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Isolating the factors underlying cognitive demands of visual environments

Isolating the factors underlying cognitive demands of visual environments

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Abstract

Exposure to urban environments over a relatively long period of time has been found to be more cognitively demanding than exposure to nature environments, even if sensory input is received only through visual cues. Yet, it remains unclear which parameters contribute to such environmentally-induced cognitive load. The aim of this thesis was to understand the causal mechanisms underlying this effect, using gait kinematics and reaction times as an objective measure of cognitive load changes in real-time. Over six studies, I teased apart factors that might contribute to cognitive load. In particular, I investigated the impact of low-level visual features (such as image statistics: contrast distribution, fractal dimensions, and the amount of "greenery" in a visual scene), visual discomfort and aesthetics on gait kinematics. Neither greenery nor contrast distribution were predictive of gait kinematics; however, walking towards images with fractal properties outside the range typically found in nature scenes slowed gait, indicating higher demands on cognitive load. This suggests that some but not all low-level image statistics play a role in environmentally-induced cognitive load. Moreover, an interaction between fractal dimensions and visual discomfort rather than aesthetics seemed to contribute to environmentally-induced cognitive load, with a strong negative relationship between visual discomfort and liking. Data presented in this thesis have gone some way towards enhancing our understanding of how different visual features of an environment impact cognitive abilities and suggest that visual stress/discomfort could be at the core of cognitive load differences between nature and urban environments. More broadly, these results may inform future design of healthy and inclusive cities, which is one of the major global health challenges.

COVID-19 Statement

The main aim of this thesis was to disentangle different visual features of environments impacting cognitive processing load, using gait kinematics and reactions times as a measure of load. Due to the COVID-19 pandemic, I was unable to conduct any face-to-face research during the entire third year of my PhD, which meant that no further walking experiments nor any other laboratory experiments could be performed and I had to change substantially the direction of my work away from my original topic. Instead of being able to conduct a planned study to investigate resilience to physiological stress induction (through CO2 exposure) on reaction times whilst viewing nature and urban scenes, I have run three online studies to further investigate the relationship between visual discomfort and liking related to the image materials used throughout my thesis (Experiments 7, 8 and 9).

Acknowledgements

I would like to express my sincere gratitude to my research supervisors, Prof. Ute Leonards and Dr. Jeremy Burn for invaluable supervision, inspiration, enthusiastic encouragement, and constructive feedback during the development of this research work. This would have not been possible without your continuous support and guidance.

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Additionally, I would like to acknowledge the University of Bristol for providing me with a PhD studentship that allowed me to conduct my research.

I would like to thank my office friends Mubaraka, Katie, Milton, and Laura who made my study in the UK a wonderful time.

Finally, special thanks go to my partner Pietro, my family and friends for their unwavering support and belief in me.

Author’s declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's *Regulations and Code of Practice for Research Degree Programmes* and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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Publications:

- Burtan, D., Joyce, K., Burn, J. F., Handy, T. C., Ho, S., & Leonards, U. (2021). The nature effect in motion: visual exposure to environmental scenes impacts cognitive load and human gait kinematics. Royal Society Open Science, 8(1). doi:10.1098/rsos.201100

The studies had been designed, executed and preliminarily analysed by Katie Joyce (Experiment 1) in the context of her MSc thesis (Joyce, 2017) and by Leny Dimitrova (Experiment 2) in the context of her undergraduate dissertation (Dimitrova, 2019). However, I entirely reanalysed both experiments to create a methodological baseline for the purpose of my subsequent work and for publication (Burtan, Joyce, et al., 2021)

Author contributions were as follows: Ute Leonards and Todd C. Handy had the original idea for the two experiments, collected the stimulus material and developed the study concept together with Katie Joyce. Katie Joyce collected the data for Experiment 1, and Leny Dimitrova and myself for Experiment 2. Image statistics: contrast distributions were calculated by Katie Joyce and fractal dimensions were calculated by Simon Ho. I performed the data analysis and interpretation under the supervision of Ute Leonards and Jeremy F. Burn, with additional input by Todd C. Handy, Katie Joyce, and Simon Ho. I drafted the manuscript, and all other authors provided critical revisions.

- Burtan, D., Burn, J. F., & Leonards, U. (2021). Nature benefits revisited: Differences in gait kinematics between nature and urban images disappear when image types are controlled for likeability. *PLoS One*, 16(8), e0256635. doi:10.1371/journal.pone.0256635

Author contributions were as follows: With support of my supervisor Ute Leonards, I developed the study concept for this experiment. I then set up the actual experiment, collected the data, performed the data analysis, and provided a first interpretation of the data as well as the first draft of the manuscript. Ute Leonards and Jeremy F. Burn provided critical revisions of the manuscript throughout the publication process.

- Burtan, D., Burn, J. F., Spehar, B., & Leonards, U. (2022). The effect of image fractal properties and its interaction with visual discomfort on gait kinematics. Manuscript submitted for publication.

Author contributions were as follows: With the support of my supervisor Ute Leonards in collaboration with Professor Branka Spehar from the University of New South Wales, I developed the study concept. Professor Spehar created the stimulus material, including stimulus characterisation. I collected the data, performed the data analysis and interpretation under the supervision of Ute Leonards and Jeremy F. Burn. I drafted the manuscript, and all other authors provided critical revisions.

Conference presentation abstracts:

Burtan, D., & Griffin L.D., Leonards U. (2018, July 3). Image aesthetics, not basic image statistics, affect human gait parameters [Conference presentation abstract]. Bristol Vision (BVI) Researchers Colloquium, Bristol, UK.

Burtan, D. (2019, July 3). The impact of visual environments on cognitive load during walking [Conference presentation abstract]. Postgraduate Conference (University of Bristol), Bristol, UK.

Burtan, D., & Leonards U. (2019, July 8). Impact of visual exposure to natural environments revisited: aesthetics preferences impact gait dynamics [Conference presentation abstract]. Bristol Vision (BVI) Researchers Colloquium 2019, Exeter, UK.

Burtan, D., & Leonards U. (2019, August 25). Revisiting the positive impact of visual exposure to nature: A case of aesthetic preference? [Conference presentation abstract]. European Conference on Visual Perception (EVCP), Leuven, Belgium.

Burtan, D., & Leonards U. (2019, December 16). Revisiting the positive impact of visual exposure to nature: A case of aesthetic preference? [Conference presentation abstract]. Applied Vision Association Xmas meeting, Cardiff, UK.

Burtan, D., Spehar, B., Burn, J. & Leonards, U. (2020, July 2). Visual discomfort, not image statistics, affect gait kinematics [Conference presentation abstract]. Bristol Vision (BVI) Researchers Colloquium, Online.

Chapter 1. General Introduction

1.1. Overview

Currently, 54% of the world's population live in cities, and the United Nations estimates that by 2050 the number of people who live in urban settlements will increase to almost 76% (Nations, 2019). People living in urban areas are more likely to suffer from mental health issues such as depression and anxiety disorders (Lederbogen et al., 2011; Peen, Schoevers, Beekman, & Dekker, 2010; Wang, 2004) and from chronic conditions such as obesity, diabetes, hypertension and cardiovascular disease (Dye, 2008). Moreover, people living close to green spaces have a better healthy life expectancy than those with less access to green spaces (Rojas-Rueda, Nieuwenhuijsen, Gascon, Perez-Leon, & Mudu, 2019). Indeed, exposure to nature environments has been found to be associated with a wide range of health benefits, including reduced stress, anxiety and depression, increased happiness, concentration and a general improvement of our immune system (e.g. Pretty, Peacock, Sellens, & Griffin, 2005; Pretty, Rogerson, & Barton, 2017; Ward Thompson et al., 2012; White, Alcock, Wheeler, & Depledge, 2013).

Whilst a positive effect of nature on human well-being has been emphasised in poetry, philosophy, religion and even science for centuries (Bratman, Hamilton, & Daily, 2012), population health has acknowledged only recently that access to nature should be a key priority for urban planning to improve citizens' health and well-being (Bush & Doyon, 2019; Frumkin, 2002; Pretty et al., 2017; Razak, Othman, & Nazir, 2016).

From a psychological perspective, prolonged exposure to urban environments has been associated with the requirements of higher cognitive processing resources than exposure to nature environments (Berman, Jonides, & Kaplan, 2008; Berman et al., 2012; Cimprich, 1992; Cimprich & Ronis, 2003; Hartig, Evans, Jamner, Davis, & Gärling, 2003; Kaplan, 1995; S. Kaplan, 2001; Kaplan & Berman, 2010; Ottosson & Grahn, 2005; Taylor, Kuo, & Sullivan, 2002; Tennessen & Cimprich, 1995). This effect, mostly referred to as "nature benefit", i.e. the beneficial effects exposure to nature brings over the effects of exposure to urban environments, can even be found if only visual information is available (e.g. Berman et al., 2008; Berto, 2005). This suggests that at least some of the beneficial effects of exposure to nature are driven by basic sensory, here visual, aspects.

A key problem with the existing psychology literature on the impact of nature vs. urban environments on cognitive abilities is that most studies on this subject use a comparative approach, in which the experience of interacting with nature environments is simply compared to the experience of interacting with urban environments without appropriate quantification of the sensory parameters of the different environments (Bratman et al., 2012). Accordingly, there is no baseline measure to which these environments could be sensibly compared to; thus, it remains largely unclear whether the exposure to nature improves cognitive abilities ("nature benefit") or whether exposure to urban environments decreases cognitive abilities ("urban cost"). Moreover, the question remains what exactly it is in the respective environments that affects cognitive functioning.

A second key problem with the existing psychology literature lays in its design requiring prolonged exposure to an environment to see its positive/negative impact on a person's cognitive performance. Most studies establishing the positive effects of nature on cognitive abilities use methods that first measure a "baseline" cognitive performance, with or without cognitively fatiguing or stressing their participants (Ulrich, 1984), and then expose their participants to nature or urban environments for a prolonged time before assessing their cognitive performance again (e.g. Berman et al., 2008; Berto, 2005). Post-exposure cognitive performance tends to be better after exposure to nature environments than after exposure to urban environments. Moreover, compared to pre-exposure performance post-exposure performance is improved after exposure to nature but not after exposure to urban scenes (e.g. Berman et al., 2008); hence, these studies talk about a nature benefit. Yet, cognitive load changes during actual exposure have not yet been observed.

We reasoned that if cognitive benefits can be observed after sustained exposure to nature but not urban environments, additional cognitive resources must have become available during the actual exposure time to nature but not urban environments (or, conversely, urban environments used up more cognitive resources). Theoretically, then, one should be able to measure this difference in cognitive resource availability *during* the actual exposure time to an environment, on a moment-to-moment basis; provided one has a measure that is sensitive enough to such fluctuations. One way to measure the moment-to-moment impact of visual environments on cognitive functioning might be through quantifying changes in gait kinematics as it is well established in the literature on dual tasking that there is a link between gait and cognitive functioning (see for a review Amboni, Barone, & Hausdorff, 2013). Indeed, gait kinematics depend on the difficulty of a cognitive task that is being performed at the same time, and changes in gait kinematics can be reliably tested in a within-participant experiment in which the difficulty of the secondary task is manipulated on a walk-by-walk (e.g. Hausdorff, Schweiger, Herman, Yogev-Seligmann, & Giladi, 2008; Hollman, Kovash, Kubik, & Linbo, 2007; Lindenberger, Marsiske, & Baltes, 2000). Performing a cognitively demanding task during walking has been shown to result in changes in participants' gait parameters such as to a slower walking speed, increased stride time and increased gait variability (Amboni et al., 2013). From such findings, it has been suggested that overlapping brain areas, in particular those involved in processing of attention, are required for both tasks and that therefore one of the tasks is prioritised over the other at any given moment in time due to limited attentional resources. This effect of "attentional switching" – here for ease defined as an increase in cognitive load - can be observed on a trial-by-trial basis.

This thesis investigated whether exposure to images of nature vs. urban environments differentially affects gait kinematics on a trail-by-trial basis, in line with the idea that exposure to urban environments requires higher amounts of cognitive processing load and thus slows self-paced gait. Moreover, converging evidence for environmentally-induced cognitive load measured in real time was collected through a reaction time measurement for a basic shape discrimination task in which task-irrelevant environmental images were present to test participants' distractibility induced by individual environments.

If environmentally-induced cognitive load changes could indeed be picked up in real time simply through exposure to visual images of different environments whilst performing an unrelated task, this would allow the investigation of core factors within these images that might underlie cognitive load changes between nature and urban environments. Such visual factors proposed in earlier research ranged from basic image statistics such as contrast distributions or fractal content (e.g. Joye, Steg, Unal, & Pals, 2016; Penacchio & Wilkins, 2015), over differences in attentional demands (e.g. Grassini et al., 2019) and higher visual cognitive aspects such as the meaning of scenes (e.g. Vo, Boettcher, & Draschkow, 2019) to more general stress (Ulrich, 1984), or aesthetic preferences (Bratman et al., 2012).

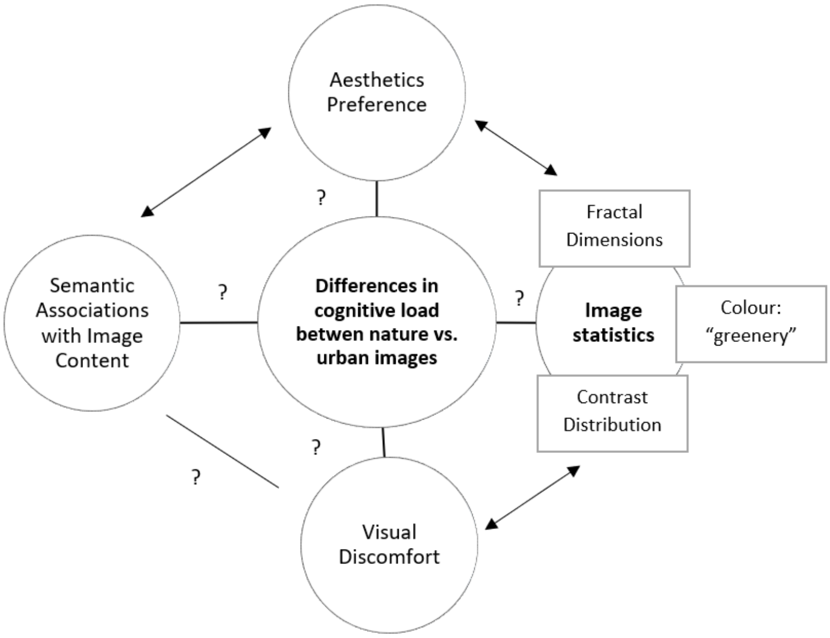

Figure 1.1: Overview of some of the core factors that might contribute to environmentally-induced cognitive load. This is a theoretical proposition based on the literature review presented in this thesis (see Chapter 1). Question marks refer to as yet unknown interrelationships between different factors. It is unclear whether the difference between nature and urban environments in their cognitive processing load demands is caused by differences in image statistics (Chapter 1.4.1.), visual discomfort (Chapter 1.4.2.), aesthetic preferences (Chapter 1.4.3.) or semantic associations (Chapter 1.4.4). Arrows are influences well described in the literature (see Chapter 1.3.). Mid- and Higher-level visual processes (Aesthetics and Visual Discomfort) are associated with low-level visual processes (Image Statistics). This graph shows that there is a link between visual discomfort and contrast distribution (Chapter 1.4.2.). Similarly, aesthetic preference is influenced by image statistics (fractal content) and semantic associations (Chapter 1.4.3.). It is unknown how the interaction between these factors impacts cognitive load.

The purpose of this thesis was to determine which of the above factors within a background environment affects the availability of cognitive resources for a task at hand (note, that for the purpose of this thesis, research was restricted to visual parameters only). After establishing first whether cognitive load differences between different (visual) environments can be measured on a trial-by-trial basis, the following questions were addressed (see Figure 1.1.):

a) Does the amount of “greenery/chlorophyll” in a visual scene impact visual cognitive processing load?
b) Do differences in cognitive load between nature and urban images still present when these two image types are equated for likeability?
c) What effect does subjective visual discomfort have on cognitive load, and thus gait kinematics?
d) Do the fractal dimensions of an image contribute to environmentally-induced cognitive load?
e) What is the relationship between visual discomfort and liking ratings?

These questions are addressed in 5 separate experimental chapters:

- Chapter 3 establishes whether the negative impact of urban environments (or positive impact of nature environments) on cognitive functioning can be measured on trial-by-trial basis, using gait kinematics and reaction times as a measure of cognitive load.
- Chapter 4 investigates whether colour as low-level image statistics, in particular the amount of “greenery”/chlorophyll in a visual scene, impacts visual cognitive processing load, using gait kinematics as a measure of load (Question a).
- Based on a converging evidence approach from both gait kinematics and reaction time approaches, Chapter 5 investigates whether differences in cognitive processing load between nature and urban scenes remain when each urban and nature scene presented are matched pairwise for their liking scores (Question b). Collecting visual discomfort measures for each scene presented further allows to measure the impact of visual discomfort on cognitive processing load irrespective of environment type (Question c).
- Chapter 6 explores whether the fractal dimensions of an image affect cognitive processing demands, using gait kinematics as the measure of cognitive demand (Question d).
- In three separate experiments, Chapter 7 finally explores the relationship between visual discomfort and liking for different image types (Question e).

1.2. Background

1.2.1. The impact of urbanisation and decreased nature exposure on physical and mental health

Nowadays, our generation has fewer daily interactions with nature than our parent's generation (Bratman et al., 2012), and this global trend is predicted to continue. This decline in human contact with nature is thought to negatively impact physical and mental health (Cox, Shanahan, Hudson, Fuller, & Gaston, 2018; Lederbogen et al., 2011), particularly affecting people who live in economically deprived urban settlements (Schwarz et al., 2015).

The decline in human-nature interactions is understood as a direct result of global urbanisation, a rapid process of rural-to-urban migration (Turan & Besiril, 2008). Indeed, for centuries, the proportion of the global population living in cities has been increasing continuously (Leon, 2008), with a dramatic rise over the past 100 years due to accelerated industrialisation, modernisation and economic development (Antrop, 2004). Urbanisation has been defined in the literature as a complex process of demographics, social, economic, and psychological changes, leading to an increased number of people living in urban areas (Turan & Besiril, 2008). The trend for rapid urbanisation has started in Europe and North America in the nineteenth and early twentieth centuries, but then spread across the world with no end in sight.

Early research in the psychological sciences on urbanisation considered mostly the positive aspects of urbanisation such as an improved quality of life as cities provided access to education, health and social services in addition to increased employment prospects (Glaeser & Steinberg, 2017). Urban environments have been considered as a source of innovation and creativity due to the high population density that is providing more opportunities to collaborate and exchange information (Knudsen, Florida, Stolarick, & Gates, 2008). Massive urbanisation has been understood as a predictor of economic growth since 1960 (Glaeser & Steinberg, 2017), with an increase in income as the density levels doubled, in both rich and poor countries (Chauvin, Glaeser, Ma, & Tobio, 2017).

Only recently, the negative consequences of living in cities became more apparent and a topic of scientific investigation. Whilst there is no doubt that urbanisation has benefits and offers access to a range of healthcare services, sanitation, and food security (Godfrey & Julien, 2005); it has been shown to be associated with a decline in physical activity (e.g. Levine et al., 2011), and a substantial increase in chronic conditions such as obesity, diabetes, hypertension and cardiovascular disease (Dye, 2008). Moreover, a widespread decrease in the population's mental health has been observed (mental health is defined in this context as "a state of well-being in which every individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community" (World Health Organization., 2004, p.10)). For example, the global shift in demographics from rural to urban settings has been shown to be associated with increased depression and anxiety disorders (Lederbogen et al., 2011; Wang, 2004), and higher incidences of schizophrenia (e.g. Krabbendam & van Os, 2005) due to a combination of poverty, social isolation, discrimination and their interactions with the environment (Gruebner et al., 2017). Social marginalisation and exclusion problems such as homelessness, alcohol disorder, and drug addiction have been found to be mostly concentrated in urban environments (Godfrey & Julien, 2005). The increase in urbanisation and associated increase in mental disorders comes at the same time as the constant increase of the world's population overall from 7.0 billion to-date to a predicted 9.7 billion in the next 30 years (Nations, 2019), due to increased life expectancy and global ageing at the population level (Leeson, 2018). As urban infrastructure growth is predicted not to develop in alignment with such population increase, the risk of poverty, mental health decline and decreasing social support further increases (Srivastava, 2009).

Beside such overarching factors, public health has been shown to be negatively associated with a range of environmental stressors associated with urbanisation such as air pollution, exhaust fumes, industrial waste, asbestos (e.g. Brunekreef & Holgate, 2002; Godfrey & Julien, 2005; Zijlema et al., 2016), auditory noise pollution (Stansfeld & Matheson, 2003), light pollution (Chepesiuk, 2009), and features of both microclimate and macro environments such as the amount of green spaces available (Jokela, Bleidorn, Lamb, Gosling, & Rentfrow, 2015; Rentfrow & Jokela, 2016), to name but a few.

Such stressors are thought to underlie a more overarching factor, namely the decreased frequency, intensity and duration of exposure to nature or blue-green infrastructure in city-dwellers (Bratman, Hamilton, Hahn, Daily, & Gross, 2015; Cox et al., 2018; Lederbogen et al., 2011); indeed, the less access people have to green spaces in form of parks or water, the higher seems the amount of mental stress people are under (Pretty, Griffin, & Sellens, 2004; Pretty et al., 2005).

The late realisation by Population Health research that a decrease in exposure to nature might pose a clear challenge to urban planning (Nations, 2014) seems surprising, if one considers that the origins of debates on a link between rural-urban migration and nature disconnection can be traced as far back as to the second half of the C18th when Romanticism arose partly as a response to industrialisation in Europe (Cloudsley, 1990). Indeed, many poets (such as, for example, William Wordsworth, Robert Bloomfield or William Blake in English-speaking countries) have drawn attention to the beauty of nature, idealised the pre-industrial past in their art and were concerned about separation from nature due to industrialism (Cloudsley, 1990; Güvenç, 2014).

1.2.2. Nature definition and categorisation of landscapes

Although the relationship between human beings and the environments they live has been a key topic throughout arts history (see Morriss-Kay, 2010), it is only over the last decade that evidence from urban planning, human geography, medicine, and psychology has been rapidly increasing to highlight the importance of exposure to nature or well-maintained urban blue-green infrastructure in the form of parks, urban gardens and closeness to blue spaces such as aquatic/marine environments containing open water sources for mental health and well-being in urban populations (e.g. Bratman et al., 2015; Dadvand et al., 2016; James, Banay, Hart, & Laden, 2015; Lin, Tsai, Sullivan, Chang, & Chang, 2014; Mitchell, Richardson, Shortt, & Pearce, 2015; Pretty et al., 2017; Roe et al., 2013; Thomas, 2015; Van den Berg et al., 2016; Volker & Kistemann, 2015; Wells, 2000; Wheeler et al., 2015). Greater access to green spaces such as living close to parks has been associated with lower stress, less depression, enhanced physical activity, improved happiness and wellbeing (Cohen-Cline, Turkheimer, & Duncan, 2015; James et al., 2015; Lee & Maheswaran, 2011; White et al., 2013), increased positive affect (Berman et al., 2012; Bowler, Buyung-Ali, Knight, & Pullin, 2010; Hartig et al., 2003), positive social interactions, improved sleep (Grigsby-Toussaint et al., 2015) and impulse inhibition (Taylor et al., 2002). A walk in a forest in nature, known as “forest air-bathing”, has been shown to reduce the level of health risk factors, such as elevated blood glucose (Ohtsuka, Yabunaka, & Takayama, 1998) and inflammatory cytokines (Mao et al., 2012). In addition, it seems that growing up in rural as compared to urban areas is associated with reduced stress responsivity (e.g. Lederbogen et al., 2011). Not only exposure to nature itself but even exposure to some elements of nature in urban environments in form of blue-green infrastructure has been associated with better health and improved cognitive functioning. For example, living in urban environments but in close proximity to green spaces such as urban parks and gardens has been associated with improved cognitive abilities (Zijlema et al., 2017).

There is thus substantial evidence that elements of nature in urban environments positively affect physical and mental health. Such evidence has led architects and urban planners to design more green and blue spaces in cities (Andreucci, Russo, & Olszewska-Guizzo, 2019; Lohmus & Balbus, 2015; White et al., 2013). Yet, little is known which features of a nature environment contribute how much to improving mental health and how to how this could be objectively measure and quantified to support decision making processes for urban planning decisions.

But why do we know so little about which features in an environment contribute how to mental health? This lack of knowledge is not least due to the fact that very few of the authors of published research studies on the benefit of exposure to nature on mental health specify the types of nature environments they are talking about (see Bratman et al., 2012). This is problematic as interacting with nature *per se* does not necessarily have to be a positive experience; indeed, it can be highly unpleasant and stressful. For instance, earthquake and hurricane-related resource loss or nature environments perceived as life-threatening can result in psychological stress (Freedy, Saladin, Kilpatrick, Resnick, & Saunders, 1994) as do natural environments affected by natural disasters (Benight et al., 1999; Bratman et al., 2012; Freedy et al., 1994). Even less extreme examples of nature environments can be expected to be less beneficial than others such as, for example, walking through a dark and overgrown forest as compared to walking in an urban well-maintained park on a sunny day. Whilst there is some evidence that nature environments that do not allow a person to observe potential dangers (e.g. predator) are less pleasant (Appleton, 1975), research has tended to focus selectively on beneficial rather than unbeneficial aspects of nature environments when comparing nature and urban environments. Therefore, it seems crucial to start with a clear definition of what is meant here when talking about nature environments as opposed to urban environments, including classifications of different types of nature environments.

In 2012, Bratman, Hamilton, & Daily proposed a system of categorization for different types of landscapes based on the analysis of stimulus sets used in studies that investigated the psychological or behavioural impact of nature images (Bratman et al., 2012). This approach facilitated the classification of ambiguous landscapes that incorporated both flora and man-made objects. In Bratman and colleagues' categorization, nature was defined as an area that contains elements of living systems, including plants and non-human animals, of different degrees of human management, implying that both "pristine wilderness" and "urban parks" are parts of nature. Nature experience in their categorization system was defined as the time spent being physically present within or looking at landscapes from a distance, including window views or simply viewing images. Moreover, Bratman and colleagues distinguished between the following types of landscapes, based on the different kinds of studies conducted at the time: urban green (Berman et al., 2008; Hartig & Staats, 2006; Tennessen & Cimprich, 1995), water bodies (Chang, Hammitt, Chen, Machnik, & Su, 2008; Ulrich, 1981), forest/woodland (Chang et al., 2008; Hartig et al., 2003), countryside/farmland (Hartig et al., 2003; Ulrich, 1981) and wilderness (Cole & Hall, 2010; Hartig, Mang, & G.W., 1991).

For the purpose of this thesis, Bratman et al.'s (2012) "nature" definition has been used to select representative images of nature environments (see Experiments 4, 5 and 9, Chapters 5 and 7 respectively): images of nature environments contained elements of living systems and presented water bodies, forests, countryside, wilderness, and urban green landscapes (without any man-made objects). Note that there were no animals in any of these images. Images of urban environments contained built-up areas with man-made objects (e.g. buildings, roads, cars) including sometimes elements of nature (e.g. parks, water bodies, flowers, sky).

1.3. Explaining the positive impact of nature on cognitive functioning

In the Psychology literature, the fundamental idea that different environments affect us differently was originally proposed by J.J. Gibson. Gibson suggested that different environments provide different "affordances" (Gibson, 1979), defining "affordances" as relations between an environment and an animal's ability to act within it. Successful interaction with environments depends on how an environment can be used and what the limits of action capabilities of an animal are. For example, a walking path "affords" (is used for) walking. Environmental affordances are not constant; as seen in particular for the built environment, environments are modified by humans to become more suitable to our everyday needs.

In contrast to Gibson's ideas about environmental affordances that would hold for any kind of environment, irrespective of whether it belongs to a nature or built environment category, research on the positive impact of nature environments but not urban environments on cognitive abilities (see Chapter 1.4.) has been dominated by evolutionary propositions since the 1980s (e.g. Kellert & Wilson, 1995; Ulrich, 1981, 1983; Wilson, 1984) such as the Biophilia Hypothesis (Kellert & Wilson, 1995) and the Savannah Hypothesis (Orians, 1980). Only two psychological theoretical frameworks - Attention Restoration Theory, ART (R. Kaplan, 2001; Kaplan & Kaplan, 1989; Kaplan & Yang, 1990; S. Kaplan, 2001) and Stress Recovery Theory, SRT (Ulrich, 1983, 1984; Ulrich et al., 1991) – have been based on scientific research in experimental psychology. The general assumption of these theories is that exposure to urban environments as opposed to exposure to nature environments leads to a higher cognitive processing load. Evidence for such an increase in requirements on cognitive resources comes from studies measuring the decline in cognitive performance in attentional tasks (e.g. Berman et al., 2008; Berman et al., 2012; Cimprich, 1992; Cimprich & Ronis, 2003; Hartig et al., 2003; Kaplan, 1995; S. Kaplan, 2001; Kaplan & Berman, 2010; Ottosson & Grahn, 2005; Taylor et al., 2002; Tennessen & Cimprich, 1995). Both, ART (see Chapter 1.3.2.) and SRT (see Chapter 1.3.3.) propose that nature environments provide us with the capacity to restore attentional resources, but explain the mechanisms underlying this restoration/restorativeness effect differently.

A more recent suggestion, described in Chapter 1.3.4., the Perceptual Fluency Account (Joye & De Block, 2011; Joye et al., 2016; Joye & Van den Berg, 2011), has put into question evolutionary accounts of nature *restorativeness* due to a lack of empirical support. It focuses instead on differences in visual processing of different environments and the role of fractals (see Chapter 1.4.1.2.).

For completion, I provide below an overview of the major propositions and theories that have been put forward to explain the mechanisms behind the cognitive processing load differences between nature and urban environments. Whilst it was not within the remit of this thesis to test or improve on these ideas, the literature with experimental outcomes derived related to some of the more scientific accounts helps to make predictions about the factors that might contribute to environmentally-induced cognitive load (see Chapter 1.4.).

1.3.1. Evolutionary Propositions: Biophilia and Savannah Hypotheses

The main assumption of evolutionary propositions is that a positive response to nature environments has been rooted in our past (Joye & Van den Berg, 2011) as an adaptive mechanism of natural selection for survival (Hunter & Askarinejad, 2015): humans are initially attracted to those kinds of natural settings that are safe and provide food resources, and thus increase the chance of survival.

Wilson's Biophilia Hypothesis claims that humans have an urge to affiliate and connect with nature, diversity of landscapes and habitats, and other forms of life (Wilson, 1984). It proposes that humans have a preference for environments that meet their biological needs crucial for survival. Within this, aesthetic preferences for some environmental features are inherited. Indeed, there is ample support for a claim that nature environments including elements necessary for survival such as water, grass, plants, or trees are preferred over built environments (see also Chapter 1.4.3.). The Savannah Hypothesis (Orians, 1980) is strongly related to the main concept within the Biophilia Hypothesis (Kellert & Wilson, 1995; Wilson, 1984), claiming that humans have an initial aesthetic preference for open landscapes in a form of savannah habitats, where crucial phases of evolution took place. A savannah is open grassland with sparse trees which provide refuge and outlook to hide from danger (Appleton, 1975; Townsend & Barton, 2018). A few studies found evidence to support the hypothesis that images presenting landscapes with features characteristic of savannah were preferred (Balling & Falk, 2016; Lohr & Pearson-Mims, 2016) over images presenting other biomes, but other studies did not (e.g. Han, 2007; Hartmann & Apaolaza-Ibáñez, 2010). This leaves the question unanswered whether aesthetics preference might be a possible driver behind the nature effect. Note, however, that such evolutionary hypotheses remain highly speculative due to the lack of testability and thus evidence.

1.3.2. Stress Recovery Theory

Stress Recovery Theory (SRT), proposed by Ulrich (Ulrich, 1981, 1983, 1984; Ulrich et al., 1991), suggests that spending time in nature environments reduces the level of psychological stress measured in the form of sympathetic and parasympathetic nervous activity (Brown, Barton, & Gladwell, 2013; Gladwell et al., 2012). Psychological stress is defined as "a particular relationship between the person and the environment that is appraised by the person as taxing or exceeding his or her resources and endangering his or her well-being" (Lazarus & Folkman, 1984, p.19). Indeed, there is evidence that even a minimum dose of nature exposure (10-40 minutes) significantly decreases stress (Meredith et al., 2019). Even looking at a nature environment through a window or viewing photographs of nature reduce activity within the sympathetic nervous system and increase activity within the parasympathetic nervous system. Based on the notion that aesthetic and affective reactions to environments are not isolated processes but are tightly linked to cognitive processes, behaviour and physiological systems, SRT therefore proposes that the recovery from physiological stress depends on the type of environment someone is exposed to.

According to SRT (Ulrich, 1983), different environments elicit different responses due to biological needs related to survival and success. Exposure to nature may maintain arousal in individuals who are not stressed and reduce arousal in individuals who are stressed. Response to the environment they are in is unconscious and is rooted in our evolutionary past as an adaptive mechanism. Exposure to nature environments presenting natural resources necessary for survival such as water and food, initiates a positive emotional reaction, which in turn, leads to a reduction in psychological and physiological stress. Not only water and vegetation were identified as environmental features that trigger positive affect responses but also more sensory factors such as complexity, depth, structure (e.g. symmetry) or surface texture (Ulrich, 1979, 1981, 1983, 1984). Indeed, there is a support for a claim that there is a link between aesthetics and low-level features such as complexity in the form of fractal dimensions (Spehar, Clifford, Newell, & Taylor, 2003; Taylor & Sprott, 2008), symmetry (e.g. Gartus & Leder, 2013), depth (e.g. Zhang, Nefs, Redi, & Heynderickx, 2014) and smooth surfaces (e.g. Bhatta, Tiippana, Vahtikari, Hughes, & Kytta, 2017). Affective benefits from interacting with nature environments thus seem grounded in both low-level and high-level cognitive processes (see Meidenbauer et al., 2020), raising the question whether an interaction between low-level and high-level cognitive processes could underlie the positive impact of nature environments on cognitive functioning. Even though there is an ample support for a claim that nature exposure reduces the stress level (see for a review Meredith et al., 2019), the evolutionary aspect of Ulrich's framework, i.e. that positive responses to nature environments are rooted in our evolutionary past as an adaptive mechanism has not been well supported by evidence.

