Road lighting for pedestrian reassurance: An investigation of methods and optimal illuminance

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy (PhD)

By

Shahab Gorjimahlabani

School of Architecture and Landscape

Faculty of Social Sciences

The University of Sheffield

February 2025

ABSTRACT

After dark, road lighting fulfils a primary need of pedestrians by helping them feel reassured that it is safe to walk. Guidelines are essential for providing road lighting that is suitable and efficient for its purpose. However, the basis of current lighting standards is unknown. This thesis aims to provide credible evidence for optimal illuminance for pedestrian reassurance, and in doing so to question the methods used to establish that threshold.

Three experiments were conducted, being field studies in Sheffield, UK. Experiment 1 was a pilot study to investigate one aspect of the day-dark method - the time of day for the daylight evaluations; daylight evaluations were conducted once at around midday and once in the evening at the same time of day as after-dark evaluations, using the biannual daylight savings clock change. Experiment 2, then used the day-dark method with a larger sample of participants and locations to investigate the relationship between pedestrian reassurance and illuminance, and the difference in reassurance evaluations given by solo and accompanied participants. Experiment 3 used travel count of pedestrian numbers in daylight and after dark at the same locations used in Experiment 2, to explore an objective method for measuring pedestrian reassurance.

The results of Experiment 1 suggested that the effect of time of day of daylight evaluations on the day-dark difference was of little practical significance. The results from Experiment 2 revealed that roads with higher mean illuminance had smaller day-dark differences, suggesting enhanced pedestrian reassurance. An optimal mean illuminance of approximately 7.2 lx for a day-dark difference of 0.5 was suggested. The differences in reassurance between solo and group evaluations were negligible. Experiment 3 results indicated that darkness had a deterrence effect on pedestrian traffic. Odds ratio determined using these data were consistent with reassurance ratings obtained in Experiment 2.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my supervisors, Professor Steve Fotios and Dr Jim Uttley, for their invaluable guidance, unwavering support, and insightful feedback throughout my doctoral journey. Their expertise and dedication were truly instrumental in shaping this research, and I am profoundly indebted to them for their mentorship and the opportunities they provided for my development as a researcher.

I would also like to thank my colleagues in the Lighting Research Group, Maan Balela, Dr Khalid Hamoodh, Dr Aysheh Alshdaifat, Dr Nima Hafezparast Moadab, Dr Yichong Mao, and Dr Demet Yesiltepe, who supported me in carrying out my experiments, and Gavin Tolan who helped with building the apparatus. To my other PhD colleagues, thank you for your constant emotional and professional support throughout this experience.

I am also deeply grateful to my parents and partner for their endless love, encouragement and sacrifices. Their unwavering support made this achievement possible, and I dedicate this accomplishment to them.

Finally, I extend my thanks to all the participants in my research, as well as everyone else who offered assistance and support, whether directly or indirectly, throughout my PhD.

Funding

Part of the work for Experiment 2 was supported by the work of Dr Yichong Mao within the HAROLD project (HAzards, ROad Lighting and Driving) which received funding from the Engineering and Physical Sciences Research Council (EPSRC), grant number EP/M02900X/1.

PAPERS ARISING FROM WORK REPORTED IN THIS THESIS

Journal papers

1. Uttley, J., **Gorjimahlabani, S.** and Fotios, S. (2024) Defining daytime in the day-dark approach to measuring the pedestrian reassurance of road lighting, *Lighting Research & Technology*, 56(5), pp. 469-480. doi: https://doi.org/10.1177/14771535241252712

2. Fotios, S., Uttley, J. and **Gorjimahlabani, S.** (2024) Extending observations of ambient light level and active travel to explore age and gender differences in reassurance. *Lighting Research & Technology*, 56(3), pp. 274-282. doi: https://doi.org/10.1177/14771535221080657

3. **Gorjimahlabani, S.**, Uttley, J. and Fotios, S. (2023) Measuring pedestrian reassurance. *Lighting Journal*, 88(9), pp.12-16

Conference papers

1. Fotios, S., Uttley, J. and **Gorjimahlabani, S.** (2025) Optimal illuminance for pedestrian reassurance. *31st Session of the CIE*. Vienna, Austria, 7-9 July 2025.

2. **Gorjimahlabani, S.**, Mao, Y., Fotios, S. and Uttley, J. (2023) Measuring pedestrian reassurance: comparing evaluations given by solo pedestrians and accompanied groups. *30th Session of the CIE*. Ljubljana, Slovenia, 15-23 September 2023. pp. 1768-1774. doi: https://doi.org/10.25039/x50.2023.PO053

3. Mao, Y., Fotios, S., Uttley, J. and **Gorjimahlabani, S.** (2023) Do female pedestrians express a lower degree of reassurance than male pedestrians? And does road lighting help? *30th Session of the CIE*. Ljubljana, Slovenia, 15-23 September 2023. pp. 616-623. doi: https://doi.org/10.25039/x50.2023.OP007

4. Fotios, S., Uttley, J. and **Gorjimahlabani, S.** (2022) A mixed methods approach to measuring pedestrian reassurance. *14th European Lighting Conference Lux Europa 2022*. Prague, Czech Republic, 20-22 September 2022. pp. 183-187

CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1. INTRODUCTION: ROAD LIGHTING FOR PEDESTRIANS

1.1 Introduction

Walking is a fundamental mode of transportation that plays a crucial role in urban mobility and public health. It is an eco-friendly way to travel short distances, promoting physical activity and reducing traffic congestion. Walking also offers economic benefits to the general population by, for example, reducing the reliance on motor vehicles. Promoting walking involves creating environments and conditions that encourage people to choose to walk rather than, for example, to drive or not leave the home. Key elements of such environments are attractiveness, comfort, convenience, and safety. Beyond these, factors like necessity and the availability of services within walking distance, significantly impact an individual's decision to walk. Necessity, in this context, refers to when walking is the only viable or most practical option due to factors such as a lack of alternative transportation, proximity making walking the most efficient choice, or the inherent nature of the activity itself (e.g., walking a pet, exercising). People also consider alternative services available, such as bus routes, when deciding if walking is the most suitable option for their specific needs and destination. The purpose of travel also plays a crucial role. For instance, walking to a local shop for groceries differs from commuting to work or walking for leisure.

This thesis focuses on one of the mentioned key elements, safety. Creating a safe walking environment is not just about preventing accidents or crime, but also about promoting a sense of security. People are more likely to walk in environments where they feel safe and secure, and are naturally hesitant to walk in places where they perceive a risk to their safety and well-being. If walking routes are perceived as unsafe, people will simply avoid walking.

A pedestrian’s sense of safety diminishes after dark due to several factors, including the reduced presence of other people and reduced visibility. Reduced human presence increases feelings of isolation and inaccessibility to help from others. Reduced visibility makes it harder to detect danger and provides cover for potential offenders, while also hindering a person’s ability to identify escape routes. The presence of artificial sources of light, such as road lighting, can improve visibility, which in turn can encourage human activity and enhance pedestrians’ feeling of safety after dark, encouraging more walking where it perhaps would otherwise not happen due to darkness.

The research presented in this thesis focuses on optimal illuminance for pedestrians’ feeling of safety after dark. Hereafter, *feeling of safety after dark* will be referred to as *pedestrian reassurance*.

This chapter discusses the primary needs of pedestrians for engaging in walking, and how road lighting can help meet one of these needs – reassurance after dark. This chapter also outlines current lighting guidelines which provide recommendations for appropriate lighting, such as target illuminances for pedestrians, and investigates the evidence underpinning these guidelines.

1.2 Key definitions and concepts

1.2.1 Road lighting

Road lighting refers to the provision of artificial lighting in public spaces and roadways by using illumination systems, mainly to enhance the safety of all road users (including pedestrians) through improving visibility of the surrounding area and making obstacles and hazards more visible (Bullough et al., 2013; Boyce, 2014). Although the term road lighting includes the word *road*, it encompasses outdoor illumination for different spaces, including lighting for footpaths and pedestrianised areas in addition to roads (Figure 1.1), and this is what is meant in this thesis when referring to road lighting.

Lighting can be described using characteristics including illuminance, the spatial distribution of illuminance and spectrum (spectral power distribution – SPD). Illuminance is the total incident luminous flux per unit area on a real or imaginary surface (CIE, 2020). In other words, illuminance is the measurement (quantification) of the amount of light falling on a surface, measured in lux. Variation in the spatial distribution of light is defined in lighting standards by uniformity, the ratio between the minimum and average illuminances across a defined area (CIE, 2020). Light spectrum describes variations in radiant power across the visible light spectrum, the portion of the electromagnetic spectrum that is visible to the human eye (CIE, 2020). Variations on light source spectrum are seen as lighting of different colour qualities.

Figure 1.1. Example of road lighting after dark for a pedestrian footpath along a road in Sheffield.

1.2.2 Pedestrian

CIE 236:2019 (CIE, 2019) defines a *pedestrian* as a person who chooses to travel on foot (i.e. walk) rather than use alternative transportation options such as cycling or driving (Figure 1.2).

Figure 1.2. A pedestrian walking along a footpath in Sheffield.

1.2.3 Reassurance

Safety is a multidimensional phenomenon that encompasses physical safety, such as the ability to detect hazards (BSI, 2020), and mental safety or feeling of safety, such as the ability to see clearly ahead and identify any escape routes, if necessary (Fisher and Nasar, 1992). Past studies have described feeling of safety as feeling protected from the fear of crime (Atkins et al., 1991; Alfonzo, 2005). However, Fotios et al. (2015) suggest the use of a new term, *reassurance*, because of the ambiguity surrounding the terms *safety* and *fear of crime* (Farrall et al., 2009). For example, *fear of crime* is sometimes used interchangeably with *perceived risk of crime* – how likely someone believes they are to become a victim. However, someone might perceive the risk of a specific crime in their area as low but still feel a significant level of fear about it. Conversely, someone might acknowledge a higher risk but not experience fear.

Reassurance is defined by CIE 236:2019 (CIE, 2019, p.2) as "the *confidence a pedestrian might gain from road lighting (and other factors) to walk along a footpath or road, in particular if walking alone after dark*". Reassurance is the action of removing fear (Oxford Learner's Dictionaries, 2024), of making someone feel less worried (Cambridge Dictionary, 2024), and of restoring confidence (Merriam-Webster, 2024). This thesis uses the broad term, reassurance, to cover the concepts used in the literature, such as feeling of insecurity (e.g. Simons et al. (1987)), perceived danger (e.g. Blobaum and Hunecke (2005)), perceived safety (e.g. Knight (2010)), and fear of crime (e.g. Atkins et al. (1991)).

1.2.4 After dark

The expression *after dark* is used in this thesis rather than *night* to direct attention towards darkness rather than time of day – at some latitudes at certain times of the year, daylight persists through the night and at others darkness persists through the daytime hours.

1.3 Road lighting for pedestrian reassurance

1.3.1 The hierarchy of walking needs

Walking offers physical and psychological health benefits to the pedestrian as well as bringing environmental and economic advantages to the wider population (Banister, 2008; Fewster, 2004; I-Meen and Buchner, 2008). Examples of such benefits are lowered risk of chronic disease such as cardiovascular disease, diabetes, and certain cancers (Lee and Buchner, 2008); reduced stress, enhanced coping ability, and improved mental health (Roe and Aspinall, 2011); less air pollution from motorised travel (Piatkowski et al., 2015); and more efficient land use by reducing the need for roads and parking facilities (Litman, 2003). Also, many people incorporate walking into their public transport journeys (such as walking from home to the bus stop), making good walking conditions essential for effective public transport (CIE, 2019). In acknowledgement of these benefits, many countries have adopted programmes and policies to promote walking (HEPA, ca. 2006; Pucher and Dijkstra, 2003). One example is the Cycling and Walking Investment Strategy (CWIS), a UK government initiative focusing on increasing walking and cycling activity, with the goal of making walking and cycling the natural choice of transportation for shorter journeys (DfT, 2017).

A person's decision to walk (rather than, for example, to drive or to avoid leaving the home) is influenced by a series of five hierarchical needs: feasibility, accessibility, safety, comfort and pleasureability (Alfonzo, 2005) (Figure 1.3). Out of these needs, the risk of criminal offense, threats, violence, and victimisation (i.e. absence of safety) is considered one of the most important factors in the decision to walk (Fyhri et al., 2010); a perception that safety is lower than desired (i.e. low reassurance) is associated with reduced likelihood of walking (Foster et al., 2016; Warr, 1990). CIE 236:2019 (CIE, 2019) also identifies feeling of safety (i.e. reassurance) as a primary need of pedestrians, alongside physical safety (e.g. identifying pavement trip hazards), the ability to see (e.g. evaluation of other pedestrians; wayfinding), and the ability to be seen (e.g. by drivers to avoid collisions).

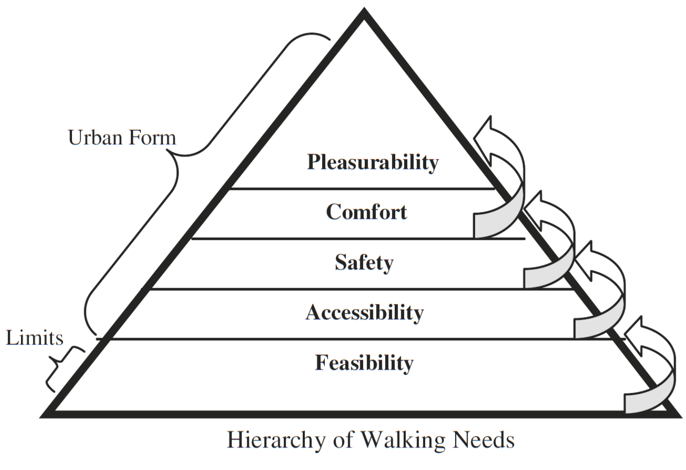


Figure 1.3. Hierarchy of walking needs (Alfonzo, 2005, p.820).

1.3.2 Factors influencing pedestrian reassurance

Past research shows reassurance is influenced by distal factors and proximal factors (Unwin and Fotios, 2011; van Rijswijk, 2016). Distal factors have an indirect influence on reassurance, and are independent of the immediate surroundings of a pedestrian. They are related to individual characteristics, such as personality and past experiences (Skogan and Maxfield, 1981), and social, political and cultural aspects, such as society norms, media coverage of crime, and the social representations of crime (Heath and Gilbert, 1996; Pain, 2000; Valera and Guardia, 2014).

On the other hand, proximal factors have a direct influence on reassurance, and are based on immediate environmental cues of a pedestrian’s surroundings. They are related to the physical characteristics of the environment such as prospect, refuge/concealment, escape/entrapment, and road lighting (Blobaum and Hunecke, 2000; Fisher and Nasar, 1992; Loewen et al., 1993; Naser and Jones, 1997; Nasar et al., 1993). Prospect is defined by how clearly the physical layout of a space allows one to see. It measures both a pedestrian's ability to see ahead and anticipate encounters, and their own visibility to others (Appleton, 1966; van Rijswijk and Haans, 2018). Along a path, natural features like bushes, and artificial features like blind corners and shadows create hiding places. These places can be used by offenders to conceal themselves and await an opportunity to attack (referred to as *concealment* in the literature), or by victims seeking to escape potential harm (referred to as *refuge* in the literature) (Fotios et al., 2015; van Rijswijk and Haans, 2018). Entrapment refers to physical barriers that hinder escape, and the availability of various exit options along a route or in a given area (Nasar and Jones, 1997). Locations with high levels of prospect, refuge and escape, and low levels of concealment and entrapment tend to be associated with higher reassurance (Boomsma and Steg, 2014; Fisher and Nasar, 1992; Greene and Greene, 2003; Haans and de Kort, 2012; Hassinger, 1985; van Rijswijk et al., 2016). Previous research also shows reassurance is improved with road lighting. For example, Fotios et al. (2015) show that road lighting increases the level of reassurance similar to that of having access to help, and surpassing that of prospect and refuge. The reason pedestrians value lighting more could be because it influences these factors in a positive manner, such as enabling them to better see and evaluate the degree of prospect and refuge in a location (van Rijswijk and Haans, 2018).

1.3.3 The role of road lighting in pedestrian reassurance

After dark, pedestrian reassurance declines because the anonymity afforded by darkness can encourage unethical behaviour, such as criminal activity (Doleac and Sanders, 2015); decrease in human presence after dark can heighten feelings of isolation and reduce the perception of accessibility to help from others (Uttley et al., 2024); and reduced visibility after dark (Plainis et al., 2005) makes it harder to identify potential threats and provides cover for those intending harm, making it more difficult for potential victims to identify escape routes, if needed (Dravitzki et al., 2003; Schaller et al., 2003). Road lighting is expected to support reassurance after dark because it reduces the sense of after dark anonymity, and deters dishonest behaviour such as criminal activity (Hirsh et al., 2011; Zhong et al., 2020). Road lighting also improves how well pedestrians can see and be seen (CIE, 2019) and, therefore, aids the visual component of evaluations of prospect, refuge and escape. For example, road lighting can increase visibility and allow pedestrians to identify potential threats at a greater distance (Boyce and Gutkowski, 1995; Caminada and van Bommel, 1980). Besides these direct visual effects, better road lighting can also indirectly improve reassurance through changing public perception about crime, increasing street activity, and influencing social dynamics, such as enhancing informal surveillance or improving community pride (Painter, 1994; Pease, 1999; Unwin and Fotios 2011; Welsh and Farrington, 2008).

Past studies, including those which specifically focus on lighting and those which do not have a specific focus on lighting, have concluded that road lighting is an important factor for pedestrian reassurance. For example, in a lighting focused study, Herbert and Davidson (1994) investigated the impact of changes to road lighting (replacing the existing low pressure sodium lamps with new high pressure sodium lamps) on reduction of fear of crime in two UK cities. This was done by conducting household interviews before and after the lighting change, from which it was concluded that the lighting improvements had clear positive impact on reducing the level of fear of crime experienced by local residents.

A focus on lighting in some studies, may perhaps force a conclusion that lighting is important. For example, in the Herbert and Davidson study the change in road lighting might have been obvious to residents, and they responded positively because they appreciated the local authority spending money in their area. Other studies have examined a wider range of environmental factors, such as prospect, refuge and escape, and these also tend to conclude that lighting plays an important role in reassurance. For example, Loewen et al. (1993) asked people to describe the environmental factors they associate with safety: after coding their responses into broad categories, lighting was the most mentioned category followed by open space (prospect) and access to refuge. In their follow-up study, these three factors were portrayed in a series of photographs, with eight different combinations (present vs absent) of the lighting, prospect and refuge in 16 photographs of outdoor scenes. Participants were asked to rate perceived safety while observing each image using a 5-point response scale which ranged from 1=*Not at all safe* to 5=*Very safe*. The results suggest that the variation in lighting had a bigger impact on ratings than did prospect or refuge (Table 1.1).

Table 1.1. Ratings of safety for different combinations of presence and absence of lighting, prospect, and refuge in photographs of outdoor scenes (redrawn from Table 2 in Loewen et al. (1993)).

	Mean ratings for combinations of light, prospect and refuge*			
	prospect + refuge	**prospect + NO refuge**	**NO prospect + refuge**	**NO prospect + NO refuge**
light	4.33	3.34	3.02	2.42
NO light	2.03	1.82	1.63	1.27
Increase in rating in presence of light	2.30	1.52	1.39	1.15

* Using a 5-point response scale which ranged from 1=*Not at all safe* to 5=*Very safe*

1.4 Guidelines of road lighting for pedestrians

Guidelines are essential for providing road lighting that is both suitable and efficient for its purpose. Lighting design recommendations for pedestrians is provided by CIE 115:2010 (CIE, 2010) as the international standard, with EN 5489-1:2020 (BSI, 2020) and EN 13201-2:2015 (BSI, 2015a) offering the national equivalent in the UK.

CIE 115:2010 (CIE, 2010) and EN 13201-2:2015 (BSI, 2015a) provide guidance for different road users including motorists, cyclists and pedestrians. The lighting design criteria for pedestrians are specified in six different P lighting classes (P1 to P6), with illuminance the primary factor distinguishing the six classes. For each lighting class, recommended average photopic horizontal illuminance and minimum horizontal illuminance are given, with minimum vertical illuminance and minimum semi-cylindrical illuminance provided as additional requirements when facial recognition is necessary (Table 1.2).

Table 1.2. P lighting classes and recommended illuminances for pedestrians (redrawn from Table 3 in EN 13201-2:2015 (BSI, 2015a, p.11)).

Lighting class	Average horizontal illuminance (lx)* [minimum maintained]	Minimum horizontal illuminance (lx) [maintained]	Additional requirement if facial recognition is necessary	
			Minimum vertical illuminance (lx) [maintained]	Minimum semi-cylindrical illuminance (lx) [maintained]**
P1	15	3.0	5.0	5.0
P2	10	2.0	3.0	2.0
P3	7.5	1.5	2.5	1.5
P4	5.0	1.0	1.5	1.0
P5	3.0	0.6	1.0	0.6
P6	2.0	0.4	0.6	0.2

* To provide for uniformity, the actual value of the maintained average illuminance shall not exceed 1.5 times the minimum average horizontal illuminance value indicated for the class.
** The minimum semi-cylindrical illuminance for P1 is 3.0 and for P6 is 0.4 in Table 7 of CIE 115:2010 (CIE, 2010, p.19)

The guidance in EN 5489-1:2020 (BSI, 2020) is based on road type rather than road user, with the guidance for subsidiary roads targeting pedestrians. The same lighting design criteria given in EN 13201-2:2015 (BSI, 2015a) is used, the difference being the number of lighting classes (four lighting classes: P3 to P6) and the criteria for choosing the appropriate P-class (traffic flow, the speed limit, and the environmental zone - see Table A.5 of that document).

CIE 115:2010 (CIE, 2010) specifies that the P lighting classes within Table 1.2 are applicable to the illumination of areas used by pedestrians and pedal cyclists, encompassing a variety of road areas and locations such as segregated footpaths, paths adjacent to roadways, paths along carriageways, and those in parking facilities.

CEN/TR 13201-1:2014 (BSI, 2014) provides guidelines on the selection of the most appropriate lighting class defined in EN 13201-2:2015 (BSI, 2015a), defining pedestrian and low speed areas as "*relevant area reserved for use by people on foot or using bicycle, and drivers of motorised vehicles at low speed (≤ 40 km/h)*" (BSI, 2014, p. 6). Given the focus of this thesis on these areas, the P class is applicable.

Selection of the appropriate P-class, and hence recommended minimum illuminance, for a given situation is based on different parameters: traffic speed, traffic volume/use intensity, traffic composition, the presence of parked vehicles, and the level of ambient luminance. Each of these parameters is given a weight (weighting value (V_W)) (Table 1.3), and the number of the appropriate P-class is calculated by subtracting the sum of the weighting values (V_{WS}) from six (see equation 1).

$$Number\ of\ P\ class = 6 - V_{WS} \quad (1)$$

If the resulting value is below zero or zero, the P1 lighting class is recommended by the guideline. If the calculations give a fractional value, the guidance recommends to round down to the next lower P-class, in other words, a higher illuminance. Effectively, P6 with the lowest illuminance is the starting point, and the weightings determine if more illuminance is necessary.

Table 1.3. Parameters for the selection of appropriate P-class for pedestrians (redrawn from Table 4 in CEN/TR 13201-1:2014 (BSI, 2014, p.13)).

Parameter	Options	Description	Weighting value V_W
Speed	Low	V ≤ 40 km/h	1
	Very low	Walking speed	0
Use intensity*	Busy		1
	Normal		0
	Quite		-1
Traffic composition	Pedestrians, cyclists and motorised traffic		2
	Pedestrians and motorised traffic		1
	Pedestrians and cyclists only		1
	Pedestrians only		0
	Cyclists only		0
Parked vehicles	Present		1**
	Not present		0
Ambient luminosity	High	Shopping windows, advertisement expressions, sports fields, station areas, storage areas	1
	Moderate	Normal situation	0
	Low		-1
Facial recognition	Necessary		Additional requirements
	Not necessary		No additional requirements

* This is called *Traffic volume* in Table 7 of CIE115:2010 (CIE, 2010, p.19) and has five options with intermediate weightings (Very high=1, High=0.5, Moderate=0, Low=-0.5, Very low=-1).
** This is 0.5 in Table 7 of CIE 115:2010 (CIE, 2010, p.19)

1.5 Evidence for guidelines of road lighting for pedestrians

The basis of current lighting standards is unknown (Fotios, 2020; Fotios and Gibbons, 2018). Specifically, CIE 115:2010 (CIE, 2010) and EN 13201-2:2015 (BSI, 2015a) fail to justify the basis of selecting six lighting classes and the recommended illuminances. Current recommendations seem to be arbitrary and based on consensus rather than sound empirical evidence (Boyce, 1996); they are mostly driven by local expectations, and the experience and subjective judgments of lighting professionals and designers. The rationale behind the weighting parameters also remains unexplained, and CIE 115:2010 (CIE, 2010) and CEN/TR 13201-1:2014 (BSI, 2014) offer limited supporting evidence. For example, no explanation is provided for the recommended changes in P-class based on the value of a single or multiple weighting values. This method relies on the assumption that weighting factors have a cumulative effect, but research (e.g. Aarts and van Schagen (2006)) has shown that these factors may also interact with each other; the effect of one factor can be influenced or changed by the presence of another factor, and it is not simply a case of adding the effects of the factors together. Without an empirical basis, the weighting values could lead to illuminance recommendations which are either too high or too low.

The data used in the guidelines is also out of date. The underlying studies in CIE 115:2010 (CIE, 2010) about crash risk and crime are not only at least 2 decades old, during which numerous relevant factors such as light sources have evolved, but are also inconclusive and acknowledged to lack sound data. For instance, a cited US study [Tien, 1979] found no significant relationship between incidences of crime and public lighting.

According to EN 5489-1:2020 (BSI, 2020, p.32) one reason for installing road lighting in subsidiary roads is to "*allow pedestrians to … feel more secure* [and] … *helping to reduce fear of crime*". CIE 115:2010 (CIE, 2010, pp.15-16) states that good lighting in a residential area "*discourages crime against the person and property... and imparts a greater sense of security*". None of the criteria set out in CIE 115:2010 (CIE, 2010) for selection of the appropriate P-class relate to the stated aims of supporting pedestrians' feelings of security, nor to the effect on perceived security of a change in lighting class.

The significant variation in lighting guidelines worldwide, especially among countries with similar infrastructure, is also a cause for question. For instance, the recommenced horizontal illuminance in Japanese guidelines is 3.0 to 5.0 lx for local roads (Japanese Standards Association, 1988), much lower than the P-class in the UK. Factors such as cultural and environmental differences explain some variation, but if guidelines were based on empirical and universal evidence, they should lead to more agreement between the recommendations.

While current guidelines offer consistency in lighting design, evidence-based criteria are crucial. This is especially important considering the potential consequences of unnecessarily high light levels (such as excessive energy use and light pollution) or low light levels (such as insufficient visual benefit to the pedestrian). Empirical evidence helps balance competing needs, such as the need for lowering light levels for better sky visibility or wildlife conservation with requirements for avoiding increased tripping hazard or reduced reassurance.

1.6 Providing sufficient light

Designing effective lighting requires careful consideration of numerous factors, including safety, light pollution, glare, energy use, cost, and environmental impact. Increasing reassurance through higher light levels often conflicts with these other concerns. The designer's role is to find the optimal balance, maximising positive outcomes while minimising harm.

Understanding the purpose of road lighting for pedestrians is essential before determining appropriate lighting levels and balancing competing factors. After dark, road lighting fulfils the primary needs of pedestrians by helping them see and be seen, and be safe and feel safe (CIE, 2019). When considering these needs in designing road lighting, in addition to the benefits of road lighting mentioned in section 1.3.3, the negative side effects that road lighting has on those beyond the direct user (i.e. pedestrian) also need to be taken into consideration (Lucas et al., 2014). Some of the negative externalities of road lighting are its impact on wildlife, the environment, and energy consumption (CIE, 2019).

1.7 Research aim

This research aims to determine the optimal road lighting illuminance necessary for pedestrian reassurance, and contributes to the evidence underpinning the road lighting standards outlined in Section 1.4. Exploration of methods used in reassurance studies forms an integral part of this aim.

1.8 Thesis structure

This thesis is divided into four parts and 10 chapters (Figure 1.4). Chapter 1 introduces the context of road lighting for pedestrians and explains the need for new evidence to support or update current guidelines. Chapter 2 presents a critical review of previous research about pedestrian reassurance and a review of existing methods used in those studies, and informs the formulation of the research hypotheses. That review concludes by raising six hypotheses that are tested in the three experiments reported in this thesis. Experiment 1 is a pilot study to refine the day-dark method used in Experiment 2, and explores the impact of the time of day for daylight evaluations on day-dark differences in reassurance ratings. Chapter 3 describes the method used in Experiment 1, with the results presented in Chapter 4. Using this refined day-dark method, Experiment 2 explores how different illuminances affect pedestrian reassurance, and whether higher illuminances diminish the disparity in reassurance between males and females. The method for Experiment 2 is presented in Chapter 4 followed by the results in Chapter 5. Experiment 2 is a subjective measure of reassurance, and therefore, to provide comparison, Experiment 3 is conducted using an objective measure – travel counts. The method and results of Experiment 3 are presented in Chapters 7 and 8, respectively. Chapter 9 provides an overview of the thesis by providing a summary and discussion of the findings of the three experiments to assess whether they support the postulated hypothesis, and provides suggestions for optimal illuminance for pedestrian reassurance. It also discusses the limitations of the current research and provides suggestions for future research. The conclusion is presented in Chapter 10.

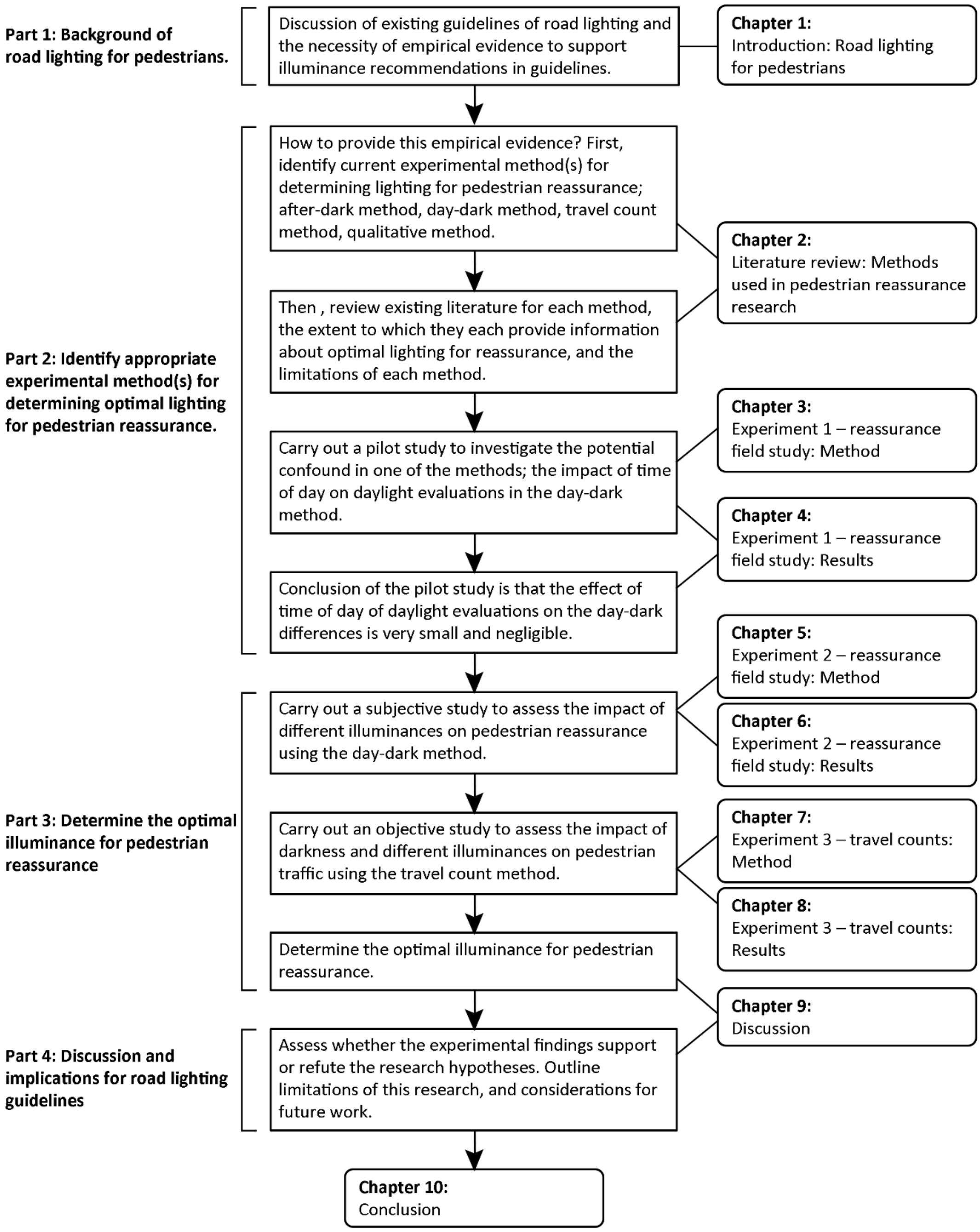


Figure 1.4. Summary of the thesis structure.

1.9 Summary

This thesis focuses on road lighting for pedestrians, and aims to provide empirical evidence regarding optimal illuminance for pedestrian reassurance. Lighting guides provide design recommendations, such as specific illuminance targets. However, the basis for these recommendations is largely unclear and undocumented, making it difficult to access and evaluate them. Further research is needed to validate these guidelines or inform the development of new ones. New evidence should be based on the primary goals of road lighting for pedestrian, one of which is pedestrian reassurance. Chapter 2 explores methods for collecting evidence on pedestrian reassurance and road lighting, and reviews existing research on the subject.

CHAPTER 2. LITERATURE REVIEW: METHODS USED IN PEDESTRIAN REASSURANCE RESEARCH

2.1 Introduction

Chapter 1 provided an overview of current UK and international road lighting standards, and outlined how road lighting contributes to pedestrian reassurance. It highlighted that current road lighting guidelines, specifically guidelines for target illuminances, lack empirical support, and emphasised the requirement to provide such empirical evidence. A key step in providing this evidence is to identify the most appropriate experimental method(s) for determining optimal lighting for pedestrian reassurance. This chapter reviews past research on pedestrian reassurance and road lighting, outlining the methods used, their limitations, and the extent to which they provide information about optimal lighting for reassurance.

