaped lawn area. Multiple paths cross the lawn area connecting the two wide paths. Depending on the time of the year, one of the paths is exposed to the sun, whereas the other is shaded by buildings. Based on this, two choice sets for participants were designed: choice set #1 for the period of June-October 2019, when the sun was in the north of

science, psychophysics and computational science to investigate the decision processes involved in pedestrian behavioural response to thermal environment. Mirroring this research, we adopt a reductive – yet repeatedly successful – approach by examining the interactive effect of two parameters: distance and temperature. In our out-of-the-lab experiment, participants were asked to perform series of binary path choices in natural urban environment of Singapore. The choice set reflects a wide – but pragmatic – combination of distance and heat to allow for a reasonable parameterisation of the involved variables. To increase precision we use wearable devices to record the experience of each individual and to account for naturalistic weather variations. We formulate a hierarchical probabilistic model of path choices and infer the value of parameters of perceived cost of walking under the sun on the individual and population levels. Moreover, results suggest that environmental shading parameters, such as shadow width or type (tree or building) have significant impact on the behaviour.

Our study demonstrates the applicability of the decision science methodology in studies of the complex pedestrian behaviour in natural environment. The results provide valuable input for policy and planning of climate-aware cities through understanding of pedestrian behavioural response to dynamic thermal environments.
the area, resulting in the northern path being shaded by the building and the southern path being exposed to the sun (Figure 5.1a). Choice set #2 was designed for the period November-December 2019 in which the sun has moved to the south leading to the southern path being shaded by the building and the northern path being exposed to the sun (Figure 5.1b). As Singapore is situated close to the equator and is characterised by a stable hot and humid climate, we assume that there was no significant impact of seasonal variation of climate (apart from the sun position) on experimental procedures and outcomes.

During each trial, participants were asked to move to the target in the area by taking of the two specified paths. Upon reaching the target, the participant proceeded to the next trial with a new target. Trial tasks were designed such that most presented a choice between a shorter sunnier path and a longer less sunny path option (Figure 5.1c-d, see Appendix 5A for the full specification of the choice sets). This is designed so as to test the presence of the behaviour of interest: minimising sun exposure by walking longer distances. Each participant completed 13 trials in total, of which one was a dummy task trial: providing a choice between a significantly longer sunny path and a shorter, less sunny, alternative. In total 74 individuals from the university students, staff and visitors took part in the experiment. Of them 4 had missing data or could not complete the experiment due to rain, 3 were dismissed due to failing the dummy trial, 9 took unspecified paths or had other navigational problems, which required intervention by the experimenter, 2 participants managed to self correct their incorrect paths without the experimenter’s intervention, but are still dismissed from the analysis. This study was preregistered prior to the analysis of the data (available at https://osf.io/aj4vk/). Details of the data processing are described in the Methods section.

A final data set of 56 participants was then used for the analysis, of which 46 participants had made at least one decision in the presence of sun (treatment decisions). In total 408 treatment decisions are analysed in this study.

Exact models of the space and sun position were implemented to facilitate precise and reproducible parameterisation of the choices of participants. This made it possible to estimate the exact composition in terms of sun-lit, tree-shaded and building-shaded fractions of each path option provided to each participant at the moment of decision (Figure 5.1a-d). The details of the
model-based estimation of these parameters can be found in the Methods section.

Choices under treatment decisions can be classified into four types depending on the properties of the chosen path (Figure 5.1f). The treatment decisions participants faced are between optimal and non-optimal paths, or between distance-minimising and sun-minimising. The latter choice type would represent the hypothesised sun-avoidance behaviour. A visual inspection of the choice matrix (Figure 5.1e) reveals several observations, which are quantitatively summarised in Figure 5.1g. 75% of the choices that minimised sun exposure were made by participants using choice set #2. This can be explained by the less pronounced, and less stable, shading patterns in a period covered by the choice set #1. To support this, we plot the width of the building shade on the wide paths next to buildings as hatched bars in Figure 5.1e. We see that as the year progresses from June to October, the building shade narrows, until disappearing completely from 12th September 2019. In this study, we assume that building shade less than 0.9 metres wide is insignificant and therefore not considered by participants as shade in their path choice process. The narrow building shade in the mid-season (September-October) results in the significantly reduced number of opportunities to adapt through path choice (note the prevalence of the blue colour in the left and middle of the matrix corresponding to choice set #1). For many participants using choice set #1, who had a significant ($\geq 0.9$ metres) width of building shade, it was still covering less than 50% of the path, resulting in the lower rate of sun-adaptive choices observed among participants. All the participants using choice set #2 had a building shade width of at least half of the path width. This observation suggests the first conclusion of our experiment: the regularity and completeness of shading of the path is an important factor influencing overall perception of the path shadiness.

Another observation, requiring further elaboration, is the considerable amount of non-optimal decisions made by participants. These decisions are not consistent with either the assumption of minimisation of overall distance or minimisation of exposure to the sun. In the next subsection we demonstrate that at least part of these decisions can be explained by a simplistic (but incorrect) initial assumption that tree shade is equivalent to building shade.
Figure 5.1: Path choice tasks, types of the choice and the resulting dataset. (a, b) At each trial participants had to walk to destination designated by cross originating from the point designated by circle. Two different choice sets were accounting for two distinct shading patterns in the experimental area: sun in the north (a) and in the south (b) resulting in either northern or southern side path being shaded by the adjacent building. (c, d) Each participant completed series of 13 trials of choice between two path alternatives, each path was characterised by sun-lit, tree-shaded and building-shaded lengths. Decisions of 56 participants are analysed, of which 36 had task set #1 and 20 had choice set #2 (e). Decisions made in the presence of the sun are are colour-coded in (c-e) according to choice-type scheme presented in (f): depending on presented options and environmental conditions, participants were facing choice either between optimal (less sunny and shorter) and nonoptimal (sunnier and longer), or between sun-minimising (less sunny, but longer) and distance-minimising (sunnier, but shorter). Here tree shade is assumed identical to building shade. Distribution of observed choices by type is provided in (g).
5.2. Results

in the choice process. Adjustment of the initial sun-minimising choice model allows us to eliminate a significant number of non-optimal choices by converting them into sun-avoiding choices.

5.2.2 Tree shade is perceived as less intense than building shade

The detailed 3D model of the experimental area makes it possible to precisely calculate the shaded (both tree and building) and sun-exposed fractions for each path choice. In the previous classification of the observed choices we assumed that, while minimising for sun exposure, participants are considering tree shade to be equivalent to building shade. With such an assumption we observe a significant number of non-optimal choices, which contradicts the expectation of rational walkers, who minimise either distance or exposure to the sun, or both.

In order to test the assumption that tree shade is not equivalent to building shade we consider the distribution of the choice types as a function of perceived tree shade relief $\rho$. With $\rho = 1$ we assume tree shade is as intense as building shade and with $\rho = 0$ tree shade is considered as perceptually identical to full sun exposure. The result of this calculation is provided in Figure 5.2a. We see that, as the perceived tree shade intensity is decreased, more choices switch from non-optimal to sun-minimising. We demonstrate this conversion by the example of trial 6 of choice set #2 (Figure 5.2b), which has 9 out of 10 treatment decisions being non-optimal under the assumption of full tree shade relief (Figure 5.2b). Assuming a 70% intensity of tree shade ($\rho = 0.7$) results in sun-shade composition of options demonstrated in Figure 5.2d. Note, that all the choices are now classified as sun-minimising rather than non-optimal.

This observation suggests that the heat relief from tree shade is not perceived equivalent to that from building shade, which has an important implication for the planning of the urban areas. To estimate its value, we integrate the tree shade intensity parameter $\rho$ into the model of choices, which is presented in Section 5.2.3.
**Figure 5.2:** Perceived tree shade intensity and its effect on the classification of choices. (a) X-axis represents the perceived tree shade intensity, ranging from full sun (0%) to full shadow (100%); Y-axis represents the fraction of sun-minimising vs. non-optimal choices. As the intensity increases the percentage of non-optimal choices increases. When tree shade is considered as relieving as building shade, the number of non-optimal (sunnier and longer) choices is comparable to the number of sun-minimising (less sunny, but longer): 49 and 60 correspondingly. Assuming tree shade is considered less relieving (i.e. part of tree shade length of the option is assigned to the building shade and remainder to the sun) results into many originally non-optimal decisions converting into sun-minimising. (b) Path choices of many participants in trial 6 of choice set #2 are classified as non-optimal under assumption of tree shade intensity equal to building shade intensity (c). (d) Setting the tree shade intensity to 70% of building shade (i.e. assigning 70% of tree shade length to building shade length and 30% to sun-lit length) results into observed choices being classified as sun-minimising. This indicates that tree shade is probably not considered as intense and relieving as building shade and this parameter plays significant role in path choices of participants and should be built into the choice model.
5.2.3 Modelling of the choices reveals perceived cost of walking under the sun

To estimate the parameter of perceived cost of walking under the sun we define the following cost function of the option:

\[ c^{(A)}_{ji} = \beta_j [a_{ji}^{\text{sun}} + (1 - \rho)a_{ji}^{\text{tree}}] + a_{ji}^{\text{shade}} + \rho a_{ji}^{\text{tree}}, \tag{5.1} \]

where \( a_{ji}^{\text{sun}}, a_{ji}^{\text{tree}}, \) and \( a_{ji}^{\text{shade}} \) are the metric distances in the sun, in the tree shade, and in the building shade respectively, of path option \( A \) of trial \( i \) presented to participant \( j \). \( \beta_j > 0 \) is the participant specific distance-inflating coefficient (cost factor) of walking under the sun, \( \rho \in [0, 1] \) is the parameter of shade intensity (relief) associated with tree shadow common for all the participants. Assuming an equivalent definition for the cost of option \( B \) \( (c^{(B)}_{ji}) \), the difference in the option costs is:

\[ \Delta c_{ji} = c^{(A)}_{ji} - c^{(B)}_{ji}. \tag{5.2} \]

The probability of choosing path option \( A \)p\( (y_{ji} = 1) \) is modelled by

\[ p(y_{ji} = 1|\Delta c_{ji}; \beta_j, \rho, \tau_k) = \frac{1}{1 + \exp(\Delta c_{ji}/\tau_k)} \tag{5.3} \]

where \( \tau_k \) is the cost-difference-scaling coefficient specific to a choice set \( k \in \{1, 2\} \). We assume that the decisions are made independently of each other, based on the sun-shade composition of the currently presented decision options. Furthermore we assume that the parameters of the participant decision model \( (\beta_j) \) are static over the course of experiment (20-30 minutes).