1.3.3. Attention Restoration Theory

An alternative theory on the positive effects of exposure to nature is Attention Restoration Theory (ART; (R. Kaplan, 2001; Kaplan & Kaplan, 1989; Kaplan & Yang, 1990; Kaplan, 1995; S. Kaplan, 2001; Kaplan & Berman, 2010) developed in the 1980s. ART puts forward the idea that exposure to nature protects us against the impact of environmental stressors (see also Chapter 1.3.) and allows us to replenish our attentional resources. Urban environments, in contrast, capture attention and fatigue the brain, causing tiredness. Kaplan's theory proposes that urban environments are filled with competing sensory stimulation (e.g. lighting) that tax top-down directed attention mechanism. Directed attention is controlled by a cognitive mechanism that has to actively select relevant information whilst suppressing distracting irrelevant information. Nature environments provide a stimulation that is soft and fascinating, capture bottom-up involuntary attention mechanism and thus allow directed-attention mechanism to be restored (R. Kaplan, 2001; Kaplan & Kaplan, 1989; Kaplan & Yang, 1990; Kaplan, 1995; S. Kaplan, 2001; Kaplan & Berman, 2010). Key here is that nature environments would far less distract from the actual task at hand.

ART identifies four characteristics of physical settings that contribute to nature restorativeness: 1) fascination - involves little to no directed attention, 2) being away - involves eliminating distractions from everyday environmental contexts, 3) extent – the environment is coherent and predictable, 4) compatibility - compatible with the range of activities leading to restoration (Kaplan & Kaplan, 1989; Lin et al., 2014).

There is ample evidence to support ART, showing that spending time in nature improves post-exposure performance on attentional tasks (Cimprich, 1992; Hartig et al., 2003; Taylor et al., 2002), even when exposure to nature is reduced to viewing simply nature images (Berman et al., 2008; Berto, 2005). ART proposes that not only looking at nature environments without any built content but also looking at blue-green infrastructure in urban environments positively impacts cognitive functioning. For example, parks, gardens and urban woodlands have been found to be restorative (Carrus et al., 2017; Tyrväinen et al., 2014; Wang, Rodiek, Wu, Chen, & Li, 2016), as well as flowers on the street, grass and trees in urban settlements (Kuo, 2001; Lindal & Hartig, 2015). However, it is unclear how to quantify the amount of nature (or the biodiversity) needed to have restorative effects.

A recent systematic review of the literature on ART concluded that three different cognitive aspects are improved after nature exposure: attentional control, working memory and cognitive flexibility (Stevenson, Schilhab, & Bentsen, 2018).

A key problem with the existing literature on nature *restorativeness* is the research approach used. Most studies use a comparative approach, in which the experience of interacting with nature environments is simply compared to the experience of interacting with urban environments without clear descriptors of the environments compared nor with any quantitative measures for sensory parameters of these environments (Bratman et al., 2012). More importantly, it remains poorly understood whether interaction with nature is indeed "beneficial" or whether interaction with urban environments is "harmful" due to a lack of baseline measures to which these environments could be compared (Bratman et al., 2012). Even though most studies use methods that first measure cognitive performance prior to exposure as a kind of "baseline" and then expose their participants to nature or urban environments for a prolonged time before assessing their cognitive performance again (e.g. Berman et al., 2008; Berto, 2005), it remains questionable whether this baseline is indeed a valid approach as nothing is known about the mental state a person is in when they arrive at the laboratory. Moreover, the methodology requires long exposure times between the pre-exposure cognitive performance assessment and the post-exposure cognitive performance assessment; thus the impact of individual factors of environments on cognitive functioning cannot not be examined.

A further well-known criticism of ART is its lack of a clear definition of the characteristics in physical settings that contribute to nature *restorativeness.* Whilst ART argues that nature is beneficial due to its "aesthetic advantage" as measured through the amount of fascination it evokes, it fails to clearly define what is meant by fascination and thus how this aesthetic advantage could be objectively quantified. Therefore, experimental approaches used to test ART fail to answer the question which factors contribute to environmentally-induced cognitive load, mostly due to the comparative approach used between the two environmental categories and the lack of clear definitions of *restorative* environments that would allow to extract and measure individual factors in a parametric way.

1.3.4. Perceptual Fluency Account

Joye and colleagues (Joye & De Block, 2011; Joye et al., 2016; Joye & Van den Berg, 2011) put forward a further model for restorative responses to nature, the so-called Perceptual Fluency Account (PFA). In contrast to the evolutionary theories above, PFA proposes that restoration and stress reduction are by-products of fluent sensory processing; in other words, the visual elements of nature environments are easier to process than those of urban environments. Similar to SRT, this theory assumes that restoration is a result of the positive affect towards unthreatening nature environments that are more aesthetically pleasing than unthreatening urban scenes. However, this aesthetic preference is not due to evolutionary predisposition to nature *per se* as proposed by SRT, but simply due to the amount of sensory (particularly visual) features within nature scenes that can be processed fluently (Joye & De Block, 2011; Joye et al., 2016; Joye & Van den Berg, 2011; Reber, Schwarz, & Winkielman, 2004; Redies, 2007). For example, Joye and colleagues found that a higher fractal content, common in nature environments but less so in urban environments, leads to more fluent visual processing (Joye et al., 2016); pointing toward low-level sensory processes being at least partially responsible for differences in cognitive processing load required for the processing of nature and urban environments.

The main shortfall of Perceptual Fluency Account (Joye & De Block, 2011; Joye et al., 2016; Joye & Van den Berg, 2011) is the current lack of sufficient empirical support; therefore, this account remains unconfirmed. However, it provides two testable assumptions that make this theoretical account interesting for the purpose of my thesis: a) its claim that the sensory parameters of a scene or components of objects within this scene such as the scene's fractal content define how easily they can be processed; and b) that there should be a positive relationship between aesthetic preferences (i.e. positive affective responses) for a scene and perceptual fluency.

1.4. Sensory (in particular visual) differences between nature and urban environments

Recent evidence suggests that even simply exposure to images of urban environments is associated with the requirements of higher cognitive processing resources than exposure to nature images (e.g. Berman et al., 2008; Berto, 2005). It thus seems cognitive processing differences can be driven by basic sensory (here visual) aspects only. Yet, it remains unclear how the different sensory aspects proposed so far might contribute to an environment's cognitive processing load.

For the purpose of this thesis, I categorise different potentially contributing aspects at different levels: following current definitions (Kubilius, Wagemans, & Op de Beeck, 2014), low-level vision involves processing of visual features of a scene (see Chapter 1.4.1.), whilst high-level vision allows us to process the meaning of a scene (see Chapter 1.4.3.). Mid-level visual processing has been described as a "bridge" between low-level and high-level visual processes as it organises visual information into objects, shapes, and surfaces (Anderson, 2020; Kubilius et al., 2014; Rosenholtz, Li, & Nakano, 2007). In addition, I include sensory processes that relate low-level visual processes to affect (in particular, visual discomfort/visual stress and aesthetics) to this intermediate stage.

1.4.1. Low-level Image Statistics

One of the most obvious sensory differences between nature and urban images are their low-level image statistics: contrast distribution, colour properties and fractal dimension.

1.4.1.1. Contrast Distributions

The majority of nature images has a "scale-invariant" spatial structure (Penacchio & Wilkins, 2015), meaning that image complexity does not change across spatial scales. Indeed, the spatial frequency distributions of natural images decrease with increasing amplitude of contrast and vice versa; therefore contrast distributions fall close to a 1/f amplitude spectrum in nature, called Fourier Spectrum (Wilkins et al., 1984). Neural processing of images with scale-invariant structure (/f distribution) is thought to be more efficient due to a neural process known as "sparse coding" (Penacchio & Wilkins, 2015; Wilkins & Hibbard, 2014), i.e. a neural firing pattern in which the majority of neurons in the primary visual cortex remains inactive as only a few neurons are needed to process the sensory information available. Such efficient neural firing leads to a decrease in metabolic demand (Olshausen & Field, 2004); therefore, it should be easier for the visual system / more energetically efficient to process images that allow sparse coding (e.g. nature images) than images that do not.

Urban environments, on the other hand, tend to have high-geometric and repetitive high-contrast patterns that are far removed from the 1/f amplitude spectrum (Wilkins, Penacchio, & Leonards, 2018), such as, for example, high-frequency stripes in paving or crosshatch patterns in the brickwork. In other words, urban images do not possess the same spatial characteristics as nature images and should thus require more activity in early visual areas, in addition to attentional areas such as cuneus activation involved in their neural processing (Tang et al., 2017).

1.4.1.2. Fractals

Together with their smaller range of contrast distributions, nature images have greater amounts of fractals than urban images (e.g. Ho, Mohtadi, Daud, Leonards, & Handy, 2019). Fractals are defined as self-similar and self-repetitive geometric patterns across different spatial scales, mostly found in nature (Spehar et al., 2003). Well-known examples of fractal structures are clouds, snowflakes, leaves, tree branches, and mountains. Fractal dimensions of an image can be measured in different ways, leading to different results. In the context of this thesis, fractal dimensions were based on Minkowski–Bouligand box-counting technique for photographic images (see Chapter 2.3.2.). For the creation of abstract images, image fractal content was established by calculating a fractal dimension parameter ("D"), which assesses the relationship between patterns and fractal scaling; thus, providing information on how complexity (i.e. fractal pattern detail) is changing across the scale of the image. The value of image fractal dimensions in such calculations is between 1-2. Repetitive smooth and sparse shapes are described as values closer to 1, whilst complex repeating structures containing a lot of details are described as values closer to 2 (Spehar et al., 2003). Fractal dimension has been used as an objective measure of image complexity and statistical image regularity for studies on aesthetics preference (Bourchtein, Bourchtein, & Naoumova, 2014). The fractal content is associated with the above mentioned 1/f amplitude spectra, with an alpha mean of 1.2 (range 0.8 – 1.5) (e.g. Tolhurst, Tadmor, & Chao, 1992).

1.4.1.3. Colour properties

Nature and urban images further differ substantially in their colour distributions. In particular, the predominately green colour of nature images could account for some of the positive impact of nature environments on cognitive functioning described for people living in urban environments but in close proximity to green spaces (Zijlema et al., 2017).

Kardan and colleagues proposed that the aesthetic preferences people usually show for nature over built environments are driven by bottom-up processing of the low-level visual features of nature, in particular their spatial and colour properties (Kardan et al., 2015). They demonstrated that the perceived "naturalness" of an image and its preference ratings could be predicted from low-level visual features such as hue, colour saturation, edges (fine texture details), edges density or brightness. Lower hue levels (yellow-green over blue-purple), greater saturation diversity (high saturation variation), and more non-straight borders (edge density) explained 31% of the variance in ratings. Note that Kardan et at. (2015) calculated the colour properties of the images, using an HSV model (Hue, Saturation, Value): in this context, Hue refers to the dominant wavelength of a colour; i.e. the degree to which the image can be classified as either similar or different to red, blue or green. Saturation refers to a degree of hue dominance (intensity), and value (brightness) refers to the colour dimension. Average hue, saturation and value (brightness) were calculated across image pixels. However, further work needs to be carried out to establish whether the amount of "greenery"/"chlorophyll" in a visual scene also impacts cognitive functioning. For the purpose of this thesis, I relied on stimulus material of green colour spectra synthesised from Griffin's five-parameter model of spectral reflectance with realistic colour distributions (see Chapter 4.1.2. for description).

1.4.2. Mid-level visual processes: Visual Discomfort

As raised above, urban images tend to diverge further from a 1/f contrast distribution than nature images (Wilkins et al., 2018, see also Chapter 1.2.1.1.). At the same time, they are more uncomfortable to look at than nature images (Ho et al., 2019), raising the question whether images of urban environments are more uncomfortable to look at than images of nature environments due to differences in their 1/f amplitude spectra. Such an assumption would be in line with findings that images diverging further from a 1/f amplitude spectrum are more likely to induce increased visual discomfort, often also called visual stress (Attwell & Laughlin, 2001; Hibbard & O'Hare, 2015; Juricevic, Land, Wilkins, & Webster, 2010; O'Hare & Hibbard, 2011; Simoncelli & Olshausen, 2001). It seems that visual discomfort for different built environments can be predicted from their image statistics: the more their image properties deviate from image properties typical of nature images, the more uncomfortable they tend to be (Le et al., 2017).

Higher visual discomfort (or visual stress) reported during looking at visual stimuli is associated with adverse physiological symptoms such as headache, nausea, drowsiness, and in extreme cases, pattern-sensitive epilepsy; and it induces illusions of shape and colours (Radhakrishnan et al., 2005; Shepherd, 2010; Wilkins, 1995; Wilkins et al., 2018). Visual discomfort is thought to be related to overactivation within the visual cortex for metabolically demanding visual information (Patterson Gentile & Aguirre, 2020). Visual discomfort is reliably induced by repetitive and highly geometric patterns diverging far from a 1/f amplitude spectrum (Wilkins et al., 1984); for example, repetitive stripy patterns with high contrast such as often seen for acoustic panelling, commonly present in urban environments have been reported to induce visual discomfort (Le et al., 2017). Visual discomfort has been found to be strongest for visual exposure to medium spatial frequencies (~3 cycles per degree of visual angle ±1 octave). Both increasing colour or luminance contrast results in increased visual discomfort, whilst balancing image levels for colour and luminance contrasts decreases visual discomfort, with the lowest visual discomfort ratings around the blue-yellow axes, i.e. colour statistics typical for nature images (Juricevic et al., 2010). In general, these findings support the hypothesis that image statistics of urban images leading to metabolic overload in visual processing

Whilst the neural processes underlying visual discomfort are still under debate, there is evidence emerging that visual discomfort is related to overactivation within the visual cortex

(Patterson Gentile & Aguirre, 2020): indeed, visual information has been shown to be processed efficiently when there is a sparse distribution of neural responses (activity of small number of neurons) in the visual cortex (Hibbard & O'Hare, 2015); see idea of sparse coding mentioned above for contrast distributions). Images diverging further from a 1/f amplitude spectrum seem highly metabolically costly to process due to their requirements of non-sparse cortical responses and increased metabolism (Attwell & Laughlin, 2001; Hibbard & O'Hare, 2015; Juricevic et al., 2010; O'Hare & Hibbard, 2011; Simoncelli & Olshausen, 2001). Increased visual discomfort for urban images induced by basic image statistics could thus reflect metabolic overload in visual processing as suggested by Barlow (see Barlow, 2012). Interestingly, in the study by Ho and colleagues, participants were significantly slower when rating nature and urban images that were more uncomfortable to look at (Ho et al., 2019) . These findings raise the question of whether the human visual system might have started to adapt to urban environments, and thus whether any restorative/stress-reducing effect of interacting with nature could be related to more efficient sensory processing.

1.4.3. Mid- and Higher-level visual processes: Aesthetics and Semantic Associations

A completely separate strand of research with a well-established literature revealed that adults' positive affective responses to nature environments but not urban environments is related to increased aesthetic preferences for nature; an effect seen whether people were physically present in the environment or simply exposed to images, slides or videos of these environments (Han, 2010; Hartig & Staats, 2006; Ibarra et al., 2017; Kaplan & Kaplan, 1989; Purcell, Peron, & Berto, 2001; Ulrich, 1981, 1983; Valtchanov & Ellard, 2015; Van Hedger et al., 2019). For instance, exercising whilst viewing photographs of pleasant rural environments was more effective in reducing blood pressure than exercising whilst viewing photographs of pleasant urban environments, unpleasant rural and unpleasant urban environments (Pretty et al., 2005), supporting the hypothesis that landscape aesthetics might be associated with the benefits of interacting with nature environments.

The question of how human beings and environment are related is as old as the study of the arts itself. According to Morriss-Kay (2010), the origin of ‘birth’ of art can be tracked to 45 000 BP when homo sapiens began migrating from the African continent to Europe. European Upper Palaeolithic rock and cave paintings and engraved stones are the oldest form of ‘art’, reflecting long history of rapid human evolution and culture (Morriss-Kay, 2010). The development of various artistic styles across millennia (e.g. Renaissance, Baroque, Modernism), and thus aesthetics diversity of “arts” reflects the interconnection between art and civilisation (Kozbelt, 2021)

Although aesthetic preference has also been shown to differentially affect cognitive processing between nature and urban environments (Bratman et al., 2012), aesthetic preferences have rarely been accounted for studies exploring the nature benefit (e.g. Berman et al., 2008). Therefore, it cannot be excluded that many of the psychological studies reporting cognitive benefits during exposure to nature as compared to urban environments showed effects that were not specific to nature *per se* but rather due to an unintended aesthetic preference-related stimulus selection bias.

But what do people really mean when they write about nature being more aesthetically pleasing than urban environments, and how much does this depend on differences in aesthetic appreciation between different types of nature environments? Before being able to attempt to answer such questions, it is crucial to look at the different definitions for aesthetics first before presenting theories that try to explain why nature is more aesthetically pleasing than urban environments and how aesthetic appreciation might impact on cognitive functioning.

Since the birth of psychology in the 19th century, the experimental study of aesthetics has been a major topic for research. Debates on how to define aesthetics (from Greek: *aisthanesthai* - to perceive) have started, however, already millennia before amongst philosophers (Brielmann & Pelli, 2018). Aesthetics tends to refer to “beauty” whilst describing the aesthetic value of an object. For example, Plato defined “beauty” as pleasure through the eye to ear (Socratic dialogs, Hippias Major). Indeed, many philosophers, dating back to Plato, see “beauty” as being related to the specific properties of the particular object judged; properties which are producing pleasure for individuals interacting with the object (Tatarkiewicz, 1970). Sophists, in contrast, suggest that beauty is not objective but subjective (“in the eye of the beholder”), emphasizing that each individual perceives beauty differently (Tatarkiewicz, 1970). Philosophical debates whether aesthetics are a function of bottom-up processing (can be measured objectively) or

whether they are purely subjective has inspired scientists across the world to study aesthetics. A pioneer, who was the first to claim that aesthetics should be studied as an empirical science was Gustav Fechner (Fechner, 1876): he suggested that aesthetics should be studied through empirical observations in a bottom-up manner rather than philosophical supposition, in order to understand how physical properties of objects affect aesthetics judgements is crucial (Fechner, 1876). This has motivated researchers to explore which object features contribute to aesthetic appeal, such as symmetry (e.g. Arnheim, 1974), contrast (e.g. Gombrich, 1984), proportion/balance (e.g. Birkhoff, 1933) and complexity (e.g. Eysenck, 1942).
However, despite many years of scientific research in empirical aesthetics, there has been no agreement on a clear definition of aesthetics among scientists (Brielmann & Pelli, 2018), nor are there standardised measurements of aesthetics (e.g. Balling & Falk, 2016; Hayn-Leichsenring, Lehmann, & Redies, 2017). A common method is based on the use of basic rating scales to obtain aesthetic preferences by asking participants to rate objects or scenes for their likeability, pleasantness, beauty, or attractiveness without specifying what these terms actually mean (e.g. Balling & Falk, 2016; Hayn-Leichsenring et al., 2017; Spehar et al., 2003).

Studies in neuro-aesthetics, an emerging field of research combining aesthetics with neuropsychology and cognitive science, suggest that aesthetics is a complex experience of knowledge, which arises from the interaction between visual features of objects and an individual's perceptual processing (Consoli, 2015). Indeed, there is evidence that visual aesthetic perception is associated with visual and sensorimotor neural circuits in the brain, in particular regions of reward (see Kirsch, Urgesi, & Cross, 2016). Therefore, based on the recent evidence, I decided to focus on two recent aesthetics models that capture the neural mechanisms underlying such basic judgements of aesthetics by focusing on the reward system, in particular the Aesthetic Triad Model (ATM, Chatterjee & Vartanian, 2014) and the Pleasure-Interest Model of Aesthetic Liking (PIA Model, Graf & Landwehr, 2015). For example, Anjan Chatterjee and Oshin Vartanian (2014) define aesthetics explicitly as the experience of interactions with objects and/or scenes that evoke emotions associated with the reward system of "liking" or "pleasure" (Aesthetic Triad Model). In contrast, Laura Graf and Jan Landwehr (2015) have developed a model of aesthetics in which aesthetics is defined as a result of two hierarchical fluency-based processes. Their Pleasure-Interest Model of Aesthetic Liking (Graf & Landwehr, 2015) distinguishes between two routes to positive aesthetic responses: pleasure-based liking (automatic processing; very much in line with Chatterjee and Vartanian's proposed reward mechanisms) and interest-based liking (controlled cognitive processing).

More recent research suggests aesthetics liking is triggered by both pleasure and interest (Graf & Landwehr, 2017). As such, 'Liking' would be defined as preference or taste, whilst 'aesthetic liking' would refer to a positive aesthetic response. In other words, 'liking' and 'aesthetics' seem largely overlapping, not clearly separable concepts. In this thesis, I measured aesthetics liking based on liking scores.

There is a considerable amount of literature on the impact of low-level image properties, in particular scene complexity on aesthetics preference for nature environments over urban environments. For example, Kaplan and colleagues (1972) demonstrated that perceived subjective complexity of nature and urban images was predictive of aesthetic preference (Kaplan, Kaplan, & Wendt, 1972). More recent studies showed that fractal dimensions of the image – an objective measure of image complexity (see Chapter 1.4.1.2.) - are associated with aesthetics preference (Aks & Sprott, 1996; Peitgen & Richter, 1986; Spehar et al., 2003), and images with mid-range fractal dimensions between 1.1-1.5 were rated as the most aesthetically pleasing (e.g. Sprott, 1993). In addition, an increase in fractal dimension deviation from natural levels was shown to result in decreased aesthetic preference judgments (Spehar et al., 2003).
However, preferences for nature environments over urban environments have been not only attributed to low-level image statistics (see Chapter 1.4.1.) but also to semantic associations with landscapes/built environments (e.g. Beute & de Kort, 2018; Korpela, Hartig, Kaiser, & Fuhrer, 2001; Ratcliffe, Gatersleben, & Sowden, 2016). For example, exposure to nature environments has been shown to elicit more positive associations than exposure to urban environments, even if people were asked to think of negative associations whilst looking at nature environments (Beute & de Kort, 2018). It has been shown that previous experience affects a person's landscape preference (Balling & Falk, 2016), as well as prior expectations with regard to whether the place is selected to live and work, or whether it is just visited (Purcell, Lamb, Mainardi Peron, & Falchero, 1994). According to Purcell (1992), experience of landscape is associated with two existing knowledge structures (Purcell, 1992): similarity of previous experiences related to this domain (overlap), and organised general knowledge structures (organised memories of particular events). Within these structures, the environment can be described either at a perceptual level in terms of visual features (e.g. colour, shapes) or at an abstract level in terms of meanings associated with the particular environment judged. Purcell (1992) provided evidence that people make landscape preference judgements based on the abstract set of characteristics, suggesting that knowledge structure could indeed be an important factor in producing an affective response to the environment. In addition, Collado

and colleagues (2016) found that children who were not familiar with nature environments described nature as more restorative than children who grew up on a farm (Collado, Staats, & Sorrel, 2016), suggesting that previous experiences contribute to landscape preference. Moreover, Ratcliffe et al. (2016) asked participants to rate bird sounds on perceived restorative potential scale and to describe semantic associations with these sounds. Bird sounds with high restorative potential values were associated with green spaces, daytime, two temperate seasons (summertime and springtime), and with outdoor activities. The authors concluded from these findings that there is a close relationship between environment semantics and *restorativeness* (Ratcliffe et al., 2016). Similarly, there seems to be an association between place attachment and nature *restorativeness* (Korpela et al., 2001), with *restorativeness* being experienced substantially in "favourite" places and mostly nature environments. "Favourite" places were commonly described as the ones which were associated with positive feelings (e.g. comfort, calmness, relaxation). This led Egner and colleagues (2020) to propose that nature *restorativeness* is simply due to conditioning (Egner, Sutterlin, & Calogiuri, 2020, Conditioned Restoration Theory; CRT), in which previous positive experience increases the likelihood of restorative responses whilst negative experience decreases them. According to this CRT framework, nature environments that had been associated with stressful experiences would then become non-restorative. Therefore, it cannot be excluded that semantics contribute to environmentally-induced cognitive load. As *restorativeness* remains a very vague term, this thesis will not investigate whether the *restorativeness* of nature images is driven by bottom-up processing of image features, but instead try to separate the effects of basic image statistics from semantics association with image content on cognitive load.

1.4.4. Thesis Outline

From the brief literature overview above it hopefully became evident that research on an environment's cognitive benefit or cost has tended to focus on comparing rather crudely categorised nature and urban environments for which it was impossible to quantify and compare their sensory parameters (Bratman et al., 2012). It thus remains unclear what exactly it was within the different environments that impacted cognitive processing.

Moreover, most research studies comparing the impact of nature and urban environments on cognition could not really answer the question whether exposure to nature improved cognitive abilities ("nature benefit") or whether exposure to urban environments decreased cognitive abilities ("urban cost") as there was usually no baseline measure to which these environments could be compared (Bratman et al., 2012). Also, none of the theories described would provide us with a clear explanation of the mechanisms underlying *restorativeness* nor would allow us to predict a particular environment's demands on cognitive resources. Therefore, the aim of this thesis was not to test or improve any of the existing theories, but instead to extract key sensory factors in visual environments that might contribute to environmentally-induced cognitive load (see Chapter 1.4.).

Visual factors related to a range of low-level, mid-level and high-level visual processes were examined for their ability to contribute to environmentally-induced cognitive load.

- Low-level visual processes: image statistics such as contrast distributions, fractal dimensions and greenery (See Chapter 3, 4, 5 and 6)
- Mid-level visual processes: visual discomfort (See Chapters 3, 5 and 6).
- Mid-level and high-level visual processes: aesthetics and semantic associations (Chapters 4, 5 and 6)

Moreover, this thesis focuses on investigating the differences in the demands on cognitive resources posed by various environments *during* actual exposure to the respective environments. For this, it will first be necessary to establish whether a nature benefit / urban cost can be reliably observed in experiments that vary sensory input on a trial-by-trial basis (see Chapter 2 for experimental methods used here).

Chapter 2. Methodologies

This chapter summarizes the major methodologies used throughout the thesis (see also Burtan, Burn, & Leonards, 2021; Burtan, Joyce, et al., 2021)[1]

First, it describes the two experimental approaches to investigate different perceptual factors that might contribute to the differences in cognitive processing demands observed for different environments; in particular, the use of 3D motion capture data of human gait as a proxy for cognitive load, and reaction times for a basic shape discrimination task in the presence of task-irrelevant environmental images to test participants' distractibility induced by individual environments.

- Then, the Chapter describes the statistical analysis, i.e. multi-level modelling, that was used to account for random variability within the data samples for a repeated-measurement design and to investigate which factors explained the data variability best.
- As multi-level modelling allowed us to include image characteristics into the statistical analysis, the Chapter finally describes how certain basic image characteristics, in particular contrast distributions and fractal dimensions, were calculated.

[1] Author contributions are described on page 15.

2.1. Experimental approaches

2.1.1. Human gait analysis based on 3D-motion capture data

As already alluded to in the introduction, differences in cognitive processing load between nature and urban environments have been mainly observed *after* prolonged exposure to these environments (Berman et al., 2008; Berto, 2005, it has been described in detail in Chapter 1.3). These studies use methods that first measure a “baseline” cognitive performance, and then expose their participants to nature or urban environments for a prolonged time before assessing their post-exposure cognitive performance. A substantial experimental constraint of such a design is that it does not allow to establish the impact of different sensory factors on environmentally-induced cognitive load in a parametric way. Therefore, I decided to use two different experimental measures that have been shown to be sensitive to cognitive demands on a moment-to-moment basis.

Please note that cognitive load is a multidimensional construct proposed by Sweller in 1988 to describe the link between task demands and working memory capacity (Sweller, 1988). Working memory is defined as a temporary storage of information during a performance of a cognitive task such as problem-solving or driving (Baddeley, 1992). Research on cognitive load often distinguishes between high cognitive load and low cognitive load (Skulmowski, Pradel, Kühnert, Brunnett, & Rey, 2016): high cognitive load requires more control and more additional cortical activity than low cognitive load. Some studies distinguish between cognitive load and perceptual load (e.g. Causse, Imbert, Giraudet, Jouffrais, & Tremblay, 2016) in which perceptual load refers to a model of attention proposed by Nilli Lavie (Lavie, 1995; Lavie & Tsal, 1994) to explain visual search data (i.e. a person has to find a target amongst distractor items). This model suggests that the selection of information processed is stimulus-dependent and varies according to the complexity of the distractor stimulus. The main difference between cognitive load and perceptual load is that high *cognitive load* leads to reduced executive control responsible for prioritising the main task but allows distractors to be processed, whilst a *high perceptual load* inhibits or blocks irrelevant information processing before it even reaches executive functioning (in the low perceptual load condition, however, the irrelevant information can be processed, as attentional resources are not depleted). To-date, there is a considerable controversy surrounding the differences between cognitive and perceptual load due to the comparatively vague definitions of the concepts outside their specific experimental setups and due to insufficient evidence. Despite these limitations, the overarching concept of cognitive load has been chosen to indicate increases in reaction times or otherwise slowing of responses such as found in changes of gait parameters i.e. slower walking speed, smaller steps, increased gait variability (Amboni et al. 2013).

Evidence from clinical, experimental, neuropsychological and neuroimaging studies suggests that gait is not as fully automated as assumed by current biomechanical models (Guertin, 2009), but requires both cognitive functioning and attention (see for a review Al-Yahya et al., 2011; Amboni et al., 2013). For example, it has been demonstrated that gait kinematics such as walking speed, step length and stride variability depend on the difficulty of a cognitive task that is being performed at the same time in a so-called dual-task paradigm (see for a review Amboni et al., 2013). More generally, if performance in a task decreases when another task is performed at the same time, then the two tasks are thought to require cortical processing within the same cortical networks; thus, they are competing for the same neural resources available (see dual-task paradigms first introduced by Pashler, 1994).

Dual-task paradigms have been widely used in clinical research to assess cognitive-motor interference during walking, mostly in older adults and clinical populations, in particular in individuals with varying degrees of cognitive and motor impairments such as individuals with dementia, mild cognitive impairment, or Parkinson's disease (see for a review Amboni et al., 2013). In such paradigms, individuals have to perform a cognitively demanding task (e.g. Trail Making Test) whilst walking. The more cognitively demanding the non-walking task, the more changes are found in participants' gait parameters such as a decrease in velocity, increased stride time, increased stride length and time variability (Amboni et al., 2013). The underlying assumption is that as attentional resources are limited, the brain is forced to prioritise one of the tasks over the other at any given moment, with task switching leading to gait slowing and increased gait variability. This, in turn, leads to increased metabolic cost for walking (e.g. Stenum & Choi, 2021), and potentially increases the risk of falls (Hausdorff, Rios, & Edelberg, 2001; Mirelman et al., 2012).

Provided environmentally-induced cognitive load differences were big enough, changes in gait kinematics might be a sensitive way to objectively quantify the impact of visual environments on cognitive processing on a moment-to-moment basis. This idea was tested using 3D motion capture to capture gait data for people walking toward nature vs. urban images (Experiment 1, see Chapter 3). The same method was later used to tease apart different visual parameters that might contribute to cognitive load (Experiments 3, 4, 6, see Chapters 4, 5, 6 respectively).

2.1.1.1. Procedure

To measure gait, small spherical retro-reflective markers were attached to participants' shoulders (lateral clavicle), knees (patella), outside of their ankles (lateral malleolus), and their feet (first metatarsal-phalangeal joint). In addition, participants were given an elasticated belt to wear at hip height with three markers to locate the left hip, right hip and lower abdomen (hereon referred to as "hip" markers). The location of these markers was detected by a motion capture system (Oqus, Qualisys AB, Sweden) with a recording frequency of 100Hz. The system consisted of 12 cameras and was calibrated prior to testing each participant, leading to a typical spatial accuracy of $1mm^3$ across a captured space of 12m x 2m x 2.4m (see Figure 2.1.). The room was dimly and consistently lit throughout the experimental session with blackout curtains all along the long sides of the room. Note that the surroundings were still clearly visible, allowing participants a good understanding of the space they were moving in with a flat, obstacle-free floor.

Gait was recorded for each walking trial, using the motion capture system (x-direction depicting lateral movement, y-direction depicting direction of travel down the laboratory, z-direction depicting vertical movement).