2.2 Visual tasks of pedestrians

In Chapter 1, the needs of pedestrians were outlined as reassurance (such as feeling safe from risk of crime), physical safety (such as trip hazard detection), being able to see (such as for interpersonal evaluations and way finding), and to be seen (such as for crash risk avoidance). This thesis focuses on reassurance, because reassurance is a determining factor of light levels in current road lighting guidelines; reassurance requires a higher illuminance than, for example, trip hazard detection or crash risk (CIE, 2019). Another reason to focus on reassurance is because it is not subject to the uncertainties surrounding other pedestrian needs, such as the use of road lighting to aid interpersonal evaluations (e.g. using road lighting to help with evaluation of a pedestrian's face as they approach, may subject that pedestrian to uncomfortable glare (Fotios et al., 2024)).

Pedestrian reassurance is important because it can lead to more walking due to the significant association between walking and perceived safety (Kerr et al., 2016); those who feel safer are more likely to walk after dark (Foster et al., 2004; Mason et al., 2013; Roman and Chalfin, 2008). Road lighting can increase feelings of reassurance (Lorenc et al., 2013; van Cauwenberg et al., 2012a) and is anticipated to lead to more likelihood of walking (Foster et al., 2016; Warr, 1990). However, there is lack of sufficient evidence for determining optimal illuminance for reassurance, one reason being the methods employed in previous research (see section 2.3).

2.3 Past studies of lighting and pedestrian reassurance

Of those studies which have investigated how road lighting affects pedestrian reassurance, some assessed lighting as a single entity, such as existing vs improved (e.g. Akashi et al. (2004)) or absent vs present (e.g. Fotios et al. (2015) and Loewen et al. (1993)), but without consideration to the precise nature of changes, if any, in lighting characteristics. Other studies explored the effect of variations in particular lighting characteristics, such as differences in illuminance (e.g. Boomsma and Steg (2014) and Ishii et al. (2007)), spectral power distribution (e.g. Boyce et al. (2000) and Knight (2010)), and spatial distribution (e.g. Haans and de Kort (2012), Hanyu (1997) and Kostic and Djokic (2014)). These studies generally tend to conclude that more lighting enhances reassurance. For example, in a study of predominantly residential areas with different illuminances and light spectrum [Svechkina et al., 2020], the level of reassurance reported by participants was rated significantly higher in well-illuminated (point horizontal illuminance > 18.52 Lux) areas compared to areas with poor illumination (point horizontal illuminance < 18.52 Lux). This thesis focuses on illuminance rather than other characteristics of light such as spatial distribution or light spectrum.

2.3.1 Different methods in past studies

The conventional method for investigating reassurance involves assessing reassurance only after dark, usually using a limited number of different light levels. Other less widely used alternatives are the day-dark method (pioneered by Boyce et al. (2000)), pedestrian travel counts (e.g. Fotios et al. (2019b)), and qualitative approaches such as interviews (e.g. Fotios et al. (2015)). In the day-dark approach, reassurance surveys are performed in daylight and after dark in the same location, and effective lighting is defined as that which minimises the difference between these two ratings. In the travel count method, the number of pedestrians travelling after-dark under different lighting conditions are compared to assess the effect of darkness on pedestrian traffic, with the assumption that if reassurance declines after dark, then fewer people will decide to walk. In interviews, participants are asked to describe their feeling (or not) of reassurance in different scenarios, but without hinting a specific focus on road lighting or reassurance.

The studies using these experimental methods employ different procedures to investigate pedestrian reassurance. These procedures can be categorised according to their provision of quantitative or qualitative data, and subjective or objective evaluations, as shown in Table 2.1.

Table 2.1. Categorisation of procedures used in the study of road lighting and pedestrian reassurance.

	Subjective	**Objective**
Quantitative	Category rating in response to questions about, e.g. the degree of safety perceived at a given location.	Counting the numbers of pedestrians passing a specific point
Qualitative	Narrative response to questions about reassurance	(Not previously used)

Quantitative studies are those that involve the collection and analysis of numerical data to describe (quantify) the magnitude of something (Brymn, 2016; Walliman, 2011), for example, how safe pedestrians feel at night. Analysis of data is done through mathematical models and statistical tests, to identify patterns and trends, and establish statistical relationships (Lampard and Pole, 2013; Walliman, 2011). Qualitative data, on the other hand, deals with non-numeric data such as images, observations, and descriptions expressed through narratives and text (Corrine, 2011; Walliman, 2011). Analysis is carried out based on interpretation and understanding of meanings of words, concepts, experiences, and perspectives, and by mapping the interconnections between them. Examples of qualitative analysis are identifying recurring themes (thematic analysis), interpreting meanings (content analysis), or examining language and communication (discourse analysis) (Esterberg, 2002). The key difference between the two lies in the data (numbers versus words or descriptions), the data analysis approach (statistical versus interpretive), and the purpose of the method (testing theories or hypotheses versus exploring and developing new theories and hypotheses).

Subjective methods involve human participants who make an evaluation of the stimulus to which they are exposed, either by report or by modifying the stimulus. The results are therefore based on the participant's opinion, perception and judgement (Boyce et al., 2000; Tsolkas et al., 2017) and can be influenced by their emotions, past experiences, interpretations and personal feelings (Robinson, 2019). Subjective methods expose the test participants' *stated preference* (i.e. what people say they do). Objective methods are remote observations of behaviour and actions where the *revealed preference* of participants is exposed (i.e. what people actually do). There is no input of cognitive thought into participants' responses; it eliminates personal biases and is based on observation (Daston and Galison, 2007).

Quantitative subjective research of pedestrian reassurance typically uses category rating scales, where the degree of reassurance (and other factors) given by a certain lighting condition is indicated by picking a category along the rating scale. Therefore, research using quantitative subjective methods helps understand what pedestrians feel when walking after-dark by using questionnaires. This, however, does not reveal why they feel that way; for this a qualitative approach by conducting interviews is required. In qualitative subjective research, the participant's response is descriptive; they respond to an open question, which can help contextualise their perceptions of safety and its relationship with road lighting. A third procedure is quantitative objective research which records observed data such as the numbers of pedestrians or their walking speed in a given situation. These are observations of pedestrian's behaviour to understand how they act upon their opinions in the real world, by measuring and quantifying their reflected behaviour. So far, no research has been carried out using qualitative objective procedures. Unlike quantitative research, which typically achieves objectivity through observation and numerical data, qualitative research aims to understand meaning, experiences, and perspectives through researcher interpretation, often derived from interactions with participants (e.g., interviews, focus groups). This inherent interpretive element might suggest that a qualitative objective procedure is paradoxical. Employing a structured analytical framework, such as a panel observing and interpreting pedestrian behaviour, could be one example of a qualitative objective study. Further research is necessary to identify a viable approach for implementing a qualitative objective procedure.

2.3.2 The after-dark method

In the conventional after-dark approach of assessing pedestrian reassurance, evaluations of different light conditions are carried out after dark (i.e. when the road lighting is switched on) or using scenes simulating after dark conditions (e.g. Boomsma and Steg (2014)). Participant responses are then compared to assess the effect of different light conditions on reassurance.

Table 2.2 presents a sample of reassurance studies using the after-dark approach to investigate how pedestrian reassurance is influenced by different road lighting conditions. Most after-dark studies are carried out as field studies in which the participants are asked to rate their level of reassurance after dark. These evaluations are conducted using either a repeated measures design where test participants repeat the evaluation in succession at a number of locations (or at a single location but with a change to the lighting), or an independent samples design where participants evaluate only one location or scenario. The degree of reassurance to a given scenario is recorded using a questionnaire with one or more category rating response scales. For example, while visiting 10 different locations, Fotios et al. (2019a) asked participants to rate how risky they felt it would be to walk alone in each location at night (amongst other questions) with responses given using a six-point rating scale ranging from 1 to 6, with 1 labelled *not at all risky* and 6, *very risky*. The resulting data were analysed by comparing mean responses to questions under different lighting conditions. If higher illuminance enhances reassurance, this would be seen as a significant decrease in the response to the question posed by Fotios et al.

In addition to field surveys, some studies used home surveys, which are self-administered surveys sent to people at home rather than recruiting specific people. One benefit is that a large number of responses can be acquired. However, the administration of the questionnaire is not always restricted to after-dark hours or in the target outdoor locations; if participants fill the survey at home, in daytime, it is unclear how well those responses correlate with real experience after dark in a road.

Other studies have used photographs of outdoor locations or simulated images of different outdoor locations. One limitation of such studies is that it is not clear whether evaluations of reassurance in a lab are the same as that in a road, as photographs or video clips cannot represent the dynamics of real-world situations (Austin and Sanders, 2007; Toet and van Schaik, 2012).

Table 2.2. Sample of past studies of lighting and pedestrian reassurance – after-dark approach.

Study	**Method**	**Sample (gender balance*)**	**No of locations / test stimuli (for lab surveys)**	**Lighting changes**	**Does road lighting have a benefit? (p-value)**
Akashi et al. (2004)	Home study	25 (not stated)	1	Light spectrum	Yes
Atkins et al. (1991)	Home study	191 (not stated)	1	Comparing two illuminances	Significant increase for F but not for M or for F & M combined - insufficient data to support statistics
Bernhoft and Carstensen (2008)	Home study	1905 (43.2% to 63% M,59.7% to 62.2% F)	Not stated	Lighting as a single entity (presence / absence of road lighting)	No
Blobaum and Hunecke (2005)	Field study	122 (53 M & 69 F)	8	Comparing two illumiances	Yes - enhanced reassurance in high light level

					locations (p<0.01)
Boomsma and Steg (2014)	Lab study (virtual environment videos)	88 (27 M & 61 F)	4	Comparing two scenes intended to represent 12lx and 17lx.	Yes - higher light levels stated as safer (p<0.001)
van Cauwenberg et al. (2012a)	Home study	48,879 (44.3% to 44.8% M & 55.2% to 55.7% F)	135 municipalities (36 urban, 50 semi-urban, 49 rural)	Lighting as a single entity (presence / absence of road lighting)	Road lighting increases the feeling of safety in some age and gender groups.
Haans and de Kort (2012)	Field study	50 (28 M & 22 F)	1	Spatial distribution	Yes (spatial distribution has significant effect on perceived safety)
Hanyu (1997)	Lab study (photographs of real locations)	28 (20 M & 8 F)	20	Brightness and uniformity	Yes (strong to moderate effect)
Herbert and Davidson (1994)	Interview of households	350 (not stated)	10	Two light levels (changes in illuminance not stated)	Yes (trends for an improvement in reassurance but no statistical analysis)
Kostic and Djokic (2014)	Field survey	112 (62 M & 50 F)	1	Illuminance and Spatial distribution	Yes (enhanced reassurance with higher uniformity)
Knight (2010)	Field survey	356 (non-equal balance)	8	Light spectrum	Yes (using white light instead of yellow light significantly enhances perceived safety at comparable average illuminances)
Morante (2008)	Home Study	80 (not stated)	2	Light spectrum	No
Nair et al. (1993)	Field Study	33 (25% M & 75% F)	1	Lighting as a single entity (unspecified improvements to lighting)	No
Painter (1994)	Field Study	Not stated (Not stated)	3	Comparing two illuminances	Yes (trends for an improvement in reassurance but no statistical analysis)
Peña-García et al. (2015)	Field Study	275 (not stated)	5	Comparing five illuminances (14.63 lx to 57.23 lx)	Yes (better uniformity and higher mean illuminances enhance feeling of safety - did not reach

					statistical significance)
van Rijswijk (2016)	Lab study (photographs of real locations)	83 (61 M & 22 F)	100	Comparing three illuminances	Yes (higher light levels stated as safer)
Svechkina et al. (2020)	Field Study	106 (not stated)	257	Comparing multiple illuminances & blue and red light	Yes (significantly higher reassurance in well-illuminated locations - point horizontal illuminance > 18.52 Lux)
Viliunas et al. (2013)	Field Study	7 (F only)	1	Spatial distribution	Yes (association between reassurance and the light source's luminous flux)
Vrij & Winkel (1991)	Field Study	160 (48 M & 112 F)	1	Comparing two illuminances (0.24 lx and 1.31 lx)	Yes - enhanced rating of safety with higher illuminance (p<0.01)

* M=male, F=female

Previous after-dark studies have generally found that among the light levels studied, the higher light level receives higher reassurance ratings. This inherent experimental range bias towards higher light levels, leads to trivial recommendations of higher illuminances, instead of determining an optimal illuminance (Fotios and Castleton, 2016); any suggested optimal illuminance is likely to be rendered insufficient by another study using a higher illuminance.

Two limitations can be associated with the after-dark approach: stimulus range bias, and location specific environmental differences.

First there is concern regarding stimulus range bias in subjective evaluations. Stimulus range bias means participants' judgment or perception of each stimulus in the experiment is influenced by the range of stimuli presented (Poulton, 1977; 1982; 1989); how participants perceive something can change depending on what other things they are comparing it to in the experiment. This means that participants tend to use the full range of response categories available to them, and instead of making absolute judgments about the reassurance gained from a particular light level, make relative judgments with reassurance gained from the other light levels experienced during the experiment (Fotios and Castleton, 2016). For example, in a study by Simons et al. (1987) participants were asked to rate their overall impression of roads lit to illuminances ranging from 1.0 to 12.0 lux, using a nine-point scale ranging from *very poor* to *very good*. In another study [de Boer, 1961], a similar nine-point scale was used, but this time applied to roads illuminated to a wider range of illuminances - 1.0 lux to 71 lux. Range bias is revealed because the illuminances suggested in each study to be suitable for a given quality of lighting were different. For example, while participants in Simons et al. (1987) considered lighting of 10 lux to be *good*, those in the de Boer (1961) study required a much higher illuminance of 21 lux to give the same rating. Range bias can also lead to recommendations of ever higher light levels. For example, consider two reassurance studies, one which compared two relatively low illuminances (0.24 and 1.31 lux) [Vrij and Winkel, 1991] and the other which compared two relatively high illuminances (12 and 17 lux) [Boomsma and Steg, 2014]. In both cases, the higher reassurance is gained with the higher illuminance of the two compared, so while Vrij and Winkel concluded in favour of 1.31 lux, Boomsma and Steg instead conclude in favour of the considerably higher 17 lux.

The second limitation is that the after-dark method does not consider the environmental differences between the test locations; the effect of variations in factors other than lighting, such as physical features affecting prospect, refuge and escape (Aultman-Hall et al., 2009; Blobaum and Hunecke, 2005; Fisher and Nasar, 1992; Foster et al., 2004; Fotios et al., 2019a) in the different locations, on a person's reassurance, is not considered. This means that when comparing different roads, any effect of variations in light level can be diminished or amplified by differences in factors other than lighting, such as the different level of prospect in the locations. Another issue with comparing after-dark ratings is that it does not account for the baseline and underlying level of reassurance in a given location. This makes it difficult to isolate the impact of road lighting (Fotios and Castleton, 2016). For example, imagine roads A and B with daylight reassurance ratings of 3 and 9, respectively (on a rating scale ranging from 1=*feel not at all safe* to 9=*feel very safe*). If after-dark reassurance rating for road A is 1 and road B is 2, one might incorrectly conclude that road B has better lighting simply due to the higher after-dark rating compared to road A, without considering the relatively larger change in the after-dark rating of road B (9-2=7) compared to road A (3-2=1). Conversely, lighting of even high illuminance may have little effect on reassurance at a location considered to be extremely threatening.

2.3.3 The day-dark method

Four studies (Table 2.3) have tried to overcome some of the limitations of the after-dark method by comparing day-dark differences in reassurance ratings. In this method, reassurance at a given location is evaluated in daytime as well as after dark, in a repeated measures design. Analysis of lighting effectiveness considers the difference between the daytime and after-dark ratings of reassurance, with good lighting defined as that which minimises the day-dark difference.

Table 2.3. Past studies of lighting and pedestrian reassurance – day-dark approach

Study	Sample (gender balance*)	No. of locations*"	Illuminance range*** (lx)	Does road lighting have a benefit? (p-value)
Boyce et al. (2000) *(field study 3)*	18 (gender balance not stated)	24	~0.5 - ~48.2	Yes - enhanced rating of perceived safety with higher median illuminance (statistical significance not reported)
Fotios et al. (2019a)	24 (12 M, 12 F)	8	4.2 - 10.6	Yes – enhanced perceived safety with higher minimum illuminance (p<0.001)
Wei et al. (2024)	35 (31 M, 4 F)	11	2.5 - 17.2	Yes – enhanced perceived safety with higher minimum illuminance (p<0.05)
Unwin (2015) *(winter study)*	46 (23 M, 23 F)	9	1.92 - 9.98	Yes - higher illuminance enhances perceived safety w (p<0.001)

* M=male, F=female

** All locations were urban roads, with the exception of Boyce et al. (2000) who examined parking lots.

*** All values are mean horizontal illuminances, with the exception of Boyce et al. (2000) which is median illuminance. Boyce et al. did not report the illuminance values and the values reported here are estimated by visually checking Figure 5 (p.83) in that source.

Studies using the day-dark difference suggest that increasing illuminance beyond a certain point doesn't necessarily improve reassurance, indicating an optimal illuminance. For example, in a study of 24 different parking lots in USA (Boyce et al., 2000), the perceived safety of groups of participants in daylight and after dark were measured and plotted against the corresponding median horizontal illuminances (Figure 2.1).

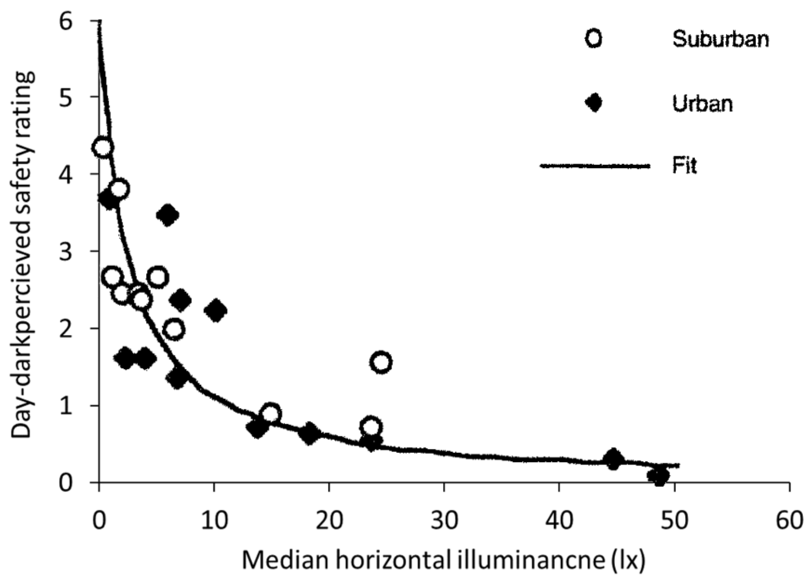


Figure 2.1. Day-dark difference in perceived safety ratings of parking lots in Albany, New York plotted against median horizontal illuminance (redrawn from Figure 7 in Boyce et al. (2000, p.84)). The black and white markers refer to the test locations which were suburban and urban parking lots.

Figure 2.1 shows that higher illuminances were associated with smaller day-dark differences in perceived safety, and that at high enough illuminances this approached zero. However, the positive effect of increases in illuminance plateaued after reaching 10 lx; increasing illuminance beyond 10 lx yielded only minimal reductions in the day-dark difference, whereas decreasing illuminance to below 10 lx resulted in a substantial increase of this difference. This can be a hint that a median of 10 lx represents the optimal illuminance. This outlines one method of determining optimal illuminance: optimal illuminance in the day-dark approach can be found by reducing the day-dark difference, and locating the point of diminishing returns for increased lighting. Other day-dark studies have tried to establish optimal illuminances by suggesting illuminances associated with small day-dark differences such as 0.5 or 1. For example, Fotios et al. (2019a), suggested a minimum illuminance of 2 lx for a day-dark difference of 0.5, and Wei et al. (2024) reported a relatively similar minimum illuminance of 1.8 lx for the same day-dark difference. The optimal lighting recommendations from these day-dark studies require further investigation.

The diminishing returns of higher illuminance observed in the day-dark studies hints at a potential mitigation of the range bias in after-dark ratings. The other limitation of the after-dark method was the risk of confound by non-lighting-related factors. The day–dark method tries to offset these confounding factors and isolate the effect of road lighting by using the daytime ratings as a normalisation factor; the daytime rating acts as the reference point for the baseline level of reassurance in a given location. This means that day-dark difference should potentially be more strongly associated with lighting characteristics such as illuminance, than after-dark ratings, with those lighting characteristics. This is confirmed in one study [Fotios et al., 2019a] which reports higher R^2 values for the association between day-dark ratings and mean and minimum horizontal illuminance, than that for after-dark ratings (Table 2.4).

Table 2.4. Degree of correlation between illuminance metrics and the mean after-dark and mean day-dark ratings in a field study of reassurance in ten locations in Sheffield, UK (redrawn from Tables 2 and 3 in Fotios et al. (2019))

	Correlation	
Horizontal illuminance measure	**Mean after-dark ratings**	**Mean day-dark ratings**
Mean	0.30	0.56
Minimum	0.69	0.79
Uniformity	0.79	0.71

A potential confound to the day-dark method is that the surveys are carried out at different times of day, with the daylight evaluations happening during daytime and the after-dark evaluations in the evenings. This means time-of-day factors can confound the results of the day-dark approach. For example, one change at different times of the day is the number of other people around; research has shown amount of ambient light influences pedestrian activity, with fewer pedestrian around in lower ambient light (Fotios et al., 2019b; Uttley and Fotios, 2017b). The presence of other people contributes to reassurance (Fotios et al. 2015) and thus, a change in the number of other people around in the daylight evaluations compared to the after-dark evaluations may confound any apparent effect of light level on reassurance. This challenges the assumption that the day-dark difference completely isolates the specific effect of road lighting. More research is needed to determine the extent to which time of day of the daylight evaluations in the day-dark approach influences the results.

2.3.4 Walking alone or in groups

CIE 236:2019 (CIE, 2019, p.2) defines reassurance as "the *confidence a pedestrian might gain from road lighting (and other factors) to walk along a footpath or road, in particular if walking alone after dark*". While the definition refers to walking *alone*, that was not the case for most previous reassurance studies listed above (Tables 2.2 and 2.3).

In some studies participants walked as a group of participants to each test location, albeit with responses being recorded after walking around the test location at temporally spaced intervals (Fotios et al., 2019; Johansson et al., 2011; Kim and Noh, 2018). The test locations may be difficult to reach, requiring participants in one study (Boyce et al., 2000) to be driven together to each location, in a minivan. This means participants were in groups and accompanied by the minivan driver, rather than being on their own. The minivan driver, who may or may not have been an experimenter, likely projected some impression of authority. Allocating participants into groups can enhance research efficiency (i.e. more responses can be collected in a short period of time) and supports participant safety during the experiment. However, group evaluations may produce responses that may not reflect individual evaluations. The presence of others, especially authority figures, can encourage socially desirable responses (Sutton and Farrall, 2005) or group conformity (Schulman, 1967), as observation can lead individuals to adhere to perceived norms. Being in a group can also make participants feel safer than if they were walking alone; the presence of others provides a sense of security, as they could potentially offer assistance (Cohen and Felson, 1979), while walking alone can heighten perceived danger (Fyhri et al., 2011).

Similarly, in some studies participants gave their responses whilst accompanied by an experimenter, or at least a person of apparent authority. Examples of this are researchers recruiting passers-by (Peña-García et al., 2015), drivers of the group minivan (Boyce et al., 2000) or researchers following a short distance behind their participant (Blöbaum and Hunecke, 2005). Evidence from Rosenthal (1976) and Rosenthal et al. (2009) shows that awareness of the presence of an experimenter influences the outcome of subjective evaluations. The experimenter or figure of authority may infer the purpose of an experiment, and participants may give responses to help confirm the inferred hypothesis (McCambridge et al., 2012).

Participants in one study [Portnov et al., 2024] visited each location unaccompanied by either the experimenter or other participants, using a map of the locations. Responses were recorded via a mobile app that also captured the time and location. While this approach aligns best with the *walking alone* aspect of the reassurance definition, it also presents other potential problems. Ideally, the participants walked alone during the survey, but it is possible that they were in the presence of others, such as informal groups or friends. Participants may also, knowingly or unknowingly, not adhere to the test instructions. When allowing participants to choose evaluation locations (such as in Portnov et al. (2024)) or recruiting passer-by (such as in Peña-García et al. (2015)), there's a possibility that evaluations will be concentrated in familiar or safe areas to the participants. It is therefore important to assess whether participant accompaniment (whether participants are alone or accompanied by other test participants and/or an experimenter) impacts results.

2.3.5 Category rating scales

Category rating scales are one of the commonly used procedures in day-dark and after-dark reassurance studies, when collecting subjective responses. However, in this procedure, participants may be compelled to evaluate items they wouldn't normally consider or deem relevant, such as road lighting (Fotios et al., 2015); rather than being their own opinion, they may have been prompted to reveal lighting to be an influential factor in reassurance. This could create a misleading impression of a factor's relevance and importance. For example, in a study by Acuña-Rivera et al. (2011) participants were presented with photographs of a deprived residential neighbourhood. In the qualitative method, participants were asked to freely state their impressions about the scenes in the photographs: participants primarily focused on physical disorder in the photos, with limited mention of crime or safety. In contrast, the quantitative method used rating scales specifically addressing disorder and safety. The findings indicated a positive association between ratings of disorder and ratings of unsafety. The rating scales elicited evaluations of reassurance, something which was absent in the qualitative method. The opposite can also be true. For example, in a study of the relationships between street characteristics and perceived attractiveness to walk [Borst et al., 2008], elderly respondents prioritised tidiness, activity and the presence of others, without any mention of lighting, because it was not listed in the 28 characteristics used by the researchers.

Data collected using category ratings can also be influenced by questionnaire design and how the questions are phrased (Farrall et al., 1997; Poulton, 1989; Schwarz, 1999; Tourangeau et al., 2000) as well as the procedures used (Fotios et al., 2015). Most importantly, it is unknown whether a person's subjective response may reflect into actual behaviour, particularly as answers from male participants are prone to socially desirable responding and they may downplay their fear of crime due to social pressure (Sutton and Farrall, 2005; Farrall et al., 2009).

2.3.6 The travel count method

The susceptibility of subjective studies to human bias means they can produce misleading recommendations, and it is important to supplement such studies with those utilising objective measures. Objective measurement can be done, for example, by recording gait characteristics such as walking speed (e.g. De Silva et al. (2017) and Franek (2013)) or involuntary physiological responses such as the pedestrian heartbeat rate or pupil size (e.g. Honig et al. (2007), Kim and Kang (2018) and Widdershoven (2023)), assessing pedestrian route choice (e.g. Basu et al. (2022)), or counting the number of people walking in daylight and darkness (i.e. travel counts) (e.g. Fotios and Robbins (2021) and Uttley and Fotios (2017)). This thesis, focuses on one of these methods, travel counts.

In reassurance studies using travel counts, rather than directly asking pedestrians about safety, which brings the risk of influencing their responses, their behaviour or actions are observed and thus it is their revealed preference which is measured. Previous studies (Table 2.5) have recorded the numbers of pedestrians in daylight, and after-dark in different lighting conditions, and then compared those numbers using an odds ratio, to assess the influence of lighting conditions on frequency of travel. This is based on the logic that if reassurance declines after dark, then fewer people will decide to walk (Uttley and Fotios, 2017). For example, using the biannual daylight savings clock change, Fotios and Robbins (2022) compared the number of pedestrians passing specific locations during the same time of day, while it was daylit on one side of the clock change and dark on the other side of the clock change (known as the case period). This was done for one week immediately before and one week immediately after the Spring and Autumn clock changes. To account for factors other than change in ambient light level (e.g. change in weather, destination, and purpose of travel) which may also influence frequencies of walking, pedestrian numbers during control periods before and after the clock change, in which lighting condition did not change, were also recorded and compared to pedestrian numbers during the case period using an odds ratio (the odds ratio and associated calculations are described in Chapter 7, section 7.7).

General findings of quantitative objective studies are in line with that of quantitative subjective appraisals; the number of pedestrians is significantly higher during daylight compared to after dark, suggesting a significant association between reassurance and daylight. However, the effect of variation in illumination levels after dark has not been assessed so far.

Table 2.5. Past studies of lighting and pedestrian reassurance using travel counts*

Study	Sample	No of locations	Does darkness deter walking?* (Odds Ratio)
Fotios and Robbins (2022)	89,392	Urban (minor, urban roads, near Cambridge the city centre, UK)	Yes (1.29)
Fotios et al. (2019b)	1,735,460	Urban (footpaths in Washington DC metropolitan area, Virginia, USA)	Yes (1.93)
Uttley and Fotios (2017)	521,316	Urban (footpaths in Washington DC metropolitan area, Virginia, USA)	Yes (1.62)

* All studies have assessed only ambient light level and recorded the number of pedestrians using automated counters. Other studies have used this method for cyclists counts (e.g. Uttley et al (2023)) and vehicle traffic (e.g. Fotios and Robins (2022)).

Some studies using this method [Fotios and Robbins, 2022; Uttley and Fotios, 2017) took advantage of the sudden change of lighting conditions during the bi-annual daylight savings clock change and compared the number of pedestrians passing specific locations during one week immediately before and after the clock change. Although assessing data for a short period of time before and after the bi-annual clock change is an efficient method, it raises the concern of reliability of results; the number of events available for analysis may be too small to reach a precise and reliable conclusion (Johansson et al., 2009). One study [Fotios et al., 2019b] tried to overcome the issue of reduced number of events by repeating the study by Uttley and Fotios (2017) but taking advantage of the seasonal change in daylight conditions and using data from across the whole-year. Pedestrian numbers were counted during a specific time of day which is always daylit for part of the year, and then compared to count numbers for the same time of day when it is dark for the other part of the year. Control hours and odds ratio are also used similar to the daylight savings method, to account for the influence of non-lighting factors. Results confirmed the finding of the daylight savings method; for the same time of day, more people engage in walking when it is daylit compared to after-dark. However, the whole-year method yielded a higher OR (1.93) than did daylight savings method (1.62). The apparent increase in pedestrian numbers was greater in the whole-year approach, which may be due to more evident changes in ambient light level in this approach. This thesis considers the biannual daylights saving clock change approach.

Quantitative objective experiments overcome the issues of stimulus range bias and location bias associated with subjective appraisals, and they do not lead participants or influence their responses.

The use of odds ratios further helps to isolate the effect of changes in lighting conditions from non-lighting factors. Despite this, some questions are raised. Uttley and Fotios (2017) gathered data for 2 weeks before and after the clock change, inspired by the work of Sullivan and Flannagan (2002) who analysed vehicle crashes during two 9-week periods on either side of the clock change. The choice of 2 or 9 weeks is arbitrary and it is not clear what the basis is. Also, it is not clear whether a longer period, for example 20 weeks, would be similar to the whole year approach. Uttley and Fotios (2017) used two control hours, 1 h and 3.5 h before and after the case hour to account for non-lighting factors. However, there is the possibility of a systematic spillover effect from the case hour to the control hours, if they are too close to the case hour (Johansson et al., 2009). For example, it is possible that pedestrians are influenced by the transition of ambient light levels during the case period for the control hours closer to the case hour. It is also not clear why four control hours were selected.

So far, data collected in quantitative objective studies do not reveal information about the age or the gender of pedestrians counted. This is because past studies have used automated counters. There is need to further develop these studies to record this data.

2.3.7 The qualitative approach

In experiments using qualitative approaches, instead of rating their degree of reassurance as a quantity, participants are asked to describe their feeling (or not) of reassurance. In one study [Fotios et al., 2015] this was done by asking participants why they are happy (or not happy) to walk in an area, with these areas being pre-selected by test participants and identified in the interviews using photographs. Here an unfocused approach is employed, intentionally avoiding specific focus on lighting or fear, in order to avoid the issues of subjective studies which may bias the respondents to indicate an association between the two.

So far only one study [Fotios et al., 2015] has used this procedure. This study included 53 participants (aged 18-34 and 55-84 years with approximately equal gender balance), whom provided photographs of 210 locations. The results (Figure 2.2) indicate reassurance is associated with the presence of road lighting (road lighting was mentioned by 62% of participants as the reason why they felt reassured or not), providing parallel support for similar results from studies utilising other methods. Although images were provided by participants meaning they were familiar with the locations, they would need to recall memory which is a limitation; an observer may assess an environment differently based on whether they are viewing it through photographs or actually experiencing it in the real world. There is tendency to remember something as lower or weaker (here less bright or safe) when it is judged based on memory compared to the original experience (Uchikawa and Ikeda, 1986; LaBoeuf and Shafir, 2006).

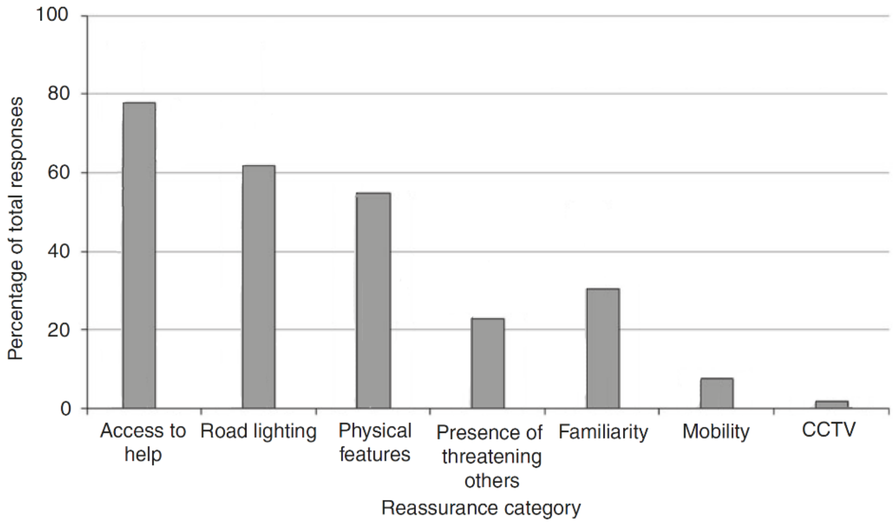


Figure 2.2. Percentage of factors associated with mobility which may aid or hinder free mobility (redrawn from figure 4 in Fotios et al. (2015)). The factors were mentioned by participants in an interview to explain feelings of reassurance when walking alone after dark in different locations, using photographs of those locations. *Mobility* refers to the ease of getting around, as affected by issues like a lack of road crossings and uneven pavements.

2.3.8 Gender

Research indicates a gender disparity in perceived fear of crime, with females expressing greater concern about victimisation than males (Chataway and Hart, 2019). One reason can be that females have a higher sensitivity to vulnerability and risk (Hillinski et al., 2011), and believe that they are less capable in defending themselves against victimisation (Killias, 1990). This can also be due to the tendency among males to discount feelings of risk and report less fear of crime (Smith and Torstensson, 1997).