We estimate the parameters in a Bayesian framework. We define a hierarchical model: we set the hyperprior distribution for the parameters of the prior distribution of \( \beta_j \). This allows the distance-inflating coefficient of the sun to be estimated for each individual participant, while still being constrained by the overall picture observed at the population level \[189\]. We use the PyMC3 \[190\] implementation of Markov Chain Monte Carlo for parameter estimation. The full specification of the Bayesian model and estimation procedure are described in the Methods section.
The results of estimating $\beta_j$, the participant-specific coefficients for the cost of walking under the sun, are presented in Figure 5.3a. We observe that most participants have an expected value $E[\beta_j] > 1$, indicating depreciation of the sun. Some participants, such as those with codes P37 and P52, have expected values of $\beta_j$ close to 1.8, indicating they perceive walking under the sun as demanding 80% more effort. We also observe that the 95% credible intervals are wide, containing values of $\beta_j < 1$. This can be explained by the relatively low number of choices per participant, which do not allow for a more certain estimation of this parameter.

When building the posterior distribution for $\beta_j$ for all decisions (Figure 5.3b) we obtain an expected value of $\beta_j = 1.16$ at the population level. With this we can conclude that, according to the observed path choices of participants and the proposed model, there is evidence of an additional perceived effort (or cost) of walking under the sun, which is on average equal to 16%. These numbers are different if we pool the decisions per choice set, (Figure 5.3c-d) giving a higher expected value of $\beta_j = 1.23$ for the choices made under choice set #2. As discussed previously, this can be explained by the more stable building shade in choice set #2. This indicates that under certain conditions (i.e. environment facilitating behavioural adaptation) we can expect an even higher estimated perceived cost of walking under the sun. In Figures 5.3b-d the credible intervals for $\beta_j$ are wide and span from as low as 0.37 to as high as 2.22. This can be explained by the high variability in the decisions, which cannot always be explained by the sun-shade composition of the path options. In the discussion section we elaborate more on the support for $\beta_j < 1$ suggested by the posterior distribution.

The expected value of the perceived tree shade intensity parameter is $E[\rho] = 0.50$. This indicates that tree shade is not considered as intense as building shade.

The 95% credible intervals of cost-difference-scaling parameter $\tau_k$ are disjoint for decisions from the two different choice sets, which confirms that our decision to estimate it separately per choice set was necessary.
5.2. Results

**Figure 5.3:** Estimated parameters of hierarchical model of path choices. (a) Expected value and 95% credible interval of participant-specific distance-inflating coefficient of the sun $\beta_j$. $\beta_j > 1$ means preference towards shade in the process of path choice. (b) Posterior distribution of the distance-inflating coefficient of the sun for path choices pooled for all participants, participants with choice set #1 (c) and choice set #2 (d). Shaded regions represent 95% credible intervals are depicted as filled regions. Hatched regions correspond to the mass of the posterior distribution over $\beta_j > 1$. (e) Posterior distribution of the perceived tree shade intensity $\rho$; the expected value of 0.50 implies that, on average, tree shade is perceived only 50% as intense as the building shade intensity. (f) Posterior distributions of cost-difference scaling parameters $\tau_k$. Disjoint 95% intervals of two distributions can be explained by different overall length of path options in two choice sets.
5.3 Discussion

Pedestrian behaviour, in particular path choice, is a complex process affected by a multitude of internal (preferential) and external (environmental) factors. Studying this process is complicated by the dynamic nature of behaviour and of the pedestrian environments. In our study we have applied the 2AFC methodology to study pedestrian decision processes in natural environments. We have studied how sun exposure in the environment affects pedestrian path choice behaviour. The decisions of participants in our experiment confirm the presence of sun avoidance behaviour through path choices. The estimated parameters of the hierarchical probabilistic model of path choices reveal the individual preference of pedestrians towards longer, but shadier paths. Tree shade intensity is considered significantly less relieving than building shade, which is reflected in the observed path choices and the estimated parameter of the path choice model.

We find the expected value of the parameter $\beta_j$, reflecting the sun-shade preference of participants, to be $E[\beta_j] = 1.16$. This indicates that participants depreciate the distance walked in the sun. In other words, our estimate implies that walking in the sun is considered by pedestrians on average 16% more demanding as compared to walking the same distance in the shade. Individual participants have exhibited path choices which indicate $E[\beta_j]$ as high as 1.8, an 80% increase in the perceived effort of walking under the sun. This finding confirms that pedestrians actively incorporate the shading of outdoor environments into path choices, demonstrating pronounced thermoregulatory behaviour through sun avoidance. It is important to provide, through smart urban planning and design, the opportunity for such behavioural adaptation to minimise heat stress of pedestrians. Urban spaces designed to accommodate pedestrians and provide more comfortable walking spaces can help promote walking, which in turn can have direct health, economic and environmental benefits [191, 192].

Our results demonstrate that in the process of path choice, participants differentiate the type of shading. Initial analysis of the data indicates that tree shade is perceived as less intense than building shade. Incorporating a parameter for this in the model of decisions, we find an expected perceived tree
5.3. Discussion

shade relief $\rho = 0.5$, or only half of that associated with building shade. The reported experiment, however, was not designed to infer the value of $\rho$ and additional dedicated experiments may be required to reduce the uncertainty in its value. With a more certain estimate it would be interesting to compare the objective physical property of tree shade density (e.g. measured by leaf area index [193]) to the one perceived by pedestrians. Nonetheless, our finding has an important implication for urban planners, suggesting that, while trees are able to provide shading relief, it is most probably not considered as intense as the one provided by the built infrastructure and thus promises less improvement of outdoor thermal comfort and smaller reduction of associated cost of walking.

While every effort was made to control the conditions of the natural outdoor environment, it is inevitable that other personal and environmental factors, such as crowding or novelty, were present during the experiment. We explain the considerable number of non-optimal path choices (choices of paths which were both longer and more exposed to the sun) by the presence of these factors. However, these choices were not excluded from the analysis, influencing the final estimates of the parameters of choice model. We argue that the significant support for values of the distance-inflating coefficient of the sun $\beta_j < 1$ in the posterior distribution (see Figure 5.3b-d) should be interpreted not as a preference for the sun (exhibited by decisions of some participants), but rather as an artefact due to the presence of other factors, such as crowding or novelty, which influenced the choices. If it were possible to totally isolate the shading factor of the environment (i.e. completely control for other factors) we could expect estimates of the sun-depreciating coefficient $\beta_j$ to be even higher. Conducting similar experiments with other environmental factors (i.e. crowding, visibility or lighting) would provide an opportunity to refine the findings of our study and to contribute further to a comprehensive model of the pedestrian decision process in outdoor environments.
5.4 Methods

5.4.1 Experimental procedure

The experiment was run during the period from June to December 2019 in the courtyard of National Institute of Education on the campus of the Nanyang Technological University, Singapore. Students, staff and visitors of the University constitute the sampling population. Participants were recruited through posters, placed on campus, advertising the study. Eligibility requirements listed ages of 21 to 55 years, an overall physical fitness level necessary for walking in outdoor environments and an absence of medical conditions preventing prolonged walking in outdoor spaces.

For each experimental session a 1.5 hour time slot was reserved. Participants arrived at a predefined instruction spot located in the outdoor environment, protected from direct sunlight. After studying the information sheet and providing their informed consent, the participant was asked to fill the pre-experiment survey containing questions on socio-demographic characteristics of the participant, his/her attitude towards Singapore’s environment and his/her lifestyle. Upon finishing the survey, a physiological wearable sensor (wristband) Empatica E4 was attached to each participant for the purposes of physiological monitoring (data not reported in this thesis). The participant was asked to read a short story (for the purpose of receiving baseline of physiological signals measured by Empatica E4, but not used in this study), after which instructions for the experiment followed. After the participant confirmed his/her readiness, an action camera was put onto her/his chest, to serve the purpose of registering the decisions and the environmental events (e.g. start and end of trials, appearance of the sun) during the experiment.

The participant was directed to the start of the experiment and informed once again about the procedure of the experiment. The participant had to make choices which were given in a choice set booklet (see 5A for the choice set booklets given to participants). Trial 0 served the purpose of exploring the environment, in it the participant was asked to walk around the lawn and reach the target. Subsequent trials (trials 1 to 13) were asking participants to reach the target with the paths specified by arrows in the booklet. The target of the previous trial served as the origin of the current one. The
participant was asked to visually identify the target and path options in the environment at each decision point. Next, the participant was asked to make decisions based on his/her own preferences, as there was no correct or incorrect choice. The participant was informed, that he/she was not tested for the speed of trial completion. Participants were provided a water bottle to avoid dehydration and were explicitly asked to make use of it at their own discretion. The experimenter has left the participant to complete the trials and was observing the participant from a distance without giving additional instructions. Participants were asked to indicate their need for any help by standing still and raising their hand. Those participants, who required the intervention of experimenter in their walking trials due to environmental conditions (rain), confusion of paths or other reasons were dismissed from the analysis reported in this chapter. Upon finishing the last trial, the participant was met by the researcher and led back to the instruction location, where sensors were detached. The participant was then asked to fill in a post-participation survey, containing questions on the overall state of the participant, as well as on their motivation for each of the chosen paths, evaluation of climate sensation, perception and acceptance during the trials. After completing the experimental procedures, the participants were debriefed and compensated for their participation with 20 Singapore dollars in cash. Neither recruitment, nor instruction materials included an explicit formulation of the research question of this behavioural study to minimise the bias in their behaviour. Instead, the goal of the study was formulated as follows: "The goal is to investigate navigational attributes, or features, of outdoor ambulation in a variety of environments within Singapore. In addition we plan to focus on the environment’s influential factors."

5.4.2 Data processing

The raw datasets resulting from the experiments consist of the video shot on the camera mounted on the participant’s chest, physiological signals originating from the Empatica E4, responses to pre- and post-experimental survey, microclimate data recorded by two Kestrel 5400 portable weather stations installed in the sun and in the shade. In this chapter the data extracted from
video recordings was used.

The video-recording of each participant was processed by student research assistants according to a protocol by entering all events from the video into a spreadsheet of a predefined structure. Times on the video, wristband and experimenter’s smartphone were synchronised by matching the synchronisation events on the video with camera’s time. The following events were coded by participants:

1. Decision event: start by participant of a particular trial.

2. End of trial event: participant stepping on the target of the current trial.

3. Sun presence event: alteration of sun from one state to another. States are:
   a. full sun (sharp shadows are visible on the ground);
   b. cloudy sun (soft shadows are visible on the ground);
   c. no sun (sun is behind the clouds and no shadows are visible on the ground).

4. Sun exposure event: alteration of exposure to sun from one state to another. States are:
   a. No shade (participant walks on the surface exposed to the sun).
   b. Tree shade (participant walks on the surface covered by the shadow cast by the tree).
   c. Building shade (participant walks on the surface covered by the shadow cast by the building).