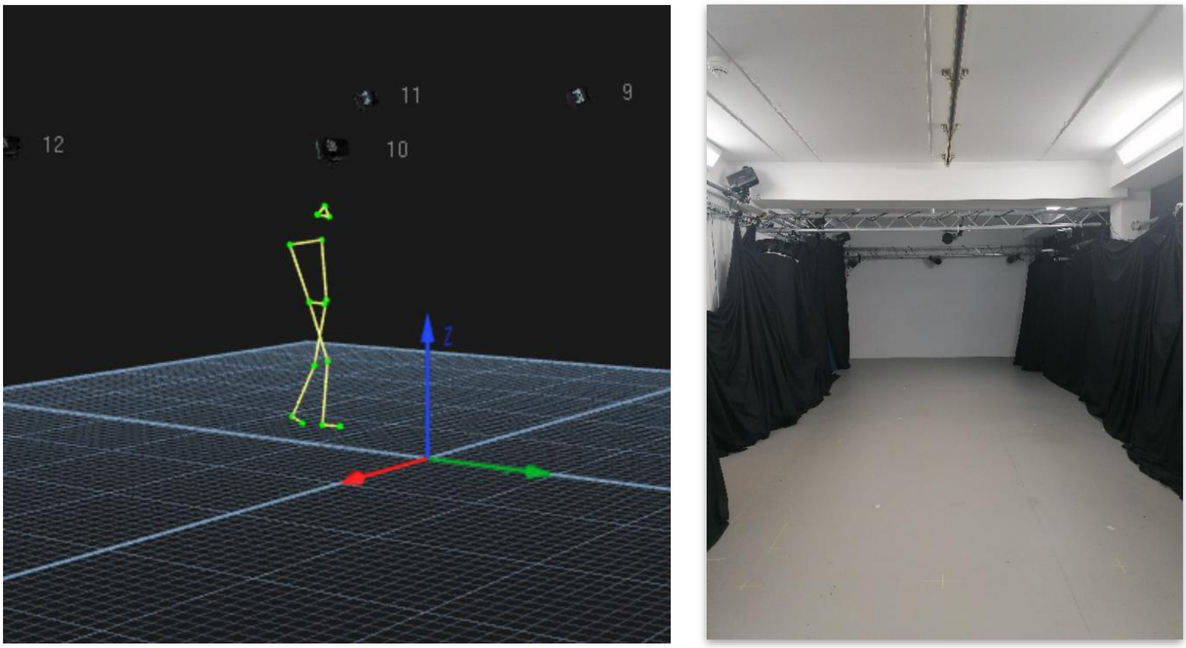

Figure 2.1: Bristol Vision Institute Movement laboratory funded by Wellcome-Trust (3D motion capture space). University of Bristol.

2.1.1.2. 3D-motion capture data and measures of gait

A pre-processing procedure was applied to the raw motion capture data. Raw data were pre-processed using proprietary software (QTM, Qualisys AB) to identify automatically the trajectories of markers. During normal walking, steps of a typical length should alternate between the left and the right foot. If the analysis revealed missing markers, steps over 1.3m in length or consecutive steps from the same foot, this was highlighted as walking inconsistency. Such trials were manually checked, and errors in labelling of the markers by the model were corrected where appropriate and possible. Any trials with missing sensor data (foot and hip markers) were removed from further analysis. A low-pass filter was applied to the raw data of interest, i.e. the foot and hip markers, to remove high frequency noise. Specifically, a bidirectional 2nd order Butterworth filter was applied with a cut-off frequency of 5Hz. Data were truncated for each trial to remove all data from the first 0.5 metres (m) and the last 2m of captured space (i.e. 5m before the wall on which images had been presented), leaving 9.5m for gait analysis per trial. This excluded those parts of each trial where the subject was accelerating or decelerating so that walking speed was approximately constant in the data used for subsequent analysis.

From the kinematic data derived from each trial, key information was extracted from the velocity and position data of the foot markers to label individual steps. Steps were defined as the stationary periods for each foot; i.e. when the marker moved less than 5cm in 0.1s. The position of a step was determined by the position of the foot marker in the middle of this stationary period. The landing time was therefore labelled as the time corresponding to the maximum deceleration of the foot on the Y axis prior to this stationary period, and the lifting time as the point of maximum acceleration on the Y axis post stationary period.

Subsequently, measures of gait were calculated from the pre-processed data for feet and hip (motion capture data from shoulders and ankles, although collected, were not considered for analysis). Specifically, trial velocity was calculated as the distance the hip marker travelled (i.e. 9.5 m) divided by the time taken to complete the walk. Step length was defined as the distance from the foot marker on one foot to the foot marker on the other foot at landing time and was calculated by subtracting the Y-position of the rear foot from the Y-position of the forward-stepping foot. Stride time was defined as the difference between one landing time and the subsequent landing time of the same foot. Finally, swing time was defined as the difference between the lifting time and the corresponding landing time of an individual foot. These data were then summarised as mean velocity, step length, stride time and swing time, respectively, for each trial. The variability in step length, stride time and swing time for each trial was also calculated. Note that for the first step for each foot as well as the last step, stride time, step length and swing time were undefined due to an indeterminate lifting time/start position of the rear foot or an indeterminate landing time/position of the front foot, respectively (as these were outside the measured area). As such, only the data for steps measured in their entirety were used for analysis.

2.1.1.3. Exclusion criteria

Participants' data were excluded from analysis if participants did not properly follow the instructions for the experimental task or were having an unusual walking style (mean gait parameters > 2.5SD from the group mean) affecting too many trials.

Individual trials were excluded on the basis of missing data (unlabelled markers) or if a participant accidentally stopped their walk before reaching the end of the motion capture space. As these errors were only detected during the analysis stage, such trials could not be repeated. On rare occasions, synchronisation between stimulus computer and motion capture system failed. In these situations, the affected trial was repeated.

2.1.2. Task - irrelevant attentional capture

Attention Restoration Theory (Kaplan, 1995; S. Kaplan, 2001; Kaplan & Berman, 2010) proposes that interacting with urban environments exhausts top-down directed-attention mechanism whilst interacting with nature environments captures bottom-up involuntary attention mechanism and allows directed-attention mechanism to be restored (see also Chapter 1.3.3.). The key factor here is that directed attention is associated with higher-order cognitive functions such as suppressing irrelevant information (see Ohly et al., 2016).

To investigate differences in environments' ability to automatically attract attention and thus distract from a task at hand, participants were asked to perform a shape discrimination task in the presence of task-irrelevant environmental images (Experiments 2 and 5; Chapters 3 and 5 respectively). It can be expected that urban environments automatically engage directed attention mechanisms and thus distract more from a task at hand than nature environments; i.e. they are harder to suppress and thus it is harder to redirect attention to the task at hand.

Image sets differed between experiments and will be described in detail in the respective chapters.

2.1.2.1. Procedure

The task consisted of a basic shape discrimination task on a computer screen (viewing distance of 57cm to the 21" monitor) in a quiet room with dimmed lighting. Each trial started with the presentation of a central fixation cross for a random duration of between 0.7 and 1.3 seconds. This was followed by the presentation of two shapes in addition to a task-irrelevant photographic image centred between them. The two shapes were a black circle (diameter of 61 pixels) and a black square (54x54 pixels); i.e., shapes matched in their overall number of pixels and thus luminance. Each shape was presented in the middle of a white circle (diameter of 130 pixels). There were four shape-pair conditions: circle (L) – circle (R), square (L) – square (R), circle (L) - square (R), and square (L) – circle (R); each of which was presented equally often, but in random order. Which of the four shape combinations and which photographic image were presented, was determined pseudo-randomly. Participants were asked to decide as quickly and as accurately as possible whether the two geometric shapes were identical or different, by pressing the according key on a keyboard in front of them. Images stayed on the screen until participants responded. If participants pressed the wrong key, a short beep alerted them of their mistake. Response accuracy and reaction times were recorded.

The photographic images subtended an area of 34° x 21° of visual angle. Shapes within their white circles subtended 3.5° of visual angle and were presented 20° degrees of visual angle from the centre of the screen, i.e. the outer line of the circle was 1.26° degrees of visual angle away from the corners of the photographic image. The screen background was a medium grey of average luminance (94.24 cd/m^2) and subtended an area of 51° x 29° of visual angle.

2.2. Multi-level modelling

A multi-level modelling technique was used to tease apart possible effects of different factors (e.g. environment, image statistics) on dependent variables such as gait kinematics (Experiments 1, 3, 4 and 6) or reaction times (Experiments 2 and 5). For gait kinematics, multi-level modelling was applied to velocity data only as I reasoned that as a composite measure of both step length and stride time, velocity should be the most sensitive gait measure to assess environmentally-induced cognitive load.

For ease of interpretation, all continuous data were transformed into Z-Scores (e.g. gait, reaction times, visual discomfort and liking scores), and categorical variables were dummy coded (e.g. environment type).

A series of models were fitted through three stages to establish the model of best fit. After each stage, the significance of each fixed effect (predictor) was assessed with chi-squared statistics, and insignificant predictors were discarded (models lettered ‘a’).

· Model 1; a cross-classified model was created with random effects: participant and image crossed at level two as random effects and trial at level one. Each individual trial was treated as a case. A cross-classified model was fitted using the Markov chain Monte Carlo (MCMC) method with the Bayesian Deviance Information Criterion (DIC) to handle more complex cross-classified models (Kass, Carlin, Gelman, & Neal, 1998).

· Model 2; independent variables/predictors were added as fixed effects (e.g. environment type, image statistics: fractal dimensions, visual discomfort and liking scores).

· Model 3; all relevant two-way interactions were added as fixed effects (e.g. environment type and image statistics: fractal dimensions, environment type and visual discomfort).

The model of best fit was selected from the final lettered ‘a’ models, showing the best combination of predictors at each stage, following the discarding of insignificant predictors. The selection of the model of best fit was based on Deviance Information Criterion (DIC) statistics. A lower DIC equates a better fit. For each model, burn-in (i.e. number of initial iterations discarded) = 500 and chain length (i.e. number of iterations after burn-in) are described. Parameters for all models are described in detail in the respective chapters.

2.3. Methods used to calculate image statistics

For all images that served as stimuli in experiments presented in this thesis, different basic image statistics were calculated: contrast distributions (Experiments 1 and 2) and fractal dimensions (Experiments 1, 2, 4, 5, 6 and 7).

2.3.1. Contrast Distribution

Contrast distributions as used for Experiments 1 and 2 were calculated by Katie Joyce (see Joyce, 2017) by applying a model developed by Penacchio & Wilkins (Penacchio & Wilkins, 2015). This method had been chosen as it had been used before to measure the link between contrast distribution and visual discomfort (see Wilkins et al., 1984; Wilkins et al., 2018). Penacchio and Wilkins’s model calculates the amplitude of contrast at all visual frequencies (limited by pixels) for all orientations and outputs the residuals after comparison with a typical

1/f distribution. Higher residuals reveal a contrast distribution further from 1/f. For this, images were transformed into greyscale, and then cropped to 800x800 pixel square to be able to apply the procedure. To obtain a measure for the entire image (1280x800 pixels), residuals for the left and right part of the image were calculated separately, and the average residual of the two image parts was taken as the value for this stimulus' residual (note that as a total image size is 1280x800 pixels, there is a substantial spatial overlap between the two image halves used to calculate contrast).

2.3.2. Fractal Dimension - Minkowski–Bouligand box-counting technique

In Experiments 1, 2, 4 and 5 fractal dimension calculations were based on the Minkowski–Bouligand fractal dimension box-counting technique (Schroeder, 1991): in brief, after normalising colour images and converting them into greyscale images, images were binarized using the mean image value before running a box counting algorithm over a range of box sizes to calculate fractal dimensions. Fractal dimensions were calculated by Simon Ho for the images used in Experiments 1 and 2 (Ho et al., 2019). Fractal dimensions for Experiments 4 and 5 were calculated by me using the code provided by Simon Ho. Box-counting is the most commonly used technique to measure fractal dimensions (Gonzato, Mulargia, & Ciccotti, 2000) but it brings limitations. For example, converting the image to greyscale, and thus losing the information about the colour prior to applying the algorithm might result in inaccurate estimation of roughness (Nayak & Mishra, 2016). Therefore, applying a different method could have resulted in a different output, for example, manipulating the image amplitude spectrum – technique used to create images with different fractal dimensions in Experiment 6 (see Chapter 6.2. for a description of this method).

Chapter 3. A novel method to measure the impact of visual environments on cognitive load

3.1. Introduction

As had been described in detail in the General Introduction, exposure to nature environments compared to exposure to urban environments has been shown to have a positive impact on cognitive functioning, an effect was observed *after* sustained environment exposure (Berman et al., 2008; Berto, 2005). Before being able to focus on key questions of my thesis about which visual environmental factors impose higher cognitive load, it was first necessary to confirm that a positive impact of nature environments (or a negative impact of urban environments) on cognitive functioning could be observed *during* exposure to the different visual environments. The aim of this study was to investigate whether a nature benefit/urban cost could be measured on a trial-by-trial basis, using gait kinematics and reaction times as proxy measures of cognitive load.

The data presented in this study have been published in Burtan, Joyce, et al. (2021)[2]

[2] Author contributions are described on page 15.

3.2. Experiment 1: Measuring changes in gait kinematics to quantify cognitive load differences between nature and urban scenes

Evidence from dual-task experiments suggests that there is a link between cognitive load and gait kinematics (see Chapter 2). Walking whilst preforming a cognitively demanding task has been shown repeatedly to lead to decreased walking speed, in addition to increased variability in stride length and stride timing (see for a review Amboni et al., 2013). The aim of this experiment was therefore to establish the impact of environment type (urban vs. nature) on cognitive processing load on a trial-by-trial basis, using changes in gait kinematics to quantify changes in cognitive load.

3.2.1. Methods

Participants: Sample size calculations took into account the substantial amount of repetitions within individual participants for all conditions of interest, and was based on modelling estimates for within-participant repeated measures correlations provided by Bakdash & Marusich (2017): to obtain 80% power for a medium effect size (0.3) and within participant repeated paired measures of 20 or more repetitions, a minimum of 12 participants would be sufficient (Bakdash & Marusich, 2017). Twenty participants (6 male; aged 18-36 years, M = 23 years) took part in this study in the Bristol Vision Institute (BVI) movement laboratory at the University of Bristol. All participants reported normal or corrected-to-normal visual acuity, no injuries or conditions that might have impacted their walking, and all gave their informed written consent prior to commencing the study. The experiment was approved by the Faculty of Life Sciences' Ethics Committee at the University of Bristol (ref: 27041635961). Participation took place by reimbursement to account for participants' time.

Stimuli: For this study, 100 images of nature and urban scenes had been selected out of a far larger image set taken by Ute Leonards (University of Bristol) and Todd Handy (University of British Columbia), in addition to five plain grey images. Images presented a range of landscapes and urban spaces across Europe and Canada (see Experiment 2 in (Ho et al., 2019), for the same image set). Image resolution was 1280x800 pixels. Firstly, nature and urban scenes had been visually matched as closely as possible for their spatial composition: for this, half of the nature scenes and half of the urban scenes included a walkable path whilst the other half did not; thus, there were four image categories: nature path (25 images), nature no path (25 images), urban path (25 images), urban no path (25 images). Secondly, images across all four categories were controlled for perceived depth (distance to the centremost point), perceptually grouping each image category by distance into five image groups: very close, close, medium, far, very far, with 5 images per distance. Each image within this 5 by 5 design had an image in the other four categories that was perceptually matched as closely as possible in its overall spatial layout as agreed on by three of the investigators involved in this study.

For each image, contrast distributions were calculated by Katie Joyce (Joyce, 2017) by applying a model developed by Penacchio & Wilkins (Penacchio & Wilkins, 2015), see description of this method in Chapter 2.3.1. In line with earlier findings (Penacchio & Wilkins, 2015), urban images had significantly higher residuals (M = 2.4E+14, ± 9.4E+13 SD) and thus sat further away from a 1/f distribution than nature images (M = 1.8E+14, ± 9.0E+13 SD); ($t(98) = 3.241$, $p < 0.01$). Fractal dimensions of images were taken from the calculations described in Ho et al., (Ho et al., 2019) for the same image set (see their Experiment 2) and based on the Minkowski–Bouligand fractal dimension box-counting technique described in Chapter 2.3.2.

Figure 3.1: Example stimuli from a set of 100 nature and urban images taken by Ute Leonards (University of Bristol) and Todd Handy (University of British Columbia).

Procedure: On arrival, participants were given written and verbal explanations of the experiment. Following this, 3D motion capture markers were attached (see the description of the procedure in Chapter 2.1.1.), before the actual experiment began. The experiment was divided into two parts, each of which required the participant to walk down the laboratory repeatedly whilst performing different secondary tasks: a) a verbal cognitive load task, and b) an image rating task. The order of the two experimental parts was counterbalanced across participants.

Experimental part 1 consisted of a *cognitive motor interference task* with walking as the motor task and a verbal trail making task (vTMT) (e.g. Nasreddine et al., 2005) as the cognitive (i.e. secondary) task: in a simple verbal version of the Trail Making A task, participants are asked to count aloud or recite the alphabet). In the verbal version of the Trial Making B task, participants have to switch repeatedly between the next letter of the alphabet and the next number (e.g. A1,B2, C3, ….) (Bowie & Harvey, 2006). This part of the experiment served as a control to establish whether our methodology was sufficiently robust to observe changes in gait kinematics associated with changes in cognitive load as has been well established in the literature (Amboni et al., 2013). In this experimental part, each participant was asked to walk repeatedly down a 15m long laboratory whilst completing one of four types of verbal tasks requiring different amounts of cognitive load: No speech (C1), "Lalala…" (C2), "ABC…" (C3) or "A1B2…" (C4). The least cognitive resources were required for C1 (no speech; i.e. no dual-task requirements, and thus no interference between cognition and walking), and the most for C4. Indeed, gait kinematics should be sensitive enough to reflect slower and more variable gait with increasing levels of cognitive load when comparing gait during the performance of a simple verbal version of the Trail Making A task (counting aloud or reciting the alphabet) as compared to the Trial Making B task (A1,B2, C3, ….) (Bowie & Harvey, 2006);

Procedure and results of this cognitive motor interference task can be found in the supplementary material of Burtan, Joyce, et al., 2021 and in Annex B.

For experimental part 2, participants were asked to perform an *environment-induced perceptual load motor interference task* as the actual task of interest. For this part of the experiment, participants walked repeatedly toward images projected onto the back wall of the laboratory (one image per walk) and rated each image for its visual discomfort.

One of the following images was displayed per walk: a nature scene (50), an urban scene (50) or a neutral grey image (5). The image display size was 3m wide x 2m high, corresponding to

11.4° x 7.6° of visual angle when viewed from the starting point of the walk, and 57 ° x 38° of visual angle when viewed from the end line of the 3D motion capture space. After each walk, participants were asked to rate the image seen for its visual discomfort. Visual discomfort ratings were given on a 7-point Likert Scale from ‘1 – extremely comfortable to view’ to ‘7 – extremely uncomfortable to view’ (participants had been familiarised with this scale and the definition of visual discomfort during the verbal briefing). All 105 stimuli (50 nature scenes, 50 urban scenes, 5 grey control images) were presented in randomised order. This part of the experiment took approximately 40 minutes to complete, and participants were offered a break at the halfway point (after trial 52). Participants could ask for additional breaks, if they deemed it necessary.

At the end of the experiment, participants were thanked for their contribution and debriefed.

Data analysis experimental part 2: walking and rating images for visual discomfort:

One participant’s data were excluded from analysis as they did not properly follow the instructions for this task. One further participant was excluded from analysis due to having an unusual walking style: mean gait parameters > 2.5SD from the group mean affecting too many trials (see also Chapter 2.1.1.3). This left 18 participants’ datasets for analysis; (5 male, 13 female), aged 18-34 (mean age = 22). After excluding individual trials for these 18 participants (see exclusion criteria in Chapter 2.1.1.3.), the minimum of trials per participant was 43 trials per environment condition (nature/urban) and 4 trials per control condition for a participant to be included in the final analysis. The mean number of trials per nature environment per participant for step analysis was 49.28 (± 1.87 SD) and for velocity analysis 49.44 (± 1.69 SD) out of 50. The mean number of trials per urban environment per participant for step analysis was 49.44 (± 1.46 SD) and for velocity analysis 49.50 (± 1.47 SD) out of 50. The mean number of trials per neutral condition per participant for both step and velocity analysis was 4.89 (± 0.32 SD) out of 5. In addition, for the multilevel modelling analysis outliers were removed from the data (walking speed per trial > 2.5 SD from the group mean). (Note that the study has not been pre- registered).

3.2.2. Results and Discussion

Visual Discomfort ratings: In line with expectations from earlier studies on visual discomfort (Wilkins et al., 2018), subjective visual discomfort ratings were higher for urban images (M = 3.38, ± 0.7 SD) than for nature images (M = 2.27, ± 0.38 SD); see Figure 3.2. A one-way ANOVA with repeated measures revealed that this effect was highly significant ($F(1,49) = 119.583$, $p < 0.001$).

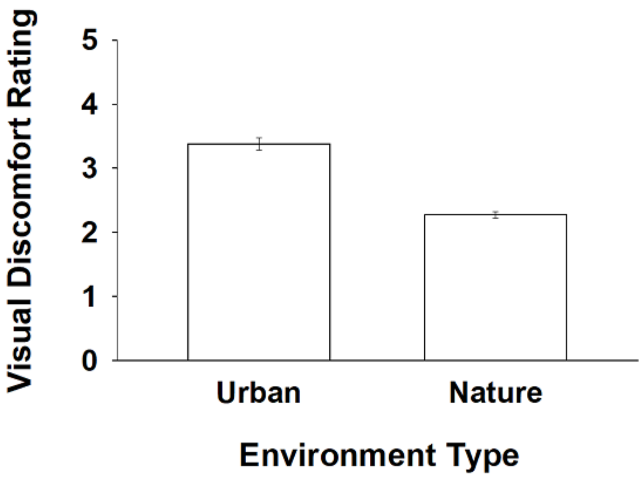

Figure 3.2: Group averages of individual visual discomfort ratings per image (7 point- Likert Scale) for the two environment types: Nature and Urban. Error bars reflect ±1SEM (Figure taken from Burtan, Joyce, et al., 2021. *Royal Society Open Science*, 8(1), p. 6 (doi:10.1098/rsos.201100)).

Gait data: Repeated measures MANOVAs were applied to the gait data of this part of the experiment, adding order of experimental parts as a between-subjects variable and environmental stimulus type (Urban/Nature/Neutral) as a within-subjects variable for seven dependent gait measures (mean velocity, mean step length, mean stride time, mean swing time, variability of step length, variability of stride time and variability of swing time).

Velocity: Analysis revealed a significant main effect of environment on mean velocity ($F(2,32) = 32.34$; $MSE < 0.05$; $p < 0.001$, partial $\eta^2 = 0.67$), see Figure 3.3. *Post-hoc* tests with Bonferroni correction revealed a significant difference between all three environmental conditions; participants walked fastest toward neutral images, significantly slower toward nature images ($p < 0.01$), and significantly slower again toward urban images (neutral – urban: $p < 0.001$, nature – urban: $p < 0.05$).

Step Length: Analysis with Greenhouse-Geisser correction showed that there was also a significant main effect of environment on mean step length ($F(1.47, 23.58) = 23.55$; MSE < 0.05; $p < 0.001$, partial $\eta^2 = 0.60$), see Figure 3.3. *Post-hoc* tests with Bonferroni correction revealed significant differences between all conditions; neutral images resulted in the longest mean step length, with a significantly shorter step length for nature images ($p < 0.01$) and significantly shorter step length again for urban images (neutral – urban; $p < 0.001$, nature – urban; $p < 0.01$).

Stride Time: In addition, analysis with Greenhouse-Geisser correction revealed that there was a significant main effect of environment on mean stride time ($F(1.39, 22.30) = 29.33$; MSE < 0.01; $p < 0.001$, partial $\eta^2 = 0.65$), see Figure 3.3. *Post-hoc* tests with Bonferroni correction showed that neutral images elicited shorter stride times than both nature ($p < 0.01$) and urban images ($p < 0.001$). However, there was no significant difference in stride time for nature and urban images ($p > 0.05$), suggesting that this measure is less sensitive than overall velocity and step length.

Swing Time: In addition, analysis with Greenhouse-Geisser correction revealed that there was a significant main effect of environment on mean swing time ($F(1.25, 20.04) = 7.66$; MSE < 0.001; $p < 0.01$, partial $\eta^2 = 0.32$), see Figure 3.3. *Post-hoc* tests with Bonferroni correction showed that neutral images elicited shorter swing times than both nature ($p < 0.05$) and urban images ($p < 0.05$). However, there was no significant difference in swing time for nature and urban images ($p > 0.05$), suggesting that this measure is also less sensitive than velocity and step length.

There was no main effect of environment on the variability of step length, the variability of stride time and the variability of swing time.

Experimental part order did not affect any of the gait measures. However, there was a significant interaction between experimental part order and environment type for velocity ($F(2,32) = 5.01$; MSE < 0.01; $p < 0.05$, partial $\eta^2 = 0.24$) and stride time ($F(1.39, 22.30) = 4.57$, MSE < 0.001; $p < 0.05$, partial $\eta^2 = 0.22$) (see Annex A for more detail).

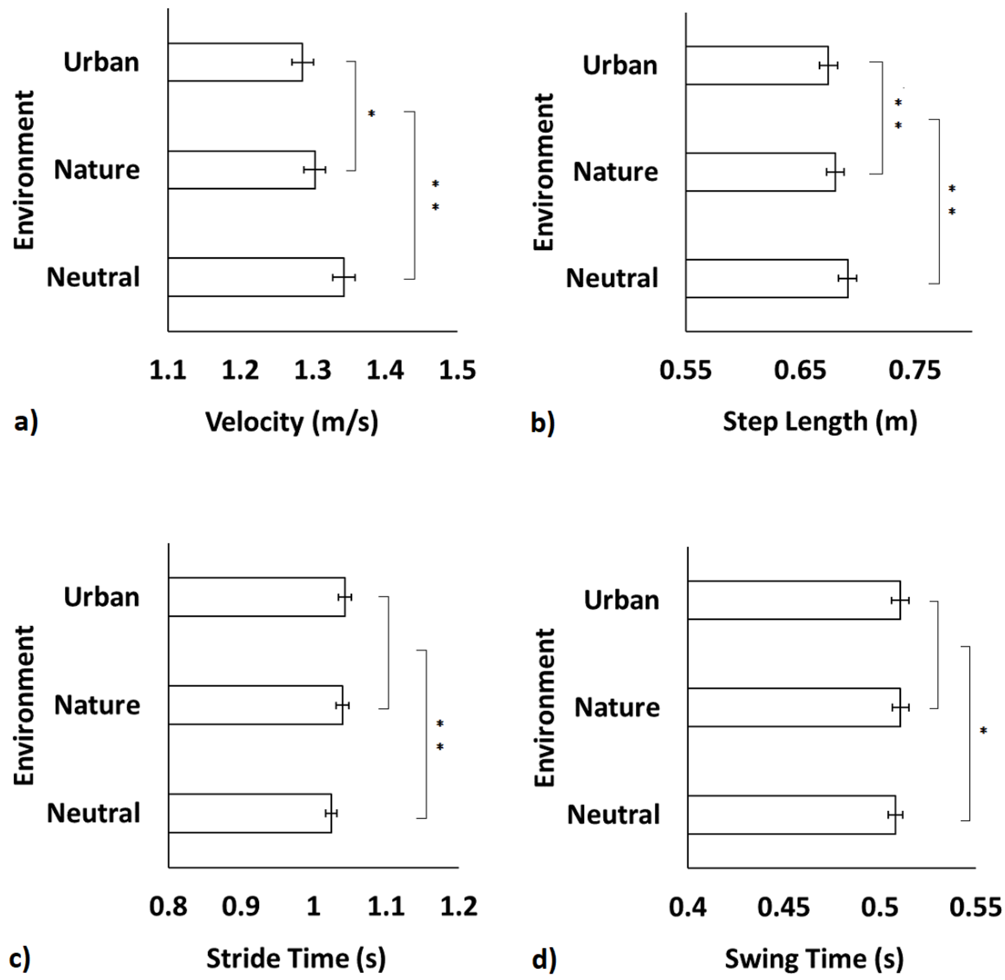

Figure 3.3: Group averages of individual mean a) velocity (metres per second), b) step length (in metres) c) stride time (in seconds) and d) swing time (in seconds) across environment type. Error bars reflect ±1SEM. * $p < 0.05$, ** $p < 0.01$. (Figure taken from Burtan, Joyce, et al., 2021. *Royal Society Open Science*, 8(1), p. 7 (doi:10.1098/rsos.201100)).

Multi-Level Modelling (Velocity): To tease apart possible effects of image statistics (i.e. contrast distributions and fractal content), subjective visual discomfort, image configuration (presence of a walkable pathway in the image) and environment type on walking speed, I applied a cross-classified multi-level model to the velocity data (see the detailed description of the method in Chapter 2.2.). See Table 3.1. for all models fitted.

Neutral image trials were excluded from this analysis due to missing data for all predictors (i.e. image statistics, image configuration and subjective discomfort ratings) other than environment. In addition, 18 trials were excluded due to outlier screening.

Table 3.1: Model fit comparisons for models estimating velocity from the characteristics of the image viewed. (Table taken from Burtan, Joyce, et al., 2021. *Royal Society Open Science,* 8(1), p. 8 (doi:10.1098/rsos.201100)).

Model	DIC	Fixed	Random
1	3483.390		PT, IM, T
2	3422.810	ENV, DIS, IMS, FD, PA	PT, IM, T
2a	3420.733	ENV, DIS, IMS	PT, IM, T
3	3419.824	ENV, DIS, IMS, ENV*DIS, ENV*IMS, DIS*IMS	PT, IM, T
3a	3422.476	ENV, DIS	PT, IM, T
4	3419.996	ENV, DIS, ENV*DIS	PT, IM, T
4a	3419.996	ENV, DIS, ENV*DIS (Model 4)	PT, IM, T

Note. PT = Participant, IM = Image, T = Trial (n = 1764), ENV = Environment, DIS = Discomfort rating, IMS = Image statistics (1/f residuals), PA = Path, FD = Fractal dimension.

The best fitting model was 4a. Parameter estimates for this model are displayed in Table 3.2.

Table 3.2: Fixed effects estimates (top) and random effect variance estimates (bottom) for the model with best fit (Model 4a; Table 3.1.) predicting velocity from the characteristics of the image viewed. (Table taken from Burtan, Joyce, et al., 2021. *Royal Society Open Science,* 8(1), p. 9 (doi:10.1098/rsos.201100)).

			95% CI		
Parameter	Estimate	Std. Error	Lower	Upper	X_1^2
Fixed					
Intercept	0.314	0.190	-0.097	0.653	1.648
Environment (Urban)	-0.222	0.085	-0.388	-0.056	2.619**
Discomfort	-0.174	0.029	-0.231	-0.118	36.604***
Dis*Env	0.076	0.037	0.004	0.148	4.276*
Random					
Participant	0.637	0.252	0.315	1.261	
Image	0.004	0.003	0.001	0.010	
Trial	0.399	0.014	0.373	0.427	
Deviance Information Criterion (DIC)					3419.996

Note. Estimates reflect size of the effect on standardised velocity. Burn-in = 500, Chain Length = 10,000. Degrees of freedom is 1 for all Chi-square (X_1^2) statistics. ***p < 0.001, **p < 0.01, *p < 0.05.

Environment (X_1^2= 2.619, p < 0.01), visual discomfort (X_1^2= 36.604, p < 0.001) and interaction between environment and visual discomfort (X_1^2= 4.276 p < 0.05) were significant predictors of velocity, with people walking more slowly whilst walking towards images of urban environments and images they perceived as more uncomfortable to look at. Subjective discomfort and environment seem thus heavily interrelated and explain at least some of the variability in walking speed.

Basic image statistics (contrast distribution and fractal dimension) and presence of walkable path did not improve model fit (higher DIC statistics). In other words, these factors did not explain any of the variance over and above the other predictors.

In line with our predictions, this part of the experiment provided first evidence that exposure to visual scenes of urban environments as compared to nature environments requires higher amounts of cognitive/perceptual resources: participants walked more slowly and with smaller steps towards urban scenes as compared to nature scenes, mirroring their behaviour in the verbal trail making control task (See Annex B for more detail) and more generally behaviour described for dual-task conditions in which walking is affected by the second task requiring higher cognitive resources (Al-Yahya et al., 2011; Amboni et al., 2013; Ho et al., 2019). The differences in cognitive/perceptual load requirements evoked by the two types of visual environment are thus big enough to be picked up on a trial-by-trial basis, using changes in gait kinematics as an objective measure of load.

Whilst these results support our main hypothesis that changes in gait kinematics can be used to measure environmentally-induced cognitive load on a trial-by-trial basis, however, it remains unclear what exactly it was for the two different environmental scene types that contributed to the differences in cognitive load requirements.

Whilst multilevel modelling revealed that environment, visual discomfort and the interaction between environment and visual discomfort explained some of the variance in gait kinematics (i.e. walking speed), neither image contrast distributions nor fractal dimensions had a predictive value on gait kinematics. This is a first indication that differences in basic image statistics between nature and urban scenes are not driving factors behind the nature benefit or higher cognitive demands induced by urban images. Chapters 4 and 6 present data in which I investigate the impact of low-level image properties: greenery (Chapter 4) and fractal geometry (Chapter 6) on environmentally-induced cognitive load.

3.3. Experiment 2: Exploring attentional capture for urban and nature images

Outcomes of Experiment 1 confirmed that cognitive processing differences between exposure to nature and urban environments are so pronounced that they can be measured as changes in gait kinematics on a trial-by-trial basis.

To confirm that this effect is task and measurement independent and environmentally-induced cognitive load can be picked up on trial-by-trial basis, UG project student Leny Dimitrova[3] and I collected reaction times in a second experiment in which participants were asked to perform a simple visual shape discrimination task in the presence of the images of nature or urban environments used in Experiment 1 (Dimitrova, 2019). In other words, this time participants did not rate the actual images, but images served as task-irrelevant distractors. The reasoning behind this experiment was that if the scene content of urban environments were to capture people's attention more readily than the scene content of nature environments (see Chapter 1.3), this should require higher amounts of cognitive processing power to disengage from such images to perform the task at hand. As a consequence, participants' responses in the unrelated shape discrimination task should be slower in the presence of urban images as compared to the presence of nature images. In addition, images were presented in both upright and inverted orientation to isolate the impact of low-level and higher-level cognitive processes. If low-level image properties rather than semantics contributed to environmentally-induced cognitive load, there should be no difference in reaction times for upright vs. inverted images.