In objective travel count studies, the investigation of gender differences in reassurance have not been possible, as past studies have used automated counters which do not reveal any information about gender. Studies using subjective self-reports have often recruited roughly equal numbers of male and female participants (e.g. Fotios et al., 2019; Kim and Noh, 2018; Van Rijswijk and Haans, 2017; Vrij and Winkel, 1991), primarily to ensure representative samples rather than to specifically investigate gender differences. In these studies, any variations in male and female responses, if any, were not analysed or reported. However, a number of reassurance studies using subjective evaluations have proposed an association between gender and reassurance with darkness, suggesting darkness to have a bigger impact on perceived safety in females compared to males, when they are outside and in public realms (Fisher and Nasar, 1992; Foster et al., 2004). For example, in one study [Gover et al., 2011] carried out at a university campus in USA, daylight and after-dark ratings of feelings of fear were recorded for male and female participants. Although both genders reported more fear after dark than in daylight, females expressed significantly more fear compared to males.

Another consideration is the impact of road lighting changes on the gender disparity in reassurance. Specifically, whether improved lighting reduces the gender gap. Two studies [Blöbaum and Hunecke, 2005; Boomsma and Steg, 2014] examining the effect of two light levels on feelings of reassurance, found that males generally reported feeling safer than females. However, neither study adequately investigated whether this gender difference varied with the level of light. Blöbaum and Hunecke (2005), for instance, found a nearly significant (p = 0.06) interaction between lighting (high vs. low) and gender, but they did not explain how this interaction manifested - that is, whether the difference between males and females was greater or smaller under the two different lighting conditions.

In a field study of various outdoor lighting types across residential, commercial, and industrial settings, Boyce et al. (2000) assessed the degree of agreement of participants (27 males, 16 females) with the statement “This is a good example of security lighting”. Female participants showed less agreement with the statement than male participants. The plot of the results against horizontal illuminance (Figure 2.3) reveals that the difference between the two genders decreases with higher illuminances, hinting at the potential greater benefit of higher light levels for females compared to males. However, it is not possible to confidently interpret the figure, due to its lack of clarity. It remains to be fully explored whether road lighting has the potential to reduce any gender disparities.

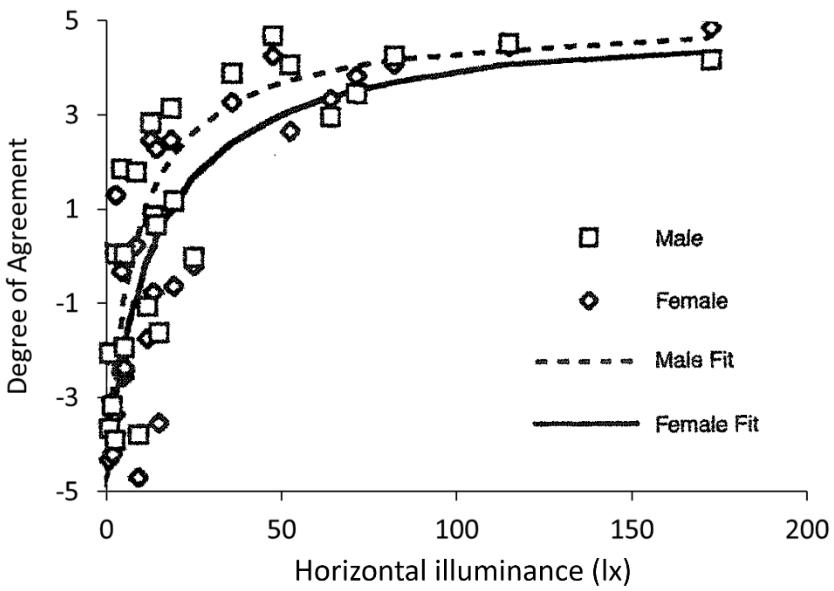


Figure 2.3. Mean degree of agreement of participants to the statement "This is a good example of security lightings" plotted against horizontal illuminance - (redrawn from Figure 3 in Boyce et al. (2000, p.81) for "Field studies 1 and 2").

2.4 Research Hypotheses

This research aims to determine the road lighting illuminance necessary for pedestrian reassurance. Following the literature review, the following hypotheses were formulated to address the research aim.

The literature suggests that the presence of road lighting supports pedestrian reassurance after dark (Fotios et al., 2015; Lorenc et al., 2013). Different studies have been conducted to investigate how pedestrian reassurance is influenced by different road lighting conditions (Tables 2.1, 2.2 and 2.5), these employing controlled changes in the illuminance and/or spectral power distribution (SPD) of lighting, with these changes possibly being accompanied by an uncontrolled and unreported change in the spatial distribution of light as might be characterised by uniformity, and controlled change in uniformity. This thesis focuses on illuminance and whether higher illuminance is associated with higher levels of pedestrian reassurance. This will be tested through H1:

H1: Higher illuminance enhances pedestrian reassurance after dark.

The day-dark approach to measuring reassurance was introduced by Boyce et al. (2000) as an alternative to after-dark ratings. Fotios et al. (2019a) compared the two approaches and found that horizontal illuminance was not significantly associated with after-dark reassurance ratings, but it did associate significantly with the day-dark difference in reassurance. This will be tested through H2:

H2: Illuminance has a stronger association with the day-dark difference than after-dark ratings.

The day-dark method can potentially be confounded by time-of-day; since daylight and after-dark surveys are conducted at different times, temporal variation factors like pedestrian traffic (which is influenced by ambient light (Fotios et al., 2019b; Uttley and Fotios, 2017b) may affect perceived reassurance (Fotios et al., 2015). This will be tested through H3:

H3: Day-dark difference in reassurance ratings obtained at the same time of day is different from day-dark difference in reassurance ratings obtained at different times of day.

The definition of reassurance given in CIE 236:2019 (CIE, 2019) specifically refers to walking alone. Most prior studies deviated from this definition, and rather than being alone, participants were accompanied by other test participants and/or experimenters. Group evaluations may not reflect individual experiences; the presence of other people can create a sense of safety (Cohen and Felson, 1979), contrasting with the heightened perceived danger of walking alone (Fyhri et al., 2011). This will be substantiated through H4:

H4: Evaluations from groups of participants will suggest higher reassurance than evaluations from solo participants for the same lighting conditions.

The literature review has revealed females tend to express a lower degree of reassurance than do males, and that this difference becomes greater after dark (Gover et al., 2011). It is possible that, after dark, using road lighting providing a higher illuminance would reduce the difference between male and female responses (as hinted by the findings of Boyce et al. (2000)). This will be tested through H5:

H5: Higher illuminances reduce the disparity between male and female reassurance after dark.

While subjective surveys gauge perceived reassurance, objective travel counts (odds ratio of the change in number of pedestrians) measure revealed reassurance, based on the principle that a decrease in walking after dark indicates lower perceived safety (Uttley and Fotios, 2017). Ideally, these two approaches should produce comparable results. This will be tested through H6:

H6: Odds ratios determined using travel counts are consistent with reassurance ratings from subjective evaluations.

Three experiments were conducted to test the hypotheses. Table 2.6 shows where these hypotheses were tested.

Table 2.6. The experiments used to test the hypotheses

Hypotheses	Experiment 1	Experiment 2	Experiment 3
H1		✓	
H2		✓	
H3	✓		
H4		✓	
H5		✓	
H6			✓

2.5 Summary

This chapter examined prior pedestrian reassurance research, revealing a general trend in the findings of past research: road lighting, and to some extent higher light levels, tend to increase reassurance. However, past studies are susceptible to biases (e.g., stimulus range, socially desirable responding) and confounding factors (e.g., time of evaluation). The findings of this chapter informed six hypotheses, tested through three experiments. Chapters 3 to 8 detail these experiments, including methods used and the results. The next chapter describes the method used in Experiment 1, a pilot study investigating the impact of time of day on daylight evaluations in the day-dark method.

CHAPTER 3. EXPERIMENT 1 – REASSURANCE FIELD STUDY: METHOD

3.1 Introduction

Chapter 2 reviewed the methods used for measuring pedestrian reassurance, suggesting that the day-dark approach is a better method for collecting subjective evaluations than after-dark-only evaluation. However, it was highlighted that the day and dark evaluations of previous studies (e.g. Boyce et al. (2000) and Fotios et al. (2019a)) were carried out at different times of day, and variations in other factors at different times of day (e.g. the number of other people present) may confound any attribution to lighting. Experiment 1 is a pilot study carried out to investigate the effect of time of day on the daylight evaluations in the day-dark approach (Hypothesis H3). In other words, is a daylight evaluation of reassurance at midday the same as a daylight evaluation of reassurance in the evening?

To do this, the daylight evaluations in Experiment 1 were carried out at two different times of the day: once at around midday (referred to hereafter as *noon daylight*), and once at the same time of day as the after-dark evaluation (referred to hereafter as *evening daylight*). The biannual daylight savings clock change made this possible; the clock change results in an immediate shift from daylight to darkness (or vice versa), meaning that a test period conducted in daylight in the week before the clock change will be in darkness the following week (or vice versa). Previous studies have taken advantage of the daylight savings clock change to study how ambient light affects crime (e.g. Fotios et al. (2021b)), traffic flow (e.g. Uttley and Fotios (2017b)), and road traffic collisions (e.g. Sullivan and Flannagan (2002)).

Experiment 1 was carried out over two separate two-week periods centred on the daylight savings clock changes in Autumn 2021 (31 October 2021) and Spring 2022 (27 March 2022). The repeated test periods enabled a balance of the transition between daylight and dark from the first week to the second week, i.e. from daylight to dark in the Autumn clock change, and from dark to daylight in the Spring clock change. Participants were taken to six locations in daylight and after dark (repeated measures design), either side of the clock change, and asked to evaluate how reassured they felt through a survey.

This chapter explains the method used in Experiment 1. The experiment received ethical approval from the University of Sheffield Research Ethics Committee (reference number 043559 approved on 08/10/2021).

3.2 Test locations

Reassurance evaluations were carried out in six urban residential locations within the Netherthorpe and Upperthorpe areas of Sheffield, England, and located in the Walkley electoral ward (Figure 3.1). All locations were near the university campus, and thus easier to access in trials, and had below average rates of crime and antisocial behaviour based on crime rate figures (CrimeRate, 2024) and the Ward profiles published by Sheffield City Council (2024).

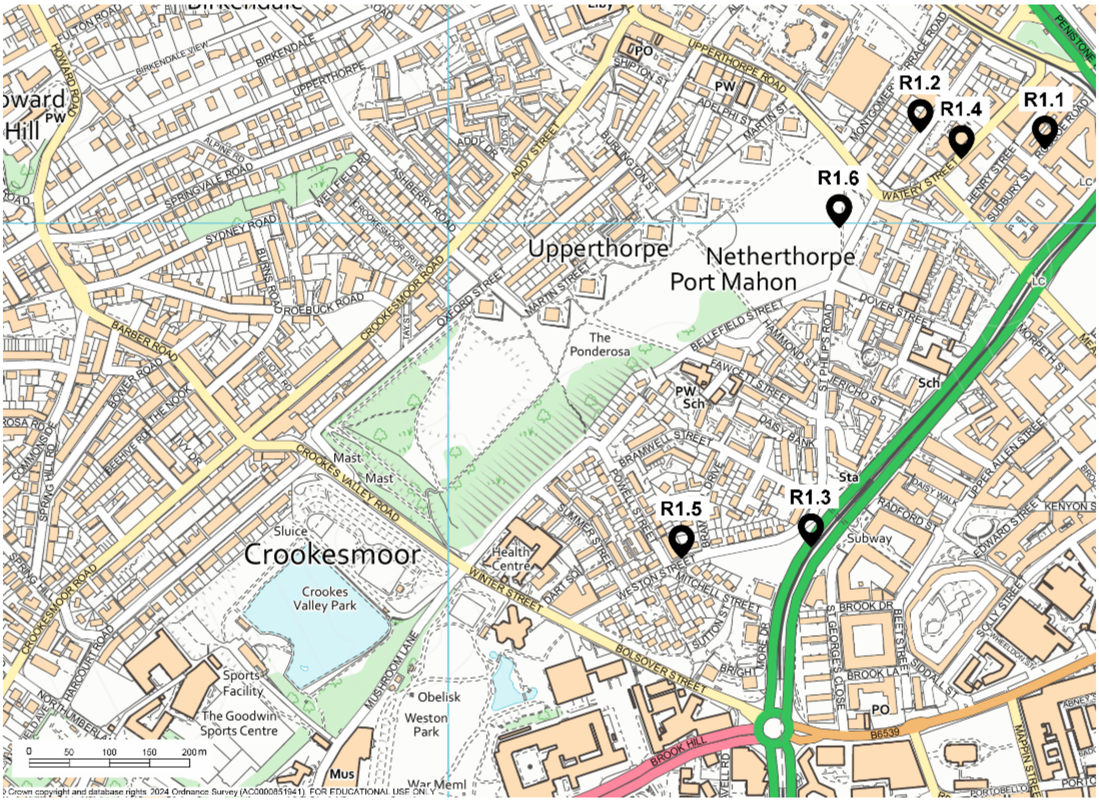


Figure 3.1. Map of the six locations in Experiment 1 (background map from Digimap (digimap.edina.ac.uk/roam/map/os) and locations added by author).

The six locations were selected from the ten locations used in a previous study [Fotios et al., 2019a; Liachenko-Monteiro, 2021] to enable analysis of replication, if necessary. The experiment test period was constrained to a 45-minute window due to the need for a time period which was daylight one week and dark the other, excluding twilight. This limited the number of locations that could be included in Experiment 2, as each location required a few minutes to carry out the evaluation and a few minutes to walk to the next location. The previous study [Fotios et al., 2019a; Liachenko-Monteiro, 2021] included three types of pedestrian footways: eight pedestrian footpaths along residential roads, one pedestrian footpath through a park, and one shared cycle and pedestrian path through an underpass. Out of these, six locations were used for Experiment 1: five randomly selected pedestrian footpaths along residential roads (labelled here as R1.1 to R1.5), and the footpath through the park (labelled here as R1.6). The underpass was excluded as it was a shared path with bicycles with higher levels of illuminance than a normal footpath. All selected paths were paved with grey asphalt. Photographs and characteristics of each location are presented in Figures 3.2 and Table 3.1.

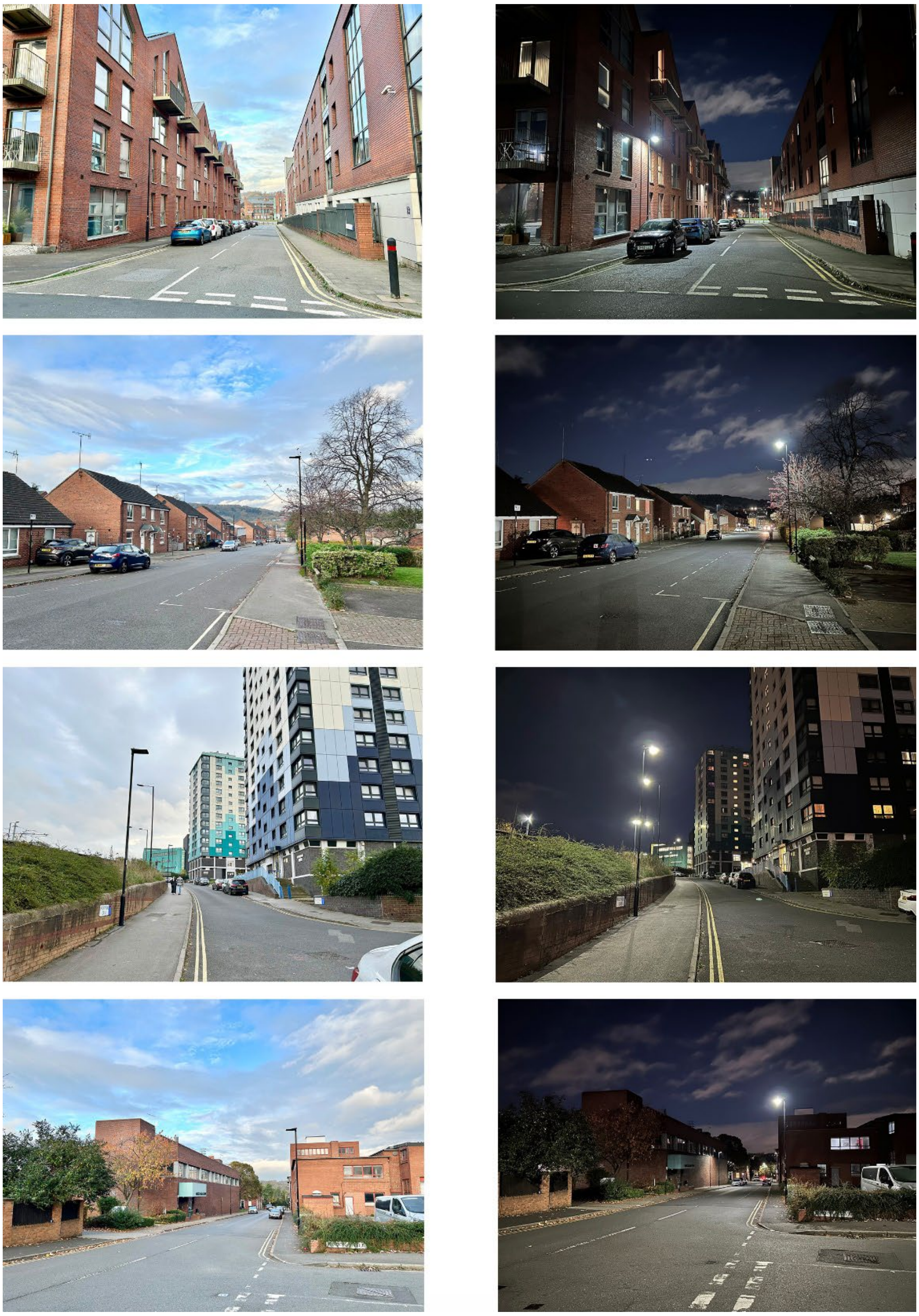


Figure 3.2. Daylight (left) and after-dark (right) photographs of the six test locations in Experiment 1 (R1.1 to R1.6 from top to bottom) – Note: Mobile phone camera enhancements make these photographs appear brighter than the actual scene.

Table 3.1. Characteristics of the six test locations in Experiment 1. The light source was LED in all locations.

Location ref*	Location coordinates	Path type**	Lighting configuration	Horizontal illuminance (lx)***		Uniformity	Distance between lampposts (m)
				Arithmetic mean	Minimum		
R1.1	53°23'18.4"N 1°28'45.2"W	A	Single sided	7.5	1.3	0.17	34.3
R1.2	53°23'19.0"N 1°28'53.3"W	A	Staggered	3.9	0.15	0.04	34.0
R1.3	53°22'58.1"N 1°29'04.2"W	A	Single sided	10.0	3.4	0.34	36.7
R1.4	53°23'17.5"N 1°28'51.8"W	A	Single sided	11.1	1.0	0.09	39.2
R1.5	53°23'02.7"N 1°29'07.3"W	A	Single sided	1.2	0.4	0.33	30.3
R1.6	53°23'14.9"N 1°28'58.3"W	B	Single sided	7.7	1.1	0.14	29.1

* In Fotios et al. (2019) these locations were labelled R1, R2, R4, R5, R8 and R9 respectively.
** A = Footpath along road, B = Footpath in park
*** From Table 21 in Liachenko-Monteiro (2021)

3.3 Light measurements

The lampposts in all locations were of the same height with a staggered or single-sided arrangement and a distance of 29.1 to 39.2 meters between two consecutive lampposts. The light sources in all locations were LED without any malfunctioning fixtures. The purpose of Experiment 1 was to compare effect of time of day on the daylight evaluations, not the effect of illuminance. Therefore, new light measurements were not carried out and the illuminances reported in Table 3.1 are those reported by Fotios et al. (2019a) and Liachenko Monteiro (2021).

3.4 Questionnaire

Evaluations at each location were carried out using questionnaires. The main focus of the questionnaire was to measure reassurance. Fear of crime is a multifaceted construct characterised by perceptual, emotional, behavioural, contextual and environmental dimensions, all of which are interconnected and influence one another other (Gabriel and Greve, 2003; Mesch, 2000; Rader, 2004; Rader et al., 2007; Wyant 2008). The questionnaire included multiple questions relating to these dimensions, rather than relying on one question to measure reassurance, with the assumption that reassurance is a latent variable with multiple facets that cannot be assessed by a single question. Including several questions about reassurance also reduces random error caused by participants' misinterpretation of the rating scale items or individual questions, and enhances the construct reliability and provides a better measure for reassurance (Clark and Watson, 2019).

Two versions of the questionnaire were used: one for the sessions that took place in daylight (referred to hereafter as *daylight questions/questionnaire*) and one for sessions that took place after dark (referred to hereafter as *after-dark questions/questionnaire*), similar to those used in previous work (Fotios et al., 2019). The daylight questionnaire included ten questions (Figure 3.3). The after-dark questionnaire was identical to the daylight one but also included five additional questions about the road lighting on the street (Figure 3.4). The additional road lighting questions were always located at the end of the questionnaire.

All questions were answered using a 6-point category rating scale, with the end points defined (e.g. 1, *very anxious* and 6, *not at all anxious*). A 6-point scale was chosen to avoid a neutral midpoint answer (Ford and Scandura, 2023). Each interval was numbered as it can provide more precision than word scales, with descriptors added only to the end points of each scale, compared with having them for each point on the scale (Menold and Tausch, 2016; Weijters et al., 2010). This helped give the respondents a clear idea of what the 6-point scale represented for each question, and also made it more appropriate to treat the data as interval rather than ordinal.

The University Of Sheffield.

Questionnaire

Participant ID No.

Date:

Time:

Order:

[Evaluation of street No.]

Please circle the number closest to your answer								
How risky do you think it would be to walk alone here at night?	Not at all risky	1	2	3	4	5	6	Very risky
How safe do you think this street is?	Very dangerous	1	2	3	4	5	6	Very safe
How anxious do you feel when walking down this street?	Very anxious	1	2	3	4	5	6	Not at all anxious
I would rather avoid this street if I could	Strongly Disagree	1	2	3	4	5	6	Strongly agree
I can see clearly around me	Strongly Disagree	1	2	3	4	5	6	Strongly agree
Apart from the researcher and any other participants, there are lots of other people on the street	Strongly Disagree	1	2	3	4	5	6	Strongly agree
This street is kept in good condition	Strongly Disagree	1	2	3	4	5	6	Strongly agree
I can see a lot of litter and rubbish on this street	Strongly Disagree	1	2	3	4	5	6	Strongly agree
How familiar are you with this particular street?	Not at all familiar	1	2	3	4	5	6	Very familiar
I was born after 1879	Strongly Disagree	1	2	3	4	5	6	Strongly agree

Figure 3.3. Questionnaire used in daylight evaluations.

Overall, how satisfied are you with the lighting on this street?	Very dissatisfied	1	2	3	4	5	6	Very satisfied
The lighting on this street is:	Not glaring	1	2	3	4	5	6	Glaring
	Unevenly spread (patchy)	1	2	3	4	5	6	Evenly spread (uniform)
	Bad	1	2	3	4	5	6	Good
	Bright	1	2	3	4	5	6	Dark

Figure 3.4. Additional questions used in the after-dark questionnaire.

Nine of the daylight questions related to the cognitive, emotional, behavioural, environmental and contextual aspects of fear of crime (Table 3.2).

Table 3.2. The nine daylight questions relating to different aspects of fear of crime.

Aspect of fear of crime	Question
Cognitive*	How risky do you think it would be to walk alone here at night? How safe do you think this street is?
Emotional	How anxious do you feel when walking down this street?
Behavioural	I would rather avoid this street if I could.
Environmental and contextual	I can see clearly around me. Apart from the researcher and any other participants, there are lots of other people on the street. This street is kept in good condition. I can see a lot of litter and rubbish on this street How familiar are you with this particular street?

* The cognitive questions are similar to those used by Boyce et al. (2000).

The remaining question was a bogus question selected from a pool of 16 questions (Figure 3.5). This question was included to check participants' attentiveness (Beach, 1989; Meade and Craig, 2012; Ward and Meade, 2023) as the answer was predictable and did not change based on location or participant. For example, '*I was born after 1879*' should have been answered as '*strongly agree*', as all participants were under the age of 39; the answer did not depend on the participant or the location being surveyed.

I was born after 1879	I always walk barefoot on the street
I shower more than once a month	I have never seen water
I have never been to other planets	I speak 35 different languages
I own a pen	I eat cauliflower every day
I am wearing clothes	I never had a cold
I usually sleep more than one hour per night	I personally met Shakespeare
I have watched a film at least once in the last 10 years	I have never been to Sheffield
I have visited every country in the world	I know how to read

Figure 3.5. The pool of 16 bogus questions

The five additional after-dark questions focused on assessment of the lighting at the location. These five questions enabled comparison of the self-reported perception of lighting and the day-dark difference in reassurance ratings at each location; because better lighting is assumed to minimize the difference between day and after-dark reassurance ratings, locations with smaller day-dark differences should have better self-evaluations of the road lighting.

Daylight and after-dark questionnaires were identical across all test locations, with the exception of choice of bogus question which changed across questionnaires. The questionnaires were administered in paper form and variation in question order, to offset an order bias, was achieved by printing 16 different questionnaire variations for each of the daylight and after-dark evaluations. For each test session, each participant randomly received six printed questionnaires out of the pool of 16 questionnaire variations. The 6-point rating scale was reversed for three questions (‘*How risky do you think it would be to walk alone here at night?*’; ‘*I would rather avoid this street if I could*’; and ‘*I can see a lot of litter and rubbish on this street*’) to prevent participants from assuming one end of the scale always indicated a more positive or negative response; for the analysis, responses were coded such that 6 always corresponded to a more positive answer.

3.5 Sample

Sixty participants were recruited for Experiment 1, including thirty participants for each of the Autumn 2021 and Spring 2022 clock changes. The sample size calculation was performed using G*Power, which requires specifying the significance level (alpha), desired statistical power, and the expected effect size. A repeated measures ANOVA (within factors) was used for the analysis, as each participant took part in three different test sessions (repeated measures design). Following standard research practice, an alpha of 0.05 and a power of 0.8 were selected (Cohen, 1992; Field, 2018; Uttley, 2019). The effect size was set at 0.18 (corresponding to a small to medium effect size per Cohen's *f*), based on estimates of the effect size in previous research that have established a statistically significant effect of road lighting on reassurance (e.g. Boomsma and Steg (2014), Boyce et al. (2000) and Nair et al. (1993)). It was found that a sample of 52 participants would be adequate to reveal differences in the day-dark ratings between the six locations (Figure 3.6). To account for potential dropouts, a sample of 60 participants were recruited, slightly exceeding the sample size suggested by G*Power to detect a small- to medium-sized effect.

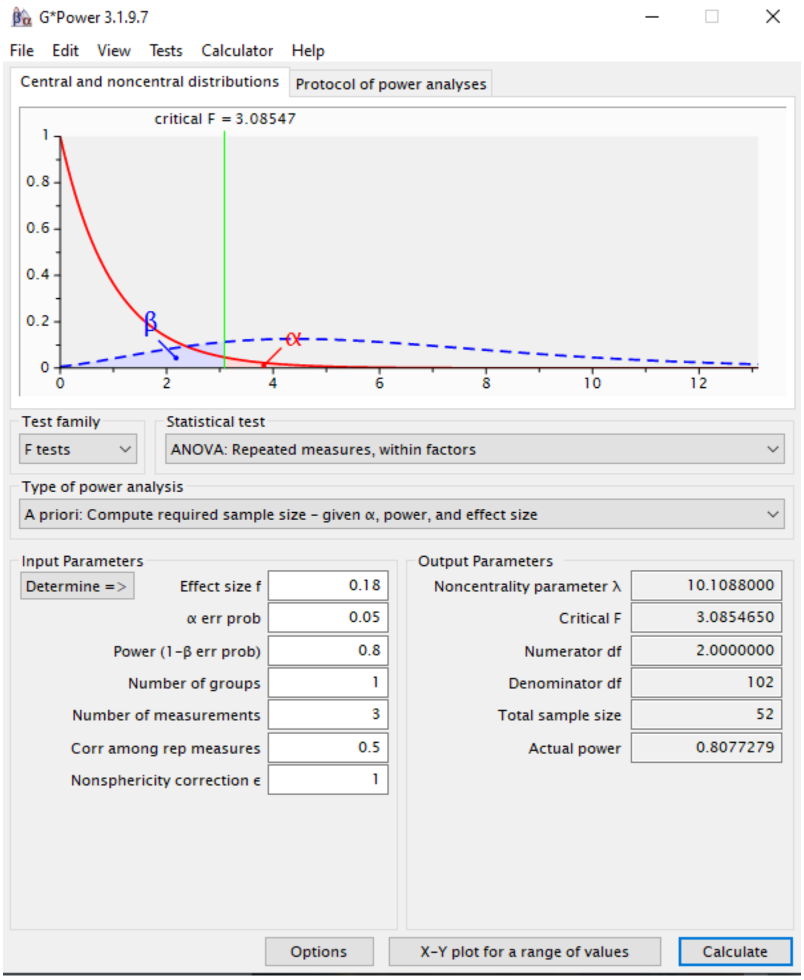


Figure 3.6. Sample size calculation for Experiment 1 in G*Power.

Participants were recruited via emails sent out to University of Sheffield students who had subscribed to the university's Research Studies volunteering email distribution list. The email included information about the experiment and a link to a Google Form to sign up. Participants were required to be aged 18 or over, have normal vision (wearing glasses or contact lenses if normally worn), and in reasonable physical health for intermittent walking. The 184 people who signed up were separated by gender, and 30 participants were randomly selected for each of the surveys conducted over the Autumn 2021 clock change and the Spring 2022 clock change, whilst taking gender balance into consideration. The selected participants were sent a second email containing a link to a Google Form to express their availability during the experiment period. Each participant was subsequently randomly allocated one noon daylight, one evening daylight, and one after-dark test session, based on their availability.

Five participants were omitted from the analysis: one person from the Autumn 2021 clock change and three people from the Spring 2022 clock change as they did not complete all three test sessions, and one person from the Autumn 2021 clock change because they gave four inattentive responses to the bogus question (see chapter 4). The overall sample was therefore 55 participants, comprising 28 male and 27 female participants, aged between 18 and 39 years with a mean age of 24 years (Table 3.3). Participants self-reported their vision status in the consent form: all indicated good visual health, and 27 wore their corrective lenses for walking. Each participant was paid £30 upon completion of all three test sessions, as reimbursement for their time.

Table 3.3. The sample characteristics in Experiment 1.

Test period	Gender	Total no. (no. wearing corrective lens)	Age range in years (mean age in years)
Autumn 2021 clock change	Male	15 (6)	18-39 (24)
	Female	13 (4)	21-35 (26)
Spring 2022 clock change	Male	13 (8)	18-31 (24)
	Female	14 (9)	18-33 (23)

3.6 Test times

Experiment 1 was conducted in two stages: a two-week period centred on the Autumn 2021 clock change (31 October 2021) and a two-week period centred on the Spring 2022 clock change (27 March 2022), to balance the order of the natural transition from daylight to darkness and darkness to daylight. For a given clock change, each participant completed three test sessions (repeated measures design): two daylight sessions (noon daylight, evening daylight) and one after-dark session. This allowed the comparison of day-dark reassurance ratings where the daylight and after-dark ratings were collected at the same time of day versus where the two ratings were collected at different times of day. Logistical challenges and participant availability meant that daylight and after-dark sessions were separated by up to eight days. Some participants took part in two different test sessions on the same day, but this occurred randomly.

For the Autumn 2021 clock change, the experiment was carried out between Monday 25 October to Saturday 6 November, excluding the day of the clock change (Sunday 31 October 2021). The noon daylight sessions and evening daylight sessions took place first, during a 45-minute period in the six days before the clock change commencing at 12:00 and 17:00 respectively. Both sessions were in daylight as the solar altitude was greater than 0°. On the day of the Autumn clock change, the clocks went back 1 hour. The after-dark session took place in the second week, during a 45-minute period in the six days after the clock change commencing at 17:00, and after the end of civil twilight. This period was now in darkness as the solar altitude was less than -6° (Figure 3.7).

For the Spring 2022 clock change, the experiment took place between Monday 21 March to Saturday 2 April, with the day of the clock change (Sunday 27 March 2022) excluded. The after-dark sessions were conducted first, during a 45-minute period beginning at 18:45, in the six days before the clock change. This period was after the end of civil twilight and in darkness, defined by a solar altitude of less than -6°. On the day of the Spring clock change, the clocks went forward 1 hour. The noon daylight sessions and evening daylight sessions took place in the six days after the clock change, during a 45-minute period commencing at 12:00 and 18:45, respectively. The sessions in the second week were in daylight as the solar altitude was more than 0° (Figure 3.8).

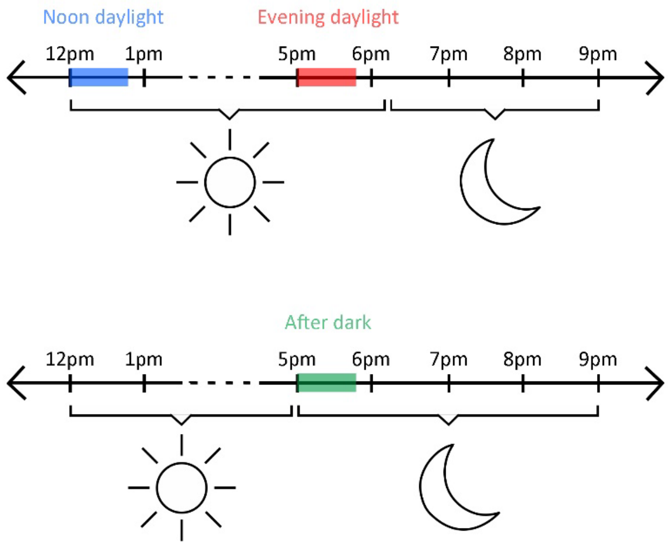


Figure 3.7. The test sessions before the Autumn 2021 clock change (top) and after the clock change (bottom).

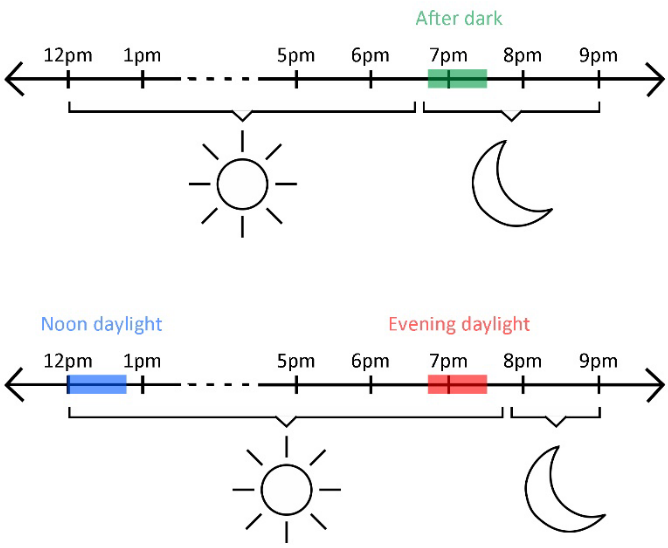


Figure 3.8. The test sessions before the Spring 2022 clock change (top) and after the clock change (bottom).