5. Water intake event: it appears at recording that participant is drinking water.

For each of the event the following attributes are recorded:

1. Event code;

2. Time of event;
3. XY-coordinates of approximate location of event probed with the mouse click in the realistic model of the space and sun position (described in the next section);

4. For decision events only: indicator of whether option A path was chosen by participant.

All the decisions and end of trial events were cross-coded by two student research assistants and checked for agreement of decision label, sun presence and timing. Data coding disagreements (events disagreeing in decision label, in sun presence or in start or end time by more than 5 seconds) were resolved by a third person (experimenter).

Events data was used in the current study and provided information on decisions made by participants and on the presence of the sun at the moment of decision (determining whether decision is considered as treatment one). Timing information of decision events was used for calculation of the sun-shade composition of the path options by adjusting the sun position in the model described in the following section.

Events diverging from the standard experimental procedure (e.g. intervention of experimenter or participant making a shortcut), or potentially ambiguous events (e.g. uncertainty regarding presence of the sun) were recorded by data coders in the notes file, which was then reviewed by the experimenter and which informed the consequent treatment of the participant’s data (e.g. dismissal from the analysis).

5.4.3 Calculation of the sun-shade composition of the options

The 3D model of experimental area was created and imported into a Unity 3D game engine and visually validated for the realistic reproduction of the shading of the the walking paths (see 5B for a comparison of video shots and reproduction of them in the model).

All the path options were incorporated into the 3D model as the polygons covering the walking surface. As the paths along the building are 6 meters wide, they were divided in 5 strips (each 1.2 meters wide). Thus, each path option had 5 polygons (path strips) assigned to it. When calculating the sun-shade composition of the path options at particular trial, the time information
Chapter 5. **Empirical study and choice modelling of pedestrian sun avoidance behaviour**

from the event files was used to adjust the sun position in the model. Then the rays covering each polygon of a path option (on a grid of 0.1x0.1 meter) were shot in a direction towards the sun. The intersection of each ray with tree or building was detected and then the fractions of rays not hitting anything, hitting a tree and hitting a building were considered as the fractions of the sun, tree shade and building shade on a particular path option polygon. For each path option, the polygon (strip) with the lowest fraction of the sun was considered as representative of the overall sun-shade composition of the path option. Building shade that covered less than 15% (i.e. less than 0.9 meters) of the wide paths along the buildings was denoted as insufficient to be considered by the participants and path options with such shading pattern were parameterised as having no building shade.

The length of the path options was calculated as the sum of the lengths of their segments. These were measured with the use of a laser distance meter by two researchers one operating the meter and another holding a mark at which laser was shot. An average of 3 repeated measurements was taken as a length of path segment. The length of the sun-lit stretch, tree shade and building shade along the option was calculated as the length of the path multiplied by the fraction of each component (calculation of which is described in the paragraph above).

### 5.4.4 Hierarchical model of the choices

The hierarchical model of the participant choices described in the equations 5.1, 5.2 and 5.3 has the following prior belief distributions of the model parameters:

\[
\begin{align*}
    d, e &\sim \text{Normal}(0, 1) \\
    \beta_j &\sim \text{Gamma}(\exp[d + e], \exp[d - e]) \\
    \tau_k &\sim \text{Gamma}(12.5, 50) \\
    \rho &\sim \text{Beta}(1, 1)
\end{align*}
\]

Here the chosen way of parameterisation of distribution of $\beta_j$ helps to avoid high correlation in parameters of Gamma distribution, allowing the NUTS
Hamiltonian Monte Carlo sampler to explore the parameter space more efficiently, to prevent divergence and help faster convergence.

The prior for $\tau_k$ is chosen such that $E[\tau_k] = 0.2$ – an approximate average down-scaled (by factor of 0.01) length difference between the path options.

The full diagram of the model is provided in Figure 5.4.

![Diagram](image)

**Figure 5.4**: Graphical representation of the hierarchical model of path choices. Continuous variables are represented by circular nodes, discrete variables are depicted as rectangular nodes. Observed variables are shaded, unobserved are not shaded. Of unobserved variables, stochastic ones are single-bordered, deterministic are double-bordered.

### 5.4.5 Markov chain Monte Carlo estimation of the model parameters

We have used the PyMC3 [190] probabilistic programming framework for Python to estimate the parameters of the model. We have used the standard No-U-Turn Sampler [194], which is based on the principles of Hamiltonian Monte Carlo sampling. The number of chains used is 4, the number of tuning steps is 2000, the number of samples is 10000 per chain. These parameters achieved a rank-normalised $\hat{R} = 1.0$ and effective sample size $> 2500$ for all parameters. Thus, there is no indication of lack of convergence of the MCMC sampler.
Acknowledgements

The procedures of behavioural experiment with human participants reported in this chapter have been reviewed by ETH Zurich Ethics Commission (approval no. EK 2018-N-94, 18 January 2019) and by the Institutional Review Board of Nanyang Technological University (reference no. IRB-2019-04-025, 23 May 2019).

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Appendix

5A Task sets of path choice behavioral experiment

Please remember
• Starting new task, identify given route options visually in an environment, make a decision and proceed to the target by walking along chosen route.
• Proceed to the next page and next task only when you have finished your current task and stopped.
• Use provided water to hydrate yourself whenever needed.
• In case of any problem or question flag the researcher with your hand raised straight up.

Task 0: walk around.
You should visit all the points marked with zeros and finish at point marked with a cross. Cross is always your target.

Task 1: reach the target with one of two paths.

Task 2: reach the target with one of two paths.

Task 3: reach the target with one of two paths.

Task 4: reach the target with one of two paths.

Task 5: reach the target with one of two paths.

Task 6: reach the target with one of two paths.

Task 7: reach the target with one of two paths.

Task 8: reach the target with one of two paths.

Task 9: reach the target with one of two paths.

Task 10: reach the target with one of two paths.

Task 11: reach the target with one of two paths.

Task 12: reach the target with one of two paths.

Task 13: reach the target with one of two paths.

Figure 5.5: Pages of the task booklet #1 with path options labeled (A and B). These labels were not present in the booklets given to participants.
Figure 5.6: Pages of the task booklet #2 with path options labeled (A and B). These labels were not present in the booklets given to participants.
5B Demonstration of the accuracy of shading pattern reproduction by the model of experimental area

**Figure 5.7**: Comparison of the shading pattern in experimental area on video camera shots (left column) and in the 3D model (right column). Participant HS-GDTZ, task set #1, 11 June 2019, 11:09. Rows from top to bottom depict decision moments of tasks: 2, 6, 7, 8 and 10.
Figure 5.8: Comparison of the shading pattern in experimental area on video camera shots (left column) and in the 3D model (right column). Participant HVJJKP, task set #2, 26 December 2019, 12:47. Rows from top to bottom depict decision moments of tasks: 2, 6, 7, 8 and 12.
Chapter 6

Computational study of the performance of innate immune system response under exposure to heat stress

The previous chapters of this thesis focus on the three levels of human response to thermal environments to gain a comprehensive understanding of the process of OTC. However, the interaction of people with their thermal environment is not just a matter of comfort: exposure to stressful thermal regimes entails risks for the healthy functioning of the main biological mechanisms of the human body. The multi-level response considered in the previous chapters is the key way to regulate this exposure and to avoid the detrimental effects of heat on health. In this chapter we demonstrate the use of the thermophysiological model and the model of behavioural thermal regulation through modulation of activity intensity to predict the performance of the human innate immune system under heat stress. This allows us to identify the environment-activity regimes which are to be avoided to preserve the proper functioning of the human innate immune system. This chapter demonstrates how the models developed in this thesis can be coupled with other models to investigate phenomena beyond OTC, which are directly and critically affected

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by exposure of people to heat.

Abstract

Background

The human body has evolved to adapt to different heat conditions by regulating its core temperature. Fever, a paramount response to inflammation, has been passed over through millions of years of evolution. However, exposure to high temperatures poses risks to the survival of the organism. Currently, there is a critical knowledge gap between the inner workings of the innate immune system in response to heat and how this relates to the body’s reaction during heat-inducing physical activities. In this chapter we present the results of bridging these concepts through computational modelling.

Methods

We couple two experimentally validated computational models: the innate immune system and thermal regulation of the human body. We first simulate the dynamics of critical indicators of innate immunity as a function of human core temperature with the use of the human innate immune system model. Next, with a model of thermal regulation, we identify environmental and physical activity regimes that lead to core temperature levels that can potentially compromise the performance of the human innate immune system. Finally, to model the response of innate immunity to various intensities of physical activities, we utilise the dynamic core temperatures generated by the thermal regulation model in the innate immune system model. We compare the dynamics of all key players of the innate immunity for a variety of stresses like running a marathon, doing construction work, and walking, all in the setting of hot and humid tropical climate of Singapore.

Results

We find that exposure to moderate heat stress leading to core temperatures within the mild febrile range $(37, 38]^{\circ}\mathrm{C}$, nudges the innate immune system
into activation and improves the efficiency of its response. Overheating corresponding to temperatures beyond 38°C, however, has detrimental effects on the performance of the innate immune system, as it further induces inflammation, which causes a series of reactions that may lead to the non-resolution of the ongoing inflammation. Among the three physical activities (marathon, construction work, and walking), marathon induces the highest level of inflammation that challenges the innate immune response with its resolution.

Conclusions

Our study advances the current state of research towards understanding the implications of heat exposure for such an essential physiological system as the innate immunity. Although we find that among considered activities, a marathon of 3 hours induces the highest level of inflammation, construction work that is done on a daily basis under the hot and humid tropical climate can produce a continuous level of inflammation triggering moieties stretched at a longer timeline beating the negative effects of running a marathon. We demonstrate that in order to preserve the normal function of the innate immune system and prevent elevation of core temperature beyond 38°C, people should employ behavioural thermal regulation and avoid prolonged strenuous activities in hot climates.

Introduction

The body’s tendency to generate heat in the form of fever is a paramount response to inflammation that has been conserved in 600 million years of evolution among warm and cold-blooded vertebrates. The fever response bestows the likely benefit of survival of the organism during inflammation [195]. Too much heat can also be detrimental. High ambient temperatures may lead to the failure of heat dissipating thermo-regulatory mechanisms after prolonged exposure or heavy exercise, where core temperatures reach 40°C, leading to severe heat stress, organ damage or heat stroke [196].

In this work, we take a closer look, down to the cellular level, on how heat affects the inner workings of the human innate immune system response,
trace this response and relate it to the body’s reaction during heat-inducing physical activities. While the effect of heat on cardiovascular [197], respiratory [198], endocrine [199] and reproductive [200] systems has been studied extensively, the interaction of the core temperature with the human innate immune system (HIIS) is not well studied in works on public and occupational heat-related health, safety and productivity [201]. In light of the global processes of climate change and urbanisation [32, 34], which put more and more people at risk against a threatening exposure to urban heat [202], this constitutes a critical knowledge gap. Thus, there is a need for comprehensive understanding of the interactions of climate, exposure, physiology and human innate immune system -to assess the associated benefits and risks and to suggest best mitigation strategies on an individual level and devise policies on a population level.

