Computational models of human response to urban heat
*From physiology to behaviour*

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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
5.1. Introduction

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 and economic 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.
Chapter 5. Empirical study and choice modelling of pedestrian sun avoidance behaviour

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
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.

5.2 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
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
5.2. Results

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
Chapter 5. Empirical study and choice modelling of pedestrian sun avoidance behaviour

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).
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 5.2c). 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.
Chapter 5. Empirical study and choice modelling of pedestrian sun avoidance behaviour

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:

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

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 \( B \left( c_{ji}^{(B)} \right) \), the difference in the option costs is:

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

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.
Chapter 5. Empirical study and choice modelling of pedestrian sun avoidance behaviour

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
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.
Chapter 5. Empirical study and choice modelling of pedestrian sun avoidance behaviour

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
Chapter 5. Empirical study and choice modelling of pedestrian sun avoidance behaviour

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
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:

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

(5.4)

Here the chosen way of parameterisation of distribution of $\beta_j$ helps to avoid high correlation in parameters of Gamma distribution, allowing the NUTS
5.4. Methods

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 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.](image)

\begin{align*}
d, c & \sim \text{Normal}(0, 1) \\
f & = \exp(d + e) \\
g & = \exp(d - e) \\
\beta_j & \sim \text{Gamma}(f, g) \\
\rho & \sim \text{Beta}(1, 1) \\
\tau_k & \sim \text{Beta}(12.5, 50) \\
A_j & = \{a_j^{\text{sun}}, a_j^{\text{tree}}, a_j^{\text{shade}}\} - \text{sun-shade composition of path option A} \\
B_j & = \{b_j^{\text{sun}}, b_j^{\text{tree}}, b_j^{\text{shade}}\} - \text{sun-shade composition of path option B} \\
e_j^{(A)} & = \beta_j [a_j^{\text{sun}} + (1 - \rho) b_j^{\text{tree}}] + a_j^{\text{shade}} + \rho a_j^{\text{tree}} \\
e_j^{(B)} & = \beta_j [b_j^{\text{sun}} + (1 - \rho) b_j^{\text{tree}}] + b_j^{\text{shade}} + \rho b_j^{\text{tree}} \\
\Delta e_j & = e_j^{(x)} - e_j^{(b)} \\
y_j & \sim \text{Bernoulli}(1/(1 + \exp(\Delta e_j/\tau_k))) \\
N_1 & = 26, N_2 = 20 \\
D_j & - \text{number of treatment decisions of participant } j.
\end{align*}

**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 one 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.
Please remember

• Starting new task, identify given route options visually in the environment, make your 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 5.6: 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.