3.3.1. Methods

Participants: Sample size calculations were based on two different assumptions to allow different analyses: a) taking a within-participant repeated measures design with multiple repetitions per condition into account as required for multi-level modelling, a minimum of 12 participants would be sufficient to obtain 80% power for a medium effect size (0.3) and a number of intraindividual repeated paired measures of 20 or more (see Bakdash & Marusich, 2017). For a repeated measures ANOVA based on mean values per condition per participant,

[3] Author contributions are described on page 15.

however, sample size calculations revealed that to obtain similar power (0.8 power) for a medium effect size of 0.3 and a conservative assumption of repeated measures correlation of 0.5 at least 24 participants were needed for individual main effects as well as the interaction effect. To account for possible drop-outs and exclusions, forty-five participants (8 males aged between 18-29 years with a mean age of 21 years, and 37 females aged between 16 and 54 years with a mean age of 22 years) took part in this study at the University of Bristol. All participants reported normal or corrected-to-normal visual acuity and normal colour vision. All gave written informed consent at the beginning of the study. Participants took part in the experiment for course credit. The experiment was approved by the Faculty of Life Sciences' Ethics Committee at the University of Bristol (ref. 28071871142).

Stimuli and Task: Participants were asked to perform a shape discrimination task (see the procedure description in Chapter 2.1.2.) in the presence of the same images of nature or urban environments used in Experiment 1. To distinguish between the impact of image statistics and associated higher-level cognitive image associations on task-unrelated distraction, each image was presented once upright and once in inverted orientation, resulting in a total of 200 trials. Image statistics remain the same irrespective of stimulus orientation; yet, it should be more difficult to detect automatically the gist of a scene when upside down, thus reducing the image's ability to capture attention. Any reaction time differences between shape discrimination task trials performed in the presence of upright as compared to inverted images should thus be due to cognitive demands associated with depicting the image's meaning.

Procedure: On arrival, participants were given written and verbal information about the study and were then seated in front of the computer on which the experiment was run. Each trial started with the presentation of a central fixation cross for a random duration of between 0.7 and 1.3 seconds. This was followed by the presentation of one of the 200 photographic images (50 nature upright, 50 nature inverted, 50 urban upright, 50 urban inverted) centred between the two shapes for the shape discrimination task. Which of the four shape combinations and which photographic image were presented, was pseudo-randomly determined. Images stayed on the screen until participants responded by pressing the according key on the keyboard. If participants pressed the wrong key, a short beep alerted them of their mistake. There was one break during the study halfway through, i.e. after 100 trials. Response accuracy and reaction times were recorded.

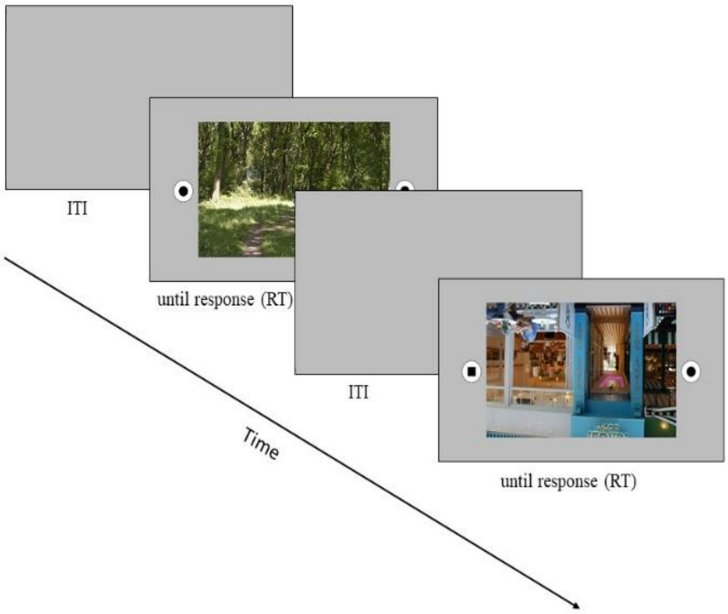

Figure 3.4: Shape discrimination task. The presentation of a central fixation cross for a random duration: ITI = Inter-Trial-Interval 0.7,0.8,0.9,1.0,1.1,1.2,1.3 (in seconds); RT = Reaction Time in seconds. (Image taken from Burtan, Joyce, et al., 2021. *Royal Society Open Science*, 8(1), p. 10 (doi:10.1098/rsos.201100)).

The first trial for each participant was removed as a practice trial. Participants with a task accuracy below 80% were excluded from analysis, leaving 41 datasets for analysis (7 males aged between 19-29 years with a mean age of 21 years, and 34 females aged between 16 and 54 years with a mean age of 23 years; mean age of 22). Per participant, the median reaction times for the four stimulus distractor conditions (nature upright, nature inverted, urban upright, urban inverted) were calculated from 5% trimmed data (removal of outliers).

3.3.2. Results and Discussion

Figure 3.5 shows group averages of individual median reaction times per image type and image orientation. A 2 (environment) x 2 (image orientation) repeated measures ANOVA with median reaction times as dependent variable confirmed a significant main effect of environment (nature vs. urban) ($F(1,40) = 23.111$, $p < 0.05$, partial $\eta^2 = 0.366$): participants performed the shape discrimination task significantly slower exposure to urban images (M = 0.79s, ± 0.14 SD) as compared to nature images (M = 0.76s, ± 0.13 SD). There was no significant main effect of orientation (upright vs. inverted) on median reaction times ($F(1,40) = 1.041$, $p > 0.05$, partial $\eta^2 = 0.025$) nor was there a significant interaction between environment type and orientation ($F(1, 40) = 0.001$, $p > 0.05$, partial $\eta^2 = 0.000$).

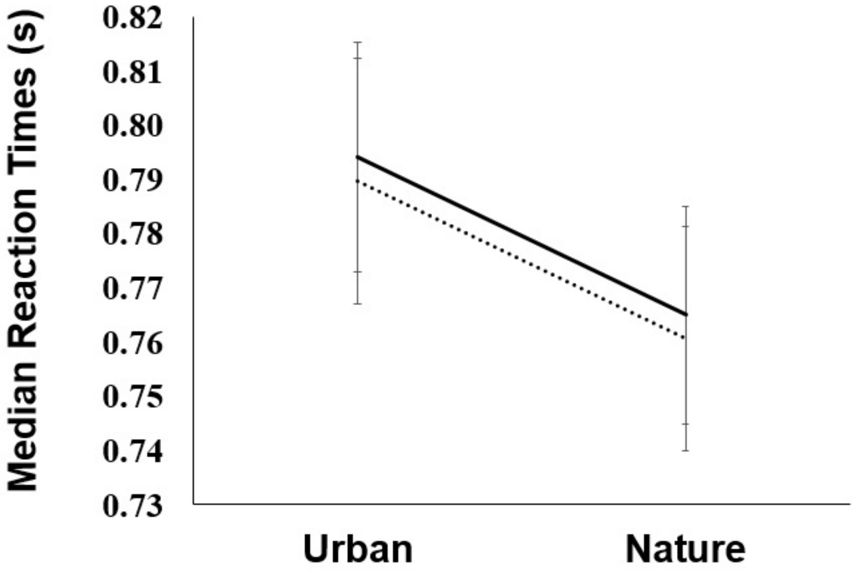

Figure 3.5: Group mean of median reaction times (in seconds) across environment (urban, nature) and orientation type (upright: dotted line; inverted: solid line). Error bars reflect ±1SEM. (Figure taken from Burtan, Joyce, et al., 2021. *Royal Society Open Science*, 8(1), p. 12 (doi:10.1098/rsos.201100)).

As for Experiment 1, I decided to go beyond analysis of this experiment included in Leny Dimitrova's thesis (Dimitrova, 2019) by applying a cross-classified multi-level model to the data to tease apart possible effects of environment type, image orientation, contrast distributions, and fractal content as predictors of variation in reaction times (see Chapter 2.2. for a detailed description of the method).

Table 3.3: Model fit comparisons for models estimating reaction time from the characteristics of the image viewed. (Table taken from Burtan, Joyce, et al., 2021. *Royal Society Open Science,* 8(1), p. 12 (doi:10.1098/rsos.201100)).

Model	DIC	Fixed	Random
1	18007.577		PT, IM, T
2	17998.087	ENV, ORI, IMS, FD	PT, IM, T
2a	17995.037	ENV, FD	PT, IM, T
3	17996.429	ENV, FD, ENV*FD	PT, IM, T
3a	17999.355	ENV	PT, IM, T

Note. PT = Participant, IM = Image, T = Trial (n = 7346), ENV = Environment, ORI = Orientation, IMS = Image Statistics (i.e. 1/f residuals), FD = Fractal dimension.

The best fitting model was 2a, with environment (urban) and fractal dimension as significant predictors. Parameter estimates for this model are displayed in Table 3.4.

Table 3.4: Fixed effects estimates (top) and random effect variance estimates (bottom) for the model with the best fit (Model 2a; Table 3.3.) predicting reaction time from the characteristics of the image viewed. (Table taken from Burtan, Joyce, et al., 2021. *Royal Society Open Science,* 8(1), p. 13 (doi:10.1098/rsos.201100)).

			95% CI		
Parameter	Estimate	Std. Error	Lower	Upper	X_1^2
Fixed					
Intercept	-0.052	0.096	-0.233	0.141	0.298
Environment (Urban)	0.143	0.028	0.088	0.199	26.235***
Fractal dimension	0.041	0.014	0.013	0.068	8.427**
Random					
Participant	0.347	0.084	0.219	0.546	
Image	0.008	0.003	0.004	0.014	
Trial	0.669	0.011	0.647	0.691	
Deviance Information Criterion (DIC)					17995.037

Note. Estimates reflect the size of the effect on standardised reaction times. Burn-in = 500, Chain Length = 10,000. Degrees of freedom is 1 for all Chi-square (X_1^2) statistics. ***p < 0.001, **p < 0.01, *p < 0.05.

As predicted, environment type was highly predictive of reaction times (X_1^2 = 26.235, p < 0.001). Also, low-level image statistics (i.e. fractal dimensions) predicted reaction times (X_1^2 = 8.427, p < 0.01); yet, predictions went in the opposite direction of what would be expected: increasing fractal dimensions predicted increasing reaction times.

Including contrast distribution (1/f residuals) as image statistics did not improve the model fit (see increased DIC statistics for model 2 as compared to model 2a), meaning that the model that included contrast distributions as image statistics did not explain as much variance as the model that included environment and fractal dimensions only.

Due to the unexpected result of increasing reaction times with increasing fractal dimensions in Model 2a when combined with environment, I wondered whether this result might be due to an unexpected interaction between image type and fractal dimensions. Therefore, two further models were created to investigate the impact of environment and fractal dimensions separately. The two models were identical in structure to Model 2a but each of them contained only one of the two fixed predictors. The independent estimates for each predictor are outlined in Table 3.5.

Table 3.5: Estimates from independent models for fractal dimension (FD) and environment (ENV). (Table taken from Burtan, Joyce, et al., 2021. *Royal Society Open Science*, 8(1), p. 8 (doi:10.1098/rsos.201100)).

Estimate		
	FD	ENV
	-0.000	
		0.096***

These additional analyses revealed that environment remained predictive of reaction time even in the absence of another predictor. Fractal dimensions, in contrast, did not seem to have predictive power on their own, $p > 0.05$.

<u>Presence of people in the urban scenes:</u>

Human faces are known to automatically attract attention (Morrisey, Hofrichter, & Rutherford, 2019). Half of the urban images used in this study contained people in the scenes but none of the nature environments contained scenes with the presence of people. This is raising the question whether the presence of people in some of the urban scenes might explain the elevated attentional capture of urban images. Therefore, an additional analysis was conducted to investigate whether the presence of people in urban scenes affected median reaction times.

For this, the 50 urban images used in the experiment were regrouped into urban scenes with people present (25 images) and urban scenes without people (25 images).

A 2 (presence of people) x 2 (image orientation) repeated measures ANOVA with median reaction times as dependent variable revealed no significant main effect of presence of people in the urban scenes (urban scenes with the presence of people vs. urban scenes without the presence of people) on median reaction times, $F(1,40) = 3.839$, partial $\eta^2 = 0.09$, $p > 0.05$. There was also no significant main effect of image orientation on median reaction times, $F(1,40) = 0.028$, partial $\eta^2 = 0.001$, $p > 0.05$. In addition, the interaction beetwen people in the urban scenes and orientation did not affect median reaction times, $F(1,40) = 0.110$, partial $\eta^2 = 0.003$, $p > 0.05$.

In line with the hypothesis that images of urban environments capture attention more readily than nature images and are more difficult to disengage from (Berman et al., 2008), results revealed that participants were slower in taking a simple shape discrimination decision when exposed simultaneously to distracting urban images as compared to nature images. Intriguingly, this effect was similarly pronounced for both upright and inverted images, suggesting that at least some low-level basic image statistics might contribute to this effect and not just higher cognitive processes evoked by the meaning of the images. As established in an additional analysis, the observed effect cannot by explained by the presence of people in urban environments.

The results of multi-level modelling revealed that both environment and low-level properties of images (fractal dimension) were predictive of reaction times when included in the same model. Contrary to expectation, increased fractal dimensions predicted increased rather than decreased reaction times when included in a model with environment type as the main predictor. On their own, however, fractal dimensions did not seem to serve as a reliable predictor for changes in reaction time whilst environment type did. As for the gait study before, this therefore suggests that there might exist a complex relationship between low and high-level visual processes involved in the impact of environment on cognitive processing.

3.4. General Discussion

The aim of the two studies presented in this Chapter was to investigate whether the impact of urban vs. nature scenes on cognitive load processing can be measured on a trial-by-trial basis. The results provided converging evidence that consistent with theoretical predictions (Berman et al., 2008; Berto, 2005) increased cognitive demands for processing of urban scenes as compared to nature scenes can also be observed on a far shorter time scale in real-time by using gait kinematics and reaction times as measures of cognitive load.

A moment-to-moment difference in impact of nature vs. urban environments on cognitive processing load was present in both tasks, suggesting that differences in cognitive load between nature and urban environments are image-related rather than task-related. However, for the gait task, these results need to be interpreted with caution: in Experiment 1, participants were asked to rate each image for its visual discomfort after each walk. It cannot be excluded that it was simply more cognitively demanding to rate urban images for visual discomfort, in line with previous findings demonstrating that participants were slower when rating images they found more uncomfortable to look at (Ho et al., 2019). Indeed, in Experiment 1 urban images had significantly higher subjective visual discomfort ratings than nature images. It raises question whether the effect of gait slowing was simply due to aversive physiological symptoms related to increased visual discomfort for urban images. Such an interpretation is unlikely given that the effect of environmentally-induced cognitive load was present in two fundamentally different tasks.

It is crucial to note that contrary to expectations, low-level image statistics: contrast distributions (Penacchio & Wilkins, 2015) and fractal content (Joye & Van den Berg, 2011) did not fully explain the changes in gait kinematics nor reaction times. Given that images were not controlled for contrast distributions nor fractal content variability, the effect might have been too little to be picked up in these two studies. To understand whether low-level image statistics impact cognitive processing load, they should parametrically vary across stimulus set to cover sufficient variability. This will be investigated in Experiment 6, presented in Chapter 6.

The positive effect of exposure to nature environment on cognitive functioning was linked to high aesthetics value (e.g. Hartig & Staats, 2006). Not only are urban images more uncomfortable to look at, but they might also be less aesthetically pleasing. Taken together, it is thus possible that environment type is confounded with both visual discomfort and aesthetics, also affecting cognitive load. It is thus important to keep in mind that the current study was not specifically designed to tease apart the impact of visual discomfort, aesthetics and environment type on cognitive load. Instead, it was the stimulus configuration / spatial layout that was controlled for. Therefore, future studies should distinguish between visual discomfort, aesthetics and environment type *per se* in their stimulus choice. Experiments 4 and 5 (see Chapter 5) will therefore focus on investigating the effect of nature vs. urban environments on gait and reaction times when these two environment types are controlled for liking scores. In Chapter 7, I will present three studies investigating the interaction between liking and visual discomfort.

It also needs to be considered that nature images used in this study were not very biodiverse as all nature images presented contained green spaces in temperate climates (UK and Canada). One possibility is therefore that it is not nature as such but the green colour within the images that was driving the differences in cognitive processing load between nature and urban images. Therefore, the aim of the next study is to investigate the impact of the amount of "greenery" in a visual scene on gait kinematics (Experiment 3, see Chapter 4).

Another factor that could have possibly affected results is the presence of people in urban scenes. Half of the urban images, used in this study, presented scenes with the presence of people while all nature images presented scenes without the presence of people. However, an additional analysis did not reveal any effect of the presence of people in urban scenes on median reaction times. This suggests that cognitive load induced by exposure to urban environments is not associated with the presence of people. Nonetheless, further studies should control the presence of people in the scenes. Therefore, images selected for the next studies are presenting only nature and urban scenes without people (Experiments 4 and 5, see Chapter 5).

Overall, this work confirmed that differences in cognitive processing load between exposure to nature environments and urban environments can be estimated on a trial-by-trial basis by using gait and reaction times as a measure of load. These results represent a compelling initial step toward developing a technique that will allow us to understand some of the mechanisms underlying the "nature benefit" (or "urban cost"), measuring effects in real time. I have used this approach throughout the thesis to tease apart different factors contributing environmentally-induced cognitive load. Chapters 4, 5, and 6 present data in which this method has been used to measure the moment-to-moment impact of low-level image properties on cognitive processing load by parametrically varying the amount of greenery (Experiment 3, Chapter 4) and fractal geometry (Experiment 6, Chapter 6) in visual scenes, in addition to understanding factors such as aesthetics and visual discomfort (Experiments 4 and 5, Chapter 5).

Chapter 4. The impact of the amount of "greenery" on cognitive load

4.1. Experiment 3: The impact of the amount of "greenery"/chlorophyll in a visual scene on gait kinematics

4.1.1. Introduction

The aim of this study was to explore whether colour as a low-level image property, in particular the amount of "greenery" in a visual scene, impacts visual cognitive processing load, using gait kinematics as a measure of load as established in Chapter 3 (see also Burtan, Joyce, et al., 2021).

This question arose from findings that blue-green infrastructure positively impacts physical and mental health (Pretty et al., 2017; Wells, 2000). Moreover, a closer look at images used in experiments 1 and 2 in Chapter 3 providing evidence that nature and urban environments affected gait kinematics, and in turn cognitive load, differently (see also Burtan, Joyce, et al., 2021), and revealed that the vast majority of our nature images consisted of primarily "green spaces" whilst the urban images had a different colour scheme.

In other words, the distribution of colours, and in particular the amount of "greenery" / chlorophyll, in environmental scenes could have affected cognitive processing load in such a way that a higher amount of greenery increased walking speed or a lower amount of greenery decreased walking speed. Therefore, in this experiment, I hypothesised that walking speed would be faster whilst walking towards images with higher amount of 'greenery'/ chlorophyll as compared to images with lower amount of "greenery" / chlorophyll.

4.1.2. Methods

Participants: On the basis of effect sizes observed in Experiment 1 (Chapter 3), twenty-two participants took part in this study (4 male, 18 female; aged 18-23 years, M = 20 years). All participants were recruited via the University of Bristol Experimental Hours Scheme online platform and reimbursed with course credits for their time. All participants reported normal or corrected-to-normal visual acuity, normal colour vision and no injuries or conditions that might have impacted their walking. All participants gave their informed written consent prior to conducting the study. Ethical approval for the study was obtained from the Faculty of Life Sciences' Ethics Committee at the University of Bristol (ref: 20111878362).

Stimuli: The stimuli for this study were 100 abstract images, parametrically varied for the percentage of chlorophyll, i.e. "greenery", they contained (0%, 25%, 50%, 75%, 100%, 20 images per condition), in addition to 5 plain grey images. Images were provided by Professor Lewis D. Griffin, University College London, UK who synthesised them from his five-parameter model of spectral reflectance with realistic colour distributions (L.D. Griffin, personal communication, October 2017): based on a Gaussian model of the distribution of natural spectral reflectance functions parameterized by analysis of images from the ImageNet database and Google StreetView images of the UK, colour histograms of images (mean RGB) were created that reproduced the colours of natural images. Please note that "100%" corresponds to the maximum amount of greenery extracted from real world images and not to an exclusively green image while 0% corresponds to the minimum amount of greenery extracted from real world images. As such, these synthetic stimuli capture the colour spectra of natural scenes as closely as at all possible. Image resolution was 1280x800 pixels.

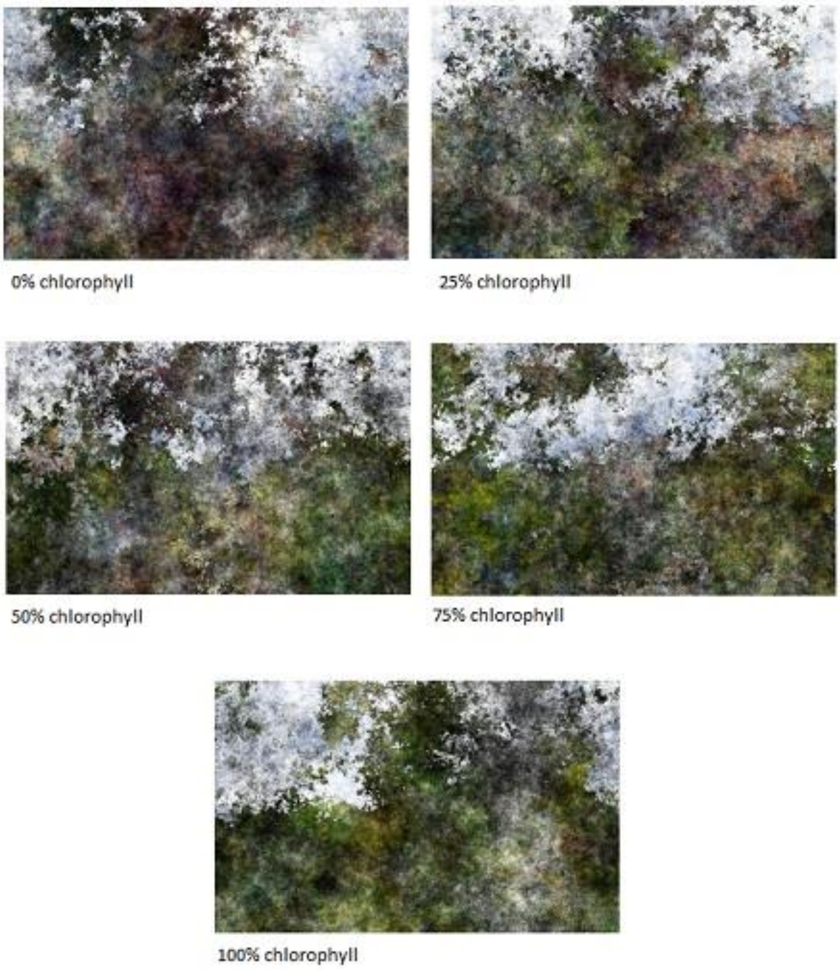

Figure 4.1: Example stimuli from a set of 100 natural images with different distribution of 'greenery'/chlorophyll synthesized from the complex colour-from-reflectance model by Prof. Lewis D. Griffin.

Procedure: Prior to the actual experiment, all participants were provided with a written explanation of the study, and they were informed about their right to withdraw at any time without having to give any explanation. They were asked to walk down the BVI Movement laboratory and perform a secondary task whilst their gait parameters were recorded with 3D motion capture (for method see Chapter 2.1.1.). There were two parts to the experiment: a) Walking whilst performing a verbal task (see Annex B for description) - as described in detail already for Experiment 1 in Chapter 3. This part of the experiment served as a control only to confirm that participants' gait kinematics were indeed affected by increases in cognitive load (outcomes are presented in Annex B), and b) Walking towards images with different amounts of "greenery" that were projected onto the far wall of the lab, followed by rating each image directly after the walk for its likeability. This was the actual task of interest. In this Experiment, participants were not asked to rate images for visual discomfort as images did not significantly differ in their spatial frequency, thus the visual discomfort ratings were expected to be similar.

The order of the two experimental parts was counterbalanced across participants (see also Chapter 3, Experiment 1 for a similar procedure).

Walking and rating images for likeability: For each trial, one of the following images was projected onto the back wall of the lab: 100% chlorophyll (20 images), 75% chlorophyll (20 images), 50% chlorophyll (20 images), 25% chlorophyll (20 images), 0% chlorophyll (20 images) or a plain grey image (5). Images were displayed in random order.

The size of a projected image was 3m x 2m (11.4° x 7.6° of visual angle from the start point of the laboratory and 57 ° x 38° of visual angle from the end point of each walk). After each walk, participants were asked to rate the image displayed for its likeability on a 7-point Likert Scale from '1 – not at all to '7 – very much', before returning to the starting point at the other side of the lab. The completion time of the two-part study task was approximately 60 minutes. Participants were offered a break between experimental parts in addition to two breaks during the experimental part of interest (after 35 and 70 trials), but they were allowed to ask for more breaks. After completing the study, participants were provided with a written debrief.

Exclusion criteria: Two participants were excluded from analysis due to having an unusual walking style (see exclusion criteria in Chapter 2.1.3.), leaving 20 participants' datasets for the analysis, 17 females and 3 males, aged 18-23 (M = 19.55, ± 1.39 SD).

4.1.3. Results

As the task "Walking whilst performing a trail making task" served as a control only, similar to the control in Experiment 1 (Chapter 3), the procedure and data are not presented here but can be found in Annex B.

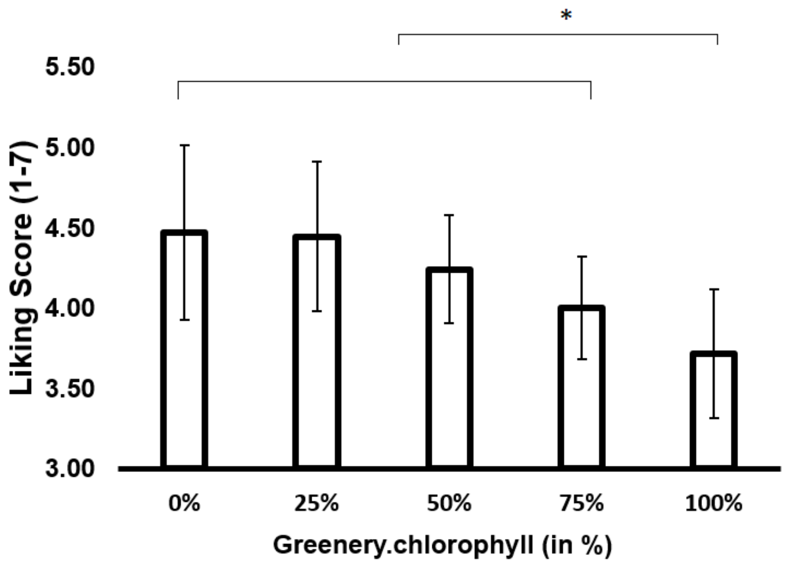

Figure 4.2: Group averages of individual mean liking ratings (7 point- Likert Scale) for the five stimulus types categorised by the amount of 'greenery'/chlorophyll in a visual scene (0%, 25%, 50%, 75%, 100%). Error bars reflect ±1SEM. * $p < 0.05$.

Liking Scores: Figure 4.2. shows participants' group mean liking scores for image categories parametrically varied for their amounts of greenery. Liking seemed to decrease with increased amounts of greenery. This was confirmed with a repeated measures ANOVA with Greenhouse-Geisser correction applied to the liking rating data of the task of interest, with stimulus type (100% chlorophyll, 75% chlorophyll, 50% chlorophyll, 25% chlorophyll, 0% chlorophyll) as within-subjects variable.

There was a significant effect of the amount of "greenery"/chlorophyll on liking ratings $F(1.363, 25.906) = 8.925$, $p < 0.05$, partial $\eta^2 = 0.320$. A Bonferroni *post-hoc* test revealed that stimulus type 100% greenery had a significantly lower liking score than any other stimulus type: 0%, 25%, 50% and 75%, $p < 0.05$.

Gait: To investigate the impact of different amounts of image greenery on gait, repeated measures MANOVAs were applied to the gait data of the task of interest, adding order of experimental parts as a between-subjects variable and stimulus type (100% chlorophyll, 75% chlorophyll, 50% chlorophyll, 25% chlorophyll, 0% chlorophyll) as a within-subjects variable for three dependent gait measures: mean velocity, mean step length, mean stride time (note that this analysis follows the same principles as the analysis presented in Chapter 3 for Experiment 1; analysis was restricted from the original 7 measures to the three measures that had been most sensitive before).

Velocity: There was no statistically significant effect of the amount of “greenery”/chlorophyll on velocity, $F(4,72) = 0.960$, $p > 0.05$, partial $\eta^2 = 0.289$.

Step Length: Analysis with Greenhouse-Geisser correction of step length data further showed that there was no statistically significant effect of the amount of “greenery”/chlorophyll on step length, $F(1.128, 47.276) = 1.128$, $p > 0.05$, partial $\eta^2 = 0.267$.

Stride Time: Moreover, there was no statistically significant effect of the amount of “greenery”/chlorophyll on stride time, $F(4,72) = 0.506$, $p > 0.05$, partial $\eta^2 = 0.164$.

Experimental part order did not affect any of the gait measures.

Multi-Level Modelling: in line with additional analyses performed for Experiment 1 in Chapter 3, a cross-classified multi-level model was applied to the velocity data to tease apart possible effects of liking and amount of “greenery” in a visual scene on walking speed.

Table 4.1: Model fit comparisons for models estimating walking speed from the characteristics of the image viewed.

Model	DIC	Fixed	Random
1	1752.810		PT, IM, T
2	1755.569	Greenery, Liking	PT, IM, T
2a	1752.810	Model 1	PT, IM, T

Note. PT = Participant, IM = Image, T = Trial (n = 1975).

The results of the multi-level analysis revealed that the best fitting model was Model 1; thus, both greenery and liking were non-significant predictors ($p > 0.05$) of walking speed.

4.1.4. Discussion

Contrary to expectations derived from earlier findings of the positive impact of blue-green infrastructure on restoration (Pretty et al., 2017), the results of this experiment suggest that the amount of “greenery”/chlorophyll in a visual scene *on its own* does not affect gait kinematics. The hypothesis that walking speed is faster whilst walking towards images with higher amount of ‘greenery’/ chlorophyll as compared to images with lower amount of “greenery” / chlorophyll had not been confirmed and thus had to be rejected. Thus, visual scenes with a lower amount of “greenery” do not seem to require higher cognitive processing load than visual scenes with higher amounts of “greenery”.

These results cannot be explained by participant’s lower sensitivity to cognitive load changes as compared to participants in Experiment 1 (see Chapter 3) as the effect size of the impact of cognitive load on gait in Trial Making Task was similar in Experiments 1 and 3 (see Annex B). Whilst interindividual gait variability was slightly higher for participants in Experiment 3 as compared to participants in Experiment 1, the effect of slowing walking speed with increased cognitive load for verbal conditions was comparable. Thus, we can exclude the possibility that our procedure was not sensitive enough to pick up on cognitive load changes, which points towards the interpretation that the different stimulus categories in this experiment might have not been varied enough even though they captured the entire range of greenery distributions observed in the UK. There were no technical issues that could have impacted the results.

Moreover, as liking scores differed significantly between the different stimulus categories, we can also exclude the possibility that participants could not distinguish between different image types. This makes it even more notable that the analysis of gait kinematics data did not reveal either that liking scores were predictive of gait changes. The reason for a lack of both liking scores and greenery predicting gait changes is not entirely clear; yet, it is tempting to speculate: the images with lower amount of 'greenery'/chlorophyll had higher liking scores as compared to images with higher amount of 'greenery'/ chlorophyll; from anecdotal evidence such as comments by the participants, the abstract nature of the images made them appear rather as "pieces of art". It could thus well be that aesthetics masked any low-level colour distribution effects, with greenery and likeability effects cancelling each other out.

If this were the case, a masking effect related to likeability could only be excluded by controlling images for liking scores which in the case of abstract images as used here with regard to greenery is impossible.

However, with regard to nature and urban real images, it is well-established that overall nature images are preferred over urban images (e.g. Han, 2010; Hartig & Staats, 2006; Ibarra et al., 2017; Purcell et al., 2001; Van Hedger et al., 2019), even though likeability varies substantially also within both nature and urban categories. Therefore, balancing out likeability between nature and urban images should be achievable in image sets. The next chapter (Chapter 5) therefore presents two experiments to investigate whether environment type (nature vs. urban) still differentially affects gait kinematics when participants are presented with images of nature and urban scenes that have been matched for their liking scores beforehand by an independent participant sample.

From the results presented in this Chapter, it is tempting to conclude that the positive effect of nature on cognitive functioning is not associated with the distribution of colour *per se* in a scene. However, even if the images created by Professor Lewis D. Griffin reproduced colour distributions of real-world scenes, the images themselves were abstract. In other words, I cannot exclude that if participants had been presented with real scenes controlled for the distribution of chlorophyll, thus preserving the meaning of the scene, the results would have been different. Indeed, people tend to make clear semantic associations between objects and colours (Palmer & Schloss, 2009).