On a molecular level, heat stress increases the synthesis of HSP 70, intracellular proteins shown to possess the capacity of inducing lasting protective immune responses [203], up to a threshold temperature, which varies according to cell type. Beyond this threshold, their syntheses is constrained and exponential cell death follows [204, 205]. The threshold, at which thermal damage occurs in the immune system, was detected in individuals suffering from heat stress or heat stroke [206].

Fever-range temperatures heighten the respiratory burst that is often linked with neutrophil activation and increasing neutrophil’s bacteriolytic activity [207-208]. An increase in granulocytes’ bactericidal capacity was observed at 40°C and 42°C relative to 37°C for majority of the bacteria population [209-210]. Thermal stress increases the recruitment of neutrophils to the sites of infection and in distant tissues [211-212]. It also increases the number of circulating neutrophils [213-215] in the body.

Heat is shown to improve the phagocytic capability of macrophages by heightening their responsiveness to inflammation triggering moieties (ITMs) [216-217]. Koch et al. have shown that thermal treatment induces the release of cytokines, such as TNF [218]. Macrophages lining the synovial tissue of rheumatoid arthritis joints produce cytokines such as IL-1b, IL-6, and TNF-a in response to increase in body temperature [219-224]. Humans and rats that are exposed to heat stress were found to have elevated
plasma concentrations of pro-inflammatory cytokines [225]. In the event of a heat stroke, both human- and animal models experience an increase in the levels of pro- and anti-inflammatory cytokines [226]. A loss of intestinal barrier integrity was observed in cows, which increased its permeability to ITMs, which implies gut leakiness activity attributed to alkaline phosphatase concentration changes [218].

For a healthy individual, where inflammatory processes are at a bare minimum, the core temperature is maintained by a complex physiological system of thermal regulation [227]. By employing mechanisms such as vasodilation and constriction, sweating and shivering, the system ensures that the body’s core temperature is maintained at the levels of approximately 36.8°C. The environmental conditions or the internal physiological processes can, however, undermine the functions of the thermoregulatory system. If the capacity of the mechanisms driving the thermal regulation is reached, hyperthermia and its associated heat illness occurs upon exposure to excessive heat, causing detrimental effects on health or even leading to mortality risks [197, 228, 79].

We trace the effect of heat starting from the inner workings of the innate immune response all the way to identifying its effects on the human physiology by coupling two validated computational models: a human innate immune system model and a model of thermo-regulatory response and core temperature dynamics. To do this, we first extend a previously developed model of HIIS [229] such that it can predict the dynamics of its key players as a factor of core temperature. This then allows us to identify the core temperature regimes, which either benefit or impede the efficient response of the innate immunity. We then couple this model of innate immunity with a model of thermal regulation of the human body [157] to investigate scenarios of heat exposure and human activity typical for the hot and humid tropical climate of Singapore. We show that even in such hot climate, the human physiology is capable of maintaining a healthy state by adapting to temperatures in the mild febrile range (37, 38°C). However, prolonged strenuous activity, typical for runners or construction workers, in the outdoor environment of cities like Singapore can have detrimental effects on efficient functioning of immune system. To understand the influence of dynamically changing core temperatures on the innate immune response, we first simulate the core temperature...
dynamics by the thermo-regulatory response model for three physical activities, namely marathon running, construction work, and walking, all in the hot and humid climatic conditions typical of Singapore. We then feed these time-dependent core temperatures into the HIIS model to investigate how varying intensities of physical activities affect the dynamics of key players in HIIS within a 36-hour time frame. All these findings have direct implications for health and well-being of urban dwellers and may suggest preventive measures [230].

The chapter is structured as follows: Section 6.1 presents a model of HIIS in conjunction with the temperature changes and a system dynamics model of the human body thermal regulation. Section 6.2 presents the results of modelling scenarios of exposure and human activity and analysis of their effect on the innate immune system functions. We discuss the limitations and directions of our future work, and suggest recommendations to experimental validation of our findings in Section 6.3 and conclude the chapter with Section 6.4.

6.1 Methods

6.1.1 The human innate immune system model

The HIIS model [229] was previously developed and experimentally validated with careful consideration of the biological mechanisms of each of the key players in HIIS: ITMs, neutrophils, macrophages, pro- and anti-inflammatory cytokines, and alkaline phosphatase.

An overview of HIIS is shown in Figure 6.1. The inflammatory response is triggered when ITMs activate resting macrophages ($M_R$), which then differentiate into "activated" macrophages ($M_A$) in the tissue (I). $M_A$ secrete pro-inflammatory cytokines ($CH$), which via a series of intermediate steps trigger the increase of permeability of the endothelial barrier (II), the thin lining that separates the bloodstream from the tissue. Via a process called diapedesis, the resting neutrophils ($N_R$) -that are in circulation- enter the tissue via the endothelial barrier (III). $N_R$ become active ($N_A$) when they enter the tissue, where they phagocytose and/or release their granules to antagonise
the inflammation (IV). If the inflammation is cleared, the neutrophils go into a programmed cell-death called apoptosis (V). $M_A$ remove the apoptotic neutrophils ($ND_A$) through phagocytosis while simultaneously inducing anti-inflammatory effect as shown by the green arrows in Figure 6.1 (VI). However, if the inflammation is too intense and not easily resolved, neutrophils go into a more chaotic death pathway called necrosis ($ND_N$) as designated by the red arrows in Figure 6.1 which then releases ITMs in the tissue (VII). The additional source of ITMs induces an inflammatory response that causes tissue damage, which then perpetuates the ongoing inflammation through macrophage activation and influx of neutrophils into the site of inflammation (VIII). Additionally, endogenous Alkaline Phosphatase ($AP$), which is naturally produced by the body, is also able to neutralise the ITMs at the site of inflammation.

The HIIS model is governed by 14 coupled ordinary differential equations, where each equation was devised to capture the biological mechanisms and the interactions of the components in the human innate immune response. A detailed description of the model, the parameters used, as well as an overview of the data sets used to validate and calibrate the model can be found in [229].

**Modelling the influence of body core temperature on the dynamics of the human innate immune system**

Assuming a normal core temperature of 36.8°C for healthy individuals, we identify 9 parameters of the HIIS model [229] that are particularly affected by high temperatures. Table 6.1 summarises the list of parameters, their behaviour with respect to increasing core temperature, and the corresponding references from literature.

We then proceed by devising a relationship between these parameters and core temperature. Although it has been shown that the Boltzmann–Arrhenius model, which is used in describing chemical reaction kinetics, can be utilised also to predict the rates of many biological metabolic processes [231], this would require the knowledge of activation energies for all the rates shown in Table 6.1 At the time of the writing of this article, these activation energies are yet unknown for the HIIS components.
Table 6.1: Table of parameters adjusted in the human innate immune system model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter Description</th>
<th>Eq.</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_{ITM</td>
<td>ND_A}$</td>
<td>Phagocytosis rate of ITMs by activated neutrophils</td>
<td>6.2</td>
</tr>
<tr>
<td>$P_{NR}^{max}$</td>
<td>Maximum permeability of resting neutrophils</td>
<td>6.1</td>
<td>[211, 212]</td>
</tr>
<tr>
<td>$N_{R}^{max}$</td>
<td>Maximum concentration of resting neutrophils</td>
<td>6.1</td>
<td>[209, 213, 214]</td>
</tr>
<tr>
<td>$\lambda_{ITM</td>
<td>M_A}$</td>
<td>Phagocytosis rate of ITMs by activated macrophages</td>
<td>6.1</td>
</tr>
<tr>
<td>$\beta_{N_A</td>
<td>ITM}$</td>
<td>Rate of pro-inflammatory cytokine production when activated macrophages/neutrophils phagocytose ITMs</td>
<td>6.1</td>
</tr>
<tr>
<td>$\beta_{M_A</td>
<td>ITM}$</td>
<td>Rate of pro-inflammatory cytokine production when activated macrophages/neutrophils phagocytose ITMs</td>
<td>6.1</td>
</tr>
<tr>
<td>$\alpha_{ACH</td>
<td>M_A}$</td>
<td>Rate at which anti-inflammatory cytokines are produced by activated macrophages</td>
<td>6.1</td>
</tr>
<tr>
<td>$P_{AP}^{max}$</td>
<td>Permeability of endothelial barrier to Alkaline Phosphatase</td>
<td>6.1</td>
<td>[218]</td>
</tr>
<tr>
<td>$\alpha_{ND_N}$</td>
<td>Rate of increase of ITMs due to necrosis</td>
<td>6.3</td>
<td>[195]</td>
</tr>
</tbody>
</table>
6.1. Methods

We tested two assumptions on the relationships between the parameters and core temperature, and found that a linear response for parameters $P^\text{max}_{NR}$, $N^\text{max}_R$, $\lambda_{ITM|M_A}$, $\beta_{NA|ITM}$, $\beta_{M_A|ITM}$, $\alpha_{ACH|M_A}$, $P^\text{max}_{AP}$, and $\lambda_{ITM|ND_A}$, while an exponential relationship for $\alpha_{ND_N}$ best models the desired shift in the effects on HIIS for core temperatures within and beyond the mild febrile range. We conjecture that other non-linear forms of equations may also be used, but in order to do this, we would need the data corresponding to these innate immune entities to calibrate our model with.

For a linear response, the change in parameters is directly proportional to the change in temperature with an arbitrary growth factor $\gamma$. For simplicity, we assume that $\gamma$ is the same for all parameters. The range of the parameter values we used still fall within or close to the accepted biological range specified in [229].
Equation 6.1 summarises this linear relationship:

\[ p(T_{\text{core}}) = p_0 + \gamma (T_{\text{core}} - T_{\text{core}0}), \quad (6.1) \]

where \( p(T_{\text{core}}) \) is the value of the parameter at temperature \( T_{\text{core}} \), \( p_0 \) is the parameter value at normal core temperature 36.8°C, \( \gamma \) is the arbitrary factor that defines the rate at which parameter \( p \) grows with increasing core temperature.