3.7 Procedure

Each test session was carried out with participants in groups of four to six, accompanied by the author. The allocation of participants was done randomly and based on availability, meaning participants may have been grouped with the same or different people for each test session. In the first week of the experiment, and immediately before the first test session, participants met the author at a meeting point near the test locations for a practice trial. First, the author handed out consent forms to participants to read and sign. They were then taken to a nearby street where the author demonstrated the experiment procedure. Participants were specifically instructed not to discuss the experiment or their survey responses with one another to ensure that each participant's responses remained independent. The author then provided instructions on how to complete the daylight and after-dark questionnaires, including how to log their responses. Specifically, the terms 'not glaring/glaring', 'patchy/uniform', 'bad lighting/good lighting', and 'bright/dark' in the after-dark questionnaire were clarified by giving definitions of each term. At the end of the practice trial, participants were provided with the chance to ask questions and each received a pen and a clipboard with the six printed questionnaires attached. For subsequent test sessions, the participants met the author at the same meeting point and were immediately taken, as a group, to the first test location of that session.

In each test session, participants walked a short route from one location to another. The order in which the six locations were visited was randomised. Upon arrival at each location, participants walked a short distance between two successive lampposts, and completed the questionnaire at the end of their walk. The procedure at each location was as follows:

- First, the author and participants gathered round the starting lamppost.
- The author then instructed each participant one by one by saying "Please walk to the next lamppost, then cross the road *(R1.1-R1.5)* or turn around *(R1.6)* and return to the starting lamppost. Then, whilst standing under the starting lamppost, face the route you have just walked and complete the questionnaire to provide your experience of this road." (Figures 3.9 and 3.10).

The same instructions were given in all test sessions and locations. To ensure they walked alone, participants were staggered approximately 10 to 15 seconds apart and asked not to group together whilst walking; specifically, participants walked unaccompanied, although the other participants and the author were present in the area.

Figure 3.9. Participants walking alone between two lampposts in an after-dark test session in location R1.5.

Figure 3.10. Participants filling the questionnaire after finishing their walk in an after-dark test session in location R1.1.

The order in which participants took part in the noon daylight sessions and evening daylight sessions was counterbalanced; half took part in the noon daylight session first and the other half took part in the evening daylight session first. The after-dark session was the first evaluation completed by the participants in the Spring 2022 survey, but was the last evaluation in the Autumn 2021 survey (see

Figures 3.7 and 3.8), meaning that order of the daylight to after-dark evaluations was also counter balanced; half of the participants began with daylight evaluations, moving to after-dark evaluations, whilst the other half started with after-dark evaluations before taking part in daylight evaluations. Reassurance was not mentioned during the entire recruitment and experiment process to avoid biasing participants' responses.

3.8 Summary

This chapter has described the method used in Experiment 1, a pilot study investigating the impact of time of day of the daylight evaluations used in the day-dark approach to measuring pedestrian reassurance. The results of this experiment are described in Chapter 4.

CHAPTER 4. EXPERIMENT 1 – REASSURANCE FIELD STUDY: RESULTS

4.1 Introduction

This chapter presents the results of Experiment 1, a pilot study examining the effect of time of day at which daylight ratings are collected for the 'day' part of the day-dark approach to measuring pedestrian reassurance. The first step was to assess internal validity and confirm the reliability of participant responses. The data were then tested for normality to determine which statistical tests to use and how to report the data. Next, the results of the day-dark differences for the three reassurance-related questions were compared, using each of the noon daylight and evening daylight scores. This helped to assess the impact of time of day of the daylight evaluations on the day-dark reassurance scores (Hypothesis H3). The significance level of the statistical tests was set at $\alpha = 0.05$.

4.2 Internal validity

A bogus question was included as a measure of internal validity; the bogus question had an objectively correct answer and was used to identify careless respondents (see Figure 3.3 and Figure 3.5). As the answer to the bogus question was independent of both the test location and the participant, it could be easily predicted; deviation from the correct answer would suggest inattentive responding, thereby raising concerns regarding the validity of the participant's other responses. Each bogus question was rated on a 1-6 scale, ranging from strongly disagree (1) to strongly agree (6), and inattentive responding was defined as a deviation from responses of either 1 or 2, or 5 or 6, depending on the particular question. An example correct response would be answering 1 or 2 to the question 'I have visited every country in the world'.

Curran (2016) suggests excluding participants with 50% or more invalid responses to bogus questions, acknowledging this to be a conservative criterion. For the current analysis, a stricter 20% threshold was used; a participant was excluded from the analysis if they gave four or more inattentive responses out of the 18 bogus questions they answered (6 locations x 3 sessions). Analysis of responses to the bogus question revealed a 96% correct response rate, suggesting very good respondent attentiveness. Inattentive responses were observed in 18 participants, primarily involving only one or two instances (Table 4.1). Only one participant was removed from the analysis due to that person giving four incorrect responses to the bogus question.

Table 4.1. Participants with inattentive responses to the bogus question in Experiment 1.

No. of inattentive responses	No. of participants		Total	Decision
	Male	Female		
1	4	5	9	Retained
2	2	6	8	Retained
4	1	0	1	Omitted

4.3 Distribution normality

Normal distribution of the results recorded in Experiment 1 was assessed using graphical tests (histograms, box plots, and Q-Q plots), measures of dispersion (skewness and kurtosis), and measure of central tendency (median and the 95% confidence interval of the mean). Statistical tests of normality (e.g. Kolmogorov-Smirnov test; Shapiro-Wilks test) were not used because they may not yield reliable results in large samples (generally sample sizes of 30 or more), as in large samples, significance tests of normality can be significant even for small and unimportant effects (Field, 2018).

1. Graphical tests – histograms, box plots, and Q-Q plots: For graphical normality tests to be reliable, a large sample size is necessary (Neter et al., 2005), suggested by Field (2018) to be a sample of at least 30. Given the large dataset in Experiment 1 (n=11,550), Q-Q plots were used over P-P plots for their greater clarity and ease of interpretation (Field, 2018). The data were considered to be normally distributed if the following were true (Figure 4.1): the histogram was not skewed and followed a normal or approximately normal distribution shape; the box plot was symmetrical or approximately symmetrical with the whiskers being of similar length above and below the box, and the median line was approximately central within the box; and the data points fell on or laid close to the straight diagonal line of the Q-Q plot (Field, 2018; Oppong and Agbedra, 2016). If two of the graphical tests suggested normal distribution and one suggested otherwise, the distribution was considered 'near normal'. If one suggested normal distribution and two suggested otherwise, or if all three suggested a non-normal distribution, then the data was considered to not be drawn from a normally distributed population.

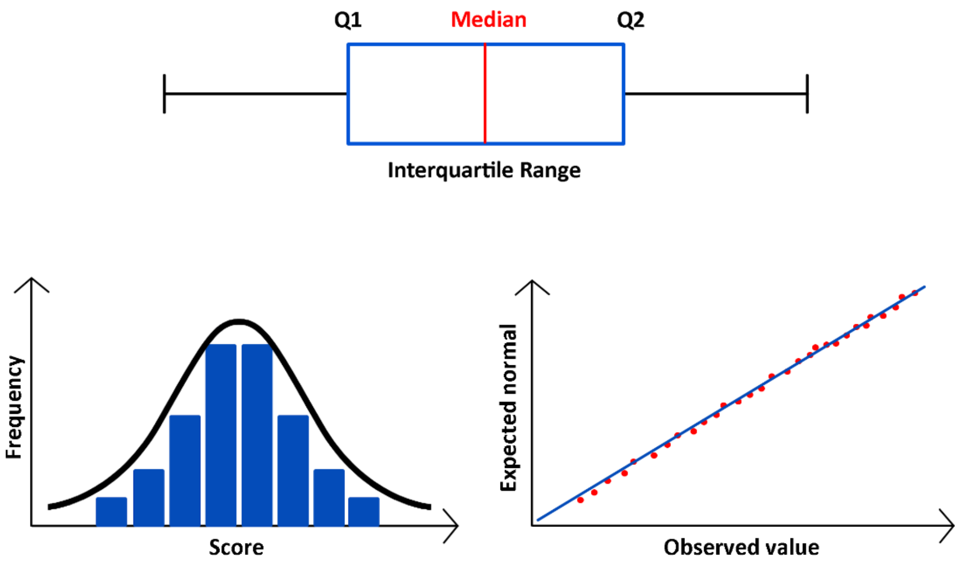


Figure 4.1. Example box plot (top), histogram (bottom left), and Q-Q plot (bottom right) in a normal distribution.

2. Measure of dispersion (skewness and kurtosis): A normal distribution has a skewness and kurtosis of near zero, with skewness falling within ±0.5 and Kurtosis falling within ±1 (Hatem et al., 2022). The data was considered to be normally distributed if the skewness and kurtosis were within these limits. If one of the numerical tests suggested normality and the other suggested otherwise, the distribution was considered 'near normal'. If both were outside the normal values, then the data was considered to not be drawn from a normally distributed population.
3. Measure of central tendency (median and the 95% confidence interval of the mean): For measures of central tendency, median is preferred for normality tests as it is less biased by outliers (Field, 2018). The data were considered to be normally distributed if the median fell within the 95% confidence interval of the mean (McCluskey and Lalkhen, 2007). Otherwise, the data was considered to not be normally distributed.

As suggested by Field (2018) and Orcan (2020), all three tests were used collectively to assess normality, given their individual limitations (e.g. there is a degree of subjectivity associated with decisions about normality based on graphical tests (Hatem et al., 2022): if all three suggested 'normality' or 'near normality' then the data were considered to be drawn from a normally distributed population, and if at least two tests suggested 'normality' or 'near normality' then the data was considered to be near normal. Otherwise, the data was considered to not be normally distributed.

Normality testing was carried out on the day-dark scores for the questions used to calculate the reassurance rating, i.e. Q2, Q3 and Q4 (see section 4.5). This was done for the Autumn 2021 clock change and Spring 2022 clock change participants separately. It was revealed that the data exhibited a normal distribution. An example normality test for question 3 in location R1.4 in a daylight session of the Spring 2022 clock change is shown in Table 4.2 and Figure 4.2. The distribution is considered to be normal because all three tests report a normal distribution: (1) the graphical test is normal (the histogram approximates the bell-curve shape for normally distributed data; the box plot is normally distributed, as the median line is central within the box and the whiskers above and below the box are almost of similar length; the Q-Q plot is near normal as the data points lay relatively close to the straight diagonal line; (2) the skewness and kurtosis values are inside the normal ranges of ±0.5 and ±1 respectively; and (3) the median falls within the 95% confidence interval of the mean.

Table 4.2. The normality test for question 3 in location R1.4 in a daylight session of the Spring 2022 clock change.

Normality Test													
Graphical				**Dispersion**			**Central Tendency**					**Overall Normality**
Histogram	Box Plot	Q-Q Plot	**Normal?**	Skewness	Kurtosis	**Normal?**	Mean	Lower 95% CI	Upper 95% CI	Median	**Normal?**	
Yes	Yes	Near	**Yes**	-0.25	-0.79	**Yes**	4.30	3.89	4.10	4.00	**Yes**	**Yes**

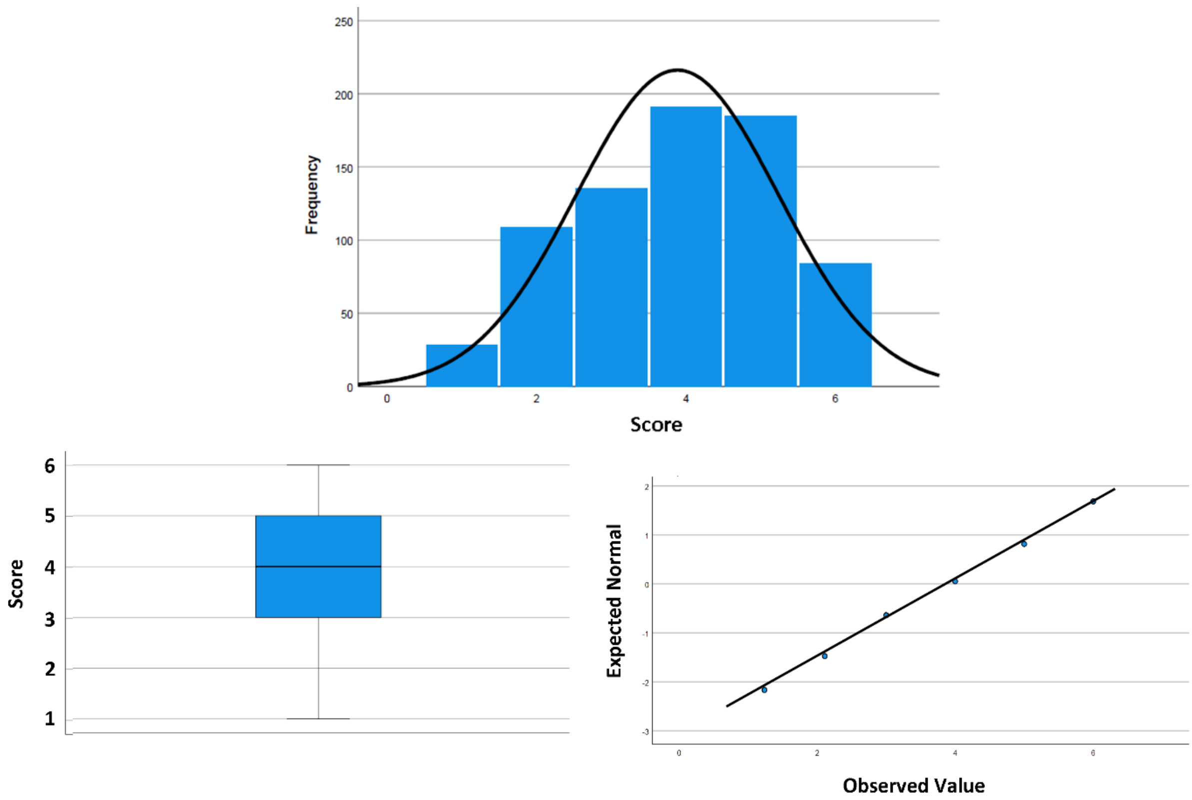


Figure 4.2. Box plot (top), histogram (middle), and Q-Q plot (bottom) of participant scores for question 3 in location R1.4 in a daylight session of the Spring 2022 clock change.

4.4 Reassurance rating

Using factor analysis, Fotios et al. (2019a) show that responses to three questions load highly onto the reassurance factor: ‘How safe do you think this street is?’, ‘How anxious do you feel when walking down this street?’, and ‘I would rather avoid this street if I could.’. In Experiment 1, participant reassurance at each location was evaluated by calculating the arithmetic mean responses to these three reassurance-related items (Q2, Q3, and Q4, shown in bold in Table 4.3). This will be referred to as the ‘reassurance rating/score’ in this chapter. Cronbach's alpha, calculated for each road and session, determined the reliability of this composite reassurance rating; only three of the eighteen calculated alphas (for three sessions across six roads each) did not reach the 0.7 threshold proposed by Bland and Altman (1997).

Prior to conducting the analysis, the scoring for Q4 was reversed, by subtracting each individual score from a constant value of 7. For example, an original score of 2 to Q4 was replaced with a score of 7-2 = 5 on the reversed scale. This ensured that, across all three questions, a higher score on the rating scale always represented greater reassurance.

Table 4.3. Questions used in the daylight and after-dark evaluations in Experiment 1.

No.*	Question	Rating scale							
Q1 (Risky)	How risky do you think it would be to walk alone here at night?	Not at all risky	1	2	3	4	5	6	Very Risky
Q2 (Safe)	**How safe do you think this street is?**	Very dangerous	1	2	3	4	5	6	Very safe
Q3 (Anxious)	**How anxious do you feel when walking down this street?**	Very anxious	1	2	3	4	5	6	Not at all anxious
Q4 (Avoid)	**I would rather avoid this street if I could.**	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q5 (Clear)	I can see clearly around me.	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q6 (Others)	Apart from people accompanying me, there are lots of other people on the street.	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q7 (Condition)	This street is kept in good condition.	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q8 (Litter)	I can see a lot of litter and rubbish on this street.	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q9 (Familiar)	How familiar are you with this particular street?	Not at all familiar	1	2	3	4	5	6	Very familiar
Q10 (Bogus)	I was born after 1879.**	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q11	Overall, how satisfied are you with the lighting on this street?	Very Dissatisfied	1	2	3	4	5	6	Very Satisfied
Q12	The lighting on this street is:	Bad	1	2	3	4	5	6	Good
Q13		Bright	1	2	3	4	5	6	Dark
Q14		Not glaring	1	2	3	4	5	6	Glaring
Q15		Unevenly spread (patchy)	1	2	3	4	5	6	Evenly spread (uniform)

* Q1 to Q10 were used in the daylight evaluations and Q1 to Q15 were used in the after-dark evaluations - questions in bold are the reassurance related questions in Experiment 1.

** The bogus question was randomly selected from a pool of 16 questions and the question in this table is one example (see Figure 3.6)

4.5 Effect of test session on reassurance ratings

Figure 4.3 shows boxplots of the overall mean reassurance ratings from all participants across all six locations, for each of the three test sessions (noon daylight, evening daylight, and after dark).

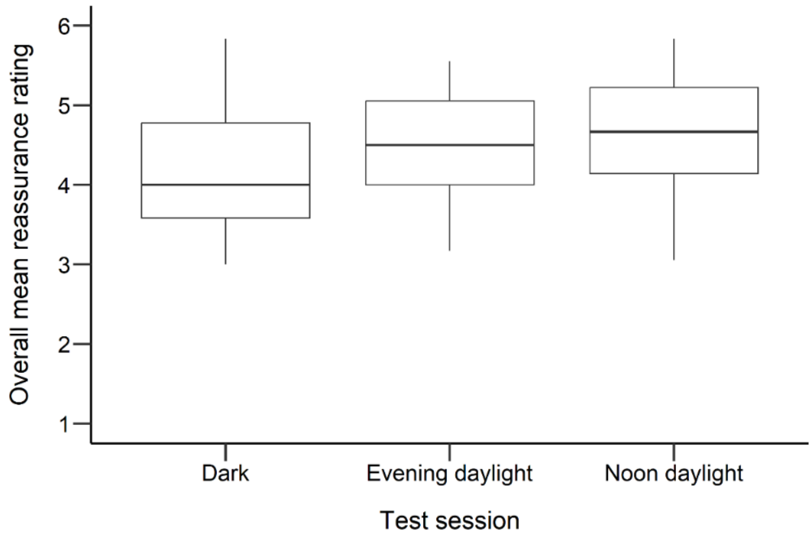


Figure 4.3. Boxplots of the overall mean reassurance ratings for each of the after dark, evening daylight, and noon daylight sessions. Higher ratings mean greater reassurance. Interquartile range (IQR) is shown by the box, and whiskers represent values within 1.5 IQR.

A linear mixed-effects model was used to compare the effects of test session (noon daylight, evening daylight, after dark) (as the independent variable) on overall mean reassurance ratings (as the dependent variable), with the test session as a fixed effect, and participant and location as random effects. A significant difference in reassurance ratings was found across the three test sessions (X^2 = 58.6, $p < 0.001$, Cohen's $d = 0.30$). Post-hoc Tukey tests demonstrated that all three reassurance ratings were significantly different from one another (After-dark mean reassurance rating = 4.20, Noon daylight mean reassurance rating = 4.67, Evening daylight mean reassurance rating = 4.51; all pairwise comparisons $p < 0.05$). The order of reassurance ratings from lowest to highest was: after-dark session, evening daylight session, and noon daylight session.

4.6 Effect of test session on day-dark differences in reassurance ratings

For each participant, day-dark differences in reassurance ratings were calculated by subtracting after-dark ratings from the daylight ratings, for each of the noon daylight and evening daylight ratings separately. A positive value would, therefore, mean that the location was considered more reassuring in daylight than after dark. Figure 4.4 shows boxplots of the mean day-dark difference across all six locations and all participants, for each of the noon daylight and evening daylight sessions.

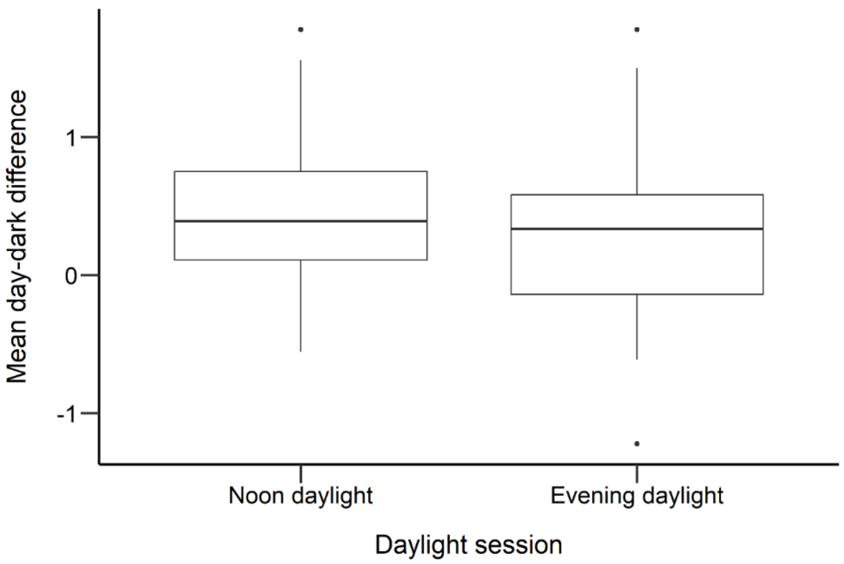


Figure 4.4. Boxplots of overall mean day-dark difference in reassurance ratings for each of the noon daylight and evening daylight sessions. A positive day-dark difference means greater reassurance in daylight. Interquartile range (IQR) is shown by the box, whiskers represent values within 1.5 IQR, and points show values beyond 1.5 IQR.

A linear mixed-effects model was used to compare the day-dark differences in reassurance ratings (obtained using the noon daylight ratings and the evening daylight ratings) (as the dependent variable). The time of day of the daylight session (noon daylight or evening daylight) was used as the independent variable, and included as a fixed effect, with participant and location as random effects. A larger day-dark difference in reassurance ratings was observed when the ratings were obtained at different times of day (mean day-dark difference = 0.47, SD = 1.08) compared to when they were obtained at the same time of day (mean day-dark difference = 0.31, SD = 1.06). This effect was statistically significant, as indicated by a chi-square test (X^2 (1) = 5.39, p = 0.020, Cohen's d = 0.15). However, the effect size was less than Cohen's established threshold of 0.20 for a small effect (Cohen, 1992).

4.7 Summary

This chapter presented the results of Experiment 1, a pilot study to investigate the influence of time of day of daylight evaluations on reassurance ratings obtained using the day-dark approach. It was found that the effect of time of day of daylight evaluations on the day-dark differences was small and of little practical significance. Given the logistical challenges and constraints of the evening daylight session, only one time of day, the noon daylight session, was used for the daylight evaluations of Experiment 2. Chapter 5 explains the method used in Experiment 2.

CHAPTER 5. EXPERIMENT 2 – REASSURANCE FIELD STUDY: METHOD

5.1 Introduction

Experiment 2 is a field study carried out to investigate whether pedestrian reassurance is affected by a change in illuminance (Hypothesis H1). As part of the findings, the effect of higher illuminances in alleviating the lesser reassurance after dark expressed by females was also assessed (Hypothesis H5).

In this experiment, reassurance was measured by self-report using the day-dark method. The literature review (chapter 2) raised two questions about this procedure:

4. Are the results affected by the time of day at which the daylight evaluation of the day-dark difference is carried out?
5. Are the results affected by whether survey respondents conduct their evaluations alone or in small groups?

Regarding time of day, results from the pilot study (Experiment 1) revealed that the difference between daylight evaluations carried out at midday and in the evening was small and of little practical significance (see Chapter 4). The daylight evaluations in Experiment 2 were therefore carried out at around midday.

The literature review (Chapter 2) revealed that in most studies of reassurance typically involve group settings in which participants are accompanied by other participants and/or a researcher or a figure of authority, contradicting the *walking alone* aspect of the definition of reassurance. To assess the influence of participant accompaniment (Hypothesis H4), test participants in Experiment 2 were allocated to one of two evaluation types; participants conducted the evaluations either alone (referred to hereafter as *solo evaluations/solo participants*), or were accompanied by other participants and two or three researchers (referred to hereafter as *group evaluations/group participants*).

Experiment 2 was conducted using a similar method as used for Experiment 1 (Chapter 3) but with the following changes:

- A different set of locations were evaluated
- Lighting conditions were measured
- An online questionnaire was used instead of a printed paper version
- Participants were allocated to either solo or group evaluations
- Only one daylight evaluation was used

This chapter explains the method used in Experiment 2. The experiment received ethical approval from the University of Sheffield Research Ethics Committee (reference number 050684 approved on 02/12/2022).

5.2 Test Locations

Evaluations of reassurance were conducted in 12 urban residential locations within the Broomhall area of Sheffield, which is located in the Broomhill and Sharrow Vale electoral ward (see section 5.2.2). This ward was chosen as it is in close proximity to the university campus, and thus easier to access in trials. It also had below average rates of crime and antisocial behaviour, based on the Ward profiles published by Sheffield City Council (2024b) and crime rate figures (CrimeRate, 2024), meaning the test participants would not be exposed to greater risk than a typical pedestrian, a requirement for ethical approval. Experiment 2 used a different set of locations to those used in Experiment 1 to achieve a wider variety of anticipated reassurance levels and illuminance levels.

5.2.1 Shortlisting potential locations

The 12 test locations were chosen to represent a range of path types, anticipated reassurance levels, and illuminances from the lower to the upper ends of the P-class (CIE, 2010). To select the 12 locations, the researcher visited all pedestrian paths in the Broomhall area to make a self-assessment of the levels of reassurance and illuminance, using a three-level scale (low, medium, or high level of reassurance / illuminance). 29 locations were shortlisted (Table 5.1).

Table 5.1. The 29 locations shortlisted for Experiment 2. The light source was LED in all locations.

Location ref	Location Coordinates	Path type*	Lighting configuration	Self-assessment by researcher	Simplified photometric measurement**		Distance between lampposts (m)
				Level of reassurance	Level of illuminance	Arithmetic mean horizontal illuminance (lx)	
PL1	53°22'24.0"N 1°29'04.9"W	C	Single sided	Medium	Low	4.6	22.8
PL2	53°22'27.5"N 1°29'06.5"W	A	Staggered	Medium	Medium	5.9	36.2
PL3	53°22'31.5"N 1°29'08.9"W	A	Single sided	Medium	Medium	6.5	39

PL4	53°22'34.1"N 1°29'07.5"W	A	Staggered	Medium	Medium	6.7	39
PL5	53°22'33.1"N 1°29'06.7"W	A	Staggered	Low	Medium	8.3	30.8
PL6	53°22'36.4"N 1°29'03.4"W	B	Single sided	Low	Medium	6.8	40.4
PL7	53°22'34.3"N 1°29'02.0"W	A	Single sided	Medium	Medium	12.0	34.3
PL8	53°22'45.4"N 1°29'09.1"W	A	Single sided	Medium	High	19.3	26.8
PL9	53°22'46.1"N 1°29'10.6"W	A	Single sided	High	Medium	11.0	31
PL10	53°22'47.1"N 1°29'09.0"W	A	Single sided	Medium	High	18.9	29.5
PL11	53°22'41.7"N 1°29'13.4"W	A	Staggered	High	High	16.2	42
PL12	53°22'40.0"N 1°29'14.2"W	A	Staggered	Medium	Medium	7.7	37
PL13	53°22'37.0"N 1°29'13.9"W	A	Staggered	Low	Medium	11.8	44
PL14	53°22'38.2"N 1°29'12.7"W	B	Single sided	Low	Low	4.3	26.2
PL15	53°22'39.7"N 1°29'18.7"W	A	Staggered	Medium	Medium	12.1	37.3
PL16	53°22'36.7"N 1°29'21.7"W	A	Single sided	Medium	Medium	9.4	32
PL17	53°22'37.8"N 1°29'25.3"W	A	Staggered	Low	high	15.5	39.7
PL18	53°22'35.8"N 1°29'24.2"W	A	Single sided	Medium	Medium	7.7	24
PL19	53°22'32.6"N 1°29'32.5"W	A	Single sided	Medium	High	15.8	35
PL20	53°22'32.2"N 1°29'24.2"W	A	Staggered	High	Medium	11.3	39.5
PL21	53°22'32.7"N 1°29'16.2"W	D	Single sided	Low	High	15.4	37.5
PL22	53°22'31.7"N 1°29'10.5"W	B	Staggered	Low	Low	3.3	28
PL23	53°22'28.0"N 1°29'11.6"W	A	Staggered	High	Medium	12.6	41.5
PL24	53°22'22.8"N 1°29'14.7"W	A	Single sided	High	High	22.7	37
PL25	53°22'20.2"N 1°29'26.3"W	A	Staggered	High	High	13.0	44
PL26	53°22'26.5"N 1°29'20.1"W	A	Staggered	High	Medium	11.5	32
PL27	53°22'27.9"N 1°29'16.4"W	A	Single sided	High	High	16.0	32
PL28	53°22'32.0"N 1°28'59.6"W	A	Single sided	Low	High	14.8	24.7
PL29	53°22'27.0"N 1°28'59.2"W	A	Single sided	High	High	17.5	38.1

* A = Footpath along the road, B = Pedestrian only path, C = Footpath through wooded area, D = Cul-de-sac to four houses, no footpath
** Calculated using equation 1

For initial consideration of location choice, a simplified photometric survey was carried out in the 29 shortlisted locations, following the process suggested by Yao et al. (2018). At each location, horizontal illuminance was measured directly underneath two successive lampposts and the mid-way point, using a Konica Minolta T-10M illuminance meter which had been calibrated withing the past 6 months. To quickly gauge relative illuminance at many locations, the meter was held at waist height for practical reasons, rather than at ground level as EN 13201-3:2015 (BSI, 2015b) specifies. This allowed for faster data collection to identify areas of low, medium, or high illuminance. The measurements were taken by the author positioned perpendicular to the direction of travel, and facing the road, to ensure light from nearby lampposts was not blocked by the body. Horizontal illuminances at 10 evenly spaced points between the two lampposts were then estimated using equation 1 (Figure 5.1). This illuminance distribution equation was then used to calculated the mean horizontal illuminances reported in Table 5.1.

$$E_1 = \frac{(E_{max}+E_{min})}{2} + \frac{(E_{max}-E_{min})}{2} \sin(\pi(d_1 - d_0)\,/w). \quad (1)$$

where E_1 is the illuminance along the longitudinal direction under point 1 (the 10 evenly spaced points between the two lamppost), E_{max} is the illuminance beneath the two lampposts, E_{min} is the illuminance halfway between the two lampposts, d_1 is the distance along the longitudinal direction for point 1, d_0 is the deviation distance to match the values at feature points, and w is half the distance between the two lampposts.

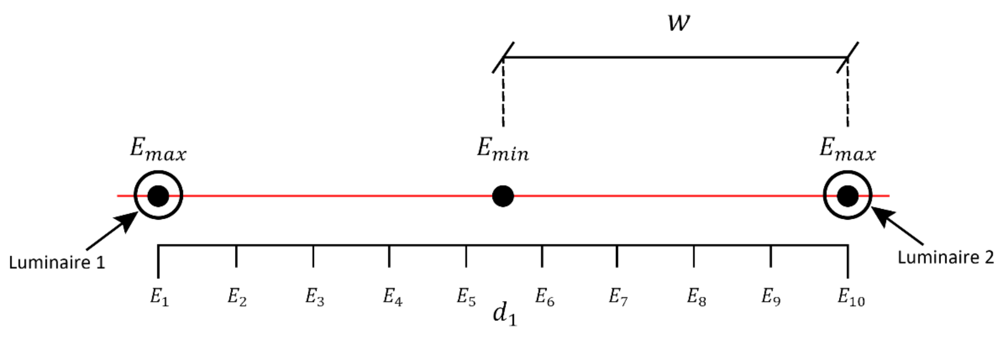


Figure 5.1. The parameters in equation 1 (redrawn from Figures 4 and 5 in Yao et al. (2018)). Full circles show the three measurement points; hollow circles show the two lampposts. E1 to E10 are the 10 evenly spaced points between the two lampposts.

An example calculation for location PL1 is provided below:

The horizontal illuminance measured directly underneath two successive lampposts was 7.58 lx, and 1.05 lx at the mid-way point between the two lampposts. Therefore:

$$E_{max} = 7.58 \text{ lx}$$

$$E_{min} = 1.05 \text{ lx}$$

$$\frac{E_{max} + E_{min}}{2} = \frac{7.58 + 1.05}{2} = \frac{8.63}{2} = 4.32 \text{ lx}$$

$$\frac{E_{max} - E_{min}}{2} = \frac{7.58 - 1.05}{2} = \frac{6.53}{2} = 3.27 \text{ lx}$$

The distance between the two lampposts was measured at 22.8 m. Therefore:

$$W = \frac{22.8}{2} = 11.4 \text{ m}$$

$$d_0 = \frac{-W}{2} = -5.7 \text{ m}$$

To divide the distance between the two lampposts into 10 evenly spaced points, the distance between any two consecutive points was:

$$\frac{22.8}{9} = 2.53 \text{ m}$$

Therefore, $\frac{d_1 - d_0}{W}$ at each point was calculated as:

For points 1 and 10: $\frac{(0\times2.53)-(-5.7)}{11.4} = \frac{5.7}{11.4} = 0.5$

For points 2 and 9: $\frac{(1\times2.53)-(-5.7)}{11.4} = \frac{2.53+5.7}{11.4} = \frac{8.23}{11.4} = 0.72$

For points 3 and 8: $\frac{(2\times2.53)-(-5.7)}{11.4} = \frac{5.06+5.7}{11.4} = \frac{10.76}{11.4} = 0.94$

For points 4 and 7: $\frac{(3\times2.53)-(-5.7)}{11.4} = \frac{7.59+5.7}{11.4} = \frac{13.29}{11.4} = 1.17$

For points 5 and 6: $\frac{(4\times2.53)-(-5.7)}{11.4} = \frac{10.12+5.7}{11.4} = \frac{15.82}{11.4} = 1.39$

Following equation 1, illuminance at each point was estimated as:

$$E_1 = 4.32 + 3.27(\sin(\pi \times 0.5)) = 7.58 \text{ lx}$$

$$E_2 = 4.32 + 3.27(\sin(\pi \times 0.72)) = 6.82 \text{ lx}$$

$$E_3 = 4.32 + 3.27(\sin(\pi \times 0.94)) = 4.88 \text{ lx}$$

$$E_4 = 4.32 + 3.27(\sin(\pi \times 1.17)) = 2.68 \text{ lx}$$

$$E_5 = 4.32 + 3.27(\sin(\pi \times 1.39)) = 1.25 \text{ lx}$$

$$E_6 = 4.32 + 3.27(\sin(\pi \times 1.39)) = 1.25 \text{ lx}$$

$$E_7 = 4.32 + 3.27(\sin(\pi \times 1.17)) = 2.68 \text{ lx}$$

$$E_8 = 4.32 + 3.27(\sin(\pi \times 0.94)) = 4.88 \text{ lx}$$

$$E_9 = 4.32 + 3.27(\sin(\pi \times 0.72)) = 6.82 \text{ lx}$$

$$E_{10} = 4.32 + 3.27(\sin(\pi \times 0.5)) = 7.58 \text{ lx}$$

The mean horizontal illuminance for location PL1 was calculated by taking the arithmetic mean of the illuminances at the 10 evenly spaced points:

$$E_{mean} = \frac{E_1 + E_2 + E_3 + E_4 + E_5 + E_6 + E_7 + E_8 + E_9 + E_{10}}{10} = 4.64 \text{ lx}$$

The arithmetic mean horizontal illuminance results from the simplified survey were classified as follows: those that suggested arithmetic mean horizontal illuminances below 5 lx (P4 to P6 in the P lighting classes) were classed as low level of illuminance; 5 to 10 lux were classed as medium level of illuminance (P2 to P4 in the P lighting classes); and above 10 lux (P1 to P2 in the P lighting classes) were classed as high level of illuminance. While this classification refers to the P lighting classes, the light measurements were at waist height rather than at ground level, and are thus likely to be higher values than at ground level. This categorisation is used for the rankings in Table 5.1, and agreed with the researcher's initial self-assessment of low, medium and high level of illuminance, as demonstrated in Figure 5.2; the clusters in Figure 5.2 show little overlap (only one point from the low illuminance cluster overlapped with the medium illuminance cluster (location PL6), and the 'low' designation of that point was changed to 'medium' in Table 5.1).