The null result in this chapter further raises the question of whether the different rating tasks used in Chapters 3 and 4 differentially affected gait results: in Experiment 1 (see Chapter 3) participants were asked to rate nature and urban images for their visual discomfort whilst in this Experiment participants were rating images for their aesthetic preferences. Therefore, the goal of Experiment 4 in the following Chapter is not only to investigate whether cognitive load differences are present when nature and urban environments are matched for liking scores, but also whether the effect occurs irrespectively of whether the task consists of memorising images or of rating images for visual discomfort.

In conclusion, the hypothesis of this Chapter that the amount of “greenery” in a visual scene (at least when presented in isolation within an abstract visual context) affects gait kinematics and thus cognitive load has not been confirmed. Moreover, liking was also not predictive of gait changes when dealing with abstract images, even though liking scores clearly varied with the amount of greenery present in the visual scenes.

Chapter 5: Do differences in cognitive load between nature and urban images still present when these two image types are controlled for likeability?

5.1. Introduction

In Chapter 3, converging evidence from two different experiments was presented that nature and urban environments impact cognitive processing load differently, and that this effect can be observed on a trial-by-trial basis by measuring gait kinematics and reaction times (Experiments 1 and 2). One of the limitations of studies on the nature benefit/urban cost, including our earlier study (Experiments 1 and 2) in Chapter 3, is that they tend not to control a key factor that could possibly impact environmentally-induced cognitive load, namely aesthetic preference (see e.g. Berman et al., 2008; Berman et al., 2012). Indeed, nature and urban environments have been repeatedly shown to differ with regard to their aesthetic properties (e.g. Han, 2010; Hartig & Staats, 2006; Ibarra et al., 2017; Purcell et al., 2001; Van Hedger et al., 2019). This is further reflected in most theories on the positive impact of nature on cognitive functioning, explicitly highlighting aesthetics as a key factor to play a role in cognitive processing benefits that nature gives us (SRT;(Ulrich, 1983), ART;(Kaplan, 1995), PFA;(Joye & De Block, 2011)).

In addition to such aesthetic differences between nature and urban images, and as discussed in Chapter 3 in more detail, experiments 1 and 2 (Chapter 3) revealed that images of urban environments were also more uncomfortable to look at than images of nature environments and that this visual discomfort was predictive of gait changes. This suggests that visual discomfort and, in turn, the physiological response to visual stimuli, might contribute to environmentally-induced cognitive load. Therefore, I reasoned that if in Experiments 1 and 2 urban images were more uncomfortable to look at than nature images (Burtan, Joyce, et al., 2021), they might also have been less aesthetically pleasing than nature images. Clearly, I cannot exclude that environment type in my earlier study was not similarly confounded with visual discomfort or aesthetics.

The aim of the Chapter here is to investigate whether differences in cognitive processing load between nature and urban scenes remain when each urban scene presented is matched for its liking score with a nature scene (see Chapter 5.2.1. for a description of the stimulus selection process). I tested this prediction with the same two experimental approaches used in Chapter 3 to investigate whether both measures of load, gait kinematics and reaction times, will be able to pick up the differences in cognitive processing load posed by exposure to nature and urban scenes. In the first experiment (Experiment 4), changes in gait kinematics were measured during exposure to nature and urban scenes that had been matched for their liking scores *a priori*. Again, people were asked to perform a dual-task; but to control for task-related confounding factors, this dual-task consisted for half of the participants of walking and memorising each image, for the other half of walking and rating each image for its visual discomfort. In the second experiment (Experiment 5), reaction times were measured during the performance of the shape discrimination task, in which the same nature and urban images matched for liking scores were presented as task-irrelevant distractors.

To control for the effect of low-level image statistics on cognitive load, fractal dimensions were calculated again for all images used.

Experiment 4 was included in a paper that has been published in *PLoS One* (Burtan, Burn, et al., 2021).

5.2. Experiment 4: The impact of exposure to nature vs. urban images on gait kinematics when these two image types are matched for their liking scores

The main aim of this experiment was to investigate the impact of environment type (urban vs. nature) on gait kinematics for an image set in which each nature image was matched with an urban image for their liking scores based on data from an independent participant sample rating a wide range of urban and nature images for their likeability. If the difference in gait kinematics during exposure to urban as compared to nature images observed in our earlier study was due to differences in likeability of these image sets rather than environment type *per se*, then differences in gait kinematics should not arise if these two image types were matched *a-priori* for their aesthetics.

Further goals were to establish whether subjective visual discomfort and/or fractal dimension (image statistics) contribute to cognitive load differences and thus differences in gait kinematics (or reaction times) between environment types when liking is controlled for. Moreover, participants were asked to either memorise images during walking or rate images for visual discomfort after each walk to investigate whether the effect is task-related rather than image related.

5.2.1. Stimulus collection (Pilot studies)

Before being able to run the actual experiment, a stimulus set had to be created in which each nature scene was matched with an urban scene for their liking scores. For this, participants were asked in two online studies using the platform Gorilla to rate images of photographic environmental scenes for their likeability on 7-point Likert Scale (n = 150 per study).

<u>Participants:</u> All participants reported normal or corrected-to-normal visual acuity. All participants were asked to read an information sheet and to provide consent prior to the beginning of the online study. Participants either volunteered by responding to social media announcements or were recruited via Prolific and reimbursed for their time. The experiment

was approved by the Faculty of Life Sciences' Ethics Committee at the University of Bristol (ref. 2410201876401). Demographics are summarised in Annex C.

Material and Task: The two online studies were both run on the 'Gorilla' Platform with the same procedure but different image sets. Images consisted of 200 nature and 200 urban scenes, which were equally distributed across the two studies; i.e. each image set consisted of 200 images of which 100 were nature images and 100 were urban images. Scenes had been selected from the "places" category of the scene recognition database (Zhou et al., 2014), in addition to containing photographs of landscape and urban spaces taken in Europe by me, and in Europe and Australia by Ute Leonards. Images presented environmental scenes where people and animals were not visible and varied substantially across landscape types, lighting conditions, colours and viewing angles. Image resolution was 1280x800 pixels.

At the beginning of the study, participants were asked to fill in a form requesting their demographics. In the actual task, participants looked at the images, one at a time, presented in random order, and rated each image for its likeability on a 7-point Likert Scale: "How much do you like the image?" from '1 – Not at all' to '7 – Very much'. There was one break during each study halfway through, i.e. after 100 trials.

Results: Liking scores for the different image types for the two studies and the results of independent t-tests are summarized in Table 5.1. Images of nature scenes had significantly higher liking scores than images of urban scenes in both studies ($p < 0.001$).

Table 5.1: Results of independent t-tests and group means of liking score per image across image type for each of the two studies. (Table taken from Burtan, Burn, et al., 2021. *PLoS One,* 16(8), p. 9 (doi:10.1371/journal.pone.0256635)).

		Nature (Mean ± SD)	Urban (Mean ± SD)	Comparison
Liking (7-point Likert Scale)	Study 1	4.86 ± 0.80	3.59 ± 0.84	$t(198)=10.88$, $p < 0.001$
	Study 2	4.75 ± 0.79	3.44 ± 0.92	$t(193)=10.76$, $p < 0.001$
	Total	4.81 ± 0.80	3.50 ± 0.88	

Matching images of nature and urban scenes for liking scores: To create the image set for the main study, I used the outcomes of the two studies to select 50 image pairs of nature and urban scenes that had received similar mean liking scores (and, where possible, similarly small variance of liking scores) within the same sample; if two images of the same environment type had similar liking scores (and variance), other selection criteria such as viewing angle were considered in addition. This resulted in a stimulus set of 50 nature-urban image pairs with liking scores ranging from 2.82 to 5.61. An independent samples t-test confirmed that for the final stimulus set there was indeed no significant difference in mean liking scores between nature and urban images (Nature: M = 4.22, ± 0.67 SD, Urban: M = 4.22, ± 0.67 SD, $t(98)= 0.001$ $p > 0.05$, mean difference = 0.00013); also Figure 5.1. Nature images were entirely free of human artefacts such as buildings as well as of animals. Some of the urban images, whilst all dominated by buildings, included partially visible blue-green infrastructure. Images were without the presence of people.

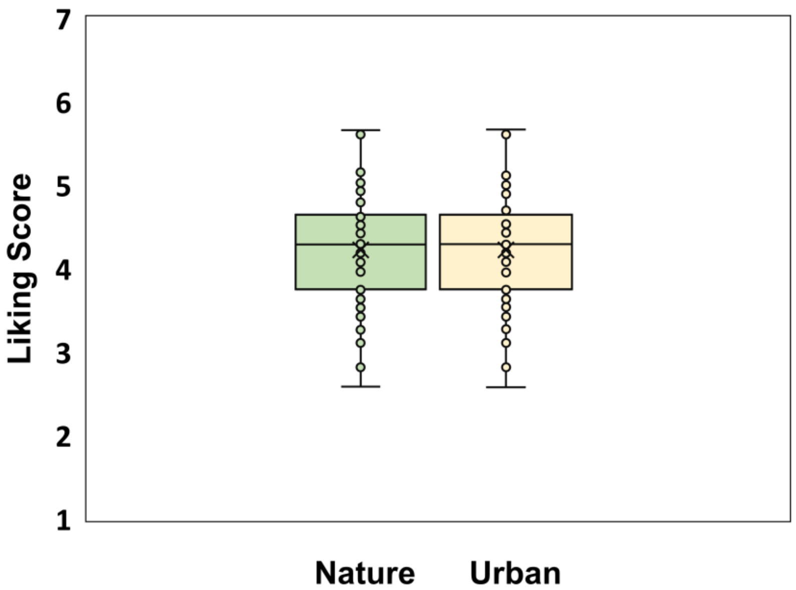

Figure 5.1: New stimulus set of 50 nature (green) and 50 urban (yellow) images matched for liking scores.

5.2.2. Methods

Main Experiment 4

Participants: Sample size calculations took into account the substantial amount of repetitions within individual participants for the conditions of interest (environment type) and were based on modelling estimates for within-participant repeated measures correlations provided by Bakdash & Marusich (2017) to obtain 80% power for a medium effect size (0.3) and within participant repeated paired measures of 20 or more, I needed a minimum of 12 participants (Bakdash & Marusich, 2017). As the cognitive task differed between participants, I doubled the number of participants per cognitive task to account for possible task-specific effects.

Fifty participants (43 females and 7 males, aged between 18 and 61 years, mean age 21 years ± 6.6 SD) took part in this study. The first twenty-seven (24 females and 3 males, aged between 18-61 years, mean age = 22, ± 8.26 SD) participants were asked to walk towards images projected onto the back wall of the lab whilst having to memorise each presented image (i.e. walking whilst performing a memory task). The other twenty-three participants (19 females and 4 males, aged between 18-35 years, mean age = 21, ± 3.86 SD) were asked to walk towards the same images and to rate each image for visual discomfort after they had reached the far side of the lab.

All participants reported normal or corrected-to-normal visual acuity as well as no neurological conditions that could affect their walking. They also confirmed that they were healthy and fit enough to walk without difficulties for an hour. All participants were provided with written and verbal information about the study and signed the consent form prior to their experimental session. They were also given information about the right to withdraw and possible breaks to take during the experimental session whenever they felt needed. Participants were either volunteers or took part in the experiment for course credit. The experiment was approved by the Faculty of Life Sciences' Ethics Committee at the University of Bristol (ref. 20111878362).

Stimuli: The stimulus set contained 50 images of nature and 50 images of urban scenes matched for their liking scores (see section on stimulus collection above), in addition to 5 plain grey images (Control). The resolution of images was 1280x800 pixels. Fractal dimensions were calculated for each image based on the Minkowski–Bouligand fractal dimension box-counting technique (see Chapter 2.3.2.). Fractal dimensions in the nature scenes (M = 1.65, ± 0.13 SD) used were found to be significantly higher than those in the urban scenes (M = 1.59, ± 0.14 SD), $t(98) = 3.567$, $p < 0.01$).

Tasks and Procedure: a detailed description of the procedure is given in Chapter 2 (2.1.1.1.).

In brief, for each trial, one of the following 105 photographs was displayed in random order: a nature scene (50), an urban scene (50), or a plain grey image as a control stimulus (5). Participants in the "walking whilst performing a memory task" condition were required to memorise each image during their walk and before returning to the starting position for the next walking trial (note that task compliance for this condition was checked in a separate behavioural experiment after the actual walking experiment had been finished – see below for further information). Participants in the "walking followed by performing a visual discomfort rating task" were required to verbally rate each image for its visual discomfort on a 7-point Likert Scale (from 1 = extremely comfortable to view to 7 = extremely uncomfortable to view; 4 = neither comfortable nor uncomfortable) after each walk before returning to the starting position. Their responses were noted by the experimenter. The walking part of the study took approximately 60 minutes to complete with breaks where needed. After participants had performed their 105 walks, they were debriefed, signed the final consent form and were thanked for participation.

After walking and before debriefing, participants in the "walking whilst performing a memory task" condition were tested to confirm whether they had indeed performed their task correctly (i.e. memorised the images seen). For this, participants were again presented with the same image set of nature and urban images, but this time randomly intermixed with 100 new images (50 nature, 50 urban). For each image, they had to decide as quickly and as accurately as possible whether they had seen this image before during the walking part of the study. Only participants who performed on this task with an overall accuracy above chance (62% correct or more) were included in data analysis. This part of the study took approximately 15 minutes to complete.

Exclusion: Five participants were excluded from analysis due to technical issues with the motion capture system during testing (e.g. missing sensor data, below 80% of data; see methods in Chapter 2 for more detail). One further participant was excluded on the basis of their memory performance in the memory compliance check. This left 22 (2 male, 20 female) participants' datasets for analysis for the "walking whilst performing a memory task" condition, aged 18 – 61 years (M = 22, ± 9.12 SD), and 22 (4 male, 18 female) participants' datasets for analysis for the “walking followed by performing a visual discomfort rating task” condition, aged 18-35 (M = 21, ± 3.85 SD).

5.2.3. Results and Discussion

Behavioural outcomes (Memory task): A non-parametric Wilcoxon signed-rank test of performance values for correctly memorised images revealed that participants remembered significantly more urban (M = 81%) than nature images (M = 70%); $Z = -3.083$, $p < 0.05$, indicating that features of urban images capture attention more easily than features of nature images. It should be kept in mind that the increased difficulty in memorising nature images might be related to their increased fractal content (self-repeating patterns) as compared to urban images (Ho et al., 2019) However, there was no significant difference in median reaction times for the two image types as confirmed by a non-parametric Wilcoxon signed-rank test rank test; $Z = -0.503$, $p > 0.05$.

Visual Discomfort Rating Task: A Paired Samples t-test revealed that there was no significant difference in subjective visual discomfort ratings between nature scenes (M = 2.95, ± 0.80 SD) and urban scenes (M = 2.76, ± 0.88 SD), $t(21) = 1.707$, $p > 0.05$).

Gait kinematics: Repeated measures MANOVAs were conducted on three dependent gait measures, combining the gait data for participants of the two cognitive tasks: mean velocity, mean step length and mean stride time with environment image type as a within-subject factor (Nature/Urban/Control) and cognitive task type as a between-subject factor (Memory Task/Visual Discomfort Rating Task); see also Figure 5.2. for group average velocity, step length and stride time per image type.

Velocity: There was a statistically significant main effect of environment on velocity determined by a MANOVA with Greenhouse-Geisser correction, $F(1.161, 48.776) = 81.947$, $p < 0.001$, partial $\eta^2 = 0.661$ (see Figure 5.2.). *Post-hoc* pairwise comparisons using Bonferroni correction revealed that the control condition had a significantly faster walking speed than both nature ($p < 0.001$) and urban conditions ($p < 0.001$). Crucially, there was no significant difference between gait velocities obtained for walking during nature and urban conditions ($p > 0.05$).

Step Length: There was a statistically significant main effect of environment on step length determined by a MANOVA with Greenhouse-Geisser correction, $F(1.173, 49.266) = 70.862$, $p < 0.001$, partial $\eta^2 = 0.628$ (see Figure 5.2.). *Post-hoc* pairwise comparisons using Bonferroni correction revealed that the control condition had a significantly longer step length than both nature ($p < 0.001$) and urban conditions ($p < 0.001$), but nature and urban conditions did not differ from each other ($p > 0.05$).

Stride Time: There was a statistically significant effect of environment on stride time determined by a MANOVA with Greenhouse-Geisser correction $F(1.336, 47.711) = 65.835$, $p < 0.001$, partial $\eta^2 = 0.611$ (see Figure 5.2.). As for the two other gait measures, *post-hoc* pairwise comparisons using Bonferroni correction revealed that the control condition had a significantly shorter mean stride time than both nature ($p < 0.001$) and urban conditions ($p < 0.001$) which again did not significantly differ from each other ($p > 0.05$).

Cognitive task (memory task vs. visual discomfort task) did not differentially affect any of the gait measures, nor were there any significant interactions between task and environment.

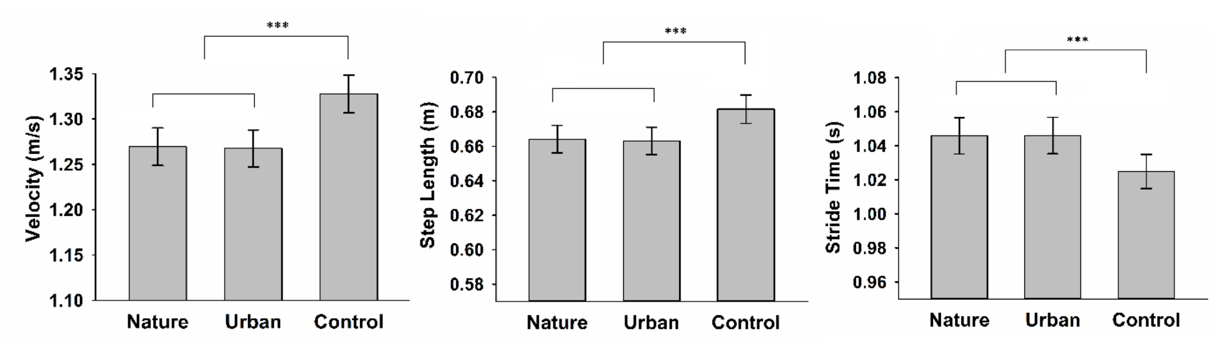

Figure 5.2: Group (n = 44) averages of a) individual mean velocity (m/s), b) individual mean step length (in metres) and c) individual mean stride time (in seconds) across environment type (nature, urban, control). Error bars reflect ± 1 SEM. (Figure taken from Burtan, Burn, et al., 2021. *PLoS One*, 16(8), p. 8 (doi:10.1371/journal.pone.0256635)).

Multi-Level Modelling: Multi-level modelling was applied to cross-classified data from both cognitive tasks (n = 44) to determine the impact of environment, pre-defined image liking scores, image fractal dimensions, and cognitive task on velocity (see Chapter 2.2. for the detailed description of the method). Control images were excluded from this analysis due to missing data for pre-defined liking scores and for fractal content.

Table 5.2: Model fit comparisons for models with standardised velocity as a dependent variable. (Table taken from Burtan, Burn, et al., 2021. *PLoS One*, 16(8), p. 9 (doi:10.1371/journal.pone.0256635)).

Model	DIC	Fixed	Random
1	4374.070		PT, IM, T
2	4374.418	ENV, LIK, TK, FR	PT, IM, T
2a	4372.084	LIK	PT, IM, T
3	4376.349	LIK, LIK*ENV, LIK*TK, LIK*FR	PT, IM, T
3a	4374.070	Model 1[a]	PT, IM, T

Random effects: PT = Participant, IM = Image, T = Trial (n = 4362). Fixed effects: ENV = Environment, LIK = Pre-defined Liking Score, FR = Fractal Dimension, TK = Task. [a] Please note that adding interactions to model 3 revealed that all predictors, including LIK, were insignificant; thus, model 3a equals model 1.

The results of the analysis revealed that model 2a was the best fitting model, with predefined liking scores being a significant predictor (X_1^2 = 4.657, $p < 0.05$) for walking speed: people walked faster towards images with higher liking scores. Parameter estimates for the model are displayed in Table 5.3.

Table 5.3: Fixed effects estimates (top) and random effect variance estimates (bottom) for the model with best fit (Model 2a; Table 5.2.). (Table taken from Burtan, Burn, et al., 2021. *PLoS One*, 16(8), p. 10 (doi:10.1371/journal.pone.0256635)).

			95% CI		
Parameter	Estimate	Std. Error	Lower	Upper	X_1^2
Fixed					
Intercept	0.023	0.128	-0.285	0.251	0.031
Liking	0.016	0.007	0.001	0.030	4.657*
Random					
Participant	0.904	0.205	0.587	1.375	
Image	0.002	0.001	0.001	0.003	
Trial	0.157	0.003	0.150	0.164	
Deviance Information Criterion (DIC)					4372.084

Note. Estimates reflect the size of the effect on standardised velocity. Burn-in = 500, Chain Length = 10,000. Degrees of freedom is 1 for all Chi-square (X_1^2) statistics. *p < 0.05.

Visual discomfort. To investigate the potential impact of subjective visual discomfort on walking towards nature and urban images matched for population level pre-determined liking scores, and to be able to compare these data to those of Experiment 1, I performed a second modelling analysis (see Chapter 2.2. for a detailed description of method). For this, I focused on the data of the "walking followed by performing a visual discomfort task" only, applying multilevel modelling to cross-classified data of this task (n = 22) on velocity. Again, control images were excluded from this analysis due to missing data for pre-defined liking scores, visual discomfort ratings, and fractal content.

Table 5.4: Model fit comparisons for models with standardised velocity as a dependent variable. (Table taken from Burtan, Burn, et al., 2021. *PLoS One*, 16(8), p. 10 (doi:10.1371/journal.pone.0256635)).

Model	DIC	Fixed	Random
1	2301.433		PT, IM, T
2	2282.580	ENV, LIK, VD, FR	PT, IM, T
2a	2279.459	VD	PT, IM, T
3	2281.759	VD, VD*ENV, VD*LIK, VD*FR	PT, IM, T
3a	2279.459	Model 2a [a]	PT, IM, T

Random effects: PT = Participant, IM = Image, T = Trial (n = 2183). Fixed effects: ENV = Environment, LIK = Predefined Liking score, VD = Subjective Visual Discomfort, FR = Fractal Dimension. [a] Please note that adding interactions to model 3 revealed that all added predictors were insignificant (VD*ENV, VD*LIK, VD*FR) while VD was significant; thus, model 3a equals model 2a.

The results of this analysis revealed that model 2a was the best fitting model. Visual discomfort was a significant predictor X_1^2 = 29.240, $p < 0.001$, with people walking more slowly towards images they perceived as more uncomfortable to look at. Parameter estimates for the model are displayed in Table 5.5.

Table 5.5: Fixed effects estimates (top) and random effect variance estimates (bottom) for the model with best fit (Model 2a; Table 5.4.). (Table taken from Burtan, Burn, et al., 2021. *PLoS One*, 16(8), p. 10 (doi:10.1371/journal.pone.0256635)).

			95% CI		
Parameter	Estimate	Std. Error	Lower	Upper	X_1^2
Fixed					
Intercept	-0.006	0.204	-0.425	0.378	0.001
Discomfort	-0.054	0.011	-0.074	-0.033	29.240***
Random					
Participant	0.961	0.329	0.516	1.795	
Image	0.002	0.001	0.000	0.004	
Trial	0.163	0.005	0.154	0.173	
Deviance Information Criterion (DIC)					2279.459

Note. Estimates reflect the size of the effect on standardised velocity. Burn-in = 500, Chain Length = 10,000. Degrees of freedom is 1 for all Chi-square (X_1^2) statistics. ***p < 0.001.

Note that under these conditions, pre-defined liking scores were not predictive of velocity changes whilst subjective visual discomfort ratings were. This raises the question of how subjective visual discomfort and group-matched liking scores are related. Results of Pearson's correlation analysis revealed that there was a negative correlation between subjective visual discomfort ratings and pre-defined group liking scores, $r^2 = -0.497$, $p < 0.001$, with liking scores explaining 5% of the variability in visual discomfort.

5.3. Experiment 5: The impact of exposure to nature vs. urban images environment on decision making when these two image types are matched for their liking scores

To see whether nature and urban environments differentially captured attention despite being matched for liking scores, a further experiment was run with the shape discrimination task in the presence of the different images as task-irrelevant distractors. To separate the impact of low-level (image statistics) and higher-level perceptual processes (cognitive associations) on reaction times, images were again presented in two different orientations: upright and inverted.

5.3.1. Methods

Participants: On a basis of effect sample sizes observed in Experiment 2 (Chapter 3), forty-six participants (34 females, 12 males, mean age 21 years, ± 2.6 SD; 18-31 years) participated in the study in exchange for course credit. All participants signed a written consent form prior to the study and confirmed through self-report that they had normal or corrected-to-normal visual acuity and normal colour vision. The experimental procedure had been approved by the Faculty of Life Sciences' Ethics Committee at the University of Bristol (ref. 28071871142).

Participant were asked to perform a shape discrimination task (see Chapter 2.1.2. for a detailed procedure description) in the presence of 50 images of nature and 50 urban environments, matched in pairs for liking scores *a priori*. Note that the stimulus set was identical to the one for Experiment 4. Each image was displayed in two orientations: upright and inverted - to control for the impact of high-level and low-level cognitive processes. Therefore, there were four conditions: nature upright, nature inverted, urban upright, urban inverted; all images were presented in random order. In total, there were thus 200 trials and one break after 100 trials.

Exclusion Criteria: The first trial for each participant was removed as a practice trial. Participants with a task accuracy below 80% were excluded from analysis, leaving 43 datasets for analysis (30 females, 13 males, mean age 21 years, ± 2.6 SD, 18 – 31 years). Median reaction times per condition were based on 5% trimmed data calculations.

5.3.2. Results and Discussion

Figure 5.3. shows participants' mean reaction times for the shape discrimination task in the presence of nature or urban images for the two different image orientations, indicating that despite matching images for likeability, participants seemed to respond faster in the presence of nature images than urban images. This was confirmed in a 2 (environment; nature vs. urban) x 2 (image orientation; upright vs. inverted) repeated measures ANOVA with median reaction times as dependent variable. There was a significant main effect of environment type, ($F(1,42) = 21.212$, $p < 0.05$, partial $\eta^2 = 0.336$): participants were slower when performing the shape discrimination task whilst being presented with urban scenes (M = 0.75 s, ± 0.11 SD) as compared to nature scenes (M = 0.73 s, ± 0.11 SD). There was no significant main effect of image orientation on median reaction times ($F(1,42) = 1.028$, $p > 0.05$, partial $\eta^2 = 0.024$). However, there was a significant interaction between environment type and orientation ($F(1, 42) = 0.001$, $p > 0.05$, partial $\eta^2 = 0.013$)(see Figure 5.3.).

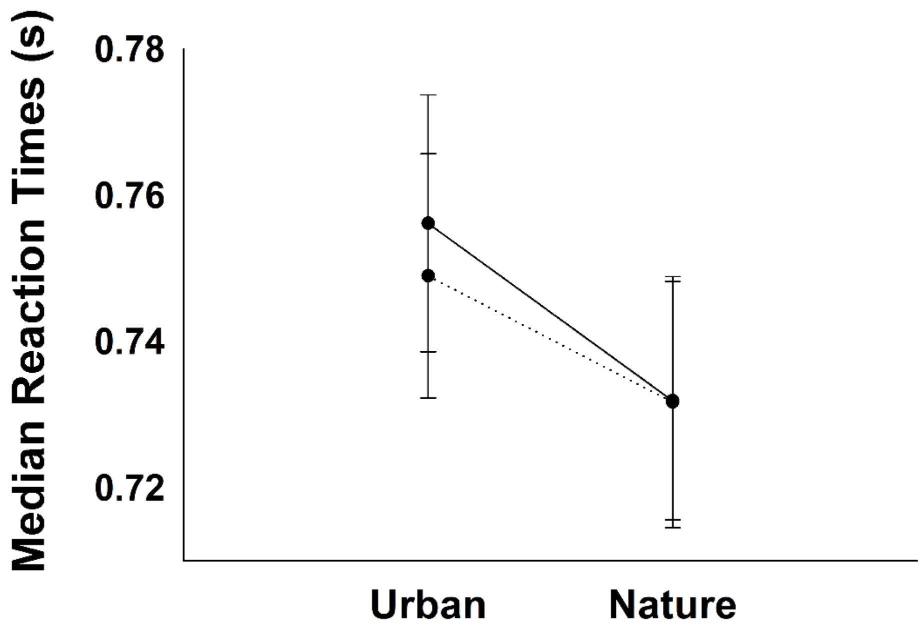

Figure 5.3: Group average of median reaction times (s) for four image types: nature upright, urban upright (dotted line), nature inverted, and urban inverted (solid line). Error bars reflect ±1SEM.

Multi-level modelling: a cross-classified multi-level model was applied to the data to tease apart possible effects of environment type, image orientation, fractal content and liking as predictors of reaction times (see Chapter 2.2. for a detailed description of the method).

Table 5.6: Model fit comparisons for models estimating reaction time from the characteristics of the image viewed.

Model	DIC	Fixed	Random
1	19581.772		PT, IM,T
2	19558.753	ENV, ORI, FD, LIK	PT, IM,T
2a	19554.836	ENV	PT, IM,T
3	19558.459	ENV, ENV*ORI, ENV*FD, ENV*LIK	PT, IM,T
3a	19554.836	Model 2a [a]	PT, IM,T

Note. PT = Participant, IM = Image, T = Trial (n = 7866), ENV = Environment, ORI = Orientation, FD= Fractal dimension, LIK = Liking Score. Burn-in = 500, Chain Length = 10,000. Degrees of freedom is 1 for all Chi-square (X_1^2) statistics. *p < 0.05. [a] Please note that adding interactions to model 3 revealed that all added predictors were insignificant (ENV*ORI, ENV*FD, ENV*LIK) while ENV was significant; thus, model 3a equals model 2a.

As shown in Table 5.6. the best fitting model was model 2a, with environment (urban) as a significant predictor model. Parameter estimates for this model are displayed in Table 5.7. Environment type was predictive of reaction times (X_1^2 = 30.989, p < 0.001) whilst image orientation, liking score and fractal dimension did not improve the model fit.

Table 5.7: Fixed effects estimates (top) and random effect variance estimates (bottom) for the model with the best fit (Model 2a ; Table 5.6.) predicting reaction time from the characteristics of the image viewed.

			95% CI		
Parameter	Estimate	Std. Error	Lower	Upper	X_1^2
Fixed					
Intercept	-0.053	0.083	-0.214	0.107	0.402
Environment (Urban)	0.110	0.020	0.071	0.149	30.989***
Random					
Participant	0.319	0.074	0.205	0.494	
Image	0.002	0.001	0.000	0.004	
Trial	0.698	0.011	0.676	0.720	
Deviance Information Criterion (DIC)					19554.836

Note. Estimates reflect the size of the effect on standardised reaction times. Burn-in = 500, Chain Length = 10,000. Degrees of freedom is 1 for all Chi-square (X_1^2) statistics. ***p < 0.001.

5.4. General Discussion

The results of Experiment 4 showed that, as predicted, environment type did not affect gait kinematics when participants were presented with images of nature and urban scenes matched for liking scores beforehand by an independent sample. It thus seems that the differences in gait kinematics observed for exposure to urban as opposed to nature images in earlier studies (Experiment 1) does not arise when images are controlled for their likeability; i.e. by presenting pairs of images in which the respective nature and urban images had similar aesthetic rating score. More importantly, Experiment 4 revealed that not only were there no differences in gait kinematics between the two environment types, but population-defined liking scores explained some of the gait variability found: pre-defined liking scores were predictive of velocity, with increased liking scores leading to increased velocity regardless of environment type. It is thus tempting to suggest that the lack of processing differences between the two image types is due to having accounted for the impact of aesthetic preference on cognitive processing (e.g. Bratman et al., 2012), in line with ideas that the more one likes the environment one is in, the less cognitively demanding it is (ART; R. Kaplan, 2001; Kaplan & Yang, 1990; Kaplan, 1995).

At first glance, the results of Experiment 4, thus seem to support the idea that liking is a key factor underlying environmental processing differences, with the results of the multi-level analysis revealing that pre-defined liking scores were a significant predictor for walking speed: people walked faster towards images with higher liking scores. However, the results of Experiment 5 revealed that liking is not the only factor contributing to cognitive processing differences between nature and urban images: reaction time differences were still found in a shape discrimination task in which nature and urban images served as task-irrelevant distractors, even after matching image pairs for liking scores. Whilst multi-level analysis revealed that environment type was predictive of reaction times, orientation of images, pre-defined liking scores, and image statistics (fractal dimensions) did not improve the model fit. Thus, differences in attentional capture between urban and nature images remained even after controlling for likeability. It thus seems that gait and reaction times as measures of cognitive load differ in terms of their sensitivity with regards to aesthetics.

Some of the differences between the two studies with regard to a possible impact of likeability could be related to differences in image exposure time. Indeed, Graf and Landwehr (2017) proposed that liking consists of two processes – a fast initial response based on pleasure and reward, and a slower response based on interest. In the first study (Experiment 4), participants were exposed to each image during the walk for 10-15 seconds, and they were asked to memorise the image or rate it for its visual discomfort. Any liking rating should thus have been based on interest and thus controlled cognitive processing (Graf & Landwehr, 2017), eliminating any nature benefit. Participants taking part in the shape discrimination in Experiment 5, in contrast, were exposed to nature and urban images on average less than 1 second, and the differences in cognitive processing load between nature and urban environments controlled for aesthetics might thus have occurred due to pleasure-based liking associated with automatic processing.