Although we want to limit the number of parameters that we calibrate for this work, we found that the growth factor for \( \lambda_{ITM|\text{ND}A} \) is different from the previously mentioned parameters in order to have the desired dynamics in HIIS with respect to change in temperature. We emphasise that we can explore more of these parameters once we get hold of necessary datasets to calibrate our model with. A parameter sensitivity analysis is also part of our future work. And thus, we model the linear behaviour of \( \lambda_{ITM|\text{ND}A} \) with respect to temperature by Equation 6.2:

\[ \lambda_{ITM|\text{ND}A}(T_{\text{core}}) = \lambda_{ITM|\text{ND}A0} + \kappa (T_{\text{core}} - T_{\text{core}0}), \quad (6.2) \]

where \( \lambda_{ITM|\text{ND}A}(T_{\text{core}}) \) is the value of \( \lambda_{ITM|\text{ND}A} \) at temperature \( T_{\text{core}} \), and \( \lambda_{ITM|\text{ND}A0} \) is the parameter value at baseline temperature \( T_{\text{core}0} = 36.8^\circ \text{C} \) and \( \kappa \) is the arbitrary factor that defines the rate at which parameter \( \lambda_{ITM|\text{ND}A} \) grows with increasing core temperature.

It has been shown that the rate at which cells are destroyed by hyperthermia exhibit an exponential behaviour with increasing temperature [232]. Since an induced cell death also induces ITMs [233], modeling the rate at which ITMs are induced due to necrosis (\( \alpha_{\text{ND}N} \)) as exponential, is further justified.

To model the exponential behaviour for \( \alpha_{\text{ND}N} \) with respect to temperature, we use Equation 6.3:

\[ \alpha_{\text{ND}N}(T_{\text{core}}) = \alpha_{\text{ND}N0} \exp[\epsilon(T_{\text{core}} - T_{\text{core}0})]], \quad (6.3) \]

where \( \alpha_{\text{ND}N}(T_{\text{core}}) \) is the value of \( \alpha_{\text{ND}N} \) at temperature \( T \), \( \alpha_{\text{ND}N0} \) is the parameter value at baseline temperature \( T_{\text{core}0} = 36.8^\circ \text{C} \), and \( \epsilon \) is the growth rate of \( \alpha_{\text{ND}N} \).
Table 6.2: Additional parameters used in the simulation of the HIIS response to increasing temperature, defined by equations 6.1, 6.2, and 6.3.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>γ</td>
<td>Slope or gradient of linear equation, defines the growth rate of parameters ( P_{\text{max}}^N ), ( N_{\text{max}}^N ), ( \lambda_{\text{TIM}</td>
<td>M_A} ), ( \beta_{N_A</td>
</tr>
<tr>
<td>κ</td>
<td>Slope or gradient of linear equation, defines the growth rate of ( \lambda_{\text{TIM}</td>
<td>ND_A} ).</td>
</tr>
<tr>
<td>ε</td>
<td>Growth rate of ( \alpha_{ND_N} )</td>
<td>4.75</td>
</tr>
<tr>
<td>( T_{\text{core}} )</td>
<td>Core temperature (°C)</td>
<td>([36.8, 37, 38, 39, 40, 41, 42, 43])</td>
</tr>
</tbody>
</table>

We summarise the parameters used in our simulations in Table 6.2. Parameter values were chosen to reproduce the desired dynamics of the shift in behaviour of key components in HIIS as the temperature traverses from the mild febrile range to a nearly fatal core temperature of \( T_{\text{core}} = 43°C \). To the best of our knowledge at the time of writing, data on temperature-dependence of the HIIS model parameters is not available, which renders further calibration of the model as part of future work.

6.1.2 Model of human thermo-regulatory response and core temperature dynamics

The human body consists of multiple tissue types, each having its own thermo-physiological properties, resulting in different temperatures observed in, for example, muscles and fat. The most prominent difference, however, is between the outer shell of human body – skin – and tissues confined within the skin – core of the body [234]. While core temperature should be kept close to 36.8°C to ensure the proper functioning of vital organs, the skin serves as the main way of heat exchange between human body and surrounding thermal environment, leading to high variation of skin temperature tolerated by the human organism [227]. Rectal temperature, having the least observed variation, is usually considered a representative of the overall thermal state of the core of the body [235].

To model the human thermo-regulatory response and core temperature dynamics, we adopt the modified Gagge’s two-node model [100], which differentiates the temperatures in core and skin components of human body.
Chapter 6. Heat stress and innate immune system response

It was extensively applied in the studies of thermal sensation and perception and prediction of thermo-physiological state of human body in static indoor thermal environments. In previous work we re-calibrated the two-node model to better reproduce the dynamics of core and skin temperature in transient outdoor environments [157] and applied it to study the implications of the urban pace of life, expressed in observed walking speeds, on thermal stress [236].

In the body temperature model, core and skin components are considered as stocks of energy. The energy is exchanged between the stocks as well as with the environment through evaporation $E$, radiation $R$ and convection $C$ from and to the skin, respiration $Re$ and mechanical work $W$ from the core. The goal of the thermo-regulatory mechanisms (such as metabolic heat production $M$, core-skin blood flow, vaso- constriction and dilation, shivering $Sh$) is to maintain the body core temperature by eventually achieving the neutral heat storage ($S$) expressed by the following heat balance equation:

$$S = M + Sh - Re - W - C - E - R \frac{W}{m^2}$$ (6.4)

The complete stocks-and-flow system dynamics representation of the model is provided in Figure 6.2. The reader is referred to [157] for a full mathematical specification of the model, its experimental validation, and a demonstration of its predictive performance in dynamic thermal conditions. The positive values of heat storage ($S > 0$) imply the accumulation of heat in the body, which is distributed between two components: skin and core. The core and skin temperatures change due to the source of the heat (internally produced or acquired from environment) and environmental parameters.
6.2. Results

6.2.1 Effect of varying core temperatures on the performance of the human innate immune system

Inflammation Triggering Moieties

Inflammation Triggering Moieties (ITMs) may refer to bacterial lipopolysaccharides and extracellular nucleotides serving as pro-inflammatory signals that trigger local and systemic inflammatory responses in HIIS. We look at two cases: one with very high initial ITM concentration patterned after patients experiencing severe inflammation like that of cardiac surgery (see \[229\], here we assumed that the core temperatures of the patients are normal at 36.8°C),
and one with low initial ITM concentration, which corresponds to healthy individuals (as low amount of ITMs are always circulating in the body in order keep the HIIS active).

In our simulations, we observe that ITM concentrations are lower for temperatures 37°C and 38°C (assumed mild febrile range) than at higher temperatures (see Figure 6.3), which can be interpreted as the beneficial effect of fever to the organism. Above the febrile range, ITM concentrations are at higher levels and may reach fatal concentrations, becoming a threat to the organism [237].

![Figure 6.3: Dynamics of inflammation triggering moieties for a temperature-dependent human innate immune system. With a baseline normal temperature of 36.8°C, we observe that ITM concentrations are lower for temperatures 37°C and 38°C than at higher temperatures.](image)

**Cytokines**

Cytokines are “messenger” proteins that orchestrate the complex mechanisms of the innate immune response. Cytokines can either be pro-inflammatory or anti-inflammatory. Pro-inflammatory cytokines are produced by immune cells called macrophages during the inflammation process and migrate to the endothelial barrier, opening it up, and thus allowing the entrance of neutrophils to the site of inflammation. Anti-inflammatory cytokines, also produced by macrophages, are immuno-regulatory molecules that control the production of pro-inflammatory cytokines.
The shift in dynamics of anti-inflammatory cytokines at temperatures in the mild febrile range is also seen in both high and low initial ITMs (Figure 6.4A and B, right panel). The heightened levels of anti-inflammatory cytokines help in the down-regulation of inflammation. Hence, the observed increase of anti-inflammatory effects for temperatures in the mild febrile range support the notion of mild temperatures pertaining to mild fever bestowing benefits to the body. Further increasing the temperature beyond the mild febrile range shows that the levels of anti-inflammatory cytokines are at much lower values than those in the mild febrile range. Pro-inflammatory cytokines, on the other hand, are generated in low concentrations for temperatures within the mild febrile range. This apparent divide is seen in Figure 6.4A and B, left panel), supporting again, the benefit of mild temperatures to the body. At higher temperatures, pro-inflammatory cytokines are produced in huge concentrations that aggravate the ongoing inflammation.

**Neutrophils**

Neutrophils are one of the key players in HIIS and one of the first responders rushing to the site of inflammation in the event of a so-called insult, where the organism is bombarded with ITMs. When the inflammation is taken care of, neutrophils go into a programmed cell death called apoptosis. However, in cases when the insult is too intense or persistent, they take on a violent death pathway called necrosis, spilling their cytoplasmic content into surrounding tissue, thus aggravating the inflammation. This delicate balance between apoptosis and necrosis has to be maintained in the body. In previous work, we studied this phenomenon using the concept of evolutionary game theory [238].

For temperatures within the mild febrile range (see Figure 6.5A), we observe higher concentrations of apoptotic neutrophils, but lower concentrations of necrotic neutrophils, again, supporting the beneficial effect of fever to HIIS. The presence of apoptotic neutrophils implies the production of anti-inflammatory cytokines, which are messenger proteins that down-regulate
Chapter 6. Heat stress and innate immune system response

Figure 6.4: Dynamics of cytokines for a temperature-dependent human innate immune system. The shift in dynamics of cytokines in the mild febrile range (37, 38°C) for anti-inflammatory cytokines is seen more prominently in high initial ITMs. Pro-inflammatory cytokines, on the other hand, are generated in low concentrations for temperatures within the mild febrile range.

the ongoing inflammation through the regulation of pro-inflammatory cytokines. Within the mild febrile range, it seems that apoptosis is mostly preferred, which may be attributed to its anti-inflammatory benefits as opposed to the harmful cost of necrosis. However, above the mild febrile core temperatures, the general trend of concentrations for the neutrophils begins to shift to the opposite direction, where apoptotic neutrophils are lower in concentrations, while necrotic neutrophils are higher in levels of concentration. We note that through necrosis, more ITMs are produced, which further aggravates the
ongoing inflammation. In the process, the body goes into overdrive, causing a cytokine storm, recruiting more and more neutrophils into the site of inflammation, which may eventually become detrimental or even fatal to the human body.

**A. High Initial ITMs**

![Graph](Image)

**B. Low Initial ITMs**

![Graph](Image)

**Figure 6.5:** Dynamics of neutrophils for a temperature-dependent human innate immune system. For temperatures within the mild febrile range (37, 38°C), we observe higher concentrations of apoptotic neutrophils, but lower concentrations of necrotic neutrophils, supporting the beneficial effect of fever to the human innate immune system.

**Alkaline phosphatase**

Alkaline Phosphatase (AP) is an enzyme widely recognised as responsible for keeping the endothelial barrier intact. Apart from this, it has been established
that AP has the capability of neutralising ITMs. High initial ITMs (see Figure 6.6A) mimic the condition of patients undergoing cardiac surgery, where AP from the liver is flushed into the bloodstream, as explained in detail in our previous work [229]. Hence we see an initial high concentration of AP in the bloodstream. Since the body is already experiencing high initial levels of ITMs, all temperatures trigger the diffusion of AP from the bloodstream into the tissue (see snippet in Figure 6.6A). AP in the tissue is then readily used up especially at higher temperatures, or those temperatures beyond the mild febrile range.