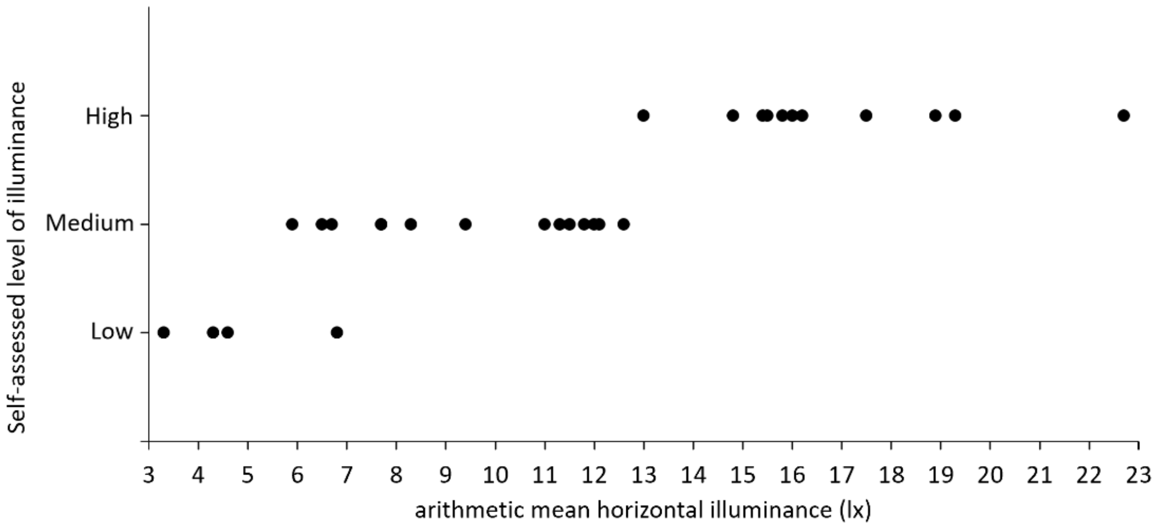


Figure 5.2. Plot of arithmetic mean horizontal illuminances calculated using equation 1 (X-axis) against self-assessed levels of illuminance (Y-axis) for the 29 potential locations in Experiment 2.

5.2.2 Final choice of locations

The final choice of test locations required a combination of the ranges of anticipated reassurance and illuminance (Figure 5.3). Note that none of the 29 shortlisted locations (Table 5.1) offered the combination of high reassurance and low illuminance.

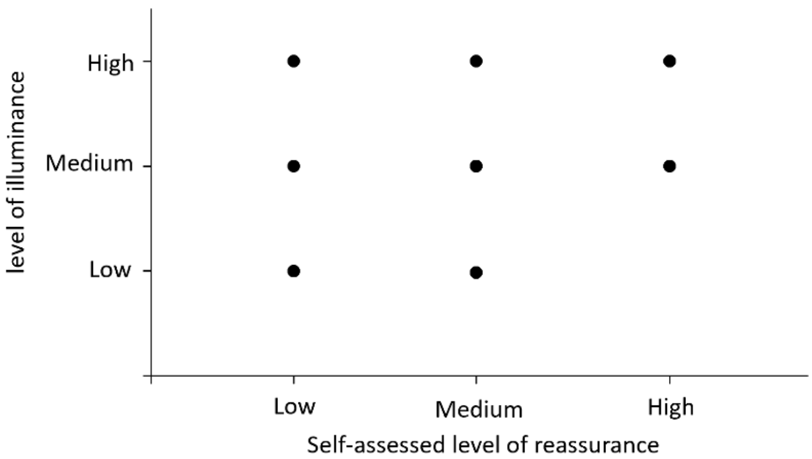


Figure 5.3. Plot of self-assessed levels of reassurance (X-axis) against levels of illuminance (Y-axis) for the 29 potential locations in Experiment 2 (see Table 5.1).

The final choice of locations was based on three considerations:

(1) Choosing at least one location from each of the regions of the graph in Figure 5.3 in order to include a variety of reassurance and illuminance combinations;

(2) The distance between locations so that a test session could be completed within about two hours, allowing for walking between locations with several different route variations; and

(3) choosing locations with a range of different pedestrian pathways (dedicated pedestrian footpath, footpath adjacent to cycle path, no dedicated footpath).

The 12 locations are labelled hereafter as R2.1 to R2.12. The map of 12 locations is presented in Figure 5.4. Photographs and characteristics of each location can be found in Figure 5.5 and Table 5.2.

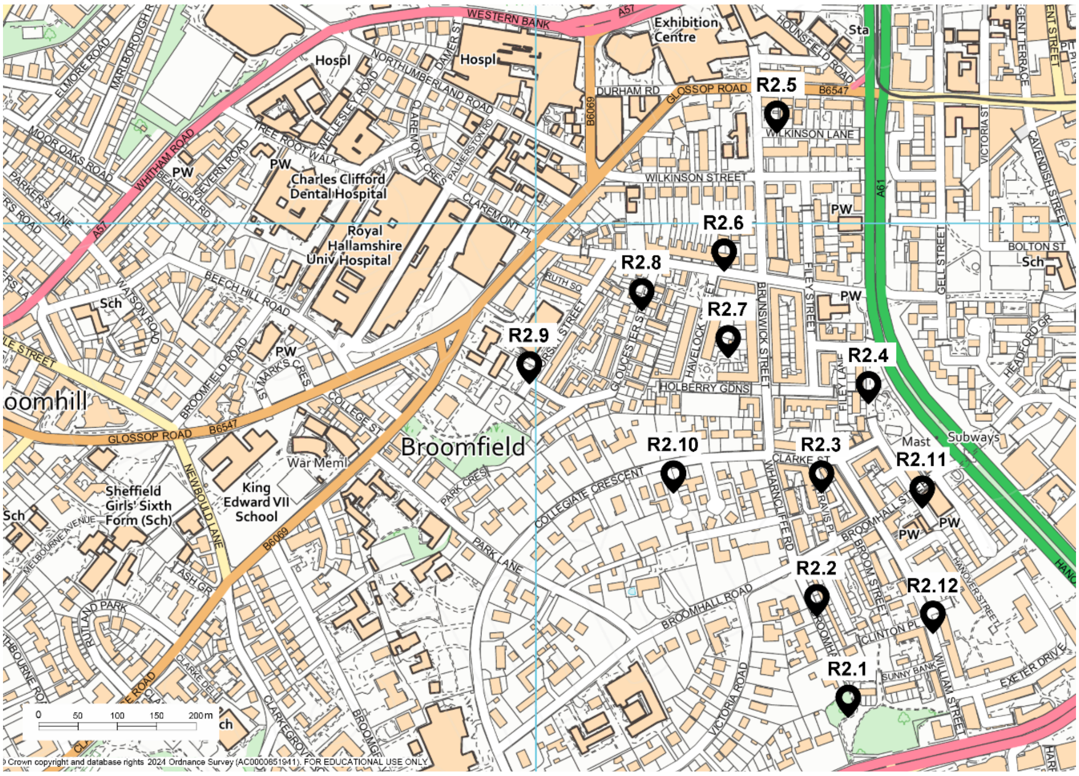


Figure 5.4. Map of the 12 locations in Experiment 2 (background map from Digimap (digimap.edina.ac.uk/roam/map/os) and locations added by author).



















Figure 5.5. Daylight (left) and after-dark (right) photographs of the 12 test locations in Experiment 2 (R2.1 to R2.12 from top to bottom).

Table 5.2. Characteristics and lighting parameters of the 12 test locations in Experiment 2. The light source was LED in all locations.

Location ref.	Ref. in Table 5.1	Location coordinates	Path type*	Lighting configuration	Self-assessment by researcher		Photometric measurements**					Distance between lampposts (m)	Calculation points**	
							Horizontal illuminance (lx)							
					Anticipated level of reassurance	Level of illuminance	Level of illuminance	Arithmetic mean	Minimum	Uniformity	CCT (K)		Total no.	No. not surveyed (% not surveyed)
R2.1	PL1	53°22'24.0"N 1°29'04.9"W	C	Single sided	Medium	Low	Low	3.2	0.4	0.13	6300	22.6	30	0 (0%)
R2.2	PL2	53°22'27.5"N 1°29'06.5"W	A	Staggered	Medium	Medium	Medium	6.2	0.4	0.07	4500	36.2	104	4 (4%)
R2.3	PL5	53°22'33.1"N 1°29'06.7"W	A	Staggered	Low	Medium	Medium	6.8	1.2	0.18	5700	30.8	66	5 (8%)
R2.4	PL6	53°22'36.4"N 1°29'03.4"W	B	Single sided	Low	Low	Low	2.6	0.2	0.08	5700	40.4	84	0 (0%)
R2.5	PL10	53°22'47.1"N 1°29'09.0"W	A	Single sided	Medium	High	High	11.8	4.3	0.36	4200	29.5	40	0 (0%)
R2.6	PL11	53°22'41.7"N 1°29'13.4"W	A	Staggered	High	High	Medium	9.1	0.7	0.08	4000	42	105	8 (8%)
R2.7	PL14	53°22'38.2"N 1°29'12.7"W	B	Single sided	Low	Low	Low	2.7	0.3	0.11	5500	26.2	30	0 (0%)
R2.8	PL15	53°22'39.7"N 1°29'18.7"W	A	Staggered	Medium	Medium	Medium	6.1	0.7	0.11	5500	37.3	91	3 (3%)
R2.9	PL17	53°22'37.8"N 1°29'25.3"W	A	Staggered	Low	High	Medium	6.9	0.4	0.06	5300	39.7	84	2 (2%)
R2.10	PL21	53°22'32.7"N 1°29'16.2"W	D	Single sided	Low	High	Medium	9.7	0.2	0.02	4200	37.5	52	2 (4%)
R2.11	PL28	53°22'32.0"N 1°28'59.6"W	A	Single sided	Low	High	Medium	7.3	1.9	0.26	5400	24.7	60	4 (7%)
R2.12	PL29	53°22'27.0"N 1°28'59.2"W	A	Single sided	High	High	Medium	5.9	0.6	0.10	5400	38.1	104	12 (12%)

* A = Footpath along the road, B = Pedestrian only path, C = Footpath through wooded area, D = Cul-de-sac to four houses, no footpath

**Illuminance measurements followed EN 13201-3:2015 guidelines (see section 5.3)

One location (R2.1) was a footpath through a wooded area with an adjacent cycle path separated by a small kerb; one location (R2.10) was a cul-de-sac to four houses and did not have a footpath, meaning pedestrians had to walk along the road; two locations (R2.4 and R2.7) were pedestrian only paths, and the rest of the locations were footpaths alongside a road. All footpaths were paved with grey asphalt, other than R2.1 which was paved with light-grey stone blocks.

It was predicted that six locations offered low, four offered medium, and two offered high reassurance. Based on the researcher's self-assessment, three locations were predicted to offer low, three to offer medium, and six to offer high levels of illuminance. However, the accurate light measurements (see section 5.3) changed the level of illuminance in locations R2.6, R2.9, R2.10, and R2.11 from high to medium, meaning that none of the 12 locations offered the combination of low reassurance and high illuminance, high reassurance and low illuminance, and high reassurance and high illuminance (Table 5.2 and Figure 5.6).

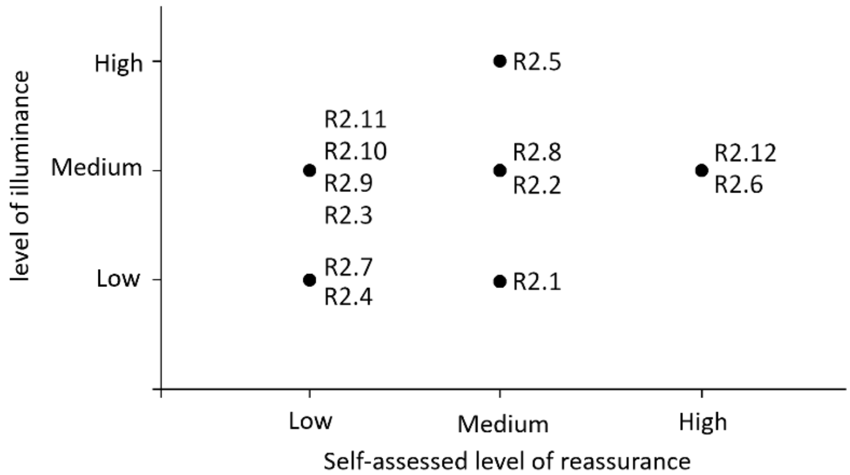


Figure 5.6. Plot of self-assessed level of reassurance (x-axis) against level of nominal illuminance for the 12 locations (y-axis). Level of nominal illuminances determined from illuminances reported in Table 5.2

5.2.3 Route choices

A pilot study was carried out before the main experiment to determine if the 12 selected locations could be visited in a random order in the two-hour test period. The author visited the 12 locations following three random route variations. In two of the three routes, it was not possible to complete the experiment in two hours, when accounting for the time required at each location to complete the evaluation and the time needed to walk from one location to the next. Extending the two-hour period was not considered due to the risk of participant exhaustion. Another option was to randomise the starting location. This was also not considered as it was predicted that solo participants would choose the easiest route and carry out the experiment with the same route for both test sessions, possibly making it difficult to achieve route variation amongst the participants. Therefore, 14 different systematically varied route orders which could be completed in two hours were determined by the author. It was predicted that the order in which the locations were visited could influence reassurance ratings; if the visit order is reversed, participants' reassurance ratings may change, as reassurance in one location can influence reassurance in subsequent locations (e.g. starting from a street with low reassurance may lead to subsequent streets feeling less safe). This was accounted for in Experiment 2, by including the reverse of the 14 route variations and balancing the order in which streets were visited. This led to a total of 28 different route variations. For each test session, participants were randomly assigned to one of the 14 routes, or the reverse of those routes, to balance the route order (Table 5.3).

Table 5.3. The 28 route variations used in Experiment 2.

	Order in which the locations are visited											
Route ref*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
RO1	R2.2	R2.1	R2.12	R2.3	R2.11	R2.4	R2.10	R2.6	R2.8	R2.9	R2.7	R2.5
RO1-r	R2.5	R2.7	R2.9	R2.8	R2.6	R2.10	R2.4	R2.11	R2.3	R2.12	R2.1	R2.2
RO2	R2.5	R2.9	R2.7	R2.8	R2.6	R2.2	R2.10	R2.4	R2.3	R2.11	R2.12	R2.1
RO2-r	R2.1	R2.12	R2.11	R2.3	R2.4	R2.10	R2.2	R2.6	R2.8	R2.7	R2.9	R2.5
RO3	R2.7	R2.11	R2.4	R2.12	R2.1	R2.2	R2.3	R2.10	R2.6	R2.8	R2.9	R2.5
RO3-r	R2.5	R2.9	R2.8	R2.6	R2.10	R2.3	R2.2	R2.1	R2.12	R2.4	R2.11	R2.7
RO4	R2.11	R2.12	R2.1	R2.4	R2.3	R2.10	R2.2	R2.5	R2.7	R2.9	R2.8	R2.6
RO4-r	R2.6	R2.8	R2.9	R2.7	R2.5	R2.2	R2.10	R2.3	R2.4	R2.1	R2.12	R2.11
RO5	R2.9	R2.5	R2.7	R2.4	R2.10	R2.3	R2.2	R2.1	R2.12	R2.11	R2.8	R2.6
RO5-r	R2.6	R2.8	R2.11	R2.12	R2.1	R2.2	R2.3	R2.10	R2.4	R2.7	R2.5	R2.9
RO6	R2.3	R2.6	R2.11	R2.1	R2.8	R2.5	R2.9	R2.12	R2.10	R2.4	R2.7	R2.2
RO6-r	R2.2	R2.7	R2.4	R2.10	R2.12	R2.9	R2.5	R2.8	R2.1	R2.11	R2.6	R2.3
RO7	R2.12	R2.7	R2.2	R2.6	R2.5	R2.4	R2.8	R2.10	R2.11	R2.1	R2.3	R2.9
RO7-r	R2.9	R2.3	R2.1	R2.11	R2.10	R2.8	R2.4	R2.5	R2.6	R2.2	R2.7	R2.12
RO8	R2.9	R2.4	R2.1	R2.10	R2.6	R2.3	R2.8	R2.5	R2.7	R2.11	R2.2	R2.12
RO8-r	R2.12	R2.2	R2.11	R2.7	R2.5	R2.8	R2.3	R2.6	R2.10	R2.1	R2.4	R2.9
RO9	R2.8	R2.4	R2.2	R2.11	R2.7	R2.9	R2.5	R2.3	R2.12	R2.1	R2.10	R2.6
RO9-r	R2.6	R2.10	R2.1	R2.12	R2.3	R2.5	R2.9	R2.7	R2.11	R2.2	R2.4	R2.8
RO10	R2.6	R2.1	R2.4	R2.5	R2.8	R2.10	R2.2	R2.7	R2.11	R2.3	R2.9	R2.12
RO10-r	R2.12	R2.9	R2.3	R2.11	R2.7	R2.2	R2.10	R2.8	R2.5	R2.4	R2.1	R2.6
RO11	R2.1	R2.7	R2.10	R2.3	R2.8	R2.5	R2.9	R2.4	R2.2	R2.11	R2.6	R2.12
RO11-r	R2.12	R2.6	R2.11	R2.2	R2.4	R2.9	R2.5	R2.8	R2.3	R2.10	R2.7	R2.1

RO12	R2.4	R2.9	R2.11	R2.10	R2.5	R2.6	R2.2	R2.12	R2.1	R2.3	R2.8	R2.7
RO12-r	R2.7	R2.8	R2.3	R2.1	R2.12	R2.2	R2.6	R2.5	R2.10	R2.11	R2.9	R2.4
RO13	R2.10	R2.4	R2.11	R2.7	R2.6	R2.5	R2.9	R2.1	R2.12	R2.2	R2.3	R2.8
RO13-r	R2.8	R2.3	R2.2	R2.12	R2.1	R2.9	R2.5	R2.6	R2.7	R2.11	R2.4	R2.10
RO14	R2.5	R2.6	R2.11	R2.1	R2.10	R2.12	R2.4	R2.9	R2.3	R2.2	R2.7	R2.8
RO14-r	R2.8	R2.7	R2.2	R2.3	R2.9	R2.4	R2.12	R2.10	R2.1	R2.11	R2.6	R2.5

* r at the end of the route reference means 'reverse' (e.g. RO1-r is the reverse of route RO1).

5.3 Light measurements

For the 12 selected locations, a more accurate photometric survey was carried out at each location, to measure horizontal illuminance and correlated colour temperature (CCT).

5.3.1 Illuminance measurements

In accordance with lighting design guidelines in the CIE 115:2020 (CIE, 2010), EN 13201-2:2015 (BSI, 2015a) and EN 5489-1:2020 (BSI, 2020), horizontal photopic illuminance was measured to determine the lighting conditions at each location. This was done using a Konica Minolta T-10M illuminance meter which had been calibrated one month before the measurements. An apparatus was used to facilitate measurements, and to avoid casting shadows on the photo sensor. The illuminance meter was mounted on a stick with the photo sensor placed level with the horizontal plane at ground level using a spirit level attached to the apparatus (Figure 5.7). The apparatus was constructed using unpainted, light-coloured wood, which may have been of higher reflectance than a black coloured stick.

Figure 5.7. The apparatus used for measuring horizontal illuminance in the 12 test locations.

Light measurements were carried out across three days on 26 April, 28 April and 30 April 2023, with all of the measurements for any one specific road completed on one night. All measurements commenced after dark, at around 22:00, after the end of civil twilight. In addition to being dark, this time helped to ensure the roads were not crowded with parked cars which could obstruct or cast shadows on the calculation points, or crowded with passing vehicles, the headlights of which would confound the illuminance readings. Table 5.4 shows conditions during illuminance measurements.

Table 5.4. Conditions during the illuminance measurements. All measurements commenced at 22:00.

Date	End of civil twilight	Moon phase (percentage illumination*)	Weather condition	Road surface condition
26 April 2023	21:05	Waxing Crescent (39%)	Clear sky	Dry
28 April 2023	21:09	First Quarter (59%)	Clear sky	Dry
30 April 2023	21:13	Waxing Gibbous (77%)	Clear sky	Dry

* Refers to the percentage of the Moon's visible disk that is lit up by direct sunlight, as seen from Earth.

The photometric survey followed the method described in EN 13201-3:2015 (BSI, 2015b); horizontal illuminance at ground level was measured at a number of evenly spaced points between the two successive lampposts at each location (Figure 5.8). The number of, and distance between, the calculation points in the longitudinal and transverse directions was determined using equations 2 and 3, respectively. The footpath was included in the calculation field.

$$D = \frac{S}{N} \tag{2}$$

where D is the spacing between points in the longitudinal direction (in metres), S is the spacing between luminaires (in metres), and N is the number of calculation points in the longitudinal direction determined as follows:

If $S \leq 30\ m$, then $N = 10$;

If $S > 30\ m$, then N is the smallest integer giving $D \leq 3\ m$.

$$d = \frac{W_r}{n} \tag{3}$$

where d is the spacing between points in the transverse direction (in metres), W_r is the width of the road or relevant area (in metres), and n is the number of calculation points in the transverse direction determined as follows:

n is the smallest integer giving $d \leq 1.5\ m$, and is always equal or greater than 3.

The spacing of the calculation points from the edges of the calculation field is $\frac{D}{2}$ in the longitudinal direction and $\frac{d}{2}$ in the transverse direction.

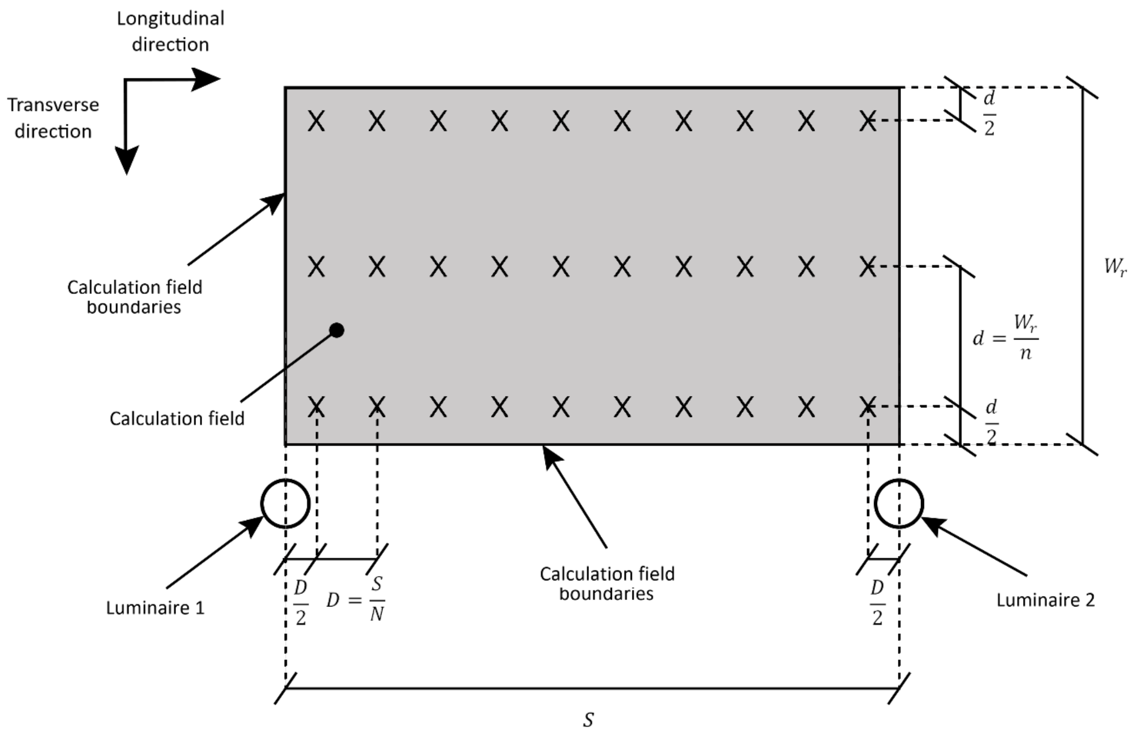


Figure 5.8. Calculation points (marked with X) for measuring horizontal illuminance (redrawn from Figure 14 in EN 13201-3 (BSI, 2015b)). For Experiment 2, the footpath was included in the calculation field.

Each afternoon, the designated photometric survey points for that evening were marked with chalk on the ground (Figure 5.9). Depending on the location size, this included 10 to 15 calculation points in the longitudinal direction, and 3 to 8 calculation points in the transverse direction, giving 30 to 105 calculation points.

Figure 5.9. Measurement points drawn on the ground in location R2.4 (see white crosses).

At each calculation point, three illuminance readings were taken, to account for any variations due to changes in surrounding light and position of the photo sensor, and the mean of these was recorded as the final value. The author waited for any cars to pass before recording any readings, and made sure not to cast any shadows on the light detector. If a parked car was blocking or casting a shadow on a calculation point, the reading at that point was omitted; in eight locations, 2% to 12% of the calculation points were not surveyed (see Table 5.2). Return visit to those locations did not allow for a reduction in the numbers of omitted calculation points. Hence, the missing values for the omitted calculation points were estimated by linear interpolation between adjacent readings.

Road lighting guidelines typically specify average illuminance, but don't clarify if this refers to the mean or median. Following definition of average luminance in EN 13201-3:2015 (BSI, 2015b), the average horizontal illuminance in each location was calculated by taking the arithmetic mean of the readings for all the calculation points in that location. From these measurements, mean and minimum illuminance values, and the uniformity were calculated. These are reported in Table 5.2. An example calculation for location R2.8 is shown below and in Figure 5.10:

Calculations for the longitudinal direction:

$$S = 37.3 \text{ m}$$

$$N = roundup\left(\frac{S}{3}\right) = roundup\left(\frac{37.3}{3}\right) = 13$$

$$D = \frac{S}{N} = \frac{37.3}{13} = 2.87 \text{ m}$$

$$\frac{D}{2} = \frac{2.87}{2} = 1.43 \text{ m}$$

Calculations for the transverse direction:

$$W_r = 10.2 \text{ m}$$

$$n = roundup\left(\frac{W_r}{1.5}\right) = roundup\left(\frac{10.2}{1.5}\right) = 7$$

$$d = \frac{W_r}{n} = \frac{10.2}{7} = 1.46 \text{ m}$$

$$\frac{d}{2} = \frac{1.46}{2} = 0.73 \text{ m}$$

Calculation of photometric values:

Mean horizontal illuminance (arithmetic mean of all the readings in Figure 5.10) = 6.1 lx

Minimum horizontal illuminance = 0.7 lx

Uniformity = $\frac{Minimum\ horizontal\ illuminance}{Mean\ horizontal\ illuminance} = \frac{0.7}{6.1}$ = 0.1

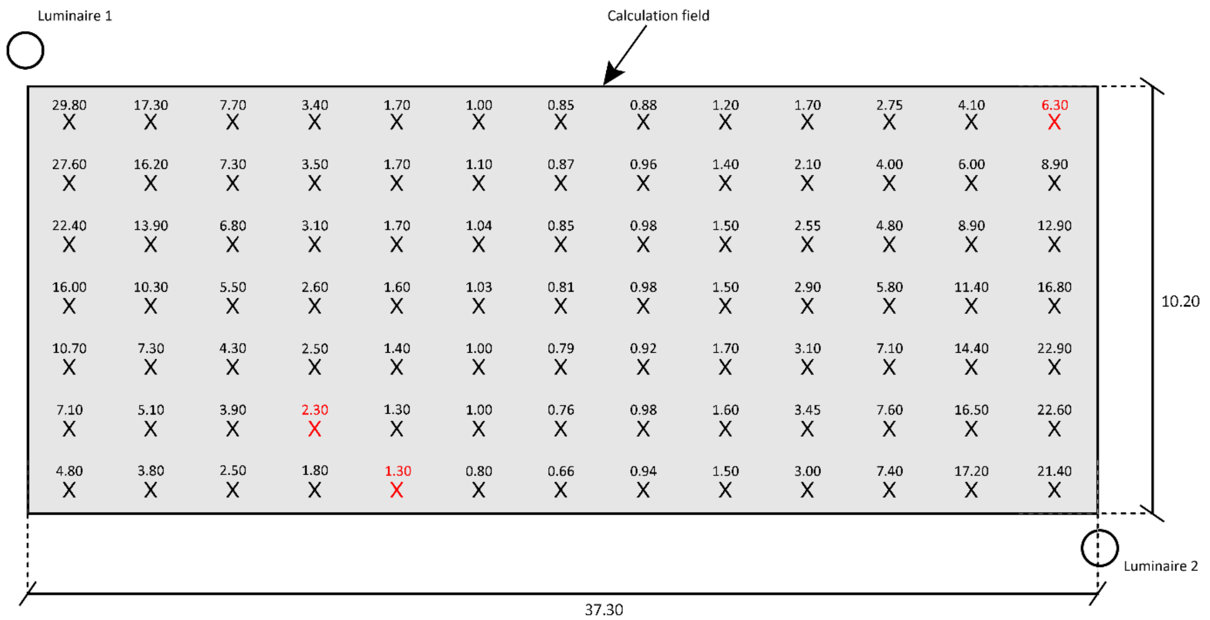


Figure 5.10. The horizontal illuminance readings (in lx) in location R2.8 (locations marked with a red X were not surveyed due to being overshadowed or blocked by a parked car: the values reported in red were determined using linear interpolation between adjacent readings in the longitudinal and transverse directions).

5.3.2 CCT measurements

At each location, CCT was measured on two separate occasions, using a Konica Minolta CL-200 chroma meter which had been calibrated in the last 6 months. Table 5.5 shows conditions during CCT measurements.

Table 5.5. Dates and conditions during the CCT measurements.

Date	Measurement time		End of civil twilight	Moon phase (percentage illumination*)	Weather condition	Road surface condition
	Start	End				
18 April 2023	21:30	22:15	20:50	Waning crescent (illumination 4%)	Clear sky	Dry
7 May 2023	22:11	22:53	21:29	Waning gibbous (illumination 98%)	Clear sky	Dry

* Refers to the percentage of the Moon's visible disk that is lit up by direct sunlight, as seen from Earth.

The measurements were done when no car lights were present, and by holding the chroma meter at waist height under the starting lamp post at each location. The values reported in Table 5.2 are the mean of the two measurements. These data show that lighting in the 12 roads presented different CCTs, suggesting different types of LED had been installed. While lamp spectra variations could influence reassurance assessments (Knight, 2010), their impact is likely less significant than changes in illuminance. Therefore, this thesis does not focus on light source.

The arithmetic mean horizontal illuminance, minimum horizontal illuminance, uniformity, and CCT for the 12 test locations are reported in Table 5.2. Mean horizontal illuminances ranged from 2.6 lx to 11.8 lx. The light source in all locations was LED without any malfunctioning fixtures, and CCTs spanning from 4200 K to 6300 K. The lampposts in all locations were of the same height with a distance of 22.6 to 42 metres between two successive lampposts. The lampposts were single-sided in seven locations and staggered in five locations.

5.4 Questionnaire

The same daylight and after-dark questions from Experiment 1 (Figures 3.3 and 3.4) were used in Experiment 2, but in an online format using Google Forms rather than printed questionnaires. The online questionnaire was accessed by participants using their own smart phone or tablet, and by scanning a QR code sticker attached to the starting lamppost in each location. A web address was included under each QR code for participants to use, in case they could not scan the QR code (Figure

5.11). A separate back up QR code was provided to solo participants, in case a QR code had been vandalised at a test location. The solo participants were specifically instructed to only use the backup QR code in the case of vandalism, and after reporting this to the researcher. For the group evaluations, the researcher carried extra QR codes of each location, for participants to scan in case a QR code had been vandalised.

Figure 5.11. A participant scanning a QR code in location R2.6 to access the online questionnaire.

The online Google Form consisted of two pages. The first page asked for a code to gain access to the questionnaire (Figure 5.12). Each participant was given a unique access code for this purpose. This prevented public access to the questionnaire, and enabled the researcher to identify participant responses while keeping the raw data anonymised. It also allowed the researcher to track the time and location of solo evaluations, ensuring participants followed instructions. The participant also had to choose which test session, daylight or after dark, they were evaluating before moving to the next page.