Further, the results of Experiment 4 support the claim that stimulus input rather than task *per se* was responsible for any changes in gait kinematics as the two types of tasks helped to exclude the caveat raised in Experiment 1 that rather than environmental differences, it was the interaction between environment type and the demands posed by the cognitive task that masked differences induced by stimulus processing itself. Indeed, whilst visual discomfort ratings had been shown to be more difficult (i.e. to take longer) for urban images (see Ho et al., 2019), it was more difficult to remember nature images than urban images. In other words, any cognitive load induced by the two cognitive tasks should have affected interactions with environment type in opposite directions. However, there was no task effect nor any task environment interaction that would support such an interpretation of these data.

Analysis of the data in Experiment 4 for the visual discomfort rating task revealed that subjective visual discomfort ratings, rather than pre-defined liking scores or fractal dimensions, were predictive of velocity changes. In addition, Experiment 5 revealed that liking scores were not predictive of reaction times either. This suggests that subjective visual discomfort is a stronger predictor of gait changes than aesthetic preference or liking, as any impact of pre-defined liking scores was absent when subjective visual discomfort was added as a factor to the multilevel model. These findings indicate that subjective visual discomfort rather than lack of aesthetic value might be at the core of gait slowing.

Note, however, that I cannot decide on the basis of these findings alone whether visual discomfort has a direct impact on gait speed. If so, results could be interpreted as supporting Ulrich's Stress Recovery Theory (Ulrich, 1984; Ulrich et al., 1991): SRT suggests that spending time in nature (with its higher aesthetic preferences) evokes positive affective responses, and thus fosters faster recovery from physiological stress (Ulrich, 1984; Ulrich et al., 1991). Spending more time in urban environments, in contrast, maintains physiological stress. Viewing images that are more uncomfortable to look at might therefore lead to perceptual distortions and other physiologically unpleasant/aversive symptoms which, in turn, make it more difficult and stressful to approach the evoking stimulus.

Whilst not the primary focus of this study, it should also be noted that there is first evidence that visual discomfort and liking scores are not independent of each other but seem to be negatively correlated. Before speculating about a possible link between these two variables, it is important to point out that any proper examination of the relationship between liking and discomfort is limited through design and beyond the scope of this study: visual discomfort ratings for individual images were provided by each individual participant whilst liking scores were average liking scores for each image across an independent observer sample.

Overall, it thus seems to be safe to conclude from the findings in this study that it is crucial to avoid aesthetics-related stimulus selection biases when investigating cognitive aspects of the different environments. However, as cognitive differences between nature and urban images were still present when the same liking-matched images were presented as task-irrelevant distractors, this suggests that in addition to such mid-level processes as liking, low-level processes and/or semantic cognitive associations also play a role in the “nature effect”. As analysis of the data in Experiment 4 revealed that visual discomfort ratings rather than pre-defined liking scores were predictive of walking speed. Moreover, visual discomfort and liking scores were not independent of each other but negatively correlated, requiring the relationship between liking and visual discomfort to be further investigated. This includes its impact on cognitive load. This will be examined in more detail in Chapter 7. In addition, these data suggest that the respective contributions of low-level and higher-level visual associations need to be examined further to gain an understanding of the positive effect of certain environments over others on cognitive functioning.

Chapter 6: The impact of image fractal properties on gait kinematics and its interaction with visual discomfort

6.1. Introduction

It has been suggested that differences between nature and urban environments in visual demands on cognitive processing load are related to low-level sensory processing (PFA; (Joye & De Block, 2011; Joye et al., 2016; Joye & Van den Berg, 2011)). PFA claims that nature scenes are processed more quickly than urban scenes as a by-product of the fluent perceptual processing of their low-level sensory features; i.e. their basic image statistics such as their increased fractal dimensions. Fractals are defined as patterns whose structural complexity is repeated multiple times across different spatial scales; the repeating pattern is identical in the so-called exact or mathematical fractals, while many natural forms and patterns exhibit statistical similarity across different spatial scales (Spehar et al., 2003).

The aim of the current study was to investigate whether the fractal dimension of an image affects cognitive processing demands, using gait kinematics as the measure of demand. As already briefly mentioned in the Introduction, the fractal properties of natural environments are related to the scale-invariant statistics revealed in their spatial frequency regularities, in particular in their 1/f amplitude spectra with an alpha range of 0.8 – 1.5 and a mean of 1.2 (e.g. Tolhurst et al., 1992), corresponding to a range of fractal dimensions (D) between 1.50-1.65. Moreover, sensitivity thresholds in the human fovea and parafovea have been found to be lowest for 1/f amplitude spectra with alphas between 1.2 - 1.4 (e.g. Hansen & Hess, 2006). If such low level statistics were to contribute to the "nature benefit", then walking towards images with fractal properties outside the range typically found in nature scenes should result in a decrease in participants' walking speed, smaller step length and an increase in stride time, in line with findings of gait changes for higher cognitive load (e.g. Amboni et al., 2013; Burtan, Joyce, et al., 2021; Ho et al., 2019; Patel, Lamar, & Bhatt, 2014).

The experiment described in this Chapter was included in a manuscript that has been submitted for publication (Burtan, Burn, Spehar, & Leonards, 2022)[4].

6.2. Methods

<u>Participants:</u> Based on effect sizes observed in earlier study (see Experiment 4, Chapter 5.2.2.), forty participants (33 females, 7 males, mean age = 20 ±3.02 SD years, aged between 18-33 years) took part in this study. They were randomly assigned to one of two groups depending on the type of rating task they had to perform: twenty participants to the *visual discomfort* rating group (16 females, 4 males, mean age = 21 years ± 3.95 SD, aged between 18-33) and the other twenty participants (17 females, 3 males, mean age = 19 years ± 3.95 SD, aged between 18-24 years) to the *likeability* rating group. Prior to their experimental session, participants were provided with both verbal and written information about the study, including information about breaks and their right to withdraw from the study at any time. Participants reported normal or corrected-to-normal visual acuity and no neurological conditions that could affect their walking. Moreover, they reported good physical health and were aware that they would have to walk for about an hour for this experiment. All participants signed a consent form, were debriefed at the end of the experiment, and received compensation for their time in

[4] Author contributions are described on page 15.

form of course credit. The experiment was approved by the Faculty of Life Sciences' Ethics Committee at the University of Bristol (ref. 10101994923).

Stimuli: The stimulus set contained 105 synthetic images: 96 images were parametrically varied in their fractal dimension /D value, and 9 were plain grey images serving as control stimuli.

Synthetic fractal images were created by Professor Branka Spehar from the University of New South Wales, Sydney, Australia, by manipulating the image amplitude spectrum (see Spehar, Walker, & Taylor, 2016; Viengkham & Spehar, 2018): two-dimensional greyscale fractal images (512 x 512 pixels) were generated in MATLAB by randomly selecting a pixel value from 0 – 255 for each pixel from a Gaussian distribution. Subsequently, a Fourier transform was applied to generate a series of amplitude frequency spectra with four different levels of amplitude spectrum slopes of alpha falloff (alpha = 0.8, 1.2, 1.6 and 2.0). An inverse Fourier transform applied each amplitude spectrum to the 512 x 512 Gaussian noise image, resulting in images possessing specific desired alpha values. Fractal properties of nature environments consist of 1/f amplitude spectra with an alpha that falls into the range of 0.8 – 1.5 and has a mean of 1.2 (e.g. Tolhurst et al., 1992); therefore, we decided to select four spectrum slopes of alpha falloff: one alpha of 1.2 as commonly found in nature, one alpha below and two above 1.2.

Four ranges of Fractal dimensions:

1) High Dimension (HD 1.75-1.90) with amplitude spectrum slopes (alpha) of 0.8;

2) Intermediate Upper Dimension (IUD 1.50-1.65) with amplitude spectrum slopes (alpha) of 1.2;

3) Intermediate Lower Dimension (ILD 1.25-1.40) with amplitude spectrum slopes (alpha) of 1.6;

4) Low Dimension (LD 1.0-1.15) with amplitude spectrum slopes (alpha) of 2.

To increase the variability in visual appearance without changing fractal-like scaling and geometric properties, each fractal dimension was presented in three different image types: *Greyscale, Thresholded,* and *Edges* (see Figure 6.1.).

The *Thresholded* image variants were created by bisecting the *Greyscale* images at the mean luminance value and converting all pixels below and above the mean luminance to black and white respectively. Finally, *Thresholded* images were used to create the *Edges* images. The edge extraction procedure was applied to create lines on a dark background.

Note that *Greyscale* images contain two-dimensional fractals (i.e. fractal variations are related to surface-texture appearances) whilst their *Thresholded* (black and white) and *Edges* counterparts contain one-dimensional fractals (i.e. fractal properties are determined by variations in fractal contours).

Therefore, the 96 fractal images were categorised into twelve image conditions, with 8 images per condition:

- HD: *Edges* (8), HD: *Greyscale* (8), HD: *Thresholded* (8);
- IUD: *Edges* (8), IUD: *Greyscale* (8), IUD: *Thresholded* (8);
- ILD: *Edges* (8), ILD: *Greyscale* (8), ILD: *Thresholded* (8);
- LD: *Edges* (8), LD: *Greyscale* (8), LD: *Thresholded* (8).

Image resolution of fractal images was 800x800 pixels.

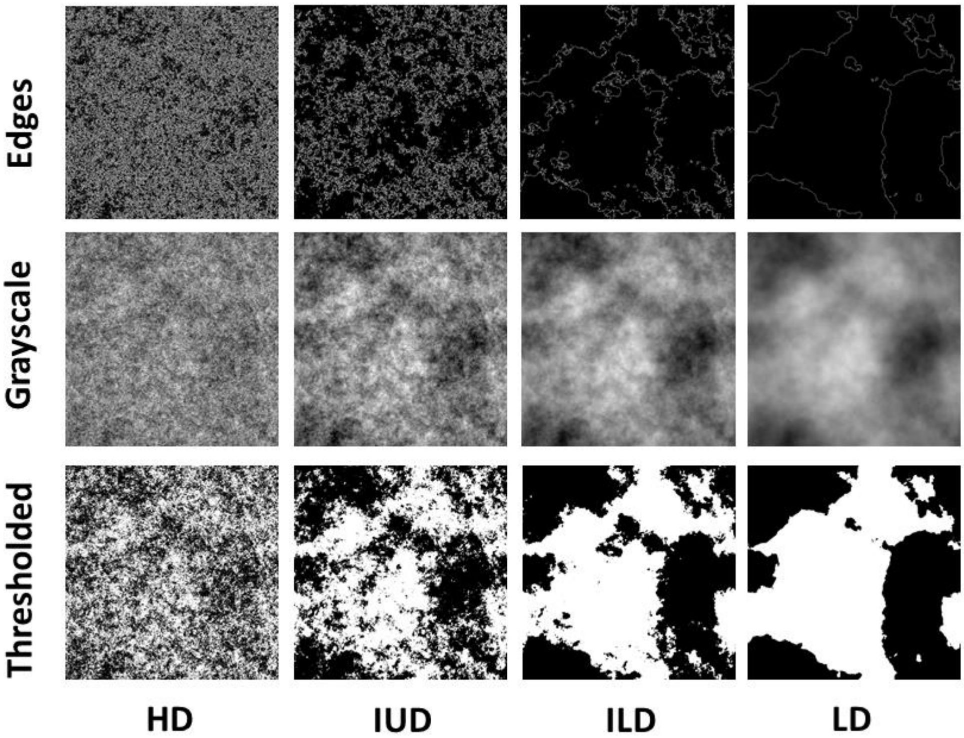

Figure 6.1: Example of selected abstract images which were parametrically varied in their fractal dimension/ D value; and from the right to left: High Dimension (HD) with amplitude spectrum slopes (alpha) of 0.8 and fractal dimensions between 1.75-1.90, Intermediate Upper Dimension (IUD) with amplitude spectrum slopes (alpha) of 1.2 and fractal dimensions between 1.50-1.65, Intermediate Lower Dimension (ILD) with amplitude spectrum slopes (alpha) of 1.6 and fractal dimensions between 1.25-1.40, and Low Dimension (LD) with amplitude spectrum slopes (alpha) of 2.0 and fractal dimensions between 1.0-1.15. Image types were *Edges*, *Greyscale* and *Thresholded* (from top to bottom).

Note that the stimulus set is quite diverse in both luminance and contrast domain. For each of the input amplitude spectrum slopes of the images, therefore the respective root mean square (RMS) contrast (SD of pixel intensities), mean luminance (cd/m^2), measured fractal dimension (D) and amplitude spectrum slope values (α) of the resulting images, as provided by Professor Spehar (Spehar et al., 2016; Viengkham & Spehar, 2018), are detailed in Table 6.1.

Table 6.1: Measured image properties (with courtesy of Professor Branka Spehar, University of New South Wales, Sydney, Australia).

		RMS Contrast		Luminance		FD		ASS	
		M	SD	M	SD	M	SD	M	SD
Edges									
	HD	118.9	0.66	81.51	1.69	2.06	0.01	-0.41	0.02
	IUD	81.24	4.93	29.42	3.98	1.73	0.04	-0.63	0.03
	ILD	36.34	5.68	5.42	1.66	1.33	0.06	-0.6	0.04
	LD	18.12	2.35	1.31	0.35	1.07	0.03	-0.52	0.02
Greyscale									
	HD	38.20	0.00	127.50	0.00	1.94	0.01	-0.79	0.01
	IUD	38.20	0.00	127.50	0.01	1.62	0.04	-1.17	0.03
	ILD	38.20	0.01	127.50	0.00	1.22	0.06	-1.6	0.08
	LD	38.20	0.00	127.50	0.00	0.93	0.03	-2.04	0.16
Thresholded									
	HD	127.50	0	127.57	0.25	1.94	0.01	-0.69	0.01
	IUD	127.03	0.07	128.78	4.76	1.62	0.04	-1.03	0.04
	ILD	127.40	0.34	130.89	11.09	1.22	0.06	-1.31	0.13
	LD	126.70	0.66	131.15	14.02	0.93	0.03	-1.49	0.10

Note. SD was calculated of all pixels, RMS Contrast = Root mean square contrast (SD of the pixel intensities), FD = Fractal Dimension (D), ASS = Amplitude Spectrum Slope (α), Luminance (cd/m^2), HD = High D, IUL = Intermediate Upper D, ILD = Intermediate Lower D, LD = Low D.

<u>Procedure:</u> Prior to the actual experiment, all participants were provided with a written explanation of the study, and they were informed about the right to withdrawn. Following this, 3D motion capture markers were attached (see the description of the procedure in Chapter 2.1.1.), before participants were asked to walk down the laboratory whilst performing a secondary task.

The participants' task was to walk repeatedly down the laboratory (15m) in their naturally preferred walking speed and in the straightest possible way towards the images projected onto the back wall, one image per walk. During each trial, one of the 105 images described above was projected in a random order. The image display size was 2m wide x 2m high, corresponding to 7.6° x 7.6° of visual angle at the start line and 38° x 38° of visual angle at the end line of the 3D motion capture space.

After each walk and before returning back to the starting position for the next experimental trial, half of the participants were asked to rate verbally the image just seen for visual discomfort (How uncomfortable is this image to view?) on a 7-point Likert Scale from 1 = 'extremely comfortable to view' to 7 = 'extremely uncomfortable to view' (visual discomfort rating group); the other half of the participants rated images verbally for likeability (How much do you like the image?) on a 7-point Likert Scale from 1 = 'not at all' to 7 = 'very much' (likeability rating group). Participants' responses were recorded by the experimenter.

There were two breaks during the session (after trials 35 and 70), and participants had been made aware that they could ask for additional breaks if required. The task took approximately 60 minutes to complete. After completing the study, participants were debriefed.

<u>Exclusion criteria:</u> One participant's data were excluded from the analysis due to a loss of sensor data during testing. This left 19 (2 male, 17 female) participants' datasets for analysis for the likeability group, aged 18 – 24 years (M = 19, SD = 1.53). Across the two task conditions, there were thus a total of 39 participants' datasets included in the analysis (7 male, 32 female), aged between 18 - 33 years (M = 19, SD = 3.06).

6.3. Results

Fractal Dimension and Gait Parameters

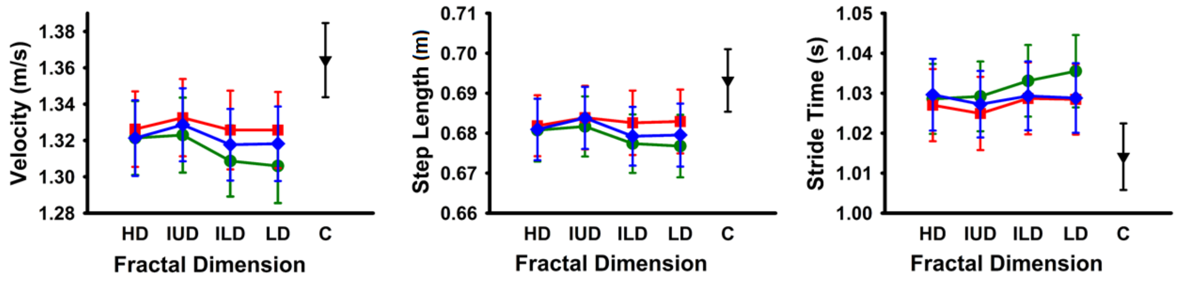

Figure 6.2: Group averages (n=39) of a) individual mean velocity (m/s), b) individual mean step length (in meters) and c) individual mean stride time (in seconds) across fractal dimensions: HD (High D: 1.75-1.90), IUD (Intermediate Upper D: 1.50-1.65), ILD (Intermediate Lower D: 1.25-1.40), and LD (Low D: 1.0-1.15) for the three image types (*Edges* – green circles; *Greyscale* – red squares, *Thresholded* – blue rhombi). Error bars reflect ± 1 SEM. Group averages for the respective control conditions are shown for comparison as black triangles.

Repeated measures MANOVAs, 2 (cognitive rating task) x 4 (fractal dimension) x 3 (image type), were conducted on the following gait measures: mean velocity, mean step length, and mean stride time. Note that this analysis did not include the control condition (see Figure 6.2. for group averages of three gait measures: velocity, step length and stride time across four fractal dimensions: HD, IUD, ILD and LD for three image types: *Edges, Greyscale, Thresholded*).

<u>Velocity:</u> There was a statistically significant main effect of fractal dimension on velocity determined by MANOVA with Greenhouse-Geisser correction, $F(2.374, 1.483) = 8.012$, $p < 0.001$, partial $\eta^2 = 0.178$ (see Figure 6.2. left panel). *Post-hoc* pairwise comparisons using Bonferroni corrections revealed that the IUD condition had a significantly faster walking speed than both ILD ($p < 0.05$) and LD conditions ($p < 0.001$). There was no significant difference between HD and IUD conditions, nor between HD and ILD or LD conditions ($p > 0.05$).

<u>Step Length:</u> There was a statistically significant main effect of fractal dimension on step length, $F (3, 111) = 7.813$, $p < 0.001$, partial $\eta 2 = 0.174$, $p < 0.05$ (see Figure 6.2. middle panel). *Post-hoc* pairwise comparisons using Bonferroni correction revealed that the IUD condition had a significantly longer step length ($p < 0.05$) than any of the other conditions.

Stride Time**:** As for velocity and step length, there was also a statistically significant main effect of fractal dimension on stride time determined by MANOVA with Greenhouse-Geisser correction, $F(2.274, 57.211)$, $p < 0.001$, partial $\eta^2 = 0.121$ (see Figure 6.2. right panel). *Post-hoc* pairwise comparisons using Bonferroni correction revealed that the IUD condition led to significantly shorter stride times than the LD condition ($p < 0.05$); but there were no significant differences between any other comparisons ($p > 0.05$).

Image Type and Gait Parameters

There was a statistically significant main effect of image type on velocity determined by MANOVA with Greenhouse-Geisser correction, $F(1.483, 54.861) = 8.500$, $p < 0.05$, partial $\eta^2 = 0.187$. *Post-hoc* pairwise comparisons using Bonferroni correction revealed that participants walked significantly slower when presented with *Edges* images than with either *Greyscale* ($p < 0.05$) or *Thresholded* ($p < 0.05$) images.

Further, there was a statistically significant main effect of image type on step length, $F(2, 74) = 8.892$, $p < 0.05$, partial $\eta^2 = 0.194$. *Post-hoc* pairwise comparisons using Bonferroni correction revealed that participants walked with significantly shorter steps towards *Edges* images as compared to both *Greyscale* ($p < 0.05$) or *Thresholded* ($p < 0.05$) images.

There was a statistically significant main effect of image on stride time determined by MANOVA with Greenhouse-Geisser correction, $F(1.546, 57.211) = 5.511$, $p < 0.05$, partial $\eta^2 = 0.130$. *Post-hoc* pairwise comparisons using Bonferroni correction revealed that participants had significantly longer stride times during exposure to *Edges* images as compared to exposure to both *Greyscale* ($p < 0.05$) and *Thresholded* images ($p < 0.05$).

Cognitive Task and Gait Parameters

Cognitive task (visual discomfort rating task vs. liking rating task) did not differentially affect any of the gait measures, nor were there any significant interactions between task and fractal dimensions, task and image type, or fractal dimensions and image type for any of the gait measures.

Fractal Dimensions and Ratings

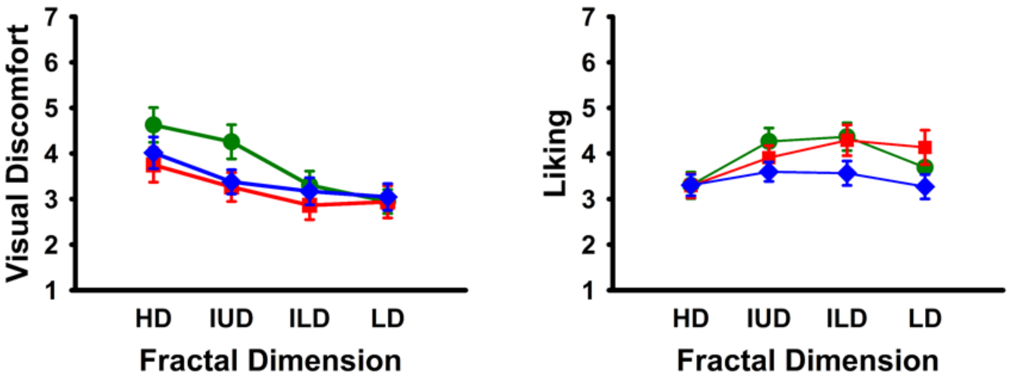

Figure 6.3: Group averages of a) visual discomfort (n=20; left panel) and b) liking (n=19; right panel) across fractal dimensions: HD (High D: 1.75-1.90), IUD (Intermediate Upper D: 1.50-1.65), ILD (Intermediate Lower D: 1.25-1.40), and LD (Low D: 1.0-1.15)] for three image types (*Edges* – green circles, *Greyscale* – red squares, *Thresholded* – blue rhombi). Error bars reflect ± 1 SEM.

Visual Discomfort: As can be seen in Figure 6.3 (left panel), visual discomfort decreased with a decrease in fractal dimensions and was particularly high for the HD and IUD images of the *Edges* type. This is reflected in the outcomes of a repeated measures ANOVA with Greenhouse-Geisser correction on visual discomfort ratings (n=20) as dependent measure, and fractal dimension [HD, IUD, ILD, LD] and image type as independent factors (E for *Edges*, G for *Greyscale*, T for *Thresholded*).

There was a statistically significant main effect of fractal dimension on visual discomfort, $F(1.265, 24.027) = 16.018$, partial $\eta^2 = 0.427$, $p < 0.001$. *Post-hoc* pairwise comparisons using Bonferroni correction revealed that the HD condition had a significantly higher visual discomfort score than IUD, ILD and LD conditions ($p < 0.05$). Moreover, IUD had a significantly higher visual discomfort score than ILD and LD conditions ($p < 0.05$). There was no significant difference between ILD and LD conditions ($p > 0.05$).

Liking: Liking ratings seemed to follow an inverted U-shape for different fractal dimensions as can be seen in Figure 6.3. (right panel). This was confirmed by a repeated measures ANOVA with Greenhouse-Geisser correction on liking scores (n=19) as the dependent measure, and fractal dimension [HD, IUD, ILD, LD] and image type (E, G, T) as independent measures. There was a statistically significant main effect of fractal dimension on liking, $F(1.483, 26.876) = 1.472$, partial $\eta^2 = 0.252$, $p < 0.05$. *Post-hoc* pairwise comparisons using Bonferroni correction revealed that the HD condition had a significantly lower liking score than IUD ($p < 0.05$) and ILD ($p < 0.05$) conditions. Also, the ILD condition had a significantly higher liking score than the LD condition ($p < 0.05$). None of the other comparisons were significant.

Image Type and Ratings

Whilst image type *per se* did not impact visual discomfort ratings ($p > 0.05$), there was a statistically significant interaction between fractal dimension and image type on visual discomfort, $F(3.551, 67.474) = 5.076$, partial $\eta^2 = 0.211$, $p < 0.05$). *Post-hoc* pairwise comparisons using Bonferroni correction revealed that the HD-E condition led to significantly higher visual discomfort scores than the corresponding HD-G and HD-T conditions ($p < 0.05$). Similarly, the IUD-E condition had a significantly higher visual discomfort score than the IUD-T condition. Visual discomfort ratings for ILD and LD conditions, in contrast, did not differ between image types.

Image type did not affect liking scores but, as for visual discomfort, there was a statistically significant interaction between fractal dimension and image type. *Post-hoc* pairwise comparisons using Bonferroni correction revealed, however, that none of the meaningful comparisons reached significance.

Multi-Level Modelling (Fractal dimensions, Image type, Task, Ratings and Gait Parameters)

Multi-level modelling was applied to cross-classified data from both cognitive tasks (n=39) to determine the impact of fractal dimensions, image type, and task on gait velocity (m/s). Note that this analysis was restricted to velocity for comparison with studies 1 (Chapter 3), 3 (Chapter 4), and 4 (Chapter 5) in which velocity had been the most sensitive of the three gait measures. Data for control images were excluded from this analysis due to missing data for fractal and image type content. Velocity data were transformed into Z-scores. See the detailed description of the method in Chapter 2.2.

Table 6.2. shows the results for all models fitted.

Table 6.2: Model fit comparisons for models with standardised velocity as a dependent variable.

Model	DIC	Fixed	Random
1	4242.919		PT, IM, T
2	4237.634	FD, IT, T	PT, IM, T
2a	4237.487	FD, IT	PT, IM, T
3	4239.068	FD, IT, FD*IT, FD*T, IT*T	PT, IM, T
3a	4242.919	Model 1	PT, IM, T

Random effects: PT = Participant, IM = Image, T = Trial. Fixed effects: FD = Fractal Dimension, IT = Image type, T = Task.

Model 2a was the best fitting model, with fractal dimension (X^2_1 = 7.022) and image type (X^2_1 = 2.231) both being significant predictors ($p < 0.05$) for velocity, in line with the results of the earlier MANOVA. Parameter estimates for the model are displayed in Table 6.3.

Table 6.3: Fixed effects estimates (top) and random effect variance estimates (bottom) for the model with the best fit (Model 2a; Table 6.2.).

			95% CI		
Parameter	Estimate	Std. Error	Lower	Upper	X_1^2
Fixed					
Intercept	0.035	0.191	-0.334	0.391	0.879
Fractal Dimension	-0.020	0.008	-0.035	-0.005	7.022*
Image Type	0.023	0.01	0.003	0.044	2.231*
Random					
Participant	0.900	0.217	0.569	1.413	
Image	0.002	0.001	0.001	0.004	
Trial	0.180	0.004	0.172	0.189	
Deviance Information Criterion (DIC)					4237.487

Note. Estimates reflect the size of the effect on standardised velocity. Burn-in = 500, Chain Length = 10,000. Degrees of freedom is 1 for all Chi-square (X_1^2) statistics. *p < 0.05.

Multilevel modelling (Visual Discomfort rating group only)

To investigate the potential impact of subjective visual discomfort on walking speed, a second multilevel modelling analysis was performed, focusing on cross-classified velocity data of the visual discomfort rating group only (n=20). Again, control images were excluded from this analysis due to missing data for fractal and image type content. Both velocity and rating data were transformed into Z-scores. See the detailed description of the method in Chapter 2.2.

Table 6.4. shows the results for all models fitted.

Table 6.4: Model fit comparisons for models with standardised velocity as a dependent variable; visual discomfort group (n=1887).

Model	DIC	Fixed	Random
1	2732.676		PT, IM, T
2	2705.245	FD, IT, VD	PT, IM, T
2a	2706.540	FD, VD	PT, IM, T
3	2703.640	FD, VD, FR*VD, FR*IT, VD*IT	PT, IM, T
3a	2703.025	FD, FD*VD	PT, IM, T

Random effects: PT = Participant, IM = Image, T = Trial. Fixed effects: FD = Fractal Dimension, IT = Image type, VD = Visual Discomfort.

The results of this analysis revealed that model 3a was the best fitting model: both, fractal dimension (X_1^2 = 6.853) and its interaction with subjective visual discomfort (X_1^2 = 32.388) were significant predictors, $p < 0.05$. Note that, in contrast to the MANOVA, the interaction between image type and fractal dimension was not a significant predictor for walking speed; also, please note that Visual Discomfort on its own did not predict walking speed.

Parameter estimates for the model are displayed in Table 6.5.

Table 6.5: Fixed effects estimates (top) and random effect variance estimates (bottom) for the model with best fit (Model 3a; Table 6.4.).

			95% CI		
Parameter	Estimate	Std. Error	Lower	Upper	X_1^2
Fixed					
Intercept	0.058	0.243	-0.427	0.539	
Fractal Dimension	-0.032	0.012	-0.056	-0.008	6.853*
FD * VD	-0.031	0.005	-0.041	-0.020	32.388**
Random					
Participant	0.883	0.331	0.455	1.706	
Image	0.004	0.002	0.001	0.009	
Trial	0.239	0.008	0.224	0.256	
Deviance Information Criterion (DIC)					2703.025

Note. Estimates reflect the size of the effect on standardised velocity. Burn-in = 500, Chain Length = 10,000. Degrees of freedom is 1 for all Chi-square (X_1^2) statistics. **$p < 0.001$, *$p < 0.05$.

Multilevel modelling (Liking rating group only)

To investigate the potential impact of subjective liking on walking speed, a further multilevel-modelling analysis was performed on the cross-classified and Z-scored velocity data of the likeability rating group only (n=19), with also Z-scoring. Note that the data from the likeability rating task suggested a nonlinear relationship between fractal dimensions and liking (see Figure 6.3.); therefore, liking-squared was included as an additional predictor variable. Control images were again excluded due to a lack of rating data. See the detailed description of the method in Chapter 2.2.

Table 6.6. shows the results for all models fitted.

Table 6.6: Model fit comparisons for models with standardised velocity as a dependent variable; likeability group (n=1816).

Model	DIC	Fixed	Random
1	1644.237		PT, IM, T
2	1643.738	FD, IT, LIK, LIK^2	PT, IM, T
2a	1639.064	FD	PT, IM, T
3	1642.242	FD, FD*IT, FD*LIK, FD*LIK^2, IT*LIK, IT^LIK^2	PT, IM, T
3a	1640.101	FD,FD*IT,IT*LIK^2	PT, IM, T

Random effects: PT = Participant, IM = Image, T=Trial. Fixed effects: FD = Fractal Dimension, IT = Image type, LIK = Liking.

The results of this analysis revealed that model 2a was the best fitting model with fractal dimension as the only significant predictor (X_1^2 = 8.366, p < 0.05) for walking speed. Please note that this differs from findings for visual discomfort ratings.

Parameter estimates for the model are displayed in Table 6.7.

Table 6.7: Fixed effects estimates (top) and random effect variance estimates (bottom) for the model with best fit (Model 2a; Table 6.6.).

			95% CI		
Parameter	Estimate	Std. Error	Lower	Upper	X_1^2
Fixed					
Intercept	-0.015	0.164	-0.358	0.276	0.008
Fractal Dimension	-0.026	0.009	-0.044	-0.008	8.366*
Random					
Participant	0.997	0.369	0.516	1.913	
Image	0.002	0.001	0.001	0.005	
Trial	0.141	0.005	0.132	0.151	
Deviance Information Criterion (DIC)					1639.064

Note. Estimates reflect the size of the effect on standardised velocity. Burn-in = 500, Chain Length = 10,000. Degrees of freedom is 1 for all Chi-square (X_1^2) statistics. *p < 0.05.

6.4. Discussion

The present study provides support for the hypothesis that the fractal dimension of an image affects a person's gait kinematics which were used here as a proxy measure of cognitive load (see Amboni et al., 2013): walking speed and step length increased whilst stride time decreased with increasing fractal dimensions from a fractal scaling range of 1.0 to 1.65. Thus, walking towards images with fractal properties outside the range typically found in nature scenes, corresponding to a range of fractal dimensions (D) between 1.50-1.65 seemed more cognitively demanding than walking towards images with fractal dimensions within this range (i.e. dimensions with an alpha mean of 1.2; (Tolhurst et al., 1992)).

Interestingly, the data also indicate that not only fractal dimensions but also image type impacts cognitive load: walking towards *Edges* images resulted in a decrease in participants' walking velocity, and smaller step length as compared to walking towards *Thresholded* and *Greyscale* images, suggesting that *Edges* stimuli were more cognitively demanding despite having the same fractal dimensions as their *Thresholded* and *Greyscale* counterparts. It is important to note, however, that the interpretation of data for *Edges* stimuli is complicated by the fact that, unlike with the *Greyscale* and *Thresholded* stimuli, their mean luminance does not remain constant across fractal dimensions. As can be seen in Table 6.1, both the mean luminance and the standard deviation of luminance values are much higher for HD and IUD images than for ILD and LD images, making the latter abstract patterns potentially harder to visually discern and rate for liking and/or visual discomfort. These decreases in walking speed, related to different image properties, are observed on top of participants' general task-related slowing as compared to the speed of natural self-paced walking without exposure to images and related rating task (i.e. control condition), a slowing effect in line with the gait literature on dual tasking (see for a review Amboni et al., 2013).