For healthy individuals, the typical concentration of AP is 50 IU/L (see Figure 6.6B.) We observe that for temperatures within the mild febrile range, AP in the bloodstream is less used by the body, as is evident from the subtle dips in AP concentration, supporting again the benefits that fever bestows upon the body. However, at much higher temperatures, we observe a drop in concentration of AP in the bloodstream and tissue, which implies that the body is in need of the current available supply of AP to neutralise the ongoing inflammation.

**Figure 6.6:** Dynamics of alkaline phosphatase in blood (main) and tissue (inset) for a temperature-dependent human innate immune system. At high initial levels of ITMs, all temperatures trigger the diffusion of AP from the bloodstream into the tissue. For healthy individuals (low initial ITMs), we observe that for temperatures within the mild febrile range, AP in the bloodstream is less used by the body, as evident from the subtle dips in AP concentrations.
6.2. Results

6.2.2 Heat exposure and exertion risks for immune system

In the previous sections, we have identified that there are two different levels of elevated core temperature, which either have a beneficial or detrimental effect on HIIS. While the immune response is improved for core temperatures rising up to \(38°C\), higher temperatures have a detrimental effect on the performance of the innate immune system.

Here we provide the results of simulations of the core temperature dynamics over a period of 3 hours for a broad range of human activities varying from light to vigorous, while exposed to typical outdoor conditions of equatorial Singapore. In these scenarios we assume a constant level of metabolic rate production due to physical activity and initial state of the thermo-physiological system in steady state (\(T_{\text{core}} = 36.84°C\), \(T_{\text{skin}} = 33.75°C\)) typical for sitting activity in thermally neutral indoor environment (\(T_{\text{air}} = 22°C\), mean radiant temperature \(T_{\text{MRT}} = 22°C\), relative humidity (RH) 50%, wind speed 0.05 m/s, clothing insulation \(I_{\text{cl}} = 1.0\) clo, metabolic heat production \(M = 80\ W/m^2\)). The levels of metabolic rates for different occupational, sportive and leisure activities are taken from the Compendium of physical activities [239].

Figure 6.7A demonstrates the core temperatures, which will be reached in sunny conditions of a Singapore-like climate under specific intensities of activities and duration. We observe that in these environmental conditions the lower-than-moderate activities \((M < 6\ \text{MET})\) do not lead to critical overheating even for a long duration. The time needed to reach the threshold value of core temperature \((38°C)\) decays exponentially as the activity intensity increases. For example, running at a speed of 9.7 km/hr (an activity of approximately 10 MET intensity) for longer than 7 minutes would result in crossing the threshold of \(T_{\text{core}} = 38.0°C\). We observe a similar behaviour in Figure 6.7B, which represents cloudy weather in Singapore-like climate (lower air and mean radiant temperatures, but higher humidity as compared to the previous scenario). The intensities of activities at the threshold level, however, are slightly higher. This is due to the absence of direct exposure to the sun. Its effect would be even higher if not for the increased relative humidity in this scenario, which reduces the evaporating capacity of the environment and consequently the opportunities of cooling through evaporation of sweat. This
complex interplay of a micro-climate and thermal regulation of the human body results in extreme levels of core temperature (i.e. $T_{core} = 42.0^\circ C$) that are reached earlier in the ‘cloudy’ (B) as compared to the ‘sunny’ (A) weather scenario.

In the last scenario, presented in Figure 6.7C, we reproduce the conditions of an early morning, no sun, suitable for a marathon. We set air velocity to a value of 3.9 m/s (14 km/hr), characteristic of the speed of an experienced medium- and long-distance runners, which significantly increases convective heat removal from the surface of the body. This level of activity would correspond to the extreme values of $M \geq 12$ MET. Thus, the 38°C threshold of core temperature would be reached after about 6 minutes into the run (or after about 1.5 km).

Considering the upper boundary of intensity of occupational construction work of 8 MET, the threshold level of core temperature would be reached after 9.5 and 11 minutes of continuous work in sunny and cloudy Singapore climate correspondingly. This implies that construction workers are subjected to the risk of compromising the functioning of immune system.

### 6.2.3 Innate immune response in three different activities

In the previous two sections, we have (1) identified the values of core temperatures that either induce benefits to the innate immune response or undermine its functions, and (2) pinpointed the regimes of physical activities and environmental conditions that these core temperature correspond to. In these simulations, core temperatures did not change over time. Those results provide a good understanding of 2 key points: how temperature affects the dynamics of the immune system and how HIIS battles the inflammation over a period of 36 hours. It however does not represent the dynamically changing core temperatures and their effects in real scenarios of physical activities and heat exposure.

In this section we investigate how HIIS responds to three physical activities: a marathon of three hours, construction work of 9 hours with an hour lunch break, and walking for 6 hours in Singapore setting. We then
6.2. Results

Figure 6.7: The dynamics of core temperature as a function of time and level of activity intensity. a) For sunny outdoor environment of Singapore, b) for cloudy outdoor conditions of Singapore, c) for cloudy morning conditions with air velocity $V_{air} = 3.9 \text{ m/s} = 14 \text{ km/hr}$ equivalent to air velocity around running person (vigorous physical activity). Contour lines indicate the regimes of activity intensity and its duration resulting in the same value of core temperature $T_{core}$. $T_{core} > 38.0^\circ C$ is predicted by our model to have detrimental effects on the performance of immune response. Thus, intensity and duration of activity in a given environment, for which $T_{core}$ exceeds 38.0 $^\circ C$, should be avoided to minimise the risk of compromising the immune system.

Observe HIIS reaction over a period of 36 hours. This period covers the entire course of the activity and the recovery that follows. The activity schedule and conditions for each of the considered scenarios are provided in Table 6.3. Other parameters values are used as specified in the previous section on HIIS-temperature model. Further, modelling a healthy individual, we assume that the human body has a low initial level of ITMs.

Inflammation Triggering Moieties

The dynamics of ITM concentrations (Figure 6.8B) in construction work and walking scenarios follow the dynamics of core temperatures (Figure 6.8A). Construction work seems to induce lesser concentrations of ITMs compared to running a marathon. It is also evident from the peaks in ITM surges that there is indeed a rest period in between 4 hours of physical activity, representing a lunch break. Walking induces the lowest levels of ITMs among the three physical activities. The two activities then show an eventual decline in ITMs, signifying an efficient resolution of the ongoing inflammation. A marathon
runners running for 3 hours in the hot and humid tropical climate of Singapore is shown to induce a high level of ITMs that initially follows the core temperature profile.

All activities have core temperatures that are slightly above the normal temperature of 36.8°C right after the physical activity. This is under the assumption that the marathon runner, construction workers, and the walkers enter an air-conditioned room after some time, where they eventually ease back to the normal core temperature. Since our model assumes that mild temperatures pose benefit to the innate immune response, we see a slight increase in ITMs after the activities, as the core temperature goes back to normal.

Finally, although a marathon induces the highest level of ITMs, the ITM concentration still decreases over time. Construction work, on the other hand, is done on a daily basis. Therefore, in the long run, construction work induces a greater impact on the innate immunity through the continuous production of ITMs at a longer period of time.
6.2. Results

**Figure 6.8:** Dynamics of core temperatures and inflammation triggering moieties during and after three physical activities. The profiles of ITMs for marathon and walking follow that of the core temperatures. Two peaks in the ITM concentrations of construction work signify a 9-hour work with an hour break in between. Marathon exhibits the highest induced ITMs, which remain at high level after 36 hours, signifying the inability of the innate immune system to resolve the ongoing inflammation.

**Cytokines**

Figure 6.9 summarises the concentrations of pro- and anti-inflammatory cytokines of marathon, construction work, and walking over a period of 36 hours. A marathon induces the highest level of pro-inflammatory cytokines among the three physical activities. We emphasise that pro-inflammatory cytokines are messenger proteins responsible for opening up the endothelial barrier, recruiting more of the circulating neutrophils into the site of inflammation, aggravating the ongoing inflammation. Anti-inflammatory cytokines are also produced, but exhausted at around 48 hours (see snippet in Figure 6.9B). The decay times for both pro- and anti-inflammatory cytokines for marathon runners were also observed in [240].

Pro-inflammatory cytokines are at low levels for construction work and walking, while anti-inflammatory cytokines remain high for both activities, signifying the efficient resolution of inflammation by HIIS. This is due to the remaining concentrations of apoptotic neutrophils in the system as we have shown in the previous section. Anti-inflammatory cytokines are produced by macrophages when neutrophils go into apoptosis as specified in our model.
However, we emphasise that the combined model is not yet calibrated to real data and thus the rates at which anti-inflammatory cytokines as well as pro-inflammatory cytokines decrease have yet to be refined to realistically model HIIS in the context of a physical activity. We note that we have kept the calibrated parameters of the modified HIIS model to only three values. As such, this work is a proof of concept of how the core temperatures affect the performance of HIIS in different physical activities. Part of our future work is to collect data on concentrations of pro- and anti-inflammatory cytokines and to calibrate the combined model.

**Figure 6.9:** Dynamics of pro- and anti-inflammatory cytokines during and after three physical activities observed for 36 hours/1.5 days (main) and 120 hours/5 days (snippet). Marathon (3 hours) induced more pro-inflammatory cytokines than construction work (9 hours with a 1 hour break in between) and walking (6 hours), while all three physical activities induced similar concentrations of anti-inflammatory cytokines. Marathon’s anti-inflammatory cytokines decline after 10 hours, signifying the depletion of immune cells that produce them.

**Neutrophils**

Simulation results for the concentration of apoptotic and necrotic neutrophils for the three physical activities are summarised in Figure 6.10. Construction work triggers the highest concentration of apoptotic neutrophils, followed by walking and then marathon. On the other hand, higher concentrations of
ITMs trigger HIIS to go into the necrotic death pathway. Necrosis encourages the body to recruit more of the circulating neutrophils into the site of inflammation, aggravating the ongoing inflammation. This is why we see a higher level of induced necrotic neutrophils in Figure 6.10B for the marathon scenario.

**Figure 6.10:** Dynamics of apoptotic and necrotic neutrophils during and after three physical activities. Construction work induces the most apoptotic neutrophils followed by walking and marathon. Marathon, which induces the highest level of ITMs, induces the most necrotic neutrophils as the innate immune system picks the necrotic death pathway to further aggravate the ongoing inflammation.