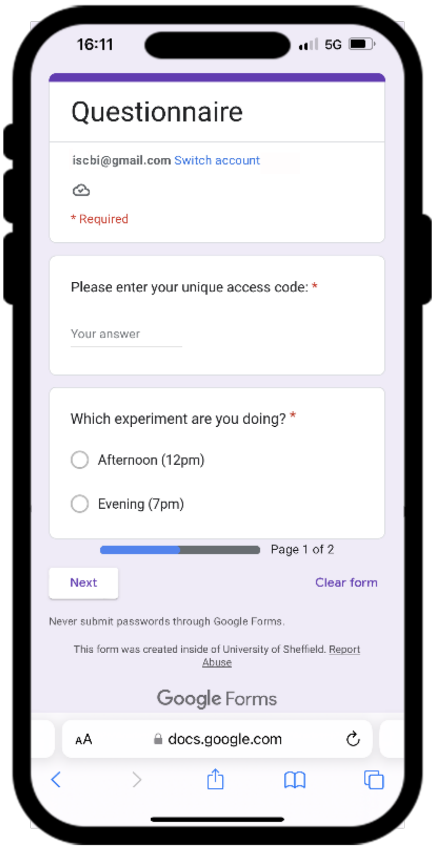


Figure 5.12. The first page of the online questionnaire displayed after scanning the QR code.

The second page of the online questionnaire included a brief instruction stating "Please, now face the path you walked and fill in this questionnaire to provide your experience of the street and (*for the after-dark questionnaire*) any lighting present", followed by the daylight or after-dark questions (Figure 5.13). The Google Form did not allow the participant to submit their responses without responding to all questions. This helped avoid the issue of blank responses in Experiment 1.

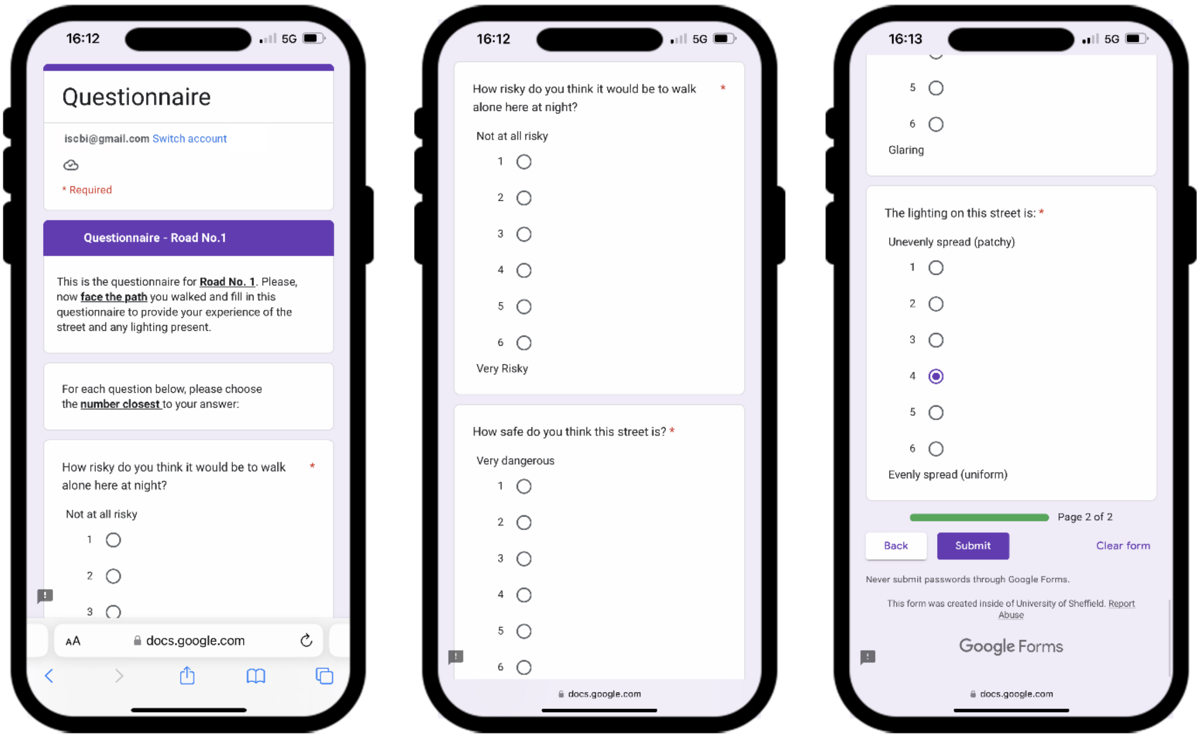


Figure 5.13. Segments of the second page of the online questionnaire for daylight evaluations.

The same daylight and after-dark questions were used in all test locations and test sessions. Using the automatic function in Google Forms, the order of the questions was randomly shuffled each time a participant accessed the questionnaire. A bogus question was randomly assigned to each of the streets, chosen from the same pool of 16 questions in Experiment 1. The same bogus question was used for all trials at a specific location (with a different question at the different locations) because there was no function in Google Forms to randomly select these. Each test location had a unique questionnaire and a unique QR code. This was to allow the randomisation of bogus questions across the locations, and was used as a second measure to monitor solo participants, to confirm they had actually visited all test locations.

5.5 Sample

The purpose of Experiment 2 was to assess the effect of illuminance on reassurance ratings and the effect of mode of evaluation (solo vs group) on reassurance ratings. Therefore, a power analysis was carried out using the software G*Power, to determine the sample size required to allow detection of an effect size of 0.5 (medium effect size according to Cohen's *d* (Cohen, 1992)), at a power of 0.8 and alpha of 0.05, for comparison of the solo and group evaluations. Using an independent samples t-test, it was revealed that a sample of 64 participants for each of the solo and group evaluations (overall sample size of 128) would be sufficient (Figure 5.14). Therefore, a sample of 140 participants was targeted for Experiment 2, slightly exceeding the sample size suggested by G*Power to detect a medium-sized effect, to account for any participant dropouts.

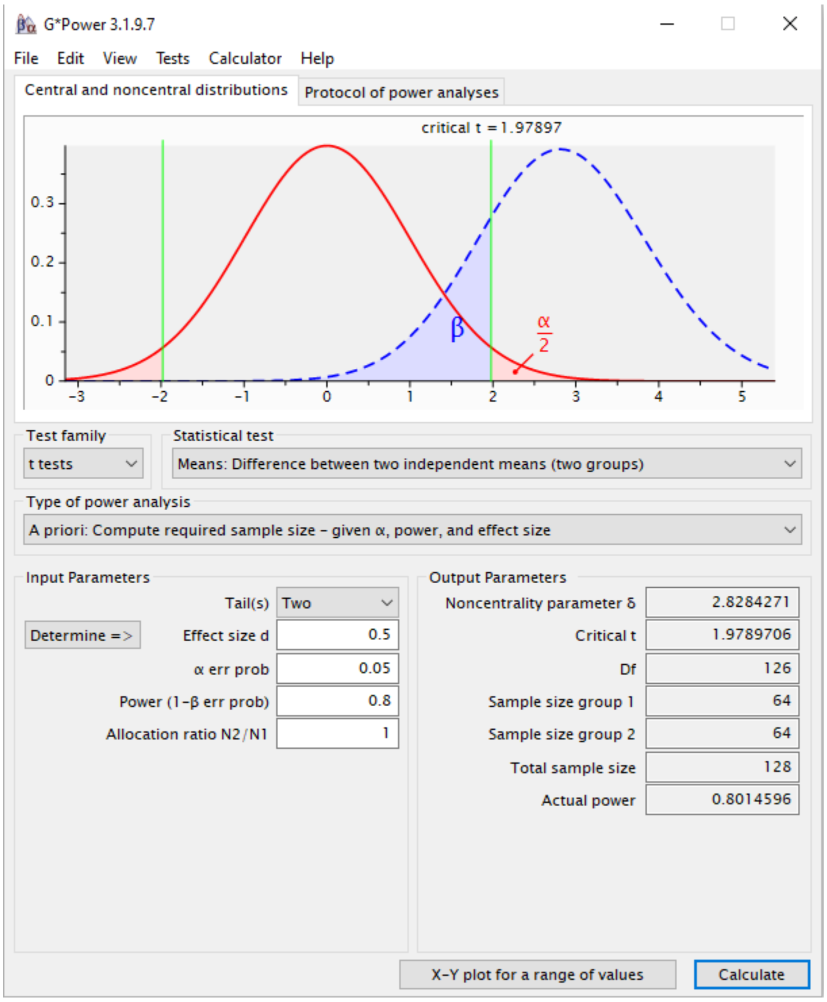


Figure 5.14. Sample size calculation for Experiment 1 in G*Power.

All participants were University of Sheffield students or University of Sheffield staff, recruited via an email sent to the university's Research Studies volunteering email distribution list. The email included information about the experiment, the participant criteria, and a link to a Google Form to sign up. Participants were required to be aged 18 or over, have self-reported normal vision (wearing glasses or contact lenses if normally worn), in reasonable physical health for intermittent walking for two hours, in possession of a phone or tablet with access to cellular data, and not to have taken part in the researcher's previous experiment (Experiment 1). The 420 people who signed up were divided into two groups of male and female participants, and 70 participants were randomly selected from each of the gender groups. Gender balance was considered to promote population representation, and to test hypotheses H5 about male and female responses. The 140 selected participants were sent a second email containing a link to a Google Form to express their availability during the experiment period. Participants were subsequently allocated two sessions in one of the solo evaluations or group evaluations; based on participant availability, 74 solo participants and 66 group participants were recruited.

Eighteen participants were omitted from the analysis: eight solo participants and two group participants withdrew before commencing the experiment, two solo participants and one group participant did not take part in the second test session, and three solo participants and two group participants were removed from the analysis because they gave five or more inattentive responses to the bogus question (see Chapter 6). The overall sample was therefore 122 participants, comprising 61 solo participants and 61 group participants. The sample included 62 males and 60 females, aged between 18 and 38 years with a mean age of 23 years (Table 5.6). Participants self-reported their vision status in the consent form: all indicated good visual health, and 57 wore their corrective lenses for walking. After completing both test sessions, each participant received a reimbursement of £40 for their time.

Table 5.6. The sample characteristics in Experiment 2.

Participant type	Gender	Total no. (no. wearing corrective lens)	Age range in years (mean age in years)
Solo participants	Male	32 (17)	18-35 (22)
	Female	29 (14)	18-36 (23)
Group participants	Male	30 (14)	18-38 (23)
	Female	31 (12)	18-37 (23)

5.6 Test times

The experiment took place on weekdays over a 7-week period from 19 January 2023 to 28 February 2023, all of which were working days and did not fall on a public holiday. Weekends were not included due to the potential change in the number of other people around on non-working days. The solo evaluations and group evaluations were carried out on separate days to avoid solo evaluations being made in the presence of group evaluations, and they commenced in adjacent periods to minimise differences in environmental conditions between the two types of evaluation; group evaluations were carried out on 24 January to 10 February, and solo evaluations took place on 19 January to 23 January, and 13 February to 28 February.

Each participant visited the pre-determined locations on two separate two-hour test sessions (repeated measures design), one in daylight with a start time of 12:00, and one in darkness with a start time of 19:00. All noon test sessions were in daylight as the solar altitude was greater than 0°, and all evening test sessions were in darkness, as they all commenced after the end of civil twilight (the end of civil twilight was 17:04 on 19 January and 18:16 on 28 February) when the solar altitude was less than -6° (Figure 5.15).

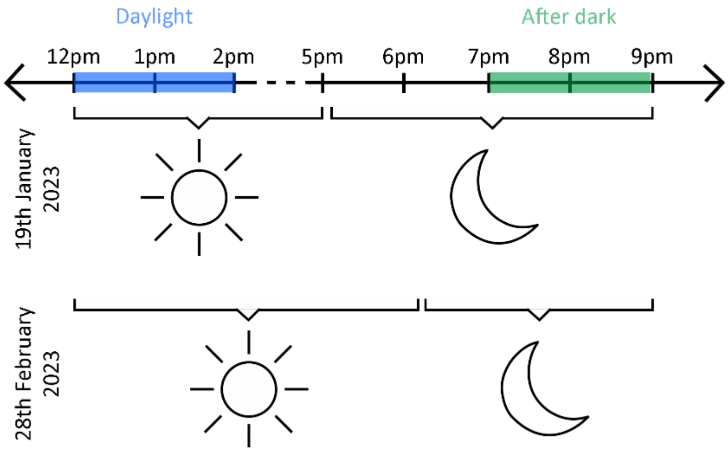


Figure 5.15. The test sessions in Experiment 2. End of civil twilight was between 17:04 and 18:16 during the experiment period from 19 January to 28 February.

The order of the daylight and after-dark sessions was balanced across participants; half took part in the daylight sessions first and the half took part in the after-dark sessions first. The two test sessions for a given participant were never on the same day, to allow time to forget responses from the previous test session; test sessions were spaced between one and eleven days apart, due to participant availability and experiment planning.

5.7 Procedure

5.7.1 Group evaluations

Participants who were allocated to group evaluations took part in test sessions in groups of two to six people. The group was accompanied by the author or a Research Associate from the Lighting Research Group, and one or two University of Sheffield Master students who were assisting the author. The allocation of participants was done randomly and based on availability, meaning for each test session, participants may have been grouped with the same people or different group of people.

During the experiment period and immediately before the first test session, the participant group met the researchers at a meeting point near the test locations to be briefed about the experiment. First, each participant received a consent form to read and sign. The participant group was then taken to a nearby street where the researcher demonstrated the experiment procedure, explained the daylight and after-dark questionnaires, and showed how to scan the QR codes and log answers. Specifically, the terms ‘not glaring/glaring’, ‘patchy/uniform’, ‘bad lighting/good lighting’, and ‘bright/dark’ in the after-dark questionnaire were clarified by giving definitions of each term. The participants were also instructed not to discuss the experiment or their survey responses with each other, in order to avoid influencing other participants’ responses. At the end of the briefing, participants were provided the chance to ask questions. For the second test session, the participant group met the researchers at the same meeting point, and was immediately taken to the first location of that session.

For each test session, the participant group walked to the 12 locations one after the other, following one of the randomly assigned 28 pre-determined routes. At each location, one of the lampposts had a QR code attached to it which acted as the starting lamppost and the evaluation point. Upon arrival, participants walked, at temporally spaced intervals, a short distance to the next lamppost, turned around (R2.1, R2.4, R2.7, and R2.10) or crossed the road (the other locations), and returned to the starting lamppost. They then scanned the QR code attached to the starting lamppost, faced the path they had just walked, and whilst standing under the starting lamppost completed the online questionnaire to report their impressions of that location (Figure 5.16). The questionnaire took no more than 2 minutes to complete at each location with a total of about 10 minutes allocated per location for the group, including travel time to the next location. Participants were asked not to group together during the walk, and started their walk in 10 to 15 second intervals so they walked alone. Upon completion of the questionnaire, the participants walked with the researchers to the next location and repeated the procedure.

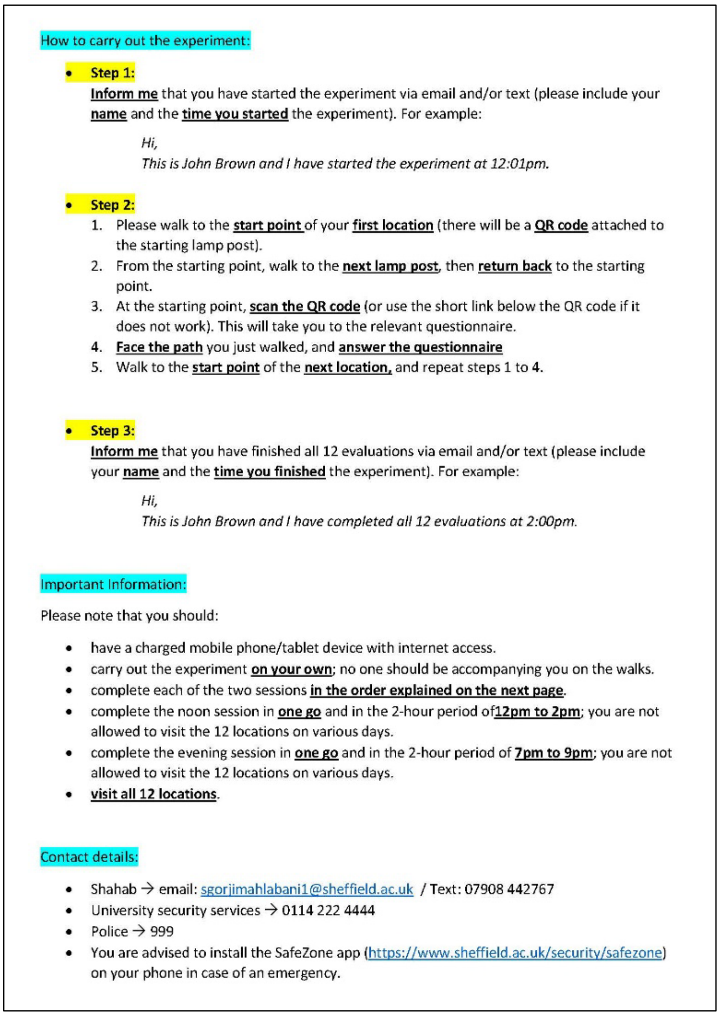
The same instructions as for Experiment 1 were given to participants in each location (see Section 3.7). The instructions were the same for all test locations and test sessions. Reassurance was not mentioned during the entire recruitment and experiment process to avoid biasing participants.

Figure 5.16. Group participants scanning the QR code in location R2.11 [left], and responding to the questionnaire in location R2.1 whilst standing under the starting lamppost [right].

5.7.2 Solo evaluations

For solo evaluations, participants visited the locations alone without being accompanied by other participants or the researcher; two to seven solo participants were allocated to each test session, but each started the experiment from a different location so they were not accompanied by other participants.

During the week before the solo evaluations commenced, the participants met the author at a meeting point near the test locations to attend one of four available briefing sessions. The participants first took part in a practice trial similar to the group evaluations. They also received a printed instruction booklet to guide them during the test sessions. The first page of the booklet included instructions about how to conduct the experiment, and necessary contact details (Figure 5.17). The second page, included the participants unique access code, a map of the locations, and the specific route the participant had to follow for their two test sessions (Figure 5.18). These were randomly assigned from the 28 pre-determined routes. The remaining pages included a map and image of each of the 12 test locations, the two lampposts the participants were required to walk between, and the direction of travel (Figure 5.19).



How to carry out the experiment:

- **Step 1:**
  Inform me that you have started the experiment via email and/or text (please include your **name** and the **time you started** the experiment). For example:

  Hi,
  This is John Brown and I have started the experiment at 12:01pm.

- **Step 2:**
  1. Please walk to the **start point** of your **first location** (there will be a **QR code** attached to the starting lamp post).
  2. From the starting point, walk to the **next lamp post**, then **return back** to the starting point.
  3. At the starting point, **scan the QR code** (or use the short link below the QR code if it does not work). This will take you to the relevant questionnaire.
  4. **Face the path** you just walked, and **answer the questionnaire**
  5. Walk to the **start point** of the **next location,** and repeat steps 1 to **4**.

- **Step 3:**
  Inform me that you have finished all 12 evaluations via email and/or text (please include your **name** and the **time you finished** the experiment). For example:

  Hi,
  This is John Brown and I have completed all 12 evaluations at 2:00pm.

Important Information:

Please note that you should:

- have a charged mobile phone/tablet device with internet access.
- carry out the experiment **on your own**; no one should be accompanying you on the walks.
- complete each of the two sessions **in the order explained on the next page**.
- complete the noon session in **one go** and in the 2-hour period of**12pm to 2pm**; you are not allowed to visit the 12 locations on various days.
- complete the evening session in **one go** and in the 2-hour period of **7pm to 9pm**; you are not allowed to visit the 12 locations on various days.
- **visit all 12 locations**.

Contact details:

- Shahab → email: sgorjimahlabani1@sheffield.ac.uk / Text: 07908 442767
- University security services → 0114 222 4444
- Police → 999
- You are advised to install the SafeZone app (https://www.sheffield.ac.uk/security/safezone) on your phone in case of an emergency.

Figure 5.17. The first page of the instruction booklet given to solo participants.

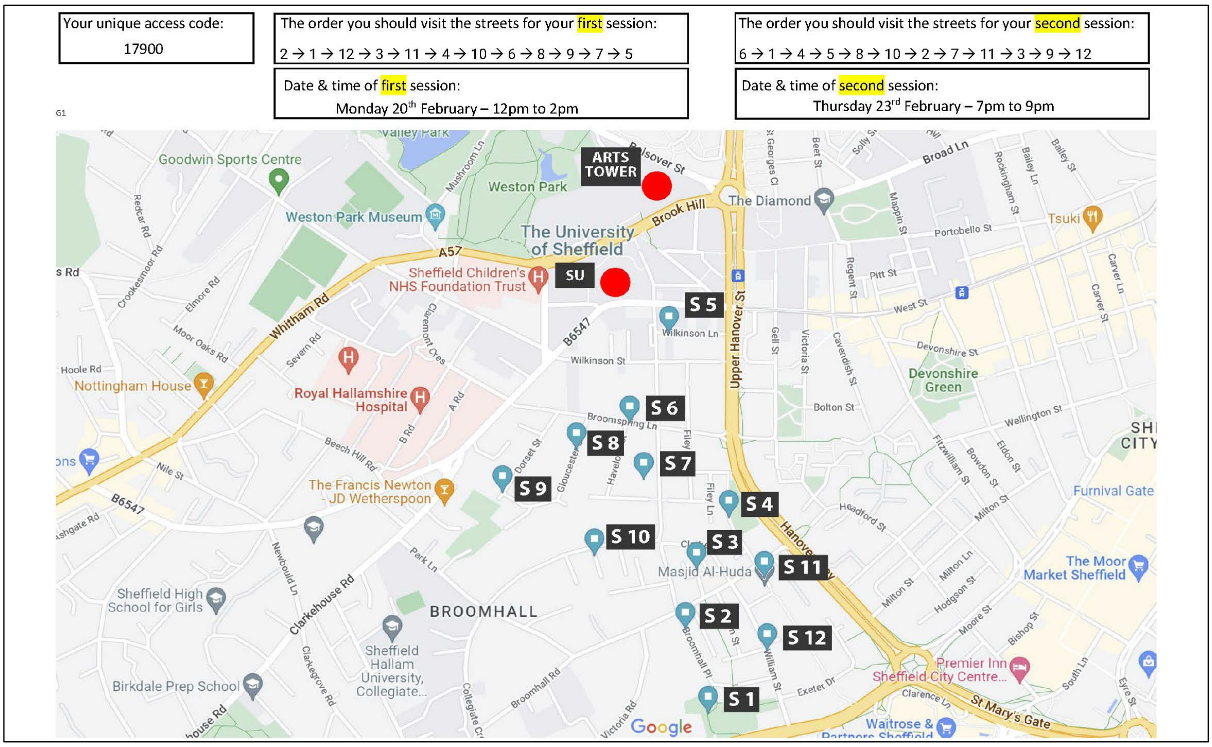


Figure 5.18. Example second page of the instruction booklet given to solo participants.

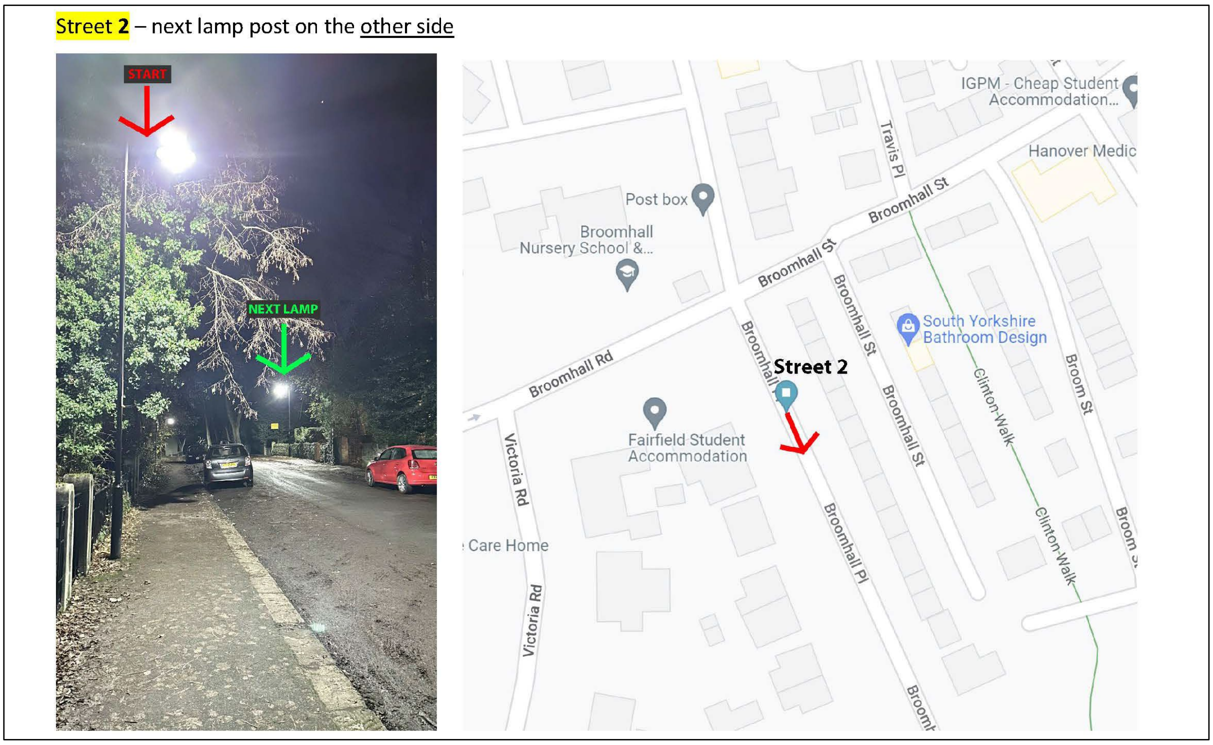


Figure 5.19. An example page of the instruction booklet showing location R2.2.

All maps were identical except for the allocated routes for the two test sessions. The author also made sure participants taking part in the same test session, received booklets with a different starting location, so they would not all group in one location.

Participants were specifically instructed to complete all the daylight evaluations in a single session, and all the dark evaluation in a single session; they were not allowed to visit the 12 locations for each of the daylight or after-dark evaluations on separate days. They were also asked to attend the sessions alone, and to not be accompanied by anyone such as friends or family. Participants were also informed that they may see other participants during the teste session, but were instructed not to talk to each other or discuss the experiment.

At the beginning of each test session, each participant informed the author with the time they had started the experiment via email or text message. Upon visiting all locations and completing the questionnaires, each participant emailed/text messaged the author again with the time they had finished the experiment. The online Google Form was used to track each participant; the time at which a participant submitted a form was logged, enabling the author to cross-check the start and finish time for each participant, and to also confirm they had followed the allocated route. The logged date and times were later assessed for reasonable evaluation times, and that they were not done simultaneously with another participant.

5.8 Summary

This chapter described the method used in Experiment 2, a field study to investigate the impact of different illuminances on pedestrian reassurance. The results of this experiment are presented in Chapter 6.

CHAPTER 6. EXPERIMENT 2 – REASSURANCE FIELD STUDY: RESULTS

6.1 Introduction

This chapter presents the results of Experiment 2, in which the impact of different illuminances on pedestrian reassurance was assessed, in two groups of solo and accompanied participants, using the day-dark approach. First, internal validity was assessed to ensure the participants' responses were reliable. Next, factor analysis was used as a statistical technique to identify which survey questions loaded highly onto the latent variable *reassurance*, and calculate a single composite reassurance score. This composite score was then used to assess the impact of variations in illuminance on pedestrian reassurance (Hypothesis H1), and the potential effect of higher illuminances in reducing gender differences in reassurance (Hypothesis H5). The results from solo and accompanied groups were also compared to address the question of whether participant accompaniment was important (Hypothesis H4). Finally, the association between illuminance and the after-dark ratings, and illuminance and day-dark differences were assessed (Hypothesis H2). The significance level of the statistical tests was set at $\alpha = 0.05$.

6.2 Internal validity

The process for assessing internal validation was similar to that explained in Chapter 4 (Section 4.2); the responses to the bogus question were assessed for inattentive responses, and a participant was excluded from the analysis if they gave 20% or more invalid responses. This was five or more inattentive responses out of the 24 bogus questions they answered (12 locations x 2 sessions). Analysis of responses to the bogus question revealed a 96% correct response rate, suggesting good respondent attentiveness. Inattentive responses were observed in 59 participants, primarily involving only one instance (Table 6.1). Five participants were removed as they gave five or more inattentive responses to the bogus question: these were three solo participants (two females and one male) and two group participants (two males).

Table 6.1. Participants with inattentive responses to the bogus question in Experiment 2.

No. of inattentive responses	No. of participants				Total	Decision
	Male		Female			
	Solo	Group	Solo	Group		
1	7	8	8	7	30	Retained
2	5	6	3	3	17	Retained
3	2	1	0	1	4	Retained
4	2	0	0	1	3	Retained
5	0	1	2	0	3	Omitted
6	0	1	0	0	1	Omitted
18	0	0	1	0	1	Omitted

For solo evaluations the time at which a participant submitted a form was logged. These were assessed to verify that evaluation times were reasonable and that submissions did not occur simultaneously with other participants. Review of logged responses confirmed that solo participants had followed instructions.

6.3 Factor analysis

Multiple survey questions were used in Experiment 2 to measure the different facets of reassurance, with the assumption that reassurance is a latent variable that cannot be directly measured (see section 3.4). Factor analysis is a common statistical technique used in analysing multivariate data such as reassurance (Bartholomew et al., 2011); factor analysis helps understand the underlying structure among the multiple variables, and identifies the underlying latent constructs that explain the relationship between the variables (Kim and Muller, 1978). Exploratory factor analysis was carried out to extract the underlying latent constructs in Experiment 2, with 'reassurance' predicted to be one of them. This was done for the daylight scores (referred to hereafter as *daylight scores/evaluations*) and after-dark scores (referred to hereafter as *after-dark scores/evaluations*) separately, to facilitate the calculation of the composite after-dark reassurance scores and composite day-dark reassurance scores. This also facilitated the comparison between the after-dark and day-dark methods.

Figure 6.1 shows the factor analysis procedure in Experiment 2. First, questions to include in the factor analysis were determined. Next, the data was screened to assess whether it met the assumptions of factor analysis. Appropriate extraction and rotation methods were then chosen, and the factor analysis was carried out. Finally, the composite reassurance score was calculated based on the results of the factor analysis. The factor analysis was carried out in IBM SPSS version 27. Screenshots of the software configurations in SPSS can be found in Appendix A.

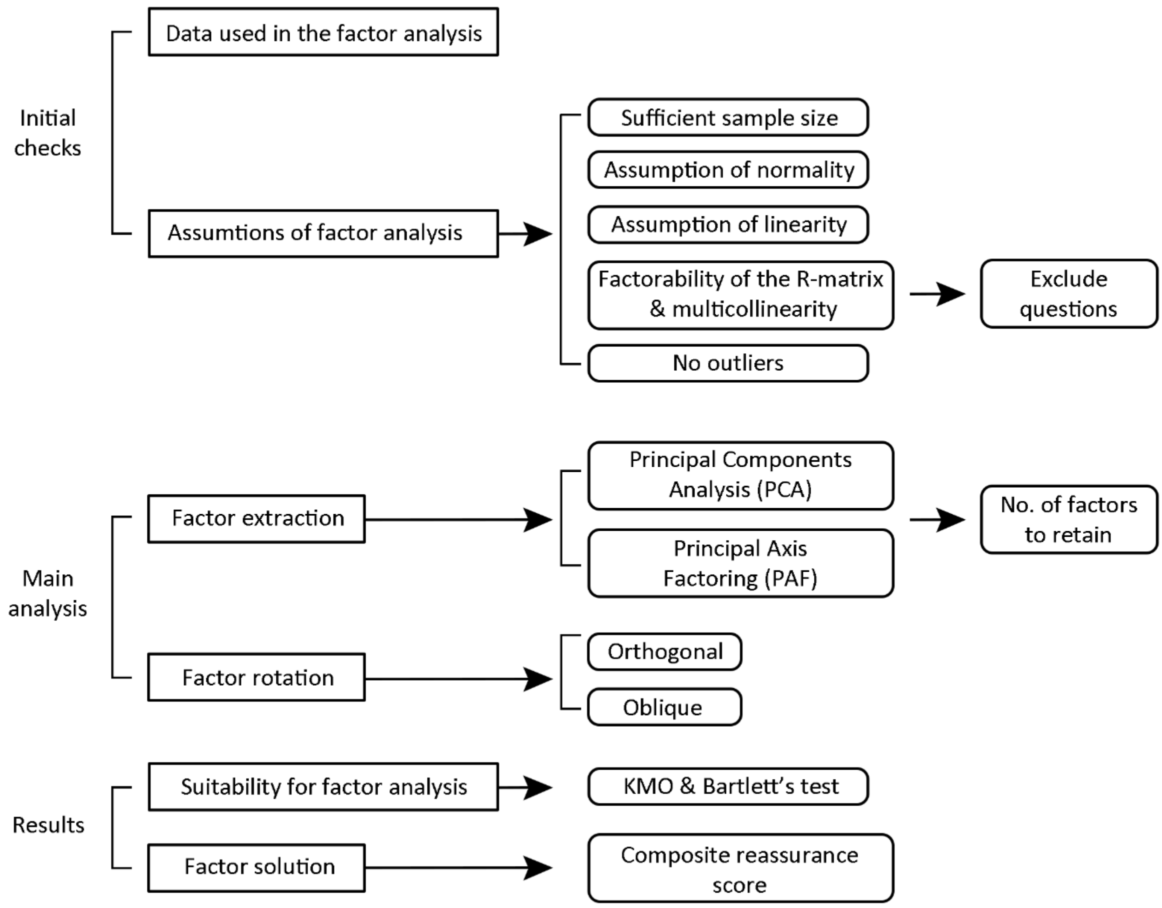


Figure 6.1. Factor analysis procedure in Experiment 2.

6.3.1 Data used in the factor analysis

The factor analysis focused on the responses to eight of the survey questions (see questions in bold in Table 6.2):

- The question '*How risky do you think it would be to walk alone here at night?*' (Q1 in Table 6.2) was removed as, for the daylight evaluations, the response required participants to imagine the environment after dark; Fotios et al. (2019a) show that reassurance ratings given for imagined after-dark conditions are lower than ratings given in real after-dark conditions.
- The bogus question (Q10 in Table 6.2) was removed as it was used as a measure of internal validation (see section 6.2).
- The additional five after-dark questions (Q11 to Q15 in Table 6.2) were about the quality of lighting rather than asking about reassurance and were, therefore, removed from the factor analysis.

Prior to conducting factor analysis on the eight remaining questions, the scoring for two questions (Q4, and Q8 in Table 6.2) was reversed, by subtracting each individual score from a constant value of 7. For example, an original score of 2 to Q4 was replaced with a score of 7-2 = 5 on the reversed scale. This ensured that, across all eight questions, a higher score on the rating scale always represented a safer or more positive evaluation.

Table 6.2. Questions used in the daylight and after-dark evaluations in Experiment 2.