Together, these findings thus seem to support Joye and colleagues' Perceptual Fluency Account (PFA; Joye & De Block, 2011; Joye et al., 2016; Joye & Van den Berg, 2011) of nature scenes being less cognitively demanding than urban scenes due to their low-level visual features; in particular, as tested here, their fractal content.

Before drawing any firm conclusions, however, there are some caveats to consider.

Firstly, it needs to be ascertained that instead of fractal content, changes in rating difficulty across the different fractal and stimulus conditions could not explain the observed gait changes. Such an interpretation is unlikely as gait kinematics did not differ between likeability rating and visual discomfort rating groups. Moreover, the likeability group revealed the same kind of gait changes for changes in fractal dimension as the visual discomfort group although liking itself was an insignificant predictor of walking speed, nor was there an interaction between likeability scores and fractal dimension. Thus, neither aesthetics nor its interaction with low level image statistics seemed to contribute to environmentally-induced cognitive load. Whilst dual tasking thus generally affects gait kinematics for all conditions compared to self-paced natural walking speed without cognitive task or without image content (see differences between coloured and black symbols in Figure 6.2.), neither the observed change in gait kinematics for different fractal dimensions nor the interaction between fractal dimensions and visual discomfort ratings can be explained by changes in task difficulty.

The second caveat concerns the observation that participants' gait seemed most affected / slowed by *Edges* stimuli, in particular when walking toward images with low fractal dimensions. Rather than an effect of stimulus type-related increase in perceptual processing load, this slowing could be simply due to a drop in overall luminance levels (e.g. Kesler et al., 2005) at the far end of the laboratory for these particular stimuli. Indeed, participants walked in a laboratory with dimmed lighting where the predominate source of illumination stemmed from the stimulus projected to the end wall. Low dimension fractal *Edges* images were generally darker than any other image type due to the high amount of black, which could thus have affected gait speed. Therefore, in the next study in which participants will be asked to rate the same images for liking and discomfort, stimulus set should include images with high-contrast black and white vertical square-wave gratings of different spatial frequencies as control stimuli instead of plain grey stimuli.

The finding of an interaction between fractal content and visual discomfort ratings predicting changes in gait speed for multi-level analysis of data for the visual discomfort group only (n = 20) seems at first glance to be in line with previous findings for real images (Experiment 1, see Chapter 3.2.): the higher the subjective visual discomfort of an environment, the slower a person walks toward it. A closer look at this interaction, however, speaks against such an interpretation: participants rated not only images with high fractal dimensions as the most uncomfortable ones, in line with predictions, but also images with intermediate upper fractal dimensions thought to fall right into the range of fractal dimensions typical for nature scenes. This rating behaviour contrasts with participants' gait kinematics, where participants walked the fastest toward intermediate upper fractal dimensions as one would predict for reduced perceptual load for image statistics within the range of fractal dimensions typical for nature. What might have induced this discrepancy between visual discomfort ratings and gait kinematics will have to be answered in future experiments.

Against expectations, participants rated images with intermediate upper fractal dimensions typical for nature scenes as more uncomfortable to look at than images with low and intermediate lower fractal dimensions. Aesthetics did not explain this effect as neither fractal dimensions nor interaction between fractal dimensions and image type affected liking scores. It is more likely that the interaction between fractal dimensions and image type played a role in this effect. *Edges* images with high fractal dimensions had higher subjective visual discomfort ratings than *Greyscale* and *Thresholded* images. Similarly, *Edges* images with high fractal dimensions had higher subjective visual discomfort ratings than *Thresholded* images for intermediate upper condition. However, it needs to be kept in mind that visual discomfort and liking ratings were collected from two different groups of participants, making it difficult to directly compare the results. Therefore, I decided to further explore the relationship between visual discomfort and liking ratings in the next experiments (See Chapter 7).

In conclusion, the hypothesis that walking towards images with fractal properties outside the range typically found in nature scenes (D = 1.50-1.65) is more cognitively demanding, has been largely confirmed, supporting Joye's Perceptual Fluency Account (Joye & De Block, 2011; Joye et al., 2016; Joye & Van den Berg, 2011). However, these data also provide evidence for a more complex interaction between low-level image statistics such as fractal dimensions and visual discomfort ratings that contributes to environmentally-induced cognitive load. It is tempting to speculate what might underlie this latter interaction. If one accepts that visual discomfort is an indicator of physiological stress (Wilkins et al., 1984), then that would align with Ulrich's Stress Recovery Theory (Ulrich, 1984), namely that physiological stress contributes to environmentally-induced cognitive load measurable as changes in gait kinematics. Moreover, it seems crucial to further investigate the exact relationship between visual discomfort and liking. Few researchers have addressed the question of the relationship between aesthetics and visual discomfort (Fernandez & Wilkins, 2008; Juricevic et al., 2010), and there is no general agreement on whether these two factors are associated with each other (Fernandez & Wilkins, 2008) or not (Juricevic et al., 2010). Therefore, the relationship between subjective aesthetics and subjective visual discomfort within the same people will be explored in more detail in Chapter 7.

Chapter 7. The relationship between liking and visual discomfort

7.1. Introduction

Throughout the walking experiments included in this thesis, participants had been asked to rate images either for their liking (Experiments 2 and 6, Chapters 4 and 6, respectively) or for their visual discomfort (Experiments 1, 4 and 6, Chapters 3, 5, and 6, respectively). Yet, the exact relationship between the two subjective measures is still comparably little understood (e.g. Juricevic et al., 2010).

The aim of the three studies presented in this Chapter was therefore to further explore the relationship between visual discomfort and liking ratings for image sets used in the previous studies. This included the synthetic images parametrically varied in their image statistics such as their fractal dimensions (Experiment 6, see Chapter 6) or their amount of "greenery" (Experiment 3, see Chapter 4), as well as images of real scenes (nature and urban environments used in the pilot study of Experiment 4, see Chapter 5).

The need to further our understanding of the relationship between visual discomfort and liking arose from findings that either subjective visual discomfort (Experiments 1 and 4) or its interaction with fractal content predicted walking speed (Experiment 6), whilst neither liking on its own (Experiments 4, 6) nor the interaction between liking and fractal content affected gait (Experiment 6), even though visual discomfort and liking scores seemed to be negatively correlated. Moreover, in Experiment 4 (see Chapter 5), although environment type did not affect gait kinematics when participants were presented with images of nature and urban scenes matched for population-defined liking scores, visual discomfort ratings but not pre-defined liking scores, were predictive of velocity changes.

These observations suggest that even though liking seems not strong enough to affect gait on its own, it interacts with visual discomfort, impacting gait indirectly.

Indeed, from a conceptual perspective, visual discomfort and aesthetic merit of a scene have been considered as related processes (Fernandez & Wilkins, 2008). For example, images closer to natural image properties have been perceived as less uncomfortable and more aesthetically pleasing (Fernandez & Wilkins, 2008), suggesting they are inversely related (similar to our findings so far); yet, visual discomfort scores for images generated from noise or rectangles varying in 1/f amplitude spectra for contrast and luminance did not correlate with aesthetic appeal ratings (Juricevic et al., 2010).

As in none of the walking experiments, liking and visual discomfort ratings had been collected from the same participants, the intrapersonal relationship between the two measures in our studies remains unclear. Here, in three exclusively behavioural experiments, the same groups of participants were therefore asked to rate the same images for both liking and visual discomfort.

7.2. Experiment 7: The impact of fractal content on liking and visual discomfort

The aim of this study was to establish the relationship between visual discomfort and liking ratings for images parametrically varied in their fractal content. Images were the same as the ones used in Experiment 6 (see Chapter 6).

7.2.1. Methods

Participants: On the basis of effect sample sizes observed in Experiment 6 (Chapter 6), twenty-two participants (2 males, 19 females, 1 prefer not to say), aged between 18 and 23 years with a mean age of 19.5 years ± 1.14 SD, took part in this study at the University of Bristol. All participants reported normal or corrected-to-normal visual acuity and normal colour vision. One participant reported suffering from migraines without aura.

Participants took part in the experiment for course credit and provided informed written consent. The experiment was approved by the Faculty of Life Sciences' Ethics Committee at the University of Bristol (ref. 040220100122).

Stimuli: The stimulus set contained 103 images. These were the 96 synthetic images parametrically varied in their fractal dimension (D) value as described in more detail in the study in Chapter 6 (See Experiment 6), and 7 images (control conditions) presenting high-contrast black and white vertical square-wave gratings of different spatial frequencies (0.30, 0.59, 1.18, 2.36, 4.72, 9.45, 18.90 cycles per degree (cpd) of visual angle). All images subtended an area of 21° x 21° of visual angle. The screen background was a medium luminance grey and subtended an area of 51° x 29° of visual angle. Image resolution was 800 x 800 pixels.

Procedure: On arrival at the laboratory, participants were given information about the study. They were asked to sit in front of the computer (21" monitor) with a distance of 57cm. The room had dimmed lighting, and participants had time to light adapt. The experiment was divided into two blocks: one block for visual discomfort judgements, and one block for liking judgements, in which participants were asked to rate one image after the other, using visual analogue scales. Each block used the same 103 images, presented in random order. The order of the two blocks was counterbalanced across participants. Individual trials started with the presentation of a central fixation cross for 1 second. This was then followed by the presentation of one of the 103 images centred on the screen. Images remained on the screen until participants had rated the image for the respective task of the experimental block they were in. In the visual discomfort rating task, participants rated the image for visual discomfort ('How uncomfortable is the image to view?' on a visual analogue scale from 'Not at all' (pixel 0) to 'Very much' (pixel 1800) with neutral at the centre of the line. In the liking rating task, participants were asked to rate the image for liking (How much do you like the image?") on a visual analogue scale from "Not at all" (pixel 0) to "Very much" (pixel 1800), again with neutral (pixel 900) at the centre of the line. Visual analogue scales were presented below the actual images, and participants used the mouse with their right hand to place a marker on the scale and clicking the left mouse button when they were happy with the position of the marker.

Between the two experimental blocks, there was a break of about 10 minutes during which participants had time to take some refreshments in addition to filling in a form requesting some demographic details, including participants' age, gender, and medical conditions that could have affected their vision. In addition, participants were presented with a 5-minutes YouTube video about the history of the camera to distract them from the actual study. Then, they performed the second block of the experiment. The study took approximately 30 minutes to complete, including the break. In addition to rating scores, reaction times were recorded.

7.2.2. Results and Discussion

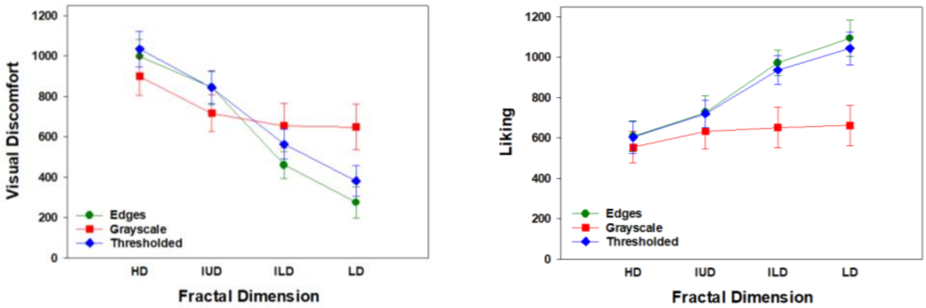

Figure 7.1: Group averages for visual discomfort (left) and liking (right) outcomes across fractal dimensions: High Dimension (HD, 1.75-1.90), Intermediate Upper Dimension (IUD, 1.50-1.65), Intermediate Lower Dimension (ILD, 1.25-1.40), and Low Dimension (LD, 1.0-1.15) for three image types (*Edges* – green circles, *Greyscale* – red squares, *Thresholded* – blue rhombi). Error bars reflect ± 1 SEM.

Figure 7.1. shows (a) participants' visual discomfort ratings and (b) their liking scores for different fractal dimensions for three different stimulus types (*Edges, Greyscale* and *Thresholded*). Visual discomfort decreased with decreasing fractal dimensions, similarly to the outcomes seen in Experiment 6. Liking scores increased with decreasing fractal dimensions while liking scores in Experiment 6 seemed to follow an inverted U-shape for different fractal dimensions. Moreover, the relationship between fractal dimension and the respective rating was far less pronounced for *Greyscale* images than for their *Thresholded* and *Edges* image counterparts, in contrast to the results of Experiment 6 in which this effect has not occurred.

A repeated measures ANOVA on rating scores with Greenhouse-Geisser correction, with task [visual discomfort, liking], image type [*Edges, Greyscale, Thresholded*] and fractal dimensions [High D (fractal dimension: 1.75-1.90), Intermediate Upper D (fractal dimension: 1.50-1.65), Intermediate Lower D (fractal dimension: 1.25-1.40), and Low D (fractal dimension: 1.0-1.15)] as within-subject-factors revealed a significant two-way interaction between fractal dimension and task, $F(1.185, 24.880) = 2.543$, $p < 0.05$, partial $\eta^2 = 0.539$, and a significant three-way interaction between fractal dimension, image type and task, $F(3.331,69.965) = 19.294$, $p < 0.05$, partial $\eta^2 = 0.479$ (see Figure 7.2.). For visual discomfort ratings of LD, there was a significant difference between *Greyscale* and both *Edges* and *Thresholded* images. For liking scores of LD and ILD, there was a significant difference between *Greyscale* and both *Edges* and *Thresholded* images.

None of the main effects or other interactions were significant ($p > 0.05$).

A Pearson's correlation of group rating averages for individual images irrespective of image type revealed that there was a negative correlation between liking and visual discomfort ($r = -0.848$, $p < 0.05$). Pearson's correlations for individual image types are plotted in Figure 7.2.

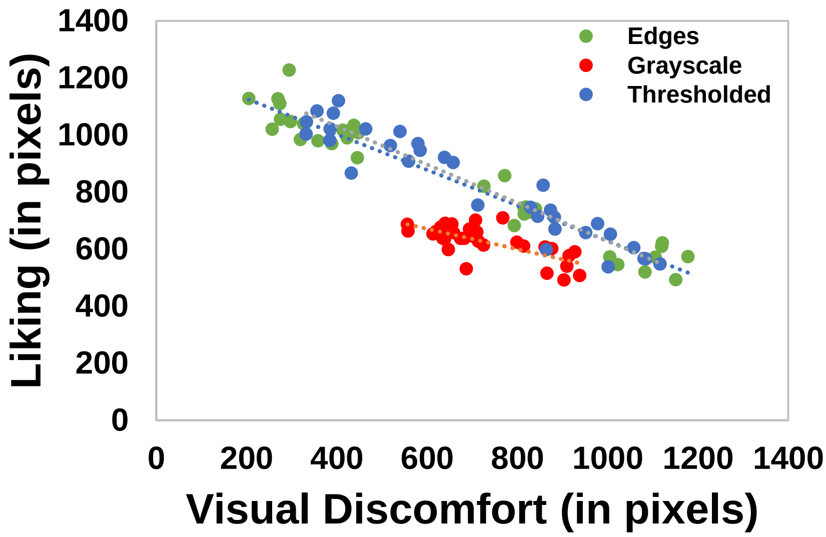

Figure 7.2: Correlation between visual discomfort and liking scores per image averaged across participants, for three image types: *Edges* – green circles; (r = - 0.97, p < 0.05), *Greyscale* – red circles (r = - 0.71, p < 0.05), *Thresholded* – blue circles (r = - 0.95, p < 0.05).

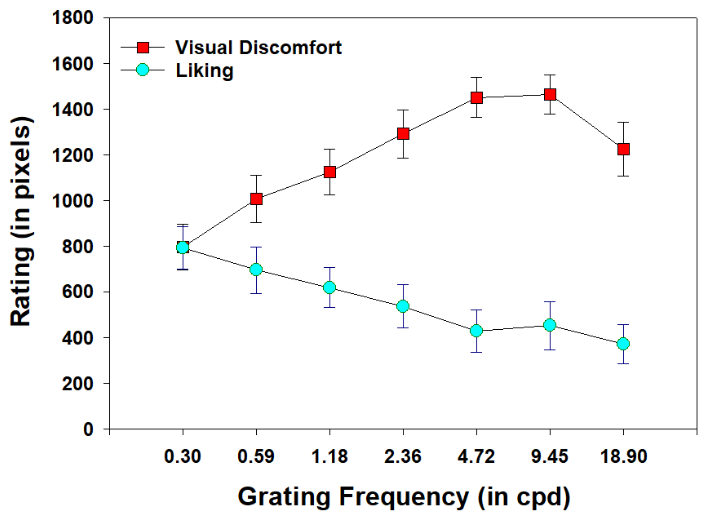

Figure 7.3: Group averages of visual discomfort (red squares) and liking scores (cyan circles) for the control patterns with high-contrast spatial frequency patterns differing in stripe width: 0.30, 0.59, 1.18, 2.36, 4.72, 9.45, 18.90 cycles per degree (cpd) of visual angle. Error bars reflect ± 1 SEM.

In line with expectations from the literature for high-contrast spatial frequency square-wave gratings (Wilkins et al., 1984), visual discomfort ratings for the control images followed an inverted u-shape (see Figure 7.3., dark yellow square symbols). In contrast to Wilkins et al. (1984) who described spatial frequencies between 2–8 cpd induced visual discomfort, discomfort ratings were slightly shifted toward higher spatial frequencies, peaking somewhere between 4.72-9.45 cpd. Moreover and also in line with expectations (Ogawa & Motoyoshi, 2020), liking ratings decreased approximately linearly with increased spatial frequencies (see Figure 7.3. dark blue circular symbols). Grating data, therefore, show a similar negative relationship between visual discomfort and liking ratings for most (but not all) of the spatial frequency range tested, similar to observations for fractal images (see Figure 7.1.).

The results of this experiment indicate that not only do fractal dimensions impact ratings, but also image type: whilst there was a linear relationship between fractal dimensions and the respective ratings for *Edges* and *Thresholded* images, this did not hold for *Greyscale* images. Spehar et al. (2016) found that *Edges* and *Thresholded* images have shallower 1/f amplitude slopes, in particular for higher amplitudes (Spehar et al., 2016) (see also image characteristics provided by Spehar in Table 6.1.). Thus, differences in 1/f amplitude slope between the three image types could be underlying these results.

This study demonstrated that when tested in the same participant, there is a clear negative correlation between liking and visual discomfort ratings for the range of fractal stimuli used, but not for the entire range of spatial frequency gratings participants had seen. These findings therefore raise the question of whether the negative linear relationship between visual discomfort and liking is related to particular types of stimuli (i.e. their fractal content) or can be generalised to other stimuli. This will be investigated in the next two studies.

Due to the COVID-19 pandemic, both of the following studies were performed online; thus requiring a slightly different setup than used so far.

7.3. Experiment 8: The impact of the amount of “greenery” in a visual scene on liking and visual discomfort

The aim of this study was to establish the relationship between visual discomfort and liking ratings for images parametrically varied in their amount of “greenery”. The same stimuli were used as those in Experiment 3 provided by Lewis D. Griffin (see Chapter 4).

7.3.1. Methods

Participants: On the basis of effect sample size observed in Experiment 7 (Chapter 7), I would have needed to recruit twenty-two participants; however, accounting for possible drop-outs, exclusions and higher noise due to lack of control over participants’ online study settings, I doubled the number of participants. Fifty participants took part in this online study with a mean age of 27 years ± 9.35 SD (17 – 64 years), 17 females (mean age = 27, ± 12.33 SD, 18 – 64 years) and 33 males (mean age = 26, ± 7.12 SD, 17 – 45). All participants reported normal or corrected-to-normal visual acuity and provided informed consent for participation at the beginning of the study. Participants were recruited via the ‘Prolific’ platform and reimbursed for their time. The experiment was approved by the Faculty of Life Sciences’ Ethics Committee at the University of Bristol (ref. 040220100122).

Stimuli: The stimuli for the study were 100 abstract images, parametrically varied for the percentage of “chlorophyll” or “greenery” they contained (0%, 25%, 50%, 75%, 100%; 20 images per condition). The stimuli are described in more detail in Chapter 4.1.2. (Experiment 3). Image resolution was 1280 x 800.

Procedure: This was an online study set up on the ‘Gorilla’ platform. Prior to performing the task, participants were asked to fill in a form with demographics questions (e.g. age, gender, eye sight) and made aware that the task needed to be performed on a computer or a laptop; not a phone or tablet. Participants were asked to look at images on their computer screen. Only one image was presented per trial, and image presentation order was randomised. The experiment was again divided into two parts: one for visual discomfort ratings (How uncomfortable is the image to view?), one for liking ratings (How much do you like the image?). In contrast to the former experiment, however, participants rated each image on a 7-point Likert Scale from ‘1 –

Not at all' to '7 – Very much'. Images remained on the screen until the participant had rated the image by clicking the (left) mouse button on the according number of the Likert Scale. The two parts of the study were again counterbalanced between participants. There was one break during the study (between two blocks, after 100 trials), but no film to distract people between tasks.

7.3.2. Results and Discussion

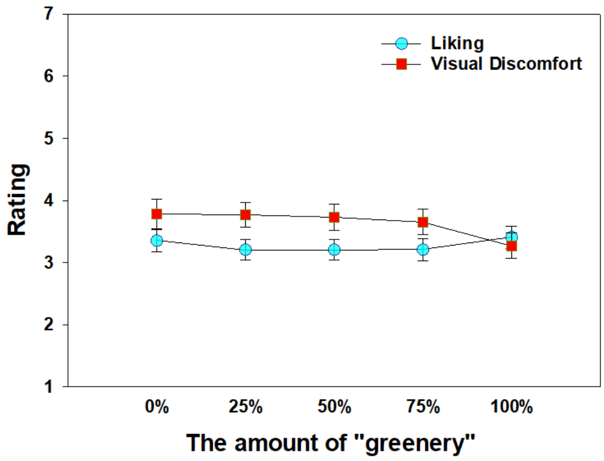

Figure 7.4: Group averages of visual discomfort (red squares), liking (cyan circles) across greenery conditions: 0%, 25%, 50%, 75%, 100%. Error bars reflect ± 1 SEM.

As shown in Figure 7.4., visual discomfort and liking ratings hardly varied between the different greenery conditions, with people rating the images as neither uncomfortable/comfortable nor likeable/dislikeable instead of using the entire Likert Scale. Despite the small variability in image ratings, a repeated measures ANOVA on rating scores with Greenhouse-Geisser correction, with task [visual discomfort, liking], and greenery [0%, 25%, 50%, 75%, 100%] as within-subject-factors, revealed a statistically significant two-way interaction between greenery and rating task, $F(1.646, 80.638) = 3.686$, partial $\eta^2 = 0.070$. *Post-hoc* pairwise comparisons, using LSD correction, revealed that the 100% greenery condition had a significantly lower visual discomfort score than all other (0%, 25%, 50%, and 75%)

greenery conditions. In addition, the 100% greenery condition had a significantly higher liking score than the 75% greenery condition, in contrast to the outcomes of Experiment 4 in which the 100% greenery condition had a significantly lower liking score than any other stimulus type: 0%, 25%, 50% and 75%.

None of the main effects were significant ($p > 0.05$).

A Pearson's correlation irrespective of image type revealed an overall negative correlation between visual discomfort and liking, $r = -0.615$, $p < 0.05$. Individual correlations per image type are shown in Figure 7.5., revealing that the correlations were primarily driven by images with higher greenery content.

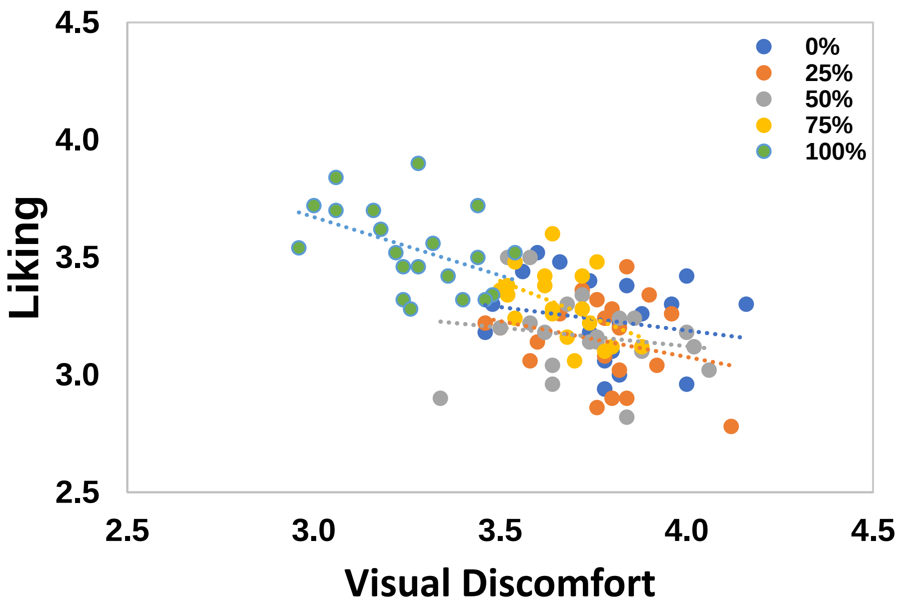

Figure 7.5: Correlations between group average visual discomfort and liking scores per image, for the five different greenery conditions: 0% greenery – blue circles ($r = -0.19$, $p > 0.05$), 25% greenery – orange circles ($r = -0.26$, $p > 0.05$), 50% greenery – grey circles ($r = -0.17$, $p > 0.05$), 75% greenery – yellow circles ($r = -0.48$, $p < 0.05$) 100% greenery – green circles ($r = -0.45$, $p < 0.05$). Note that there was a low variability in ratings between the images with different amounts of "greenery".

The results of the experiment therefore suggest that both the amount of greenery and the task (liking vs. visual discomfort rating task) impact ratings, with visual discomfort and liking being again negatively related, in particular for images with higher content of greenery for which inter-stimulus responses were more variable than for images with lower greenery content.

Interestingly, the findings for liking in this experiment do not correspond to the ones in Experiment 3 (see Chapters 4), in which participants were asked to walk towards the same images and rate them for liking. In the walking condition, images with 100% greenery had consistently lower liking scores than images with 0%, 25%, 50%, and 75% greenery. It is difficult to know what might underlie these differences in likeability scores between the two studies. Potential candidates are differences in the experimental setup. This experiment here consisted of simple rating tasks performed online, whilst Experiment 3 consisted of a dual-task which required both walking toward the images and then rating them. This means that not only the distance from the image changed in Experiment 3, meaning that image size increased when approaching the stimulus, but exposure to the image before providing the aesthetics judgement was far longer than in the current experiment (around 12 seconds compared to around 1 second). Indeed, it has been shown that aesthetic judgements change with extended exposure times from milliseconds to seconds, with longer exposure times involving higher cognitive judgements (see Augustin, Leder, Hutzler, & Carbon, 2008).

Note that visual discomfort scores were not collected in Experiment 3. However, it is tempting to speculate that the close negative relationship between visual discomfort and likeability, at least for abstract images such as the ones used here, can only be found when participants are performing a very fast rating judgement.

To conclude, the negative correlation between visual discomfort and liking ratings for abstract images found in the current study, irrespective of the amount of "greenery" in the visual scene, further supports the hypothesis that liking and visual discomfort ratings are highly correlated - at least when these judgements are based on comparably brief image presentation times. The next study examines whether the same relationship between liking and visual discomfort can be found for real images of different environments.

7.4. Experiment 9: The impact of nature vs. urban scenes on liking and visual discomfort

The aim of this final study was to establish the relationship between visual discomfort and liking ratings for real-world nature and urban images. Images used were the same as those for the Pilot study in Experiment 4 (see Chapter 5).

7.4.1. Methods

Participants: Based on similar assumptions as in Experiment 8, fifty-one participants took part in this online Gorilla study with a mean age of 27 years ± 8.94 SD (18 – 55 years), 23 females (mean age = 25, ± 5.33 SD, 19 – 39 years) and 27 males (mean age = 29, ± 11.04 SD, 18 – 55), 1 non-binary (age = 20). All participants had normal or corrected-to-normal visual acuity and provided informed consent for participation at the beginning of the study. Participants were recruited via ‘Prolific’ and reimbursed for their time. The experiment was approved by the Faculty of Life Sciences’ Ethics Committee at the University of Bristol (ref. 040220100122).

Stimuli: The stimuli for this study were 200 images of nature and urban environments (100 nature images, 100 urban images), selected from the image database “Places” (Zhou et al., 2014), in addition to photographs of landscape and urban spaces taken in Europe by me, and in Europe and Australia by Ute Leonards. The same images had been part of the image sets used for the stimulus collection part of Experiment 4 (see Chapter 5). Images did not contain people or animals. Image resolution was 1280x800 pixels.

Procedure: The procedure was identical to the one described for Experiment 8.

7.4.2. Results and Discussion

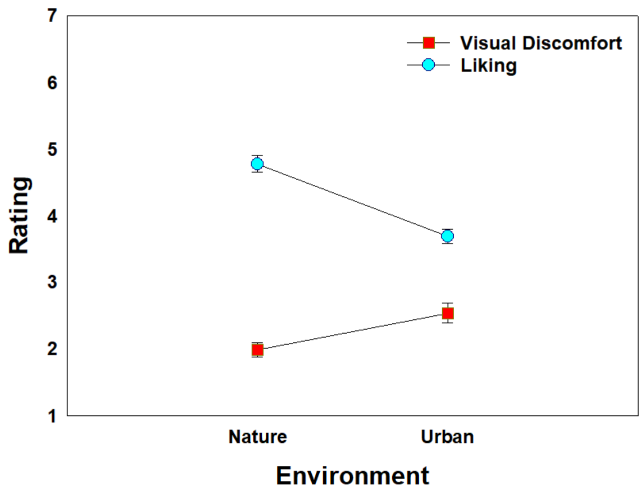

Figure 7.6: Group averages of visual discomfort (red squares) and liking (cyan circles) across nature and urban environments. Error bars reflect ± 1 SEM.

Figure 7.6. shows group averages of visual discomfort and liking ratings across nature and urban environments. A repeated measures ANOVA with Greenhouse-Geisser correction was conducted on rating scores, with task [visual discomfort, liking], and environment [nature, urban] as a within-subject factors. There was a significant main effect of environment, $F(1,50) = 24.943$, $p < 0.05$, partial $\eta^2 = 0.333$, a significant main effect of task, $F(1,50) = 133.390$, $p < 0.05$, partial $\eta^2 = 0.727$ with liking ratings significantly higher than visual discomfort ratings, and there was a statistically significant two-way interaction between environment and task on ratings, $F(1,50) = 63.485$, $p < 0.05$, partial $\eta^2 = 0.559$. Nature images had significantly lower visual discomfort scores but higher liking scores than urban images (see Figure 7.6.).

To establish again the relationship of visual discomfort ratings and liking ratings for individual images, a Pearson's correlation was performed. It revealed again a clear negative correlation between visual discomfort and liking ($r = -0.789$, $p < 0.001$) irrespective of stimulus environment type. Furthermore and more importantly, correlations for nature and urban environments did not differ (see Figure 7.7.).

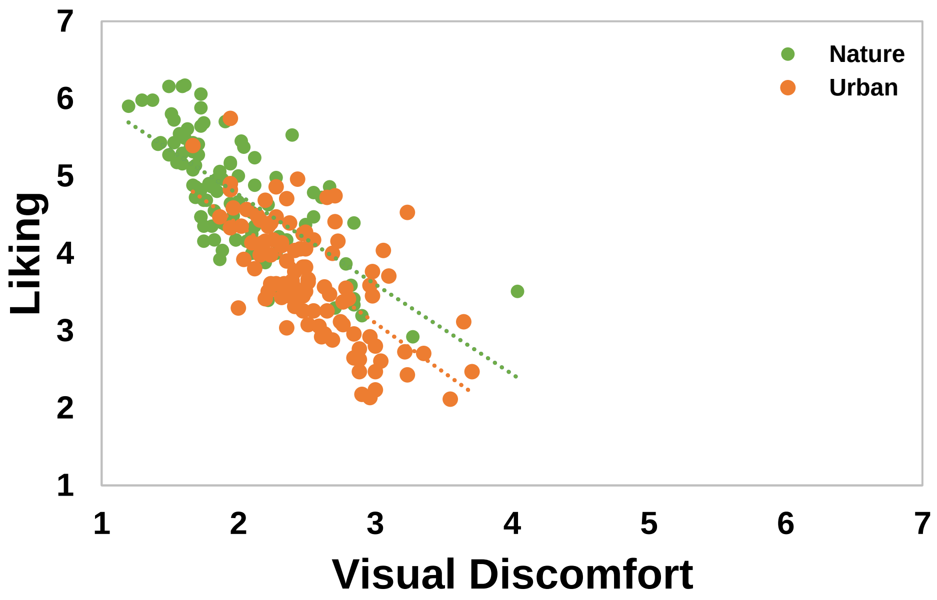

Figure 7.7: Correlation between mean visual discomfort and liking scores for nature images - green circles ($r = -0.71$, $p < 0.05$) - and urban images - orange circles ($r = -0.67$, $p < 0.05$). Correlations for nature and urban environments do not significantly differ.

In line with expectations from the literature, nature images as compared to urban images had overall higher liking scores (e.g. Hartig & Staats, 2006) and lower visual discomfort scores (see also e.g. Wilkins et al., 1984); yet liking and discomfort *variability* between images of the same environment type was comparable for nature and urban images. Moreover, a similarly strong negative relationship between liking and visual discomfort was found for both types of environment.