**Alkaline Phosphatase**

Alkaline phosphatase helps neutralising inflammation. Hence, the stronger the stimulus is (that is, the more ITMs there are in the body) the more AP is induced to fight the ongoing inflammation. Alkaline phosphatase concentrations in blood as well as in tissue are shown in Figure 6.11. The snippets correspond to the same concentrations for a period of 120 hours or 5 days. Here we show that a marathon, the physical activity that contributes most of the ITMs, induces the strongest surge of AP from the bloodstream into the tissue (see Figure 6.11) and immediately uses it up to neutralise the ongoing inflammation. This is followed by construction work and walking. The behavior we see in marathon beyond 3 hours is again for two reasons: 1) the body has consumed much less of the AP at this point, therefore implying that
ITMs are being resolved and 2) pro-inflammatory cytokines, the messenger proteins that open up the endothelial barrier, are still at high concentrations, this allowing more of the AP from the bloodstream to enter the tissue. After about 36 hours, AP in the bloodstream begins to go back to normal levels. After some time, when the inflammation is nearly resolved for all activities, we see an increase in AP in blood as the the concentration goes back to normal.

![Figure 6.11: Dynamics of alkaline phosphatase in blood(A) and tissue(B) during and after three physical activities. observed for 36 hours/1.5 days (main) and 120 hours/5 days (snippet). Marathon induces the highest level of alkaline phosphatase in tissue, followed by construction work and walking. Alkaline phosphatase is known to neutralise inflammation, hence, the more intense the inflammation is, the stronger it is induced.](image)

**Figure 6.11**: Dynamics of alkaline phosphatase in blood(A) and tissue(B) during and after three physical activities. observed for 36 hours/1.5 days (main) and 120 hours/5 days (snippet). Marathon induces the highest level of alkaline phosphatase in tissue, followed by construction work and walking. Alkaline phosphatase is known to neutralise inflammation, hence, the more intense the inflammation is, the stronger it is induced.

### 6.3 Discussion

Although the human body has evolved to adapt to changes in ambient temperature, the imminent threat of climate change, which promises more heatwaves, will inevitably cause the rise of heat-related health problems. Despite the urgency of knowing the risks associated with a rising core temperature to the innate immune response, there is an apparent knowledge gap between understanding the underpinning cellular mechanisms and the associated processes of the innate immune system and its implications for the human body, and consequently the types of healthy physical activities humans are constrained to do in given thermal environment.
We bridged this gap by coupling two validated and established computational models: the human innate immune system model and a model of thermo-regulatory response and core temperature dynamics.

In order to do so, we first needed to modify the existing model of the human innate immune system in such a way that it takes temperature changes into consideration. We identified the parameters in a previously developed model of the innate immune response that are directly impacted by temperature. Since appropriate data to calibrate the modified HIIS model with respect to temperature is currently unavailable, we only chose those parameters that best describe the qualitative dynamics of HIIS based on known behaviours documented in literature. We found that a simple linear response for majority of the parameters coupled with an exponential increase in the rate for induced ITMs with respect to increasing core temperature, capture the shift of the dynamics of key components in HIIS from the beneficial regime of mild fever to a detrimental effect above 38.0°C. What we have shown is numerical evidence of the beneficial effect of mild febrile range of body core temperature (37, 38]°C to HIIS. Temperatures above the mild febrile range trigger a stronger and even detrimental effect on HIIS, which is more prominent at higher initial concentrations of ITMs. We conjecture that since the body has already been exposed to ITMs, and thus has already activated and charged up to resolve the ongoing inflammation, the effect of temperature only adds up on top of this resolving reaction of HIIS.

A total of nine parameters from the original HIIS model were identified to be affected by temperature. The next logical step is to trim down the parameters that truly contribute to the variance of results of the model. Model calibration and detailed validation is a next step, once the data become available.

Lastly, we looked into the dynamics of HIIS during and after three physical activities: a marathon, construction work, and walking, all in the hot and humid tropical climate of Singapore. We did so by modelling the dynamic core temperatures during the course of the activity, as well as the resting period that follows for a total period of 36 hours. We then fed these dynamic core temperatures into the HIIS-temperature model. Our simulations capture how a marathon of 3 hours induced the most ITMs, as compared to a 9-hour
construction work or a 6-hour walk. HIIS was able to resolve the inflammation induced by both construction work and walking. However, an extreme sport such as a marathon in hot humid conditions challenged the function of the innate immune system, inducing an inflammation that lasts long after the 3 hour physical activity. However, it is also important to note that although marathon induces the most intense level of inflammation, it eventually subsides at some point. Construction work, on the other hand, is a daily routine. And thus, the induced levels of ITMs due to construction work will even surpass that of a marathon once the body recovers. To the best of knowledge, this is the first time that the immune response due to running a marathon has been analysed using computational models. We hope to leverage our claims by collecting supporting data, specifically concentrations of immune cells for marathon runners, to calibrate our model and validate our results.

6.4 Conclusions

Combining the innate immunity model with a thermo-regulatory model, we identified climate-intensity-duration regimes which lead to body core temperature exceeding the threshold level of 38.0°C. In hot environmental conditions, prolonged strenuous activities, such as running or construction work, pose a risk of crossing the threshold of overheating, which results in compromising performance of the innate immune system response. As a proof of concept, we show how three physical activities affect the innate immune response by incorporating dynamic core temperatures into the HIIS-temperature model. We showed that a marathon for three hours in the hot and humid tropical climate of Singapore induces a high level of inflammation that challenges the function of the innate immune system. However, it is important to note that construction work is done on an almost daily basis as compared to a marathon of 3 hours, which then stretches construction work’s induced inflammation over a prolonged timeline. Thus, these activities should be limited in duration or other measures such as active cooling should be put in place to protect people from hazardous heat stress.

To the best of our knowledge this is the first time that core temperature is modeled in conjunction with the human innate immune response. This
6.4. Conclusions

allows for a better understanding of the underlying mechanisms of the human innate immune system in response to heat, and for us to be able to probe its consequent beneficial or detrimental effects on the human physiology.

In order to validate our claims, we recommend collecting data on concentrations of key players in HIIS, more specifically anti- and pro-inflammatory cytokines as well as neutrophil and alkaline phosphatase levels, for patients undergoing heat treatments. Often times, temperatures used during these procedures vary from 40-43°C, which raises the core temperature by 1-2°C from that of normal [241]. More so, a recommended good experiment is to collect swabs for samples of cytokines from people doing rigorous exercises as well as documenting their temperatures. All these can aid us in validating, and further enhancing our model. Finally, we aim to dig deeper into the devised HIIS-temperature model through sensitivity analyses to gain more insights on the model behaviour as well as its structure by probing its temperature-dependent parameters.

Our work aims to contribute to the existing knowledge on how changes in human thermoregulation affect innate immunity – not only on the cellular level, but more importantly, its implications on individuals and subsequently on society.

List of abbreviations

HIIS – Human Innate Immune System
ITM – Inflammation Triggering Moieties
AP – Alkaline Phosphatase
RH – Relative Humidity
Chapter 7

Summary and conclusions

The urban climate has a direct impact on health and well-being of people living in cities. Understanding the complex process of outdoor thermal comfort (OTC) is necessary in order to improve people’s thermal experiences in outdoor environments of current and future cities. This thesis has focused on building the understanding of human response to thermal stimulation through computational modeling of this response on multiple levels: physiological, psychological and behavioural.

Chapter 2 provided the full formulation of a two-node model of human body thermal regulation. We presented the model in terms of a system dynamics stocks-and-flows diagram, which allows for understanding of the complex causal relations between parameters of the physiological system of thermal regulation and the environment. We found that the model, while realistically reproducing steady state conditions, is lacking accuracy when predicting the dynamics of skin temperature – a critical parameter reflecting the thermal state of a body. Using the causal diagram, we identified the core-skin blood flow as the most probable component responsible for observed discrepancies in the model’s performance in dynamic scenarios. We optimised the parameters of this component within the ranges found in literature. The new vector of parameters of the skin-blood flow component of the system achieved significantly improved dynamics, comparable to those demonstrated by more complicated and computationally intensive models. We calibrated the model on a wide range of moderate-to-hot environments and validated on data for extremely hot conditions, which are beyond the range the model was calibrated on. The model demonstrated excellent prediction of the dynamics of the skin temperature. Additionally, we found good agreement of predicted
evaporative heat loss with that found in literature, which is an indicator of a correct prediction by our model of a sweating rate term – an important parameter of thermal regulation and sensation. Due to the primary focus of this research our model would require additional validation before being applied in cool and cold environments. We demonstrated that our model is comparable, or even outperforms, the more complex multi-node multi-part models in terms of the dynamics of average skin temperature. Our model is limited to the scenarios of assessing the overall thermophysiological state of a person. More sophisticated models should be used in studies of differential thermal comfort and sensation as well as in the scenarios of non-uniform spatial exposure to thermal stimulation. Overall, the combination of accurate dynamics and low computational cost makes this model an excellent candidate for a model of physiological response to dynamic outdoor thermal environments at an individual level. Moreover, the model can be used in other studies, such as understanding the implications of walking speed on additional heat stress as reported in Chapter 4 and prediction of core temperatures to investigate the effect of thermal environments and physical activity on the performance of the innate immune system response reported in Chapter 6.

Chapter 3 serves as an important connector between the model of physiological response and studies of behavioural response to the thermal environment reported in Chapters 4 and 5. In this chapter, the measures of instantaneous physiological index and accumulated heat stress are proposed as indicators of thermal perception and drivers of thermoregulatory behaviour. As discussed in the introduction of this thesis, thermal perception, a psychological response to the thermal environment, is a complex and under-investigated process. This makes the creation of comprehensive computational models currently not possible. Instead, the research in this thesis relies on the studies of thermal perception of climate performed in particular geographical regions to map values of the physiological index of thermal environment to average perception. The instantaneous value of the physiological index is calculated with the use of our physiological model and can be used along with the localised perception scale to approximate thermal satisfaction and acceptance. This thesis contributes in understanding thermal perception through measuring behaviour. Being a response in-between physiology and behaviour, it can
be parameterised based on the observed physiological state and behaviour. Assuming that the magnitude of thermoregulatory behavioural response is governed by the thermal perception, the latter can be inferred through the former. For example, in Chapter 4 we observe no speed adaptation to varying thermal environment, which allows us to conclude, that this environment and associated heat stress (calculated with physiological model) is perceived as satisfactory, i.e. requiring no adaptation, for the observed activity. Alternatively, a pronounced sun avoidance behaviour reported in Chapter 5 suggests that the participants were exposed to stressful thermal environments and that associated heat stress was not thermally acceptable, forcing the participants to employ the behavioural adaptation. These two pedestrian behaviours, speed and path adaptation, are among four hypothesised in Chapter 3 based on the studied literature. Two remaining hypotheses, namely reactive thermal attraction and proactive route planning, could be an interesting subject for future work. Overall, this chapter has an important conceptual and goal-setting role in this thesis and future developments beyond. It formulates a general framework of agent-based modelling of pedestrian movement in physical and dynamic thermal environments, and the remaining chapters of this thesis describe the components of this framework in more detail.