No.*	Question	Rating scale							
Q1 (Risky)	How risky do you think it would be to walk alone here at night?	Not at all risky	1	2	3	4	5	6	Very Risky
Q2 (Safe)	**How safe do you think this street is?**	Very dangerous	1	2	3	4	5	6	Very safe
Q3 (Anxious)	**How anxious do you feel when walking down this street?**	Very anxious	1	2	3	4	5	6	Not at all anxious
Q4 (Avoid)	**I would rather avoid this street if I could.**	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q5 (Clear)	**I can see clearly around me.**	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q6 (Others)	**Apart from people accompanying me, there are lots of other people on the street.**	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q7 (Condition)	**This street is kept in good condition.**	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q8 (Litter)	**I can see a lot of litter and rubbish on this street.**	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q9 (Familiar)	**How familiar are you with this particular street?**	Not at all familiar	1	2	3	4	5	6	Very familiar
Q10 (Bogus)	I was born after 1879.**	Strongly Disagree	1	2	3	4	5	6	Strongly Agree
Q11	Overall, how satisfied are you with the lighting on this street?	Very Dissatisfied	1	2	3	4	5	6	Very Satisfied
Q12	The lighting on this street is:	Bad	1	2	3	4	5	6	Good
Q13		Bright	1	2	3	4	5	6	Dark
Q14		Not glaring	1	2	3	4	5	6	Glaring
Q15		Unevenly spread (patchy)	1	2	3	4	5	6	Evenly spread (uniform)

* Q1 to Q10 were used in the daylight evaluations and Q1 to Q15 were used in the after-dark evaluations - questions highlighted in bold are used in the factor analysis of Experiment 2.

** The bogus question was randomly selected from a pool of 16 questions (see Figure 3.5)

The eight questions were screened for any missing values. Only 72 of the 23,424 data entry points (~0.3%) were missing. In factor analysis, missing data for each participant can be handled in one of three ways:

- exclude cases listwise - if a participant has any missing data for any of the questions, that participant's entire data is excluded from the analysis;
- exclude cases pairwise - if a participant has missing data for a particular question, they are excluded from calculations involving that question, but are still included in calculations involving other questions where they have complete data;
- replace with mean – the missing values are estimated by replacing them with the mean of all the available values for that specific question.

Pairwise deletion was chosen for Experiment 2 as it utilises more data than listwise deletion, and can yield more accurate results. Replacing missing values with the mean was not used because missing data did not exhibit a non-random pattern, and the sample size remained adequate after deletion (Field, 2018; Tabachnick and Fidell, 2019).

6.3.2 Assumptions of factor analysis

Factor analysis rests on several key assumptions (Tabachnick and Fidell, 2019):

1. Sufficient sample size
2. No outliers
3. Assumption of normality
4. Assumption of linearity
5. Factorability of the R-matrix and multicollinearity

Prior to factor analysis, the data was screened for assumption violations. This also helped with the choice of extraction method used in the factor analysis (see section 6.3.3). It was found the assumptions of factor analysis were met.

6.3.2.1 Sufficient sample size

Sufficient sample size is crucial for obtaining reliable results in factor analysis (Field, 2018). Many rules of thumb assess the absolute size of the sample and the sample-to-variable ratio. Existing guidelines for absolute sample size are varied, but a minimum absolute sample size of 50 is often recommended for factor analysis, with a sample size of 100-200 generally considered sufficient, and a sample size of

300 often regarded as a large and robust sample (Boomsma, 1985; Comrey and Lee, 1992; Kline, 1994; MacCallum et al., 1999). The ratio of participants to variables is generally considered to be more important than the absolute sample size (Kline, 1994). Commonly accepted sample-to-variable ratios range from 5:1 to 10:1, suggesting a sample of at least 5 to 10 times the number of variables necessary for factor analysis (Comrey and Lee, 1992; Everitt, 1975; Kerlinger, 1986; Nunnally, 1978).

Absolute rules for sample size should, however, be approached with caution. For example, it has been shown that factor solutions tend to be stable regardless of the sample-to-variables ratio (Arrindell and van der Ende, 1985; Kass and Tinsley, 1979). This is because the sufficiency of the sample size also depends on other elements such as the factor loadings and communalities of variables (de Winter et al., 2009; Field, 2018; MacCallum et al., 2001; Mundfrom et al., 2005; Velicer et al., 1982). When considering factor loadings, a factor is considered reliable if it has at least four loadings above 0.6 (regardless of sample size), ten or more loadings above 0.4 (with a sample size over 150), or if it has few low loadings but a large sample size (over 300) (Guadagnoli and Velicer, 1988). In terms of communalities, there is an inverse relationship with sample size: with high communalities (above 0.6), small samples (under 100) are sufficient; with moderate communalities (around 0.5), samples of 100-200 may suffice if there are few factors with a small number of variables loading onto each factor; and with low communalities (below 0.5) and a large number of extracted factors, larger samples (over 500) are recommended (Fabrigar et al., 1999; MacCallum et al., 1999).

One limitation with the factor loadings and communalities criteria is that they can only be used after the experiment has been conducted and the data has been gathered; judgment of sufficient sample size before conducting an experiment can only be based on rules of thumb. The sample of 122 participants in Experiment 2 was judged to be sufficient as it was within the 100-200 recommended rule of thumb range, and met the stricter criterion of sample-to-variable ratio of 10:1; eight questions were included in the factor analysis, suggesting a minimum sample size of $8 \times 10 = 80$ necessary. Factor loadings and communalities calculated after gathering the data for Experiment 2, also suggested a sample of 100-200 to be sufficiently large enough for factor analysis; the number of extracted factors were small, and each factor had a small number of variables loading onto it, with four or more communalities above the 0.6 threshold (see sections 6.3.3).

6.3.2.2 No outliers

Univariate or multivariate outliers can disproportionately influence factor solution, and need to be identified and addressed before running a factor analysis. For continuous variables, outliers are sought among all cases at once, with cases with very high or very low z-scores (greater than 3.29 or less than

-3.29, $p < 0.001$, two-tailed test) considered outliers (Tabachnick and Fidell, 2019). Scores for the eight questions included in the factor analysis were converted to z-scores. Six scores were identified as outliers (z-score = -4.14). The six scores were not deleted because the extremeness of a z-score is related to sample size, and in larger samples, a few scores above 3.29 or below -3.29 are expected (Tabachnick and Fidell, 2019).

6.3.2.3 Assumption of normality

In factor analysis, the assumption of normality usually refers to multivariate normality, meaning all the variables being analysed are normally distributed, and all linear combination of the variables also follow a normal distribution. This assumption is, however, not a strict requirement and depends on the aim of the factor analysis and the specific extraction method used. Factor analysis, when used descriptively to summarize relationships among many variables, doesn't strictly require distributional assumptions; while normality enhances the solution, results remain plausible with minor deviations from normality (Tabachnick and Fidell, 2019). Some factor analysis techniques are more robust to violations of multivariate normality; multivariate normality is a requirement for Maximum Likelihood Estimation method, but Principal Axis Factoring and Principal Components Analysis do not explicitly rely on this assumption (Zygmont and Smith, 2014). The extraction method used in Experiment 2 is Principal Axis Factoring (see section 6.3.3) and, therefore, the assumption of multivariate normality is relaxed. However, Experiment 2 was assessed for severe violations of normality, as this can impact the results of the factor analysis, especially when making statistical inferences such as determining the number of factors to retain (Tabachnick and Fidell, 2019).

The assumption of multivariate normality is applied differently depending on the type of multivariate analysis. In analyses involving grouped data, the sampling distributions of means should be normally distributed. For analyses when cases are not grouped, the assumption applies to the distribution of the variables themselves, or to the residuals. (Tabachnick and Fidell, 2019). For grouped data with sufficiently large samples (generally sample sizes of 30 or more), the Central Limit Theorem assures normality of the sampling distribution, regardless of the distribution of the variables (Field, 2018; Kwak and Kim, 2017; Lumley at al., 2002; Tabachnick and Fidell, 2019; Weiss, 2012; Wilcoxon, 2010). Normal distribution of the variables in Experiment 2 was assessed using a mix of graphical tests (histograms, box plots, and Q-Q plots), measures of dispersion (skewness and kurtosis), and measure of central tendency (median and the 95% confidence interval of the mean), similar to that explained for Experiment 1 (see Chapter 4 for a detailed explanation). Statistical tests of normality (e.g. Kolmogorov-Smirnov test; Shapiro-Wilks test) were not used because of the large sample in Experiment 2 (Field, 2018). Multivariate normality tests (e.g. Mardia's Test; Henze-Zirkler Test) were also not used as they are overly sensitive, and may reject normality even when the deviations are minor in large samples (Tabachnick and Fidell, 2019).

Normality testing was carried out on the eight daylight and eight after-dark questions used in the factor analysis (section 6.3.1), for the solo participants and group participants separately. The normality test followed the same procedure outlined in chapter 4 (see section 4.3). It was revealed that the data for both the solo evaluations and group evaluations exhibited a near normal distribution. An example normality test for question 2 in a daylight session and for a solo evaluation is shown in Figure 6.2 and Table 6.3. The distribution of the question is considered to be normal because two of the three tests report a normal distribution: (1) the graphical test is near normal (the histogram approximates the bell-curve shape for normally distributed data; the box plot is normally distributed, as the median line is central within the box and the whiskers above and below the box are almost of similar length; the Q-Q plot is not normal as the data points form an s-shape around the straight diagonal line); (2) the skewness and kurtosis values are inside the normal ranges of ±0.5 and ±1 respectively; and (3) the median falls within the 95% confidence interval of the mean.

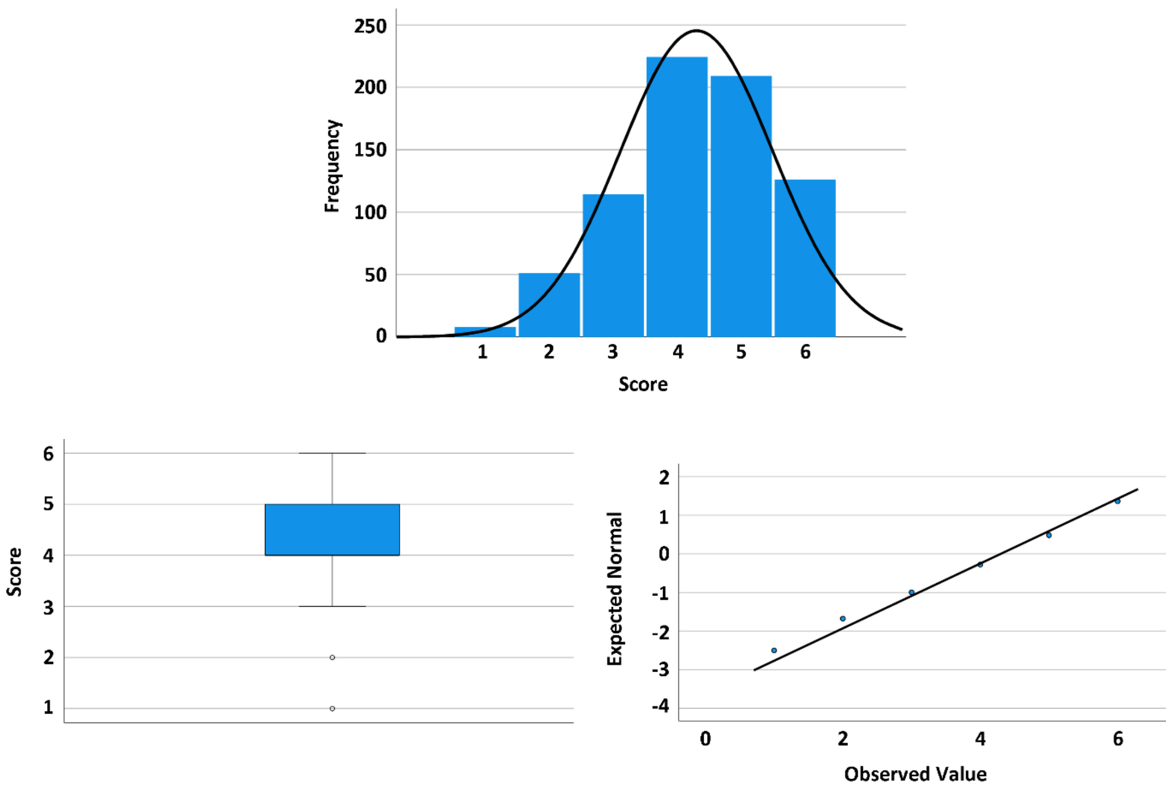


Figure 6.2. Box plot (top), histogram (middle), and Q-Q plot (bottom) of participant scores for question 2 - daylight session, solo evaluations.

Table 6.3. The normality test for question 2 - daylight session, solo evaluation.

Normality Test												
Graphical				**Dispersion**				**Central Tendency**				**Overall Normality**
Histogram	Box Plot	Q-Q Plot	**Normal?**	Skewness	Kurtosis	**Normal?**	Mean	Lower 95% CI	Upper 95% CI	Median	**Normal?**	
Yes	Yes	No	**Near**	-0.39	-0.40	**Yes**	4.30	4.22	4.39	4.00	**Yes**	**Yes**

Although some parts of the data are not normally distributed, the assumption of normality is met due to the central limit theorem; with a large sample size (generally considered 30 or more (Field, 2018)), the sampling distribution will be approximately normal regardless of the shape of the population or sample data (Lumley at al., 2002).

6.3.2.4 Assumption of linearity

Because factor analysis assumes multivariate normality, it also assumes that the relationships between pairs of variables are linear. Non-linear relationships can weaken the factor analysis. Scatterplots are used to assess the linearity between pairs of variables. The presence of differing skewness values among the variables suggests that some variable pairs may have non-linear relationships. With 16 variables, examining all 120 pairwise scatterplots was impractical, and a few plots were examined to check for non-linearity. A worst case is plotting a variable with strong positive skewness against a variable with strong negative skewness (e.g. Q2 in the solo after-dark evaluation). Figure 6.3 shows one example for the solo daylight evaluations, with Q5 (skewness = - 1.516) plotted against Q9 (skewness = 1.012). The scatterplot's non-oval shape suggests a departure from linearity; however, there's no clear indication of a true curvilinear relationship.

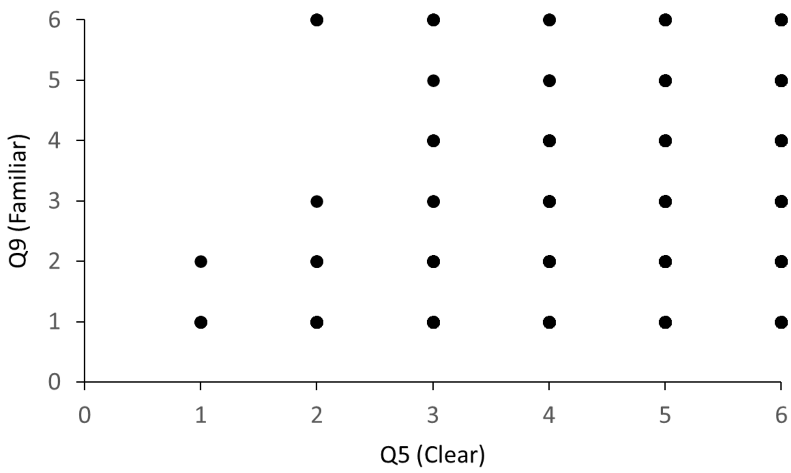


Figure 6.3. Scatter plot of Q5 against Q9 in the solo daylight evaluation.

6.3.2.5 Factorability of the R-matrix and multicollinearity

An R-matrix (or correlation matrix) is a table that displays the correlations between all pairs of variables (i.e. the survey questions in Experiment 2) in the dataset, and serves as the input for the factor analysis procedure. Each cell in the matrix represents the correlation coefficient between two variables, with the diagonal of the matrix always containing 1s as each variable is perfectly correlated with itself. For an R-matrix to be suitable for factor analysis, it needs to exhibit several strong correlations among the variables. However, very low or very high correlations can lead to problems in factor analysis. Very low correlation between variables makes it difficult to identify underlying latent variables, rendering factor analysis ineffective and unreliable for interpreting the data. While sample size plays a role in correlation strength (a larger sample often means smaller correlations), it is recommended for correlations to ideally exceed 0.3 for factor analysis to be meaningful; variables with very few correlations above 0.3 indicate a potential fit problem. Extreme multicollinearity (i.e. variables that are highly correlated) and singularity (i.e. variables that are perfectly correlated) make it difficult to determine which variables are truly contributing to the variance explained by each factor, leading to unstable factor solutions and inaccurate interpretations. Correlation coefficients values above 0.9 typically indicate problem with multicollinearity. Variables with multicollinearity or singularity need to be omitted from the analysis (Field, 2018; Tabachnick and Fidell, 2019).

The correlation matrix of pairs of questions for the daylight and after-dark scores were assessed separately, to identify values that were either too weak (many correlation coefficients below 0.3) or excessively strong (correlation coefficients above 0.9) (Tables 6.4 and 6.5).

Table 6.4. The correlation matrix of the eight questions for the daylight scores (*r* values below 0.3 are in bold).

	Correlation matrix for daylight scores							
	Q2 (Safe)	**Q3 (Anxious)**	**Q4 (Avoid)**	**Q5 (Clear)**	**Q6 (Others)**	**Q7 (Condition)**	**Q8 (Litter)**	**Q9 (Familiar)**
Q2 (Safe)	1.000	0.636	0.676	0.304	**0.051**	0.507	0.394	**0.086**
Q3 (Anxious)	0.636	1.000	0.619	0.301	**0.031**	0.401	0.333	**0.169**
Q4 (Avoid)	0.676	0.619	1.000	**0.234**	**0.126**	0.451	0.382	**0.200**
Q5 (Clear)	0.304	0.301	**0. 234**	1.000	**0.070**	**0.180**	**0.099**	**0.074**
Q6 (Others)	**0.051**	**0. 031**	**0.126**	**0.070**	1.000	**0.083**	**- 0.042**	**0.179**
Q7 (Condition)	0.507	0.401	0. 451	**0.180**	**0.083**	1.000	0.710	0.067
Q8 (Litter)	0.394	0.333	0.382	**0.099**	**- 0.042**	0.710	1.000	0.020
Q9 (Familiar)	**0.086**	**0.169**	**0.200**	**0.074**	**0.179**	**0.067**	**0.020**	1.000

Table 6.5. The correlation matrix of the eight questions for the after-dark scores (r values below 0.3 are in bold).

	Correlation matrix for after-dark scores							
	Q2 (Safe)	**Q3 (Anxious)**	**Q4 (Avoid)**	**Q5 (Clear)**	**Q6 (Others)**	**Q7 (Condition)**	**Q8 (Litter)**	**Q9 (Familiar)**
Q2 (Safe)	1.000	0.748	0.761	0.525	**0.061**	0.495	0.367	**0.093**
Q3 (Anxious)	0.748	1.000	0.731	0.523	**0.031**	0.409	**0.291**	**0.102**
Q4 (Avoid)	0.761	0.731	1.000	0.480	**0. 109**	0.462	0.351	**0.105**
Q5 (Clear)	0.525	0.523	0. 480	1.000	**0.099**	0.301	**0.146**	**0.026**
Q6 (Others)	**0.061**	**0. 031**	**0.109**	**0.099**	1.000	**0.064**	**0.001**	**0.166**
Q7 (Condition)	0.495	0.409	0. 462	0.301	**0.064**	1.000	0.689	**0.109**
Q8 (Litter)	0.367	**0.291**	0.351	**0.146**	**0.001**	0.689	1.000	**0.090**
Q9 (Familiar)	**0.093**	**0.102**	**0.105**	**0.026**	**0.166**	**0.109**	**0.090**	1.000

For both the daylight and after-dak scores, except for Q6 and Q9, all questions correlated reasonably well with other questions, and none of the correlation coefficients were higher than the 0.9 threshold. The determinant of the correlation matrix was 0.079 for the daylight scores and 0.038 for the after-dark scores, well above the 0.00001 threshold, indicating that there was no severe multicollinearity or singularity problem. Therefore, no questions were eliminated from the analysis. The weak correlations observed for questions Q6 and Q9 (all below 0.3) suggested a potential fit problem with the other questions. Communalities (see section 6.3.3) also suggested Q6 and Q9 did not share much variance with the other questions and were potentially not well-explained by the extracted factors. To assess the impact of Q6 and Q9, factor analysis for each of the daylight and after-dark evaluations was conducted on two separate sets of data: one including Q6 and Q9 (referred to hereafter as *eight-question sample*), and one excluding Q6 and Q9 (referred to hereafter as six-*question sample*). The factor solution guided the decision to retain or exclude Q6 and Q9 (see section 6.3.5).

6.3.3 Factor extraction and number of factors to retain

The two most common extraction methods used in factor analysis are Principal Components Analysis and Principal Axis Factoring. The choice of extraction method depends on the aim of the experiment. Principal Components Analysis is the method of choice when the aim is to reduce dimensionality (reduce a large number of variables down to a smaller number of components). However, if the aim is to identify underlying latent variables (i.e. factors), then Principal Axis Factoring is used (Field, 2018; Tabachnick and Fidell, 2019; Zygmont and Smith, 2014). Principal Axis Factoring was used in Experiment 2 as the aim was to identify the latent variable, reassurance.

Factor retention decisions typically rely on two criteria (Gorsuch, 1983; Zwick and Velicer, 1986). Kaiser’s criterion suggests only retaining factors with eigenvalues greater than 1, as they explain more variance than a single variable (Kaiser, 1970). The scree test of eigenvalues plotted against the factors, determines the number of factors to retain based on the point of inflexion or elbow point in the scree plot (the point where the slope of the plot changes) (Cattell, 1966). The choice of criterion depends on the sample size, number of variables, and resulting communalities after extraction. Kaiser's criterion is a reliable method when either of these conditions is met: (1) there are fewer than 30 variables and all communalities are above 0.7, or (2) the sample size is greater than 250 and the average communality is 0.6 or higher. The scree plot is easier to interpret when the sample size is large (over 200), communalities are high, and each factor has multiple variables which load highly on it (Gorsuch, 1983; Stevens, 2002).

For the eight-question after-dark evaluations, Kaiser's criterion suggested three factors (eigenvalues > 1), while the scree test indicated two (the elbow point in the scree plot occurred at the second data point). With six questions, both methods supported a two-factor solution. For the daylight analysis, both criteria suggested two factors, for both the eight-question and six-question samples (see Table 6.6 and Figure 6.4).

Table 6.6. Initial eigenvalues for the daylight and after-dark evaluations, for the eight-question and six-question sample separately - extraction method: Principal Axis Factoring.

	Initial eigenvalues			
	Daylight evaluations		After-dark evaluations	
Factor	**Eight-question sample**	**Six-question sample**	**Eight-question sample**	**Six-question sample**
1	3.211	3.170	3.515	3.486
2	1.235	1.063	1.163	1.151
3	0.995	0.786	1.140	0.574
4	0.850	0.385	0.834	0.293
5	0.754	0.328	0.565	0.264
6	0.377	0.268	0.292	0.232
7	0.321	N/A	0.260	N/A
8	0.256	N/A	0.231	N/A

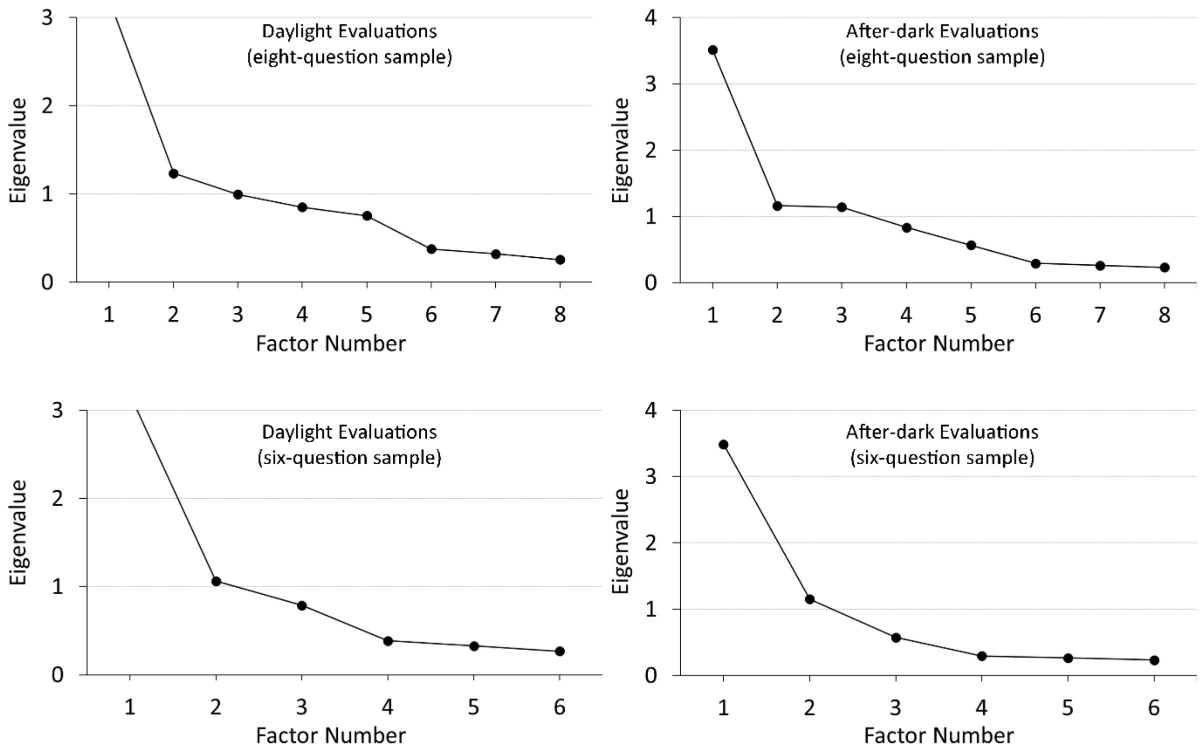


Figure 6.4. Scree plot for the daylight evaluations and after-dark evaluations, for the eight-question and six-question sample separately - extraction method: Principal Axis Factoring.

For the daylight evaluations two factors were retained. For the after-dark evaluations, most extracted communalities were below 0.7, and with an average of 0.592 for the eight-question sample and 0.679 for the six-question sample (see Table 6.7). Because communalities fell short of the threshold for Kaiser's criterion, and the recommended sample size and number of variables per factor were not met for the scree test, both two-factor and three-factor solutions were explored for the after-dark evaluations. For the daylight evaluations two solutions were explored: *Solution Day 1* with two factors and eight questions; *Solution Day 2* with two factors and eight questions. For the after-dark evaluations, three solutions were explored: *Solution Dark 1* with three factors and eight questions; *Solution Dark 2* with two factors and eight questions; and *Solution Dark 3* with two factors and six questions.

Table 6.7. Extracted communalities for the after-dark analysis and day-dark analysis, for the eight-question and six-question sample separately - extraction method: Principal Axis Factoring.

	Extracted communalities			
	Daylight evaluations		**After-dark evaluations**	
Question	**Eight-question sample**	**Six-question sample**	**Eight-question sample**	**Six-question sample**
Q2 (Safe)	0.672	0.711	0.787	0.788
Q3 (Anxious)	0.593	0.607	0.744	0.737
Q4 (Avoid)	0.654	0.619	0.720	0.718
Q5 (Clear)	0.130	0.127	0.359	0.358
Q6 (Others)	0.023	N/A	0.589	N/A
Q7 (Condition)	0.637	0.739	0.613	0.610
Q8 (Litter)	0.839	0.694	0.865	0.864
Q9 (Familiar)	0.054	N/A	0.057	N/A
Arithmetic mean across all questions	**0.450**	**0.583**	**0.592**	**0.679**

Communalities show how well the extracted factors explain each variable's variance, with higher values indicating better representation by the factors (Tabachnick and Fidell, 2019). Communalities also help determine if enough factors have been retained, as they reflect the amount of information lost during factor extraction (Field, 2018).

The small differences in communalities between the eight-question and six-question samples in Table 6.7 suggested the two solutions were very similar. Further assessment of the proportion of variance explained by each factor for the daylight evaluations, showed Solution Day 2 explained more variance in the data than did Solution Day1. For the after-dark evaluations, Solutions Dark 1 and Dark 2 were very similar, while Solution Dark 3 explained more variance than the first two solutions (Table 6.8). Another important observation was the low communality for Q9 (daylight evaluations = 0.054; after-dark evaluations = 0.057), hinting that Q9 did not align well with other questions and was not well-represented by the factors. The findings from the analysis were inconclusive and hence, the number of factors and the inclusion of Q6 and Q9, was determined by comparing the different factor solutions (see section 6.3.5).

Table 6.8. Percentage of variance explained by each factor for each of the solutions in the daylight and after-dark evaluations - extraction method: Principal Axis Factoring.

	Daylight analysis		After-dark analysis		
	Solution Day 1	**Solution Day 2**	**Solution Dark 1**	**Solution Dark 2**	**Solution Dark 3**
Factor 1	%35.64	%47.02	%40.15	%40.08	%53.07
Factor 2	%9.39	%11.29	%11.23	%11.07	%14.84
Factor 3	N/A	N/A	%7.81	N/A	N/A

6.3.4 Factor rotation

Following the extraction of factors, rotation was employed to simplify the factor structure and enhance its interpretability. Factor rotation does this by maximizing the correlations between factors and the variables they load highly on, while minimising correlations with other variables (Stevens, 2002). The choice of rotation method was between orthogonal and oblique. While orthogonal rotation simplifies interpretation and reporting of the results, it assumes the factors are independent from each other. Oblique rotations, on the other hand, allow the underlying factors to correlate. Running the analysis with both orthogonal and oblique rotation and comparing the strength of the correlations between the factors can help determine the appropriate rotation method; correlations above 0.32 suggest sufficient variance overlap (10% or more) to justify oblique rotation (Field, 2018; Pedhazur and Schmelkin, 1991; Tabachnick and Fidell, 2019).

Orthogonal rotation can be carried out in IBM SPSS Statistics using one of three procedures: varimax which aims to simplify the identified factors, quartimax which focuses on simplifying the variables, and equamax which is a hybrid of the two and simultaneously simplifies factors and variables. As the focus of this work was simple factors rather than simple variables, varimax was chosen as the orthogonal rotation method. Direct oblimin and promax are the family of oblique rotation procedures available in IBM SPSS Statistics. Direct oblimin was chosen for the analysis, as promax is a quicker procedure used in very large data sets, which is not the case for Experiment 2. When using direct oblimin, the amount of correlation permitted between factors is determined by a constant called delta, with values above 0 permitting high correlation between factors and below 0 permitting less correlated factors (Tabachnick and Fidell, 2019). For Experiment 2, a delta of 0 was chosen to avoid very high or very low correlation between factors, and allow the extraction of more stable and distinguishable factors.

Principal axis factoring with varimax and direct oblimin rotations were compared to determine the appropriate rotation method for the daylight and after-dark evaluations. Figures 6.5 and 6.6 shows the Factor Correlation Matrix following each rotation method, for the different solutions in the daylight and after-dark evaluations. Generally, small differences were observed between the oblique and orthogonal rotations. This was anticipated, as large samples with strong correlations, consistent factor numbers, and similar communalities, typically yield nearly identical solutions regardless of rotation method (Velicer and Jackson, 1990; Fava and Velicer, 1992). Because some factor correlations exceeded 0.32, it was not possible to assume independence between latent variables. Thus, the oblique rotation was selected. Field (2018) and Tabachnick and Fidell (2019) also argue that it is unrealistic to assume that a set of related variables will have entirely independent underlying dimensions; on theoretical grounds, oblique rotation seems more appropriate for Experiment 2, as it is highly unlikely that a psychological construct like reassurance will not be in any way correlated with some other construct(s).

	Solution Day 1 (oblique rotation)	
Factor	**1**	**2**
1	1.000	- 0.279
2	- 0.279	1.000

	Solution Day 1 (orthogonal rotation)	
Factor	**1**	**2**
1	0.745	0.667
2	- 0.667	0.745

	Solution Day 2 (oblique rotation)	
Factor	**1**	**2**
1	1.000	- 0.532
2	- 0.532	1.000

	Solution Day 2 (orthogonal rotation)	
Factor	**1**	**2**
1	0.772	0.636
2	0.636	- 0.772

Figure 6.5. Factor correlation matrix for the two solutions in the daylight evaluations - oblique rotation (left) and orthogonal rotation (right).

	Solution 1 (oblique rotation)		
Factor	1	2	3
1	1.000	0.458	0.246
2	0.458	1.000	0.188
3	0.246	0.188	1.000

	Solution 1 (orthogonal rotation)		
Factor	1	2	3
1	0.851	0.502	0.154
2	- 0.496	0.865	- 0.080
3	- 0.173	- 0.008	0.985

	Solution 2 (oblique rotation)	
Factor	1	2
1	1.000	0.478
2	0.478	1.000

	Solution 2 (orthogonal rotation)	
Factor	1	2
1	0.823	0.568
2	- 0.568	0.823

	Solution 3 (oblique rotation)	
Factor	1	2
1	1.000	0.458
2	0.458	1.000

	Solution 3 (orthogonal rotation)	
Factor	1	2
1	0.845	0.534
2	- 0.534	0.845

Figure 6.6. Factor correlation matrix for the three solutions in the after-dark evaluations - oblique rotation (left) and orthogonal rotation (right).

6.3.5 Factor solution

6.3.5.1 KMO and Bartlett's Test

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were used to assess the data's suitability for factor analysis (Field, 2018). KMO varies between 0 to 1, with values closer to 1 indicating the data is well-suited for factor analysis, and values below 0.5 considered unacceptable for factor analysis (Tabachnick and Fidell, 2019). If Bartlett's test is statistically significant (p<0.05), it suggests that the variables are sufficiently correlated to make factor analysis a useful approach (Bartlett, 1954). The results of the KMO and Bartlett's test for the daylight analysis and after-dark analysis are shown in Table 6.9. The KMO measure verified the sampling adequacy for the analysis (KMO = 0.764 to 0.809), and Bartlette's test suggested corelations were significant enough (p < 0001) to proceed with factor analysis.

Table 6.9. KMO and Bartlett's test results for the different solutions in the daylight and after-dark evaluations.

	Daylight evaluations		**After-dark evaluations**	
	Eight-question sample	**Six-question sample**	**Eight-question sample**	**Six-question sample**
KMO (classification*)	0.764 (middling)	0.780 (middling)	0.803 (meritorious)	0.809 (meritorious)
Bartlett's Test	< 0.0001	< 0.0001	< 0.0001	< 0.0001

* Kaiser and Rice's (1974) classification: Unacceptable: values below 0.50; Mediocre: values in the 0.60s; Miserable: values in the 0.50s; Middling: values in the 0.70s; Meritorious: values in the 0.80s; Marvellous: values in the 0.90s.