These findings further support the hypothesis that there is a negative linear relationship between liking and visual discomfort.

7.5. General Discussion

Over three experiments with very different stimulus material, my hypothesis that liking and visual discomfort ratings are negatively correlated, has been confirmed. All three experiments showed similar results, suggesting that both liking and visual discomfort tap into similar underlying mechanisms.

However, a number of limitations need to be considered that could have influenced the results obtained.

Experiments 8 and 9 have differed from Experiment 7, not only with regard to the type of stimuli used, but also in their experimental design enforced by the need to move to online testing due to the COVID-19 pandemic: Experiment 7 had been conducted in a fully controlled environment on a fully calibrated computer screen in the laboratory whilst both Experiments 8 and 9 were run on online platforms with very little control over perceived image size or exact colours etc. In addition, in Experiment 7 participants were asked to rate images on visual analogue scales, whilst in the two other studies 7-point Likert Scales were used. The negative relationship of the data for the two scales seems to be robust as similar findings were obtained in these three studies despite the differences in experimental design. However, these two online experiments should be replicated in a more controlled laboratory environment to tease out small details/ differences.

Interestingly, the results of the Experiment 7 demonstrated that there was a linear relationship between fractal dimensions and the respective ratings for *Edges* and *Thresholded* images; this did not hold for *Greyscale* images. Note that there is a difference in 1/f amplitude slope between the three image types: *Edges* and *Thresholded* images have shallower 1/f amplitude slopes compared to *Greyscale* images (see Spehar et al., 2016), which might explain these results.

Last but not least, I have focused here on contrasting visual discomfort as a negative rating scale and liking as a positive rating scale. To fully understand their relationship, it is important to keep in mind that some literature suggests that disliking and liking judgements are not on a continuum but based on different underlying processes, with liking being associated more with affective processing (Zajonc, 1980) and disliking being a more controlled cognitive process (see Page & Herr, 2002). Similarly, discomfort and comfort are thought not lie on opposite sides of a continuum as the absence of visual discomfort does not lead to visual comfort (Vink & Hallbeck, 2012). This raises the question whether instead of comparing liking with visual discomfort, a comparison of disliking ratings with visual discomfort would have been more appropriate. Future studies might therefore want to include disliking ratings instead of liking ratings throughout.

Chapter 8: General Discussion

Exposure to nature environments has been found to be less cognitively demanding than exposure to urban environments, leading to extensive psychological theories about the mechanisms underlying the so-called *nature benefit* or also urban cost (Berman et al., 2008; Berman et al., 2012; Cimprich, 1992; Cimprich & Ronis, 2003; Hartig et al., 2003; Kaplan, 1995; S. Kaplan, 2001; Kaplan & Berman, 2010; Ottosson & Grahn, 2005; Taylor et al., 2002; Tennessen & Cimprich, 1995). Yet, issues with experimental design and a lack of objective measures hamper progress in understanding the sensory factors leading to differences in environmentally-induced cognitive load. The aim of this thesis was therefore to quantify and objectively measure different visual parameters that might contribute to environmentally-induced increases in cognitive load, answering primarily three questions:

a) Do low-level image statistics ("greenery/chlorophyll" and fractal dimension) impact visual cognitive processing load?

b) Do differences in cognitive load between different environmental stimulus categories, i.e. nature and urban images, still present when these two image categories are controlled for likeability?

c) What effect does subjective visual discomfort have on cognitive load, and thus gait kinematics?

In this General Discussion, I will revisit the research aims, and address each of these aims separately. As individual experiments have already been discussed in detail, this General Discussion should be understood as a more general summary and evaluation of the most relevant findings, and reflection on my experimental approach rather than as an extensive review. I will outline the strengths and limitations of my research, provide an outlook of future research directions and finish with some more general remarks on potential impact of this kind of work.

8.1. Summary of Findings

The positive impact of exposure to nature environments (or negative impact of urban environments) on cognitive functioning has been observed only *after prolonged* exposure to these environments (Berman et al., 2008; Berto, 2005). At the start of my work, it was thus first necessary to establish whether cognitive processing differences could be observed *during* brief exposure to different visual environments, and measured on a trial-by-trial basis. Only if this was possible, would I be able to isolate different sensory factors contributing to environmentally-induced cognitive load by parametrically varying individual stimulus parameters within environmental scenes.

In two experiments using fundamentally different approaches (see Chapter 3), converging evidence was presented that, indeed, cognitive processing differences evoked by urban and nature scenes could be captured in real-time and on a trial-by-trial basis: changes in gait kinematics revealed that participants walked slower with smaller steps when exposed to images of urban environments as compared to nature environments, in line with results from dual-task studies (Al-Yahya et al., 2011; Amboni et al., 2013). Also, using reaction time measures, participants responded much slower in a simple shape discrimination task when urban images instead of nature images were presented as task-irrelevant distractors.

Even though performing a shape discrimination task and performing a dual-task (walking towards an image and performing a cognitive task) are based on different cognitive mechanisms – the shape discrimination task requires suppression of task-irrelevant information to perform the task at hand whilst the dual-task requires task switching - they both established a simple method by which the impact of different visual environments on cognitive processing load could be tested in a fully randomised within-participant experimental design. This provided me with a methodology that allowed me to conduct six studies in which I investigated the impact of low-level visual processes (image statistics : greenery, fractals), mid-level visual processes (visual discomfort) and high-level visual processes (aesthetics) on gait kinematics and reaction times.

8.1.1. Low level image statistics: Greenery and Fractal Dimensions

As nature images differ in some of their low-level visual image statistics, in particular their colour and fractal compositions (Ho et al., 2019; Kardan et al., 2015), it was first tested whether the amount of "greenery" or the fractal composition of a scene impacted cognitive functioning. In Chapter 4 (see Experiment 3), I demonstrated that the parametrically varied amount of "greenery"/"chlorophyll" in otherwise abstract images did not impact gait kinematics. From these results, it seemed thus unlikely that the differences between nature and urban environments in cognitive processing load requirements were due to differences in the amount of low-level image characteristics such as "greenery" in the scenes, at least not when greenery was presented in isolation (see Figure 8.1 greenery).

In contrast to colour, Experiment 6 (see Chapter 6) revealed that walking towards images with fractal properties outside the range typically found in nature scenes was more cognitively demanding: people walked more slowly towards abstract black-and-white fractal images with Intermediate Low D and Low D (1.0-1.4) as compared to images with Intermediate Upper D (1.50-1.65) fractal properties. These findings suggest that cognitive load differences between nature and urban scenes could at least partially be due to differences in fractal content. These data thus seem to support Joye and colleagues' Perceptual Fluency Account (PFA; Joye & De Block, 2011; Joye et al., 2016; Joye & Van den Berg, 2011) of urban scenes being more cognitively demanding than nature scenes due to their low-level visual features; in particular, as tested here, their fractal content (see Figure 8.1 fractal dimensions).

8.1.2. Mid- and higher-level visual processes: Visual Discomfort and Image Aesthetics

Yet, nature and urban images do not only differ in their low-level image statistics, but also in associated higher-level processes such as visual discomfort and aesthetic properties associated with an environment. For example, urban images had been found on average to be more uncomfortable to look at than nature images (e.g. Ho et al., 2019). In line with this literature, multi-level modelling revealed that visual discomfort and its interaction with environment type (nature vs. urban) explained some of the gait variability found in my first experiment (Chapter 3) comparing nature and urban scenes. Similarly, multi-level modelling of the data of Experiment 4 in which individual nature images had been matched for their likeability with urban images showed that visual discomfort ratings were predictive of walking speed (see Chapter 5) (see Figure 8.1 visual discomfort). If one accepts that visual discomfort is an indicator of physiological stress (Wilkins et al., 1984), these findings would thus be supporting Ulrich's Stress Recovery Theory (Ulrich, 1984), which claims that physiological stress contributes to environmentally-induced cognitive load.

Also aesthetic preference had been claimed in the literature to differentially affect cognitive processing between nature and urban environments (for review see Bratman et al., 2012); yet to the best of my knowledge such differences were not controlled for in the studies explicitly examining the nature benefit / urban cost idea (see e.g. Berman et al., 2008; Kaplan & Berman, 2010; Ulrich, 1984). Experiment 4 (see Chapter 5) therefore established whether cognitive load differences between environment types (nature vs. urban) could still be detected when images of nature and urban scenes were matched for liking scores beforehand by an independent participant sample. Whilst indeed, no differences in gait kinematics were observed between environmental categories (nature and urban scenes), environment type still affected cognitive load differentially when assessed with the shape discrimination task. Any conclusion that liking might explain some of the differences in cognitive demands between nature and urban scenes would thus be premature (see Figure 8.1 aesthetics). As argued in detail in Chapter 5, one of the potential reasons for finding cognitive load differences between liking-matched images of urban and nature scenes for reaction times but not for gait kinematics could be the differences in stimulus exposure duration between the two experimental setups. During the walking experiment (e.g. Experiment 4; see Chapter 5), participants were exposed to each image for at least 10 seconds, whilst during the shape discrimination task (e.g. Experiment 5; see Chapter

5), participants were exposed to each image serving as task-irrelevant distractors for a few hundred milliseconds only. Following Stress Recovery Theory (Ulrich, 1981, 1984), aesthetic and affective reactions to environments are not isolated from but strongly linked to cognitive processes. If one accepts the definitions of aesthetics provided in this theory, one can thus reasonably assume that differences related to attentional capture of the two environment types in Experiment 5 were driven by pleasure-based liking (automatic processing) for the short exposure times rather than interest-based liking (controlled cognitive processing) that requires longer exposure times (Graf & Landwehr, 2017).

As shown in Chapter 7, aesthetics cannot be entirely separated from visual discomfort as visual discomfort and liking ratings were shown to be negatively correlated (Experiments 7 , 8 and 9), irrespective of the type of stimulus material used. It was out of the scope of this thesis to investigate this relationship in more detail, but future work should explore the exact nature of this relationship in more detail in order to understand the exact impact they might have on environmentally-induced cognitive load.

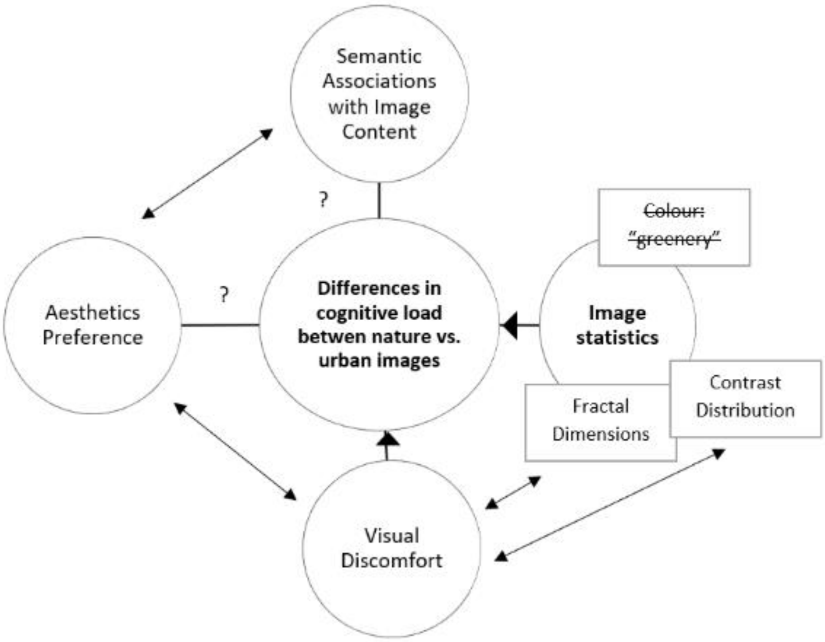

Figure 8.1: Overview of some of the core factors suggested to contribute to environmentally-induced cognitive load based on research presented in this thesis. The question marks refer to the still unknown impact of semantic associations with image content and aesthetics on environmentally-induced cognitive load. "Greenery" has been crossed out as it did not seem to impact processing load (see Experiment 3). Arrows are influences of visual parameters that contribute to environmentally-induced increases in cognitive load, and relationships between variables demonstrated in this thesis. See Figure 1.1. for a comparison. Note, in particular, that image stats and visual discomfort seem highly inter-dependent factors as are visual discomfort and aesthetics, in contrast to original suggestions in Figure 1.1.

8.2. Novelty and Strength of the current approach

Differences in cognitive processing demands evoked by exposure to nature and urban environments have long been established in the literature (for review see Bratman et al., 2012; Corazon, Sidenius, Poulsen, Gramkow, & Stigsdotter, 2019; Weber & Trojan, 2018); yet, what makes an environment more or less cognitively demanding is, as yet, little understood. Moreover, the mechanisms underlying different cognitive processing demands remain unclear, with most of the psychological theories focusing on "restorative" responses to nature environments and thus assuming a cognitive benefit induced by exposure to nature rather than a cognitive cost induced by exposure to urban environments (see Chapter 1.3. for review of psychological theories such as Stress Recovery Theory (Ulrich, 1984), Attention Restoration Theory (S. Kaplan, 1995, 2001) and Perceptual Fluency Theory (Joye et al., 2016).

All above proposals assume that there is a fundamental difference between nature and urban environments in their cognitive processing load; i.e. that they are two distinct categories like cats and dogs. A closer look at the data presented here, however, raises the question whether such a dichotomy really exists or whether environmentally-induced cognitive load depends rather on low-level, mid-level and higher-level cognitive processes irrespective of environment category.

Throughout this thesis, I demonstrated that the use of gait kinematics and reaction times as a measure of the moment-to-moment cognitive state provides a method to objectively quantify and track the impact of different visual environments on cognitive processing load. Crucially, cognitive load differences could be observed in real-time and on a trial-by-trial basis. It is this novel approach of measuring the impact of cognitive processing load during the actual exposure, that allowed me to parametrically vary individual components within environmental stimuli and thus establish the contributions low-level, mid-level or high-level visual factors might have on environmentally-induced cognitive load.

The most remarkable result to emerge is that walking towards images with fractal properties outside the range typically found in nature scenes is more cognitively demanding. This suggests that low-level cognitive processes explain at least some of the differences in cognitive demands between nature and urban environments. At first glance, these findings seem to support Joye and colleagues' Perceptual Fluency Account, PFA (Joye & De Block, 2011; Joye et al., 2016; Joye & Van den Berg, 2011). PFA claims that nature environments are easier to process than urban environments due to their low-level image properties, in particular the amount of fractals. However, as clearly seen in Chapter 6, not only fractal content but also its interaction with visual discomfort were predictive of gait kinematics, with visual discomfort being a far stronger predictor than fractals. This not only suggests that there is a more complex interaction between low-level and mid-level cognitive processes that contributes to environmentally-induced cognitive load, but also opens up the possibility that visual stress is the core factor to explain cognitive load differences, in line with previous studies suggesting that nature environments reduce physiological stress (e.g. Hedblom et al., 2019; Jiang, Chang, & Sullivan, 2014; Ulrich et al., 1991; Wang et al., 2016), and thus supporting Stress Recovery Theory (Ulrich, 1981, 1984; Ulrich et al., 1991, see also Chapter 1.4.).

As already alluded to, another important finding of this thesis is that results seem to speak against a fundamental dichotomy between the impact of nature and urban environments on cognitive processing load. Indeed, when these two environments were matched for liking scores, no differences in gait kinematics could be observed, suggesting that the comparative approach between nature and urban used in previous studies should better be rejected (see Bratman et al., 2012). The data presented in this thesis suggest that differences between nature and urban environments fall on a continuum with a clear overlap in terms of sensory (in particular visual) parameters between these two environments. As such, these findings therefore lend support to Gibson's (1979) environmental affordances theory that different environments affect us differently depending on their sensory parameters, irrespective of whether they belong to nature or built environment.

8.3. Challenges and Limitations

The key limitations of the present studies lie in the selection of the stimulus material used. Indeed, none of the image sets used in this thesis were able to control for all possible criteria that could underlie environmentally-induced cognitive load, with both the use of real-world images and abstract images bringing their own sets of limitations. In addition, the visual stimuli used in these studies were static. A full understanding of environmentally-induced cognitive load would require the addition of dynamic stimulus material; something that needs to be considered in future work.

Although nature and urban images used in Experiments 1, 2, 4 and 5 were controlled for their images' spatial composition and perceived depth (Experiments 1 and 2) or for their aesthetic properties (Experiments 4 and 5), it was not really possible to control for all of these factors at the same time. Moreover, a range of other factors (such as the presence of people) had not been considered (although a separate analysis revealed that the few urban images containing people in Experiment 1 did not seem to contribute more to the amount of cognitive load than the urban images without people). The main concern was that images were not controlled for image statistics (e.g. symmetry, spatial frequencies, hue, saturation, luminance, or, most crucially, image complexity). Moreover, due to the vast range of scenes that could be included in such overarching environmental categories, it seems next to impossible to control for all parameters at the same time; a reason why future studies might want to aim to continue isolating the impact of different parameters on environmentally-induced cognitive load rather than investigating the seeming categorical differences between nature and urban scenes. Regarding the limitations of image selection, it could also be argued that some of the urban images, whilst all dominated by buildings, included partially visible blue-green infrastructure and thus contained a certain amount of nature content. Future studies might want to try to parametrically vary the amount of nature as compared to urban components within images to gather further insights into the cognitive processing demands nature and urban environments impose.

Whilst the use of abstract images as in Experiments 3 and 6 (see Chapter 4 and 6 respectively), parametrically varied for their amount of “greenery” (Experiment 3) and fractal dimensions (Experiment 6), seemed the strongest approach to stimulus selection as it allowed me to isolate individual low-level image characteristics and investigate them for their ability to affect cognitive processing load, even this approach showed clear limitations. In particular, even for the null result for “greenery”, I cannot exclude that other factors such as image liking – which turned out to be higher for images with smaller amounts of greenery (see Experiment 3) – cancelled any cognitive benefits colour brings. In other words, greenery might still contribute to environmental benefits if images had been controlled for liking (if this is at all possible). In Experiment 8, visual discomfort and liking rating were more variable for images with higher content of greenery than images with lower greenery content. Moreover, I cannot conclude that colour presented together with other low-level or higher-level image properties common in nature could add to the cognitive load differences found between nature and urban images. Indeed, if participants had been presented with real images controlled for low-level image statistics such as colour whilst preserving the meaning of the scene, cognitive differences between nature and urban scenes might have indeed been largely reduced. Future studies should look at this, in addition to investigating how the meaning of scenes affects cognitive processing load. Note, however, that this will first require a solution to the many pitfalls current methods have to measure semantic associations in a scene (see Chapter 1.3).

At the current stage, it seems safe to conclude that low-level factors on their own such as fractal content can explain at least some of the variance in cognitive processing between different environments, whilst higher-level factors such as visual discomfort (and potentially aesthetics) and their interactions with low-level factors explain a far higher amount of cognitive load differences between environments.

Another apparent limitation of the studies is the method used to measure visual discomfort. Present evidence relies on subjective ratings of visual discomfort and thus fails to provide a comprehensive assessment of (visual) stress, defined as a physiological response to stimuli. Future work exploring whether stress (Ulrich, 1984) rather than attention (S. Kaplan, 1995) is at the core of any "nature benefit"/"urban cost" should aim to use objective measures of physiological stress (e.g. wearable devices to measure heart rate variability). Also, future research might want to use eye-tracking to further our understanding of what is capturing someone's attention in a visual scene and what exactly is causing visual discomfort. The definition of visual discomfort used here originally stems from research looking into the relationship between contrast distributions and an aversive physiological response (e.g. Juricevic et al., 2010). In this thesis, findings suggest that there might be a similar relationship between visual discomfort and fractal dimensions; therefore, the concept of visual discomfort needs to be revisited.

Similarly to the limitations for visual discomfort, also aesthetics was measured on a basis of subjective liking ratings as it is still poorly understood how to quantify and objectively measure aesthetics (Bratman et al., 2012). A first attempt to resolve this issue for future studies might be to provide participants with a clearer definition of aesthetics prior to participation in the actual experiments. Whilst several authors have attempted to define aesthetics before (e.g. Chatterjee & Vartanian, 2014; Graf & Landwehr, 2017), none of the proposed definitions is as yet more widely accepted; thus hampering any objective quantification of aesthetic preference.

Last but not least, two further aspects have to be considered:

The studies included in this thesis were not specifically designed to test involvement of directed attention nor other cognitive processes in environmentally-induced cognitive load. However, findings nevertheless suggest that both directed attention (as tapped into by the shape discrimination task) and other cognitive processes such as those involved in dual-tasking (Strobach, Wendt, & Janczyk, 2018) were differentially affected by exposure to different environments. Future work might want to focus specifically on factors such as automatic attentional capture and the need to suppress irrelevant information as a factor defining affordances of an environment.

This thesis does not answer the question of whether exposure to nature *improves* cognitive abilities ("nature benefit") or whether exposure to urban environments *decreases* cognitive abilities ("urban cost"). Participants walked fastest toward neutral images, significantly slower toward nature images and slower again toward urban images, suggesting that urban environments are more costly to process as compared to nature environments, but nature environments are more costly than a completely empty environment. Also, reaction times for the shape discrimination tasks in the presence of any distractor stimulus are slower than without distractors; raising the question of what exactly the baseline of cognitive abilities is from which to measure an environment's cognitive impact. This points to another limitation of this work and the literature more widely, namely that the conceptualisation of cognitive load is not yet fully developed; including the distinction between cognitive load and perceptual load.

8.4. Potential wider impact of research

Whilst the research presented in this thesis was performed to further our fundamental understanding of how a person's environment impacts their cognitive abilities, it is tempting to consider it for its wider impact for society and, in particular, population health. Indeed, understanding and tackling environmental stressors of urban environments is one of the major global challenges: 54% of the world's population lives in cities with an expected increase to almost 76% in the next 30 years (Nations, 2014). A deeper understanding of what makes an environment as expressed in sensory terms more comfortable and cognitively less demanding is thus a fundamental prerequisite to the future design of healthy and inclusive cities. My research shows that environmental stressors are not only those currently considered such as air, sound or light pollution (see Evans, 2001; Rentfrow & Jokela, 2016), but include visual factors such as low-level image statistics and aspects of sensory discomfort and aesthetics. Moreover, measuring gait changes (at least for flat hazard free environments) might become a way to measure an environments affordances in the real world in an objective way.

8.5. Conclusions

The current studies demonstrated that cognitive processing load differences between nature and urban environments are not due to a fundamental dichotomy between these environments but that they share their underlying mechanisms. A such, they have gone some way towards enhancing our understanding of how different sensory factors contribute to environmentally-induced cognitive load, using gait kinematics and reaction times as an objective measure of cognitive load changes. Being able to measure cognitive load changes induced by an environment during actual exposure is a crucial step toward understanding how even subtle changes in the sensory makeup of an environment affect cognitive functioning, and, in turn, a person's health and wellbeing.

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Annex A (Experiment 1): Interaction between environment and experimental block order for gait parameters

Interaction between environment and experimental block order for velocity and stride time in environmentally-induced perceptual load – motor interference task.

See Table below for Group averages of mean velocity (m/s) + standard deviations across environment type and order.

	Order 1		Order 2	
Velocity	M	SD	M	SD
Nature	1.30	0.07	1.30	0.06
Urban	1.29	0.07	1.28	0.06
Neutral	1.33	0.07	1.36	0.06

Note. Order 1 = cognitive motor interference control task as the first task and environmentally-induced perceptual load – motor interference task as the second task; n = 10, Order 2 = environmentally-induced perceptual load – motor interference task as the first task and cognitive motor interference control task as the second task; n = 8.

See Table below for Group averages of mean stride time (in seconds) + standard deviations across environment type and order.

Stride Time	Order 1 M	Order 1 SD	Order 2 M	Order 2 SD
Nature	1.04	0.04	1.04	0.04
Urban	1.04	0.04	1.05	0.04
Neutral	1.03	0.03	1.02	0.03

Note. Order 1 = cognitive motor interference control task as the first task and environmentally-induced perceptual load – motor interference task as the second task; n = 10, Order 2 = environmentally-induced perceptual load – motor interference task as the first task and cognitive motor interference control task as the second task; n = 8.

These data suggest that participants who were asked to perform the cognitive motor interference control task as the first task and the environmentally-induced perceptual load – motor interference task as the second task, were walking slower with longer stride times towards neutral images, as compared to the group with reversed experiment order. It is possible that participants who performed the environmentally-induced perceptual load – motor interference task (105 trials) as the first task and cognitive motor interference control task (20 trials) as the second task were walking faster with shorter stride times towards neutral images as they settled into a more sustained rhythm of walking as they have been already walking for an hour.

Annex B: Cognitive motor interference control tasks (Experiments 1 and 3).

Experiments 1 and 3 included cognitive motor interference control task, a control to establish whether the methodology was sufficiently robust to observe changes in gait kinematics associated with changes in cognitive load as has been well established in the literature (Amboni et al., 2013).

Procedure**:** Using a repeated measures design, each participant walked repeatedly down a 15m long laboratory whilst completing verbal trail making tasks requiring different amounts of cognitive load (vTMT). Dependent on condition, each trial required one of the following vocalisations to be completed: No speech (C1), "Lalala…" (C2), "ABC…" (C3) or "A1B2…" (C4). The least cognitive resources were required for C1 (no speech; i.e. no dual-task requirements, and thus no interference between cognition and walking), and the most for C4.

For each trial, the participant started by standing on a marked cross at one end of the laboratory. The respective trail making condition was then indicated by text projected onto the floor in front of them. When the participant was ready, the text would disappear and the participant walked the length of the laboratory in their natural walking speed whilst carrying out the relevant trail making condition through audible vocalisation. On reaching the end of the laboratory, the participant stopped the verbal task before returning to the starting cross at the other side of the lab. Four practice trials were carried out (1 for each trail type), followed by 20 experimental trials; 5 of each condition, presented in random order. This part of the study took approximately 10 minutes.

Note that even though I recorded participants' actual trail making performance to ensure task compliance, I did not include any verbal task performance measures into the analysis.

Experiment 1 (Methods and Results)

Participants were the same as in Experiment 1 (see Chapter 3.2.1.).

Exclusion criteria**:** One participant was excluded from the analysis due to a technical problem with the motion capture system. One further participant was excluded from analysis due to having an unusual walking style (see the exclusion criteria in Chapter 2.1.1.3.). This left 18 participants' datasets for analysis; (6 male), aged 18-34 (M = 22).

Results: To determine the impact of verbal trail making-induced cognitive load on gait, repeated measures MANOVAs were applied to the gait data of the verbal trail making task, with order of experimental parts (Control task; Experiment 1 main task) as a between-subjects variable and trail making task condition as a within-subjects variable (Cognitive Load; C1/C2/C3/C4) for seven dependent gait measures (gait velocity, mean step length, mean stride time, mean swing time, step length variability, stride time variability and swing time variability).

Velocity: Analysis showed a significant effect of cognitive load on overall velocity ($F(3,48) = 20.82$; $MSE = 0.05$; $p < 0.001$, partial $\eta^2 = 0.57$). *Post-hoc* tests using Bonferroni correction revealed that participants walked significantly slower during C4 trials (highest cognitive load) than during all other conditions (C1 and C2 $p < 0.001$, C3 $p < 0.01$). All other *post-hoc* comparisons yielded insignificant results.

Step Length: Analysis with Greenhouse-Geisser correction showed that there was also a significant main effect of cognitive load on mean step length ($F(2.14, 34.28) =11.52$; $MSE < 0.01$; $p < 0.001$, partial $\eta^2 = 0.42$). *Post-hoc* tests using Bonferroni correction showed a significantly shorter Step Length for C4 trials (highest cognitive load) as compared to all other conditions (C1 $p < 0.05$, C2 and C3, $p < 0.01$). All other *post-hoc* comparisons yielded insignificant results.

Stride Time: Analysis with Greenhouse-Geisser correction showed that there was a significant main effect of cognitive load on mean stride time ($F(1.97, 31.51) = 17.24$; $MSE < 0.001$; $p < 0.001$, partial $\eta^2 = 0.52$). *Post-hoc* tests using Bonferroni correction revealed significantly longer stride times for C4 trials (highest cognitive load) as compared to all other conditions (C1 and C2 $p < 0.01$, C3 $p < 0.05$). Moreover, stride times for C3 trials were also significantly longer than for C1 trials ($p < 0.01$) and C2 trials ($p < 0.05$).

Swing Time: There was a significant main effect of cognitive load on mean swing time ($F(3,48) = 6.42$; MSE < 0.001; $p < 0.01$, partial $\eta^2 = 0.29$). *Post-hoc* tests using Bonferroni correction showed a significantly longer swing time for C4 trials (highest cognitive load) as compared to C1 ($p < 0.05$). Moreover, swing times for C3 trials were also significantly longer than for C1 trials ($p < 0.05$).

There was no main effect of cognitive load on the variability of step length, the variability of stride time and the variability of swing time.

There was no effect of experimental part order on any of the seven dependent measures. However, there was a significant interaction between cognitive load and part order for swing time ($F(3,48) = 3.36$; MSE $p < 0.001$; $p < 0.05$, partial $\eta^2 = 0.17$). *Post-hocs* with Bonferroni correction revealed that swing times were slower for higher cognitive load tasks when the cognitive load task was performed after the actual walking task, potentially indicating fatigue.

See the Table below for Group averages of mean velocity (m/s), step length (m) stride time (s), and swing time (s) + standard deviations across varying levels of cognitive load.

	Velocity (m/s)		Step Length (m)		Stride Time (s)		Swing Time (s)	
	M	SD	M	SD	M	SD	M	SD
C1	1.38	0.02	0.70	0.01	1.01	0.01	0.51	0.004
C2	1.38	0.02	0.71	0.01	1.02	0.01	0.51	0.005
C3	1.36	0.02	0.70	0.01	1.03	0.01	0.51	0.005
C4	1.30	0.03	0.68	0.01	1.05	0.01	0.51	0.005

Note. C1 = no speech, C2 = lalala, C3 = ABC, C4 = A1B2.

Experiment 3 (Methods and Results)

Participants were the same as in Experiment 3 (see Chapter 4.1.2.).

Exclusion criteria**:** Two participants were excluded from analysis due to having an unusual walking style (see the exclusion criteria in Chapter 2.1.3.), leaving 20 participants' datasets for the analysis, 17 females and 3 males, aged 18-23 (M = 19.55, ± 1.39 SD).

Results: To determine the impact of verbal trail making-induced cognitive load on gait, repeated measures MANOVAs were applied to the gait data, with experimental order as a between-subjects variable and trail making task condition as a within-subjects variable (Cognitive Load; C1/C2/C3/C4) for three gait measures (mean velocity, mean step length, mean stride time). Note that swing times were not included in the gait analysis of Experiment 3 due to the insignificant effects of environmentally-induced cognitive load (nature vs. urban environments) on swing times in Experiment 1.

Velocity: Analysis determined that there was a statistically significant effect of cognitive load on velocity, $F(3, 57) = 29.563$, $p < 0.001$, partial $\eta^2 = 0.622$. *Post-hoc* tests using Bonferroni correction revealed that participant walked significantly slower during C4 trials as compared to C1, C2 and C3 conditions ($p > 0.05$).

Step Length: There was a statistically significant effect of cognitive load on step length, $F(3, 57) = 7.012$, $p < 0.05$, partial $\eta^2 = 0.280$. *Post-hoc* tests using Bonferroni correction showed a significantly shorter step length for C4 trials as compared to C2 and C3 conditions ($p < 0.05$).

Stride Time: There was a statistically significant effect of cognitive load on stride time, $F(3, 57) = 13.876$, $p < 0.001$, partial $\eta^2 = 0.435$. *Post-hoc* tests using Bonferroni correction showed a significantly longer stride times for C4 trials as compared to C1 and C2 trials ($p < 0.05$). There was no significant difference between C3 and C4 conditions.

Experimental part order did not affect any of the gait measures.

See Table below for Group averages of mean velocity (m/s), step length (m) and stride time (s) + standard deviations across varying levels of cognitive load.

	Velocity (m/s)		Step Length (m)		Stride Time (s)	
	M	SD	M	SD	M	SD
C1	1.38	0.13	0.70	0.05	1.01	0.05
C2	1.37	0.14	0.70	0.06	1.02	0.05
C3	1.36	0.15	0.70	0.06	1.03	0.06
C4	1.29	0.16	0.69	0.07	1.07	0.09

Note. C1 = no speech, C2 = lalala, C3 = ABC, C4 = A1B2.

Overall, these results confirm that performing a cognitively demanding task lead to gait changes (see for a review Amboni et al., 2013). In both experiments, participants were walking slower with smaller steps and longer stride times when asked to perform high cognitive load task as compared to lower cognitive load tasks.

Annex C: Online rating task (Experiment 4)

In Experiment 4, participants were asked in two online studies to rate images of photographic environmental scenes for their likeability on 7-point Likert Scale (see the description of the procedure in Chapter 5.2.1.).

Participant demographics for the two studies are summarized in table below:

	Study 1	Study 2
Age range (and mean age)	18-81 (31 years)	17-66 (31 years)
Gender	60 males, 90 females	76 males, 72 females, 2 gender not disclosed
Migraine	33	17
Grew up in a city (> 100.000 inhabitants)	67	70
Grew up in the town (< 100.000 inhabitants)	58	55
Grew up in the countryside	28	22
Grew up in two places	2: city and countryside, 1: city and town	1: city and town, 1: countryside and town
Places where participants grew up	Africa (1), America (18), Asia (2), Australia (1), Europe (123), America-Asia (1), America-Europe (3), Prefer not to say (1)	Africa (1), America (25), Asia (9), Europe (108), Africa-America (1), Asia-Europe (3), Australia-Europe (1) Prefer not to say (1)