Chapter 4 presents a study of walking speed as a means of behavioural thermal regulation. We introduce the heat-stress-optimal walking speed $V_{HS}^*$ as the one which minimises the accumulated heat stress over the period of walking. Using the physiological model described in Chapter 2 we have estimated the values of heat-stress-optimal walking speed for a broad range of outdoor environments. We find that this speed is minimal (0.88 m/s) in the most thermally neutral environment of 20°C, and to minimise heat stress in other environments one should increase walking speed. The values of $V_{HS}^*$ result from the complex interaction of metabolic heat production, heat removal through convection and evaporation and time of exposure. We test the theoretically found values against walking speeds observed in the urban environment of Singapore. We find, that the observed walking speeds are systematically higher than those predicted by our model, implying that additional heat stress is incurred by people. We also find that these speeds are not significantly different for three different air temperatures within the range of [27.5,
32.3°C, suggesting that people do not adapt their activity intensity (walking speed) while walking in microclimates within this range. There are multiple explanations which can be given for this observation, one is that Singapore’s pace of life is determined by other social and environmental factors and this overpowers the needs for thermal regulation. Interestingly, we find that the use of smartphones or walking in a group significantly decreases the walking speed, which enhances the thermal experience. Thus, social engagement and interaction might be a factor that compensates for the urban pace of life and environmental over-stimulation resulting in improved thermal comfort. Another reason for no observed walking speed response to change in thermal environment might be due to the relatively low relief promised by such adaptation, which does not justify the change in the walking speed – an inherent parameter of basic human locomotion. Therefore, we might expect to observe this adaptation in conditions in which thermal stimulation has a higher gradient: in different climates or under direct exposure to the sun. Both questions constituting an interesting direction for future work. Overall, the study reported in Chapter 4 provides another, climatic, perspective on the increased pace of life in cities. That is, elevated walking speeds due to pace of life do not only manifest social and environmental pressure, they also result in additional heat gain. Cities that offer environments facilitating relaxed slower walks can reduce the thermal and overall stress of people.

In Chapter 5 we described the results of a behavioural experiment with human participants in a natural outdoor environment in Singapore. The goal of this study was to investigate whether the path planning behaviour is affected by the visually apparent microclimate properties of the space. We found that people are willing to take longer but less sunny path options demonstrating sun avoidance behaviour. We employed video capturing and a 3D model of the experimental area to calculate the position of the sun in order to precisely characterise path options in terms of sun, tree shade and building shade. We proposed a hierarchical model of observed decisions governed by the sun-shade composition and length of the alternatives. With this it was possible to estimate the distance-inflating coefficient of walking under the sun. We have built a perceived tree shade intensity parameter into the model and found an indication that tree shade intensity is perceived by people as less intense (less
relieving) than building shade. We found the expected level of this parameter to be 0.5, i.e., path choices observed in our experiment suggest that on average tree shade is considered only half as relieving as building shade under the decision model assumed. The experiment, however, was not designed to infer this parameter and we suggest that dedicated experiments should be designed to properly characterise this parameter. Nevertheless, our findings have direct implications when considering shading potential of green and built infrastructure. The distance-inflating coefficient of sun $\beta_j$ has an expected value of 1.16 when pooling decisions of all participants. This implies that according to observed path choices, under the assumed model of decisions, participants associate on average 16% more effort when walking under the sun as compared to walking in the shade. The resulting posterior distributions of the distance-inflating coefficient of the sun $\beta_j$ have significant mass for values less than 1, which corresponds to appreciation of the sun. We argue, that this fact should not be interpreted as evidence of the preference for the sun in some decisions. Rather, other factors which were present in the environment have influenced the observed decisions. If it were possible to perfectly isolate the sun-shade factor in a natural experimental setting, we could expect even higher values of $\beta_j$. Nevertheless, decisions of individual participants suggest a personal $\beta_j$ as high as 1.8. Variation in $\beta_j$ can be explained not only by differences in individual properties of the participants, but also by the property of the shading available in the environment. This underlines that provision of opportunities for behavioural adaptation results in a higher observed level of adaptation. As behavioural thermal regulation is the only feasible option to maintain thermal comfort in the long run, urban planning and policy for OTC should focus on providing such opportunities in urban environments. The results of our experiment and model of path choices can be directly built into models of pedestrian navigation behaviour in thermal environments. Moreover, the unique combination of microclimate, survey, behaviour, physiological and video-recording data collected in this experiment will serve as a basis for further investigation of all three components of human response to thermal environments covered in this thesis: physiology, perception and behaviour.

Chapter 6 covered an important and under-investigated question of the
Chapter 7. Summary and conclusions

effect of heat stress on the functioning of the human innate immune system (HIIS). We used a computational model of HIIS to estimate ranges of body core temperatures, which are beneficial and detrimental to performance of HIIS. We found that core temperatures beyond 38°C have detrimental effects on the performance of HIIS response. Using the physiological model of thermal regulation formulated in Chapter 2 we identified the regimes of exposure to the thermal environment and levels of physical activity, which result in body core temperature crossing a threshold value of 38°C. In tropical climate conditions of Singapore the core temperature would cross the threshold after 6.35 minutes or only 1.5 km (3.6%) into the run. These results suggest that behavioural adaptation (i.e. regulation of activity intensity and duration of exposure) is critical to not only maintain the thermal comfort, but to preserve proper functioning of the HIIS. Overall, gaining a comprehensive understanding of heat stress effect on human short- and long-term health is an important challenge for future research.

The work in this thesis has identified a number of research gaps and directions for future work.

While our physiological model reported in Chapter 2 provides means for personalised prediction of thermal state, through parameters of clothing, activity level (metabolic heat production), height and weight, additional parameters such as gender, age, fitness and acclimatisation and their effects on the system could be integrated in the future. Making the model of thermal regulation more individualised is crucial to not only make it more precise, but also to account for the variation in the physiological response among individuals, which is driving the observed differences in thermal perception and behaviour of people.

The perception of the thermal environment depends on physiological state as well as psychological condition of individual and properties of the environment. This complex and highly personal process still requires a major interdisciplinary research effort. Advancing the understanding about the thermal perception of people will require extensive controlled experimentation and development of means of quantitative measurement of human psychological
response to thermal stimulation, using the tools of such disciplines as neuroscience and behavioural science. In our studies we demonstrated the application of the latter for objective measurement of individual perception of the thermal environment, as opposed to subjective measures, to which previous research resorts almost exclusively.

In our human behaviour studies we took the reductionist approach to isolate thermal parameter of environment. This allowed us to measure the effect of heat on human behavioural response with utmost certainty. Natural human environments, however, vary in multitude of other stimuli and integrating the thermal response into an overall model of human-environment interaction constitutes a challenge for future work. In Chapter 3 we propose an agent-based framework for modelling this phenomenon, but implementation of the complete model would require gaining understanding of human response to other individual stimuli and integration of these responses into an overall response to the environment. This thesis proposed the comprehensive approach of multi-level modelling of human response to environmental stimuli. Its application in studying thermal environments suggests further adoption for investigation of other environmental factors such as noise, lighting and social interactions. The latter is especially important at the time of writing of this thesis as the ongoing Covid-19 pandemic emphasises the need to control the spread of the virus while minimising the impact on social life and economic activity.

Understanding the long- and short-term consequences of heat stress for health is crucial for an informed response on individual and population levels. Accurate computational models are invaluable to gain this understanding, and empirical data is critical to inform, calibrate and validate these models. In our study of the interaction of heat stress and the human innate immune system (HIIS), the qualitative dynamics of HIIS parameters in response to heat from the existing literature was used to inform the model. The next step would require dedicated experiments to obtain quantitative information on the dynamics of selected parameters to validate and improve the accuracy of the model.

For the prevention of heat stress and related illness, methods of objective, continuous, non-invasive monitoring and detection of heat stress should be
developed. In our experiments with human participants we used biofeedback wristbands to collect several physiological signals of participants while simultaneously recording their exposure through video-cameras and weather stations. This dataset can be used to develop statistical methods of monitoring, prediction and prevention of heat stress.

This thesis provides a comprehensive understanding of the complex response of people to dynamic thermal environments. For each level of response – physiological, perceptual and behavioural – computational models are proposed. The models can be readily built into existing platforms of agent-based simulation of pedestrian flows to assess, predict and enhance outdoor thermal comfort of people in current and future cities. Individual models can be used in studies of the interaction of the thermoregulatory response with other systems and processes. Approaches taken in our study of human response to heat can be adopted to investigate the human response to other stimuli paving the way towards complete understanding of overall process of human-environment interaction.
Publications


PMAS conceived the idea for this study. VM conducted the literature review, formulated the models, performed the simulations and wrote a draft of the paper. VVK and PMAS validated the methodology and results and edited the paper.


VM performed the literature study, formulated the model, performed calibration of the model parameters, validation of the model and sensitivity analysis, wrote a draft of the paper. VVK and MHL conceptualised the study, validated the model and the results of computational experiments, edited the paper. PMAS conceived the idea for this study, validated the system dynamics model and sensitivity analysis and edited the paper.


VM designed and performed empirical and computational experiments, conducted their analysis and wrote a draft of the paper. VVK conceptualised the computational study and validated it, MHL validated computational study, conceptualised empirical study and validated its analysis. PMAS initiated the research and validated the methodology and results. All authors participated in drafting and editing the paper.

VM designed and conducted the experiment, created the computational models, performed the analysis of the data and drafted the paper. GIC conceptualised the experiment, validated the experimental design and procedures, data analysis. VVK and MHL validated the experimental design and procedures, computational models and their results. PMAS conceptualised the study, validated the methodology and results. All authors participated in drafting and editing the paper.


AP extended and performed simulations of the computational model of HIIS. VM provided thermoregulatory model and simulated the scenarios of heat exposure. AP and VM contributed equally in conceptualising the study, obtaining and validating the results, writing a draft of the paper. VVK conceptualised the methodology and validated the results of computational study. PMAS conceived the idea for this research, conceptualised the methodology and validated the results. VVK and PMAS edited the paper.

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Afterword

“Only in small Russian towns is the pedestrian still loved and respected. There he still owns the streets; he strolls along in the road without a care...”

Ilya Ilf and Yevgeny Petrov,
The Little Golden Calf, 1931

Extremely hot days are now common in the summer even in Nordic Saint Petersburg. And during such days it is a special kind of pleasure and privilege to find yourself carelessly strolling on the streets of one of its many satellite towns – heritage of its imperial past. The observation on small Russian cities, made 90 years back, holds true to a large extent even nowadays.

The studies of this thesis provide a comprehensive understanding of the phenomenon of human response to outdoor thermal environments. The developed models serve as tools for urban scientists and planners to study this response in different scenarios. These tools will help to propose solutions for thermally comfortable urban environments, so that pedestrians regain their ownership of the streets in large cities worldwide.
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