6.3.5.2 Factor loadings and factor interpretation

After determining the possible number of factors to retain in section 6.3.4, the next step was to identify which variables loaded well onto each factor. This was done by examining factor loading values in the rotated loading matrix. Factor loading shows the strength and direction of the relationship between variables and factors, indicating the importance of a given variable to a given factor (Field, 2018). What constitutes a strong factor loading depends on different elements such as the interpretation of the loading matrix and the sample size - larger samples allow for lower factor loading thresholds (Tabachnick and Fidell, 2019). However, a general rule of thumb is to exclude variables with factor loadings below 0.30 (Stevens, 2002), with stricter criteria suggesting to only interpret factor loadings greater than 0.4 (Field, 2018). Comrey and Lee (1992) also proposed a set of interpretive guidelines for factor loadings, defining thresholds for excellent (≥ 0.71), very good (≥ 0.63), good (≥ 0.55), fair (≥ 0.45), and poor (≥ 0.32) classifications.

Whether a factor is well defined depends on the number of variables that load highly onto it. Factors defined by only one or two variables are unreliable, prone to overfitting, and difficult to interpret. A factor with a single high loading is non-stable and poorly defined, and should not be interpreted. A factor with two variables is potentially reliable only if the two variables correlate strongly with each other ($r > 0.70$), and weakly with other variables (Tabachnick and Fidell, 2019). Factors with three or more variables are generally considered reliable, especially if at least four of those variables have loadings above 0.6, in which case reliability is independent of sample size (Guadagnoli and Velicer, 1988).

Tables 6.10 through 6.14 present the rotated factor loadings for the different solutions in the daylight and after-dark evaluations.

Table 6.10. Rotated factor loadings for the daylight analysis - Solution Day 1 - Extraction method: principal axis factoring, rotation method: direct oblimin (rotation converged in 5 iterations).

	Factor*	
Questions	**1**	**2**
Q4 (Avoid)	**0.697**	- 0.259
Q3 (Anxious)	**0.684**	- 0.211
Q2 (Safe)	**0.676**	**- 0.312**
Q5 (Clear)	**0.345**	- 0.045
Q9 (Familiar)	0.241	0.044
Q6 (Others)	0.159	0.053
Q8 (Litter)	- 0.069	**- 0.933**
Q7 (Condition)	0.172	**- 0.733**

* Loadings above 0.3 are in bold.

Table 6.11. Rotated factor loadings for the daylight analysis - Solution Day 2 - Extraction method: principal axis factoring, rotation method: direct oblimin (rotation converged in 4 iterations).

	Factor*	
Questions	**1**	**2**
Q2 (Safe)	**0.786**	- 0.099
Q3 (Anxious)	**0.777**	- 0.004
Q4 (Avoid)	**0.736**	- 0.089
Q5 (Clear)	**0.380**	0.048
Q8 (Litter)	- 0.047	**- 0.857**
Q7 (Condition)	0.096	**- 0.805**

* Loadings above 0.3 are in bold.

Table 6.12. Rotated factor loadings for the after-dark analysis - Solution Dark 1 - Extraction method: principal axis factoring, rotation method: direct oblimin (rotation converged in 4 iterations).

	Factor*		
Questions	**1**	**2**	**3**
Q3 (Anxious)	**0.884**	- 0.019	- 0.061
Q2 (Safe)	**0.853**	0.082	- 0.027
Q4 (Avoid)	**0.806**	0.066	0.038
Q5 (Clear)	**0.616**	- 0.066	0.039
Q8 (Litter)	- 0.093	**0.971**	- 0.015
Q7 (Condition)	0.197	**0.661**	0.047
Q6 (Others)	- 0.050	- 0.106	**0.788**
Q9 (Familiar)	0.027	0.059	0.210

* Loadings above 0.3 are in bold.

Table 6.13. Rotated factor loadings for the after-dark analysis - Solution Dark 2 - Extraction method: principal axis factoring, rotation method: direct oblimin (rotation converged in 5 iterations).

	Factor*	
Questions	**1**	**2**
Q3 (Anxious)	**0.857**	- 0.005
Q2 (Safe)	**0.834**	0.100
Q4 (Avoid)	**0.805**	0.088
Q5 (Clear)	**0.622**	- 0.050
Q6 (Others)	0.101	- 0.008
Q8 (Litter)	- 0.136	**0.978**
Q7 (Condition)	0.170	**0.692**
Q9 (Familiar)	0.071	0.081

* Loadings above 0.3 are in bold.

Table 6.14. Rotated factor loadings for the after-dark analysis - Solution Dark 3 - Extraction method: principal axis factoring, rotation method: direct oblimin (rotation converged in 4 iterations).

	Factor*	
Questions	**1**	**2**
Q3 (Anxious)	**0.868**	- 0.022
Q2 (Safe)	**0.847**	0.083
Q4 (Avoid)	**0.811**	0.074
Q5 (Clear)	**0.622**	- 0.056
Q8 (Litter)	- 0.100	**0.971**
Q7 (Condition)	0.202	**0.668**

* Loadings above 0.3 are in bold.

For both the after-dark analysis and day-dark analysis four questions (Q2, Q3, Q4, and Q5) loaded strongly on Factor 1, and two questions (Q7 and Q8) had high loadings on Factor 2 (all loadings were above 0.3 in the daylight evaluations, and above 0.6 in the after-dark evaluations). Q6 and Q9 loaded poorly on the factors (most loadings < 0.3), which was also indicated by their central position on the factor loading plots (Figure 6.7). Factor 3 was poorly defined in the after-dark analysis with only one substantial loading (0.788 for Q6). Factor 3 also accounted for very little variance (~ 3%) in the data, as shown in Table 6.8. Therefore, Solution Day 2 (for the daylight evaluation) and Solution Dark 3 (for the after dark evaluations), each consisting of two factors (Factor 1 defined by Q2, Q3, Q4 and Q5; Factor 2 defined by Q7 and Q8) were the final factor solutions selected.

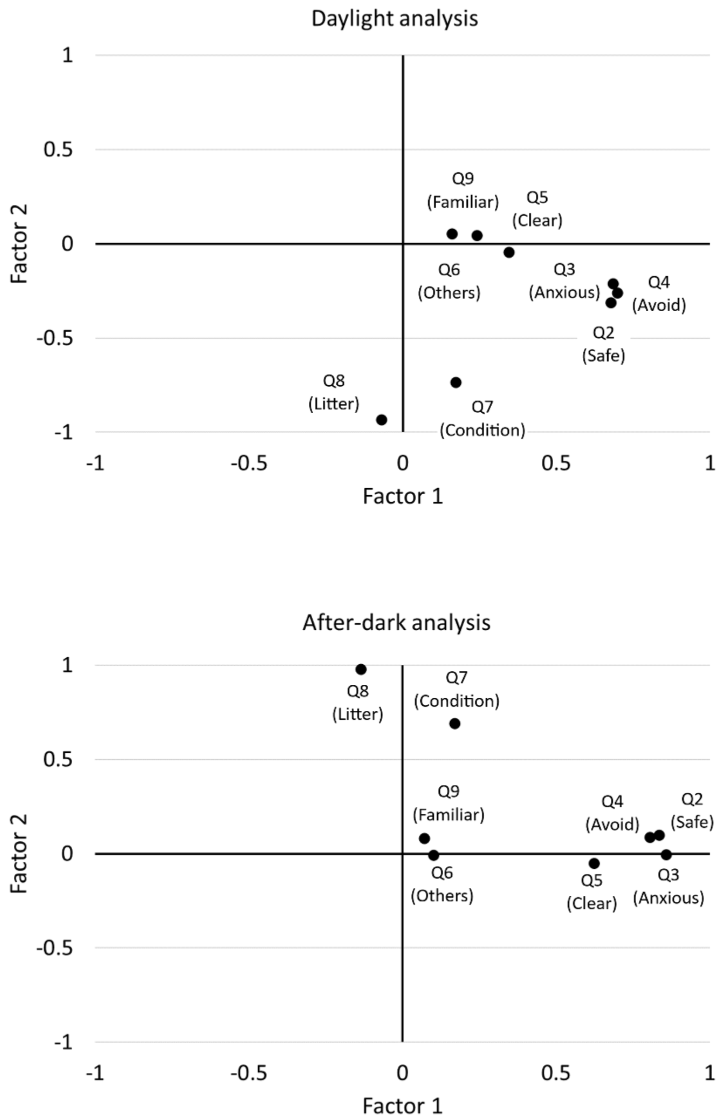


Figure 6.7. Example rotated loading plot for Solution Day 1 (top) and Solution Dark 2 (bottom).

For Factors 1 and 2, each question loaded primarily onto a single factor (no cross-loadings), indicating the factors were distinct and captured unique aspects of the data. The presence of four questions with high loadings suggested that Factor 1 was well-defined in both the after-dark and day-dark analyses. However, Factor 2 was only reliable in the after-dark analysis because Q7 and Q8 were highly correlated with each other (daylight: $r = 0.71$, after-dark: $r = 0.69$) and relatively uncorrelated with other variables (daylight: $r < 0.51$ for Q7 and $r < 0.40$ for Q8; after-dark: $r < 0.50$ for Q7 and $r < 0.37$ for Q8) (see Table 6.4 and 6.5). Because they were well-defined, both Factor 1 and Factor 2 were interpreted.

Rummels (1988) recommends examining the content of highly loading questions within each factor, to identify common themes and label factors. Factor 1 was interpreted as representing ‘reassurance’ as the four questions that loaded highly onto it related to the feeling of safety and fear of crime. Factor 2 was labelled 'signs of incivility' as the two questions loading highly onto it related to the upkeep and condition of the physical environment. This thesis focuses on the 'reassurance' factor (Factor 1) only.

6.3.5.3 Composite reassurance score

A single composite score that considered all six survey questions (Q2, Q3, Q4, Q5, Q7, and Q8) was calculated for the reassurance factor, for the daylight and after-dark scores separately. The composite score, is an estimate of the score that a participant would have given to the reassurance factor, had it been measured directly (Tabachnick and Fidell, 2019). For all further analysis, the composite reassurance score was used instead of the individual scores for the six survey questions.

A variety of methods can be used to calculate the composite score. A simple approach is to average the scores of the questions loading highly onto the reassurance factor (Comrey and Lee, 1992). A drawback of this method is that it assumes all questions contribute equally to the composite score, ignoring the fact that they have different factor loadings. A better approach is to use factor loadings as weights in a weighted sum. This method is not recommended for factor analysis because it is overly simplistic, and does not allow for comparison of composite scores between experiments or questions with different measurement scales (Field, 2018). A more robust approach is to standardise the original scores (i.e. convert them to z-scores) to ensure that all variables are on the same scale, and use factor score coefficients as weights, rather than the factor loadings (Tabachnick and Fidell, 2019). Calculating a z-score also helps compare responses across participants by standardising the data. This is useful because each participant has an internal baseline for how they answer the survey questions. Z-scores help reveal how a participant's response deviates from their own typical pattern, making their answers comparable even if their overall responses differ from other participants.

Factor score coefficients can be calculated in IBM SPSS Statistics using one of three methods: regression, Anderson-Rubin, and Bartlett. For Experiment 2, the regression method was used, as it is the method of choice when the aim is to use the composite scores in subsequent analysis, and there is no requirement for the composite scores to be uncorrelated (Tabachnick and Fidell, 2019). Table 6.15 shows the factor score coefficients for the reassurance factor, for the after-dark analysis and day-dark analysis separately. The coefficient for each question indicates its contribution to the overall reassurance score; questions which load highly onto the reassurance factor (Q2, Q3, Q4, and Q5) have a higher weight and contribute more to composite score, and questions that are less relevant to reassurance (Q7 and Q8 with factor loadings < 0.3) weight less into the composite score.

Table 6.15. Factor score coefficients for the reassurance factor (Factor 1) in the daylight and after-dark evaluations - Extraction method: principal axis factoring, rotation method: direct oblimin, factor score method: regression.

	Factor score coefficient	
Questions	**Daylight evaluations**	**After-dark evaluations**
Q2 (Safe)	0.410	0.381
Q3 (Anxious)	0.306	0.319
Q4 (Avoid)	0.277	0.260
Q5 (Clear)	0.062	0.090
Q7 (Condition)	0.068	0.069
Q8 (Litter)	- 0.015	- 0.039

The composite reassurance score for each participant was estimated by multiplying the standardised score for each question by the corresponding factor score coefficient from Table 6.15, and summing up the results. The range of the composite scores was -2.86 to +1.32 for the daylight scores and -2.18 to +1.67 for the after-dark scores. Hence, a linear transformation using equation 1 was applied to the composite scores to rescale them to original score range of 1 to 6.

$$y = \frac{(x - min) \times (max' - min')}{max - min} + min' \qquad (1)$$

where y is the rescaled score, x is the composite score, min and max are the minimum and maximum composite scores respectively, and min' and max' are the minimum and maximum original scores respectively.

Table 6.16 presents the transformed mean composite reassurance scores and respective standard deviations for each location, for the daylight, after-dark, and day-dark evaluations separately. The day-dark composite scores were calculated by subtracting each participant's daylight composite score from their after-dark composite score. Lower composite scores for a road indicate a smaller difference in perceived reassurance between daytime and nighttime, suggesting more effective road lighting. The negative score for R2.5 suggests that participants felt more reassured after-dark than in daytime in that location; a positive score means the opposite.

Table 6.16. Transformed mean daylight, after-dark, and day-dark composite reassurance scores in Experiment 2.

	Transformed daylight composite score		Transformed after-dark composite score		Transformed day-dark composite score*	
Location ref.	**Mean**	**Std dev**	**Mean**	**Std dev**	**Mean**	**Std dev**
R2.1	4.18	1.08	3.00	1.19	1.18	0.95
R2.2	4.61	0.89	3.98	1.07	0.64	1.02
R2.3	4.93	0.80	4.41	0.92	0.51	0.82
R2.4	4.80	0.90	3.35	1.13	1.44	1.13
R2.5	4.78	0.84	4.94	0.80	- 0.15	0.80
R2.6	4.96	0.72	4.53	0.80	0.44	0.78
R2.7	3.04	1.06	2.29	0.90	0.75	0.94
R2.8	4.93	0.80	3.88	0.98	1.05	1.01
R2.9	3.89	1.03	3.32	0.93	0.57	1.07
R2.10	4.82	1.03	4.66	1.11	0.16	0.87
R2.11	3.98	1.05	3.94	1.12	0.05	1.00
R2.12	4.18	1.12	3.69	1.02	0.49	1.02

* Day-dark composite score = daylight composite score – after-dark composite score.

6.4 The effect of illuminance

Figures 6.8 to 6.13 show mean after-dark and day-dark composite reassurance scores at each location plotted against the arithmetic mean horizontal illuminance, minimum horizontal illuminance, and horizontal uniformity. A linear function provided the best fit for these relationships.

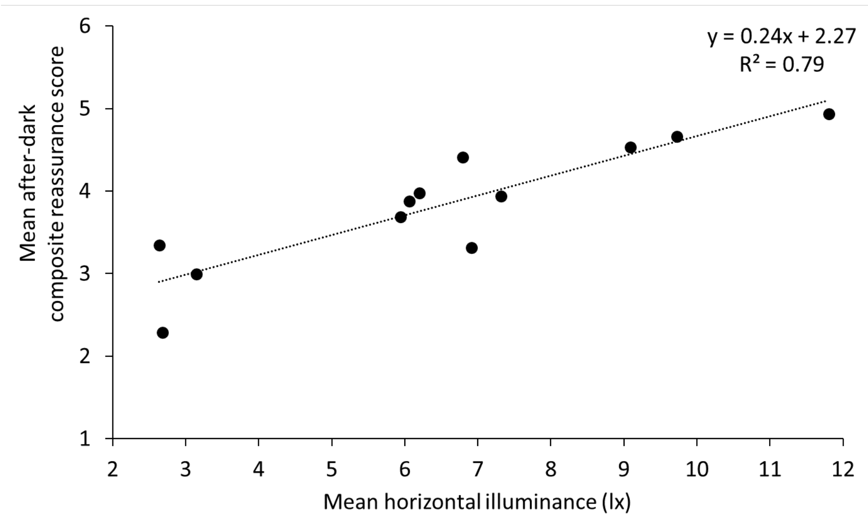


Figure 6.8. Mean after-dark composite reassurance score plotted against arithmetic mean horizontal illuminance in the 12 test locations. Regression line uses a linear function.

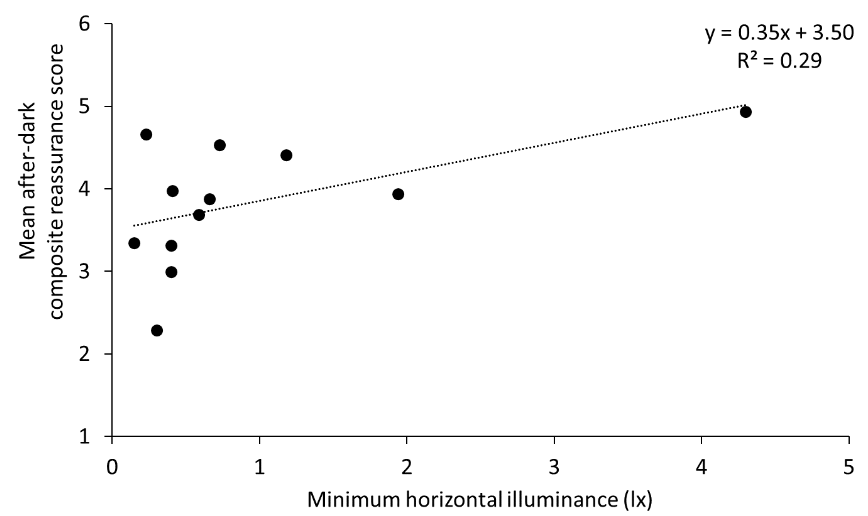


Figure 6.9. Mean after-dark composite reassurance score plotted against minimum horizontal illuminance in the 12 test locations. Regression line uses a linear function.

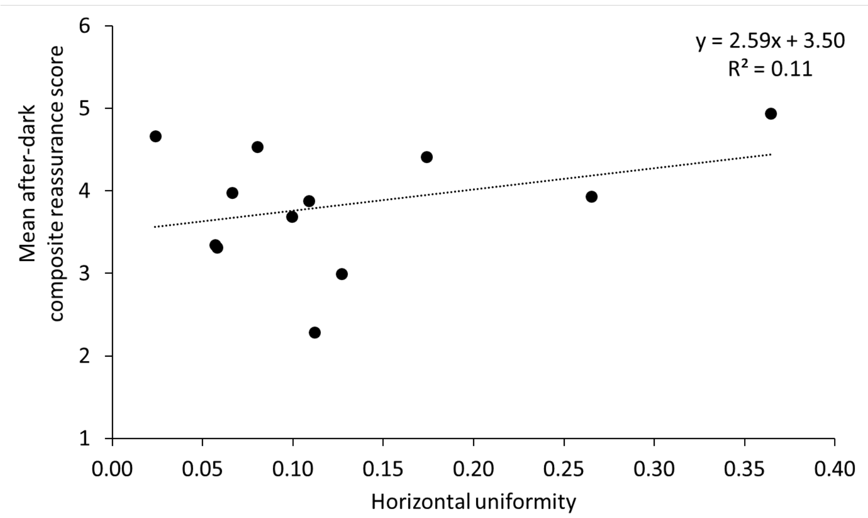


Figure 6.10. Mean after-dark composite reassurance score plotted against horizontal uniformity in the 12 test locations. Regression line uses a linear function.

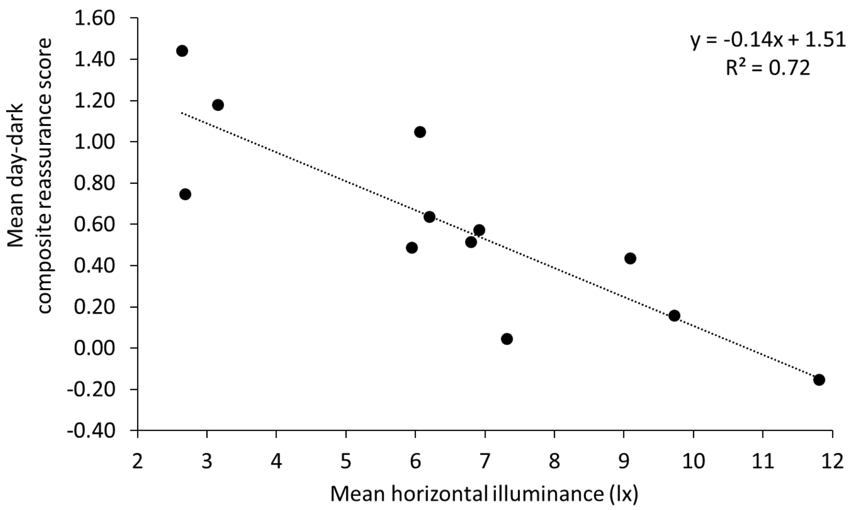


Figure 6.11. Mean day-dark composite reassurance score plotted against arithmetic mean horizontal illuminance in the 12 test locations. Regression line uses a linear function.

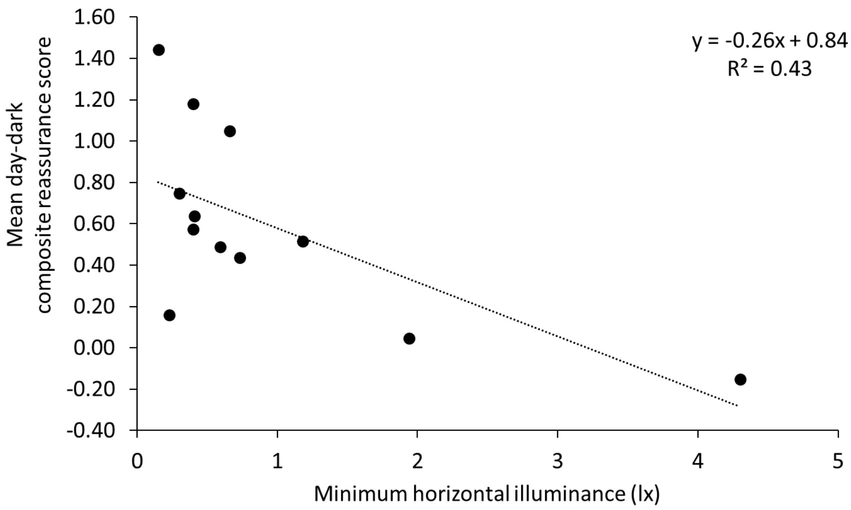


Figure 6.12. Mean day-dark composite reassurance score plotted against minimum horizontal illuminance in the 12 test locations. Regression line uses a linear function.

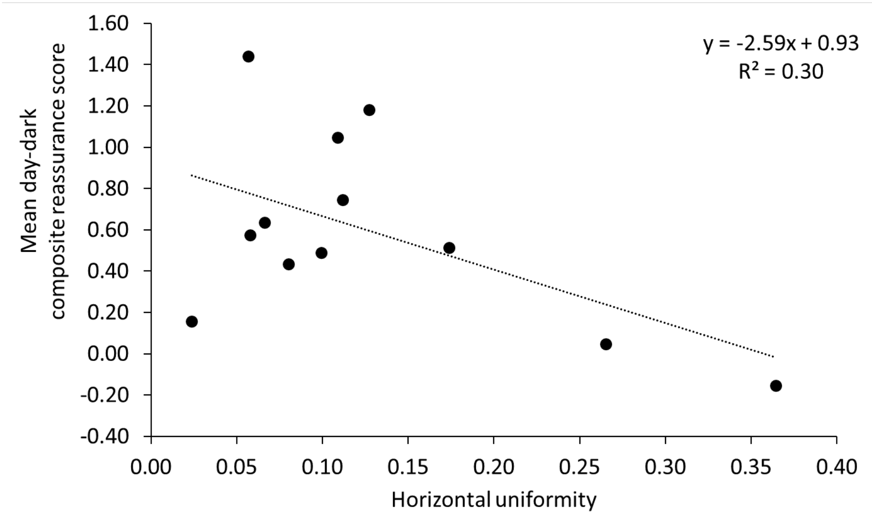


Figure 6.13. Mean day-dark composite reassurance score plotted against horizontal uniformity in the 12 test locations. Regression line uses a linear function.

The degree of association of both the after-dark and day-dark composite reassurance scores, shown by the coefficient of determination (R^2), was considerably stronger for mean horizontal illuminance (after-dark: R^2= 0.79, n=12, *p*<0.01; day-dark: R^2= 0.72, n=12, *p*<0.01) than for minimum horizontal illuminance and horizontal uniformity (Table 6.17). As evidenced by the R-squared values presented in Table 6.17, mean horizontal illuminance exhibited a stronger association with after-dark scores, while minimum horizontal illuminance and horizontal uniformity demonstrated a stronger association with day-dark scores.

Table 6.17. Goodness of fit of linear function in explaining after-dark and day-dark composite reassurance scores plotted against the arithmetic mean horizontal illuminance, minimum horizontal illuminance, and horizontal uniformity.

	After-dark composite reassurance score		**Day-dark composite reassurance score**	
Illuminance measure	**R^2**	**p-value**	**R^2**	**p-value**
Arithmetic mean	0.79	*p*<0.01	0.72	*p*<0.01
Minimum	0.29	*p*<0.05	0.43	*p*<0.01
Uniformity	0.11	*P*=0.07	0.30	*p*<0.05

The plots show that with higher arithmetic mean horizontal illuminances, reassurance increases (Linear best-fit line: R^2=0.79, n=12, *p*<0.01), and the day-dark difference gradually declines (linear best-fit line: R^2=0.72, n=12, p<0.01). In contrast to the general trend, the day-dark difference in location R2.5 was less than zero (see Table 6.16), meaning participants felt more reassured after dark than during daylight. Overall, the results from both the after-dark ratings and day-dark differences indicate that roads with higher mean illuminance enhance pedestrian reassurance.

6.5 Solo versus group evaluations

A separate analysis of solo and group evaluation was conducted to investigate the potential influence of evaluation mode on the findings. It was predicted that group evaluations would have an overall higher rating compared to solo evaluations. Graphical and statistical analyses suggested the data were drawn from a normally distributed population. Therefore, parametric tests were used.

Table 6.18 and Figure 6.14 show the after-dark ratings. In nine locations, group participants reported higher feelings of reassurance than did solo participants. The differences between reassurance ratings of group and solo participants (group – solo) were small across the 12 locations (mean difference = 0.07, range: -0.14 to 0.34). An independent samples t-test revealed that this difference was not statistically significant (p = 0.83).

Table 6.18. Mean after-dark composite reassurance scores, for solo and group evaluations separately.

	Mean after-dark composite reassurance score		
Location ref.	**Solo evaluations**	**Group evaluations**	**Group - Solo**
R2.1	2.91	3.08	0.16
R2.2	3.97	3.99	0.02
R2.3	4.24	4.58	0.34
R2.4	3.32	3.38	0.06
R2.5	4.98	4.89	-0.09
R2.6	4.47	4.59	0.12
R2.7	2.21	2.37	0.15
R2.8	3.79	3.96	0.16
R2.9	3.34	3.29	-0.05
R2.10	4.62	4.71	0.09
R2.11	3.93	3.94	0.01
R2.12	3.76	3.62	-0.14

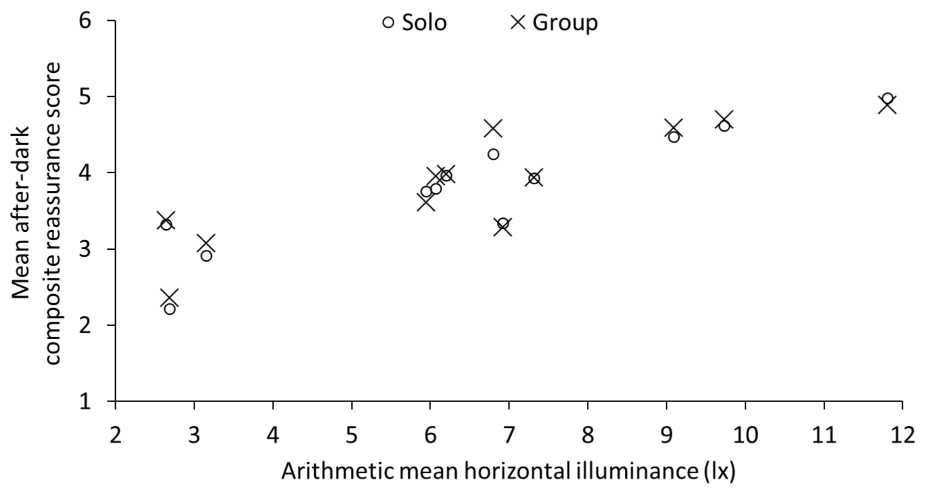


Figure 6.14. Mean after-dark composite reassurance scores plotted against arithmetic mean horizontal illuminance in the 12 test locations, for solo and group evaluations separately.

Table 6.19 and Figure 6.15 show the day-dark ratings. In six locations, the day-dark difference in reassurance ratings was smaller for group participants than that for solo participants. Similar to the after-dark ratings, the differences (group – solo) were small across the 12 locations (mean difference = -0.03, range: -0.26 to 0.27). An independent samples t-test revealed that this difference was also not statistically significant (p = 0.88).

Table 6.19. Mean day-dark composite reassurance scores, for solo and group evaluations separately.

	Mean day-dark composite reassurance score		
Location ref.	**Solo evaluations**	**Group evaluations**	**Group - Solo**
R2.1	1.22	1.14	-0.08
R2.2	0.57	0.71	0.14
R2.3	0.52	0.51	0.00
R2.4	1.57	1.31	-0.26
R2.5	-0.08	-0.23	-0.16
R2.6	0.43	0.44	0.01
R2.7	0.70	0.80	0.10
R2.8	1.04	1.06	0.03
R2.9	0.63	0.52	-0.11
R2.10	0.02	0.29	0.27
R2.11	0.07	0.02	-0.05
R2.12	0.60	0.37	-0.23

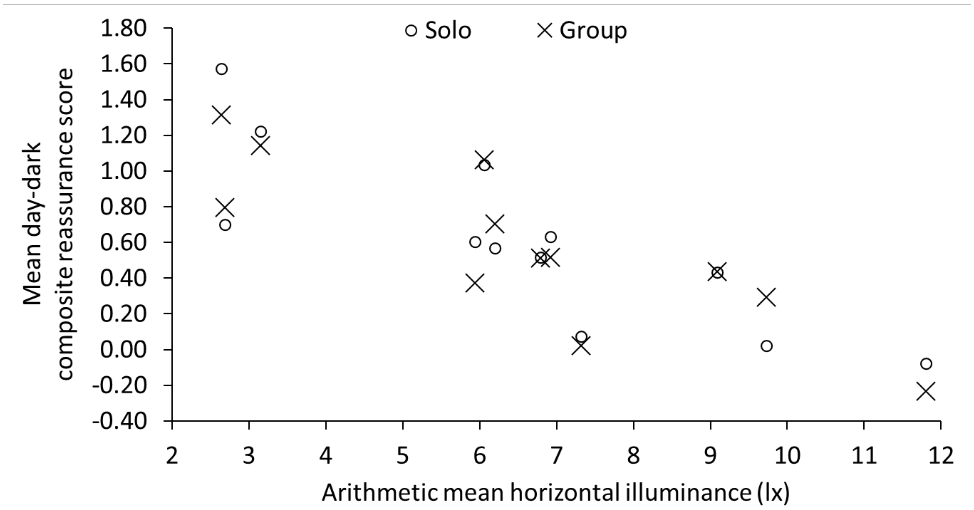


Figure 6.15. Mean day-dark composite reassurance scores plotted against arithmetic mean horizontal illuminance in the 12 test locations, for solo and group evaluations separately.

6.6 Gender

The results were disaggregated for the male and female participants, to assess whether there was a gender difference in reassurance. It was predicted that, overall, male participants would report feeling more reassured compared to female participants, and that the male-female difference would be smaller on roads with higher illuminances. Graphical and statistical analyses suggested the data were drawn from a normally distributed population. Therefore, parametric tests were used.

Table 6.20 and 6.21 show the mean composite daylight and mean composite after-dark ratings, respectively. In daylight, males gave higher ratings in nine locations, with differences (Male – Female) between 0.04 and 0.25. However, in three locations, female ratings were generally higher than male ratings, with differences (Male – Female) ranging from -0.05 to -0.02. After dark, male ratings generally remained higher than female ratings in ten locations (Male – Female differences between 0.04 and 0.38), with two locations where females gave higher ratings (Male – Female differences between -0.15 and -0.08).

The overall mean composite score across the 12 locations is summarised in Table 6.22, for the daylight and after-dark ratings separately. Overall, males reported feeling safer than females in both daylight (male: mean = 4.47, SD = 0.57; female: mean = 4.38, SD = 0.61) and after dark (male: mean = 3.89, SD = 0.72; female: mean = 3.77, SD = 0.81). The difference between male and female participants were small and not suggested to be statistically significant (daylight: Male – Female = 0.09, *p*=0.72; after-dark: Male – Female = 0.09, *p*=0.68).

Table 6.20. Mean daylight composite reassurance scores, for male and female participants separately.

	Mean daylight composite reassurance score		
Location ref.	**Male participants**	**Female participants**	**Male - Female**
R2.1	4.16	4.19	-0.03
R2.2	4.70	4.52	0.18
R2.3	5.00	4.85	0.14
R2.4	4.87	4.73	0.14
R2.5	4.83	4.73	0.09
R2.6	4.94	4.99	-0.05
R2.7	3.12	2.95	0.17
R2.8	4.94	4.91	0.04
R2.9	4.01	3.77	0.25
R2.10	4.81	4.83	-0.02
R2.11	4.02	3.94	0.08
R2.12	4.20	4.15	0.05

Table 6.21. Mean after-dark composite reassurance scores, for male and female participants separately.

	Mean after-dark composite reassurance score		
Location ref.	**Male participants**	**Female participants**	**Male - Female**
R2.1	3.19	2.80	0.38
R2.2	4.02	3.93	0.09
R2.3	4.49	4.33	0.17
R2.4	3.48	3.21	0.27
R2.5	5.00	4.87	0.12
R2.6	4.46	4.61	-0.15
R2.7	2.43	2.15	0.28
R2.8	3.96	3.79	0.17
R2.9	3.39	3.24	0.16
R2.10	4.71	4.61	0.10
R2.11	3.96	3.92	0.04
R2.12	3.65	3.73	-0.08

Table 6.22. Difference between mean male composite reassurance score and mean female composite reassurance score, for the daylight and after-dark evaluations separately.

	Mean composite reassurance score (standard deviation)		Difference in mean composite reassurance score (Male - Female)	Significance of difference
Evaluation session	**Male participants**	**Female participants**		
Daylight	4.47 (0.57)	4.38 (0.61)	0.09	$p = 0.72$
After-dark	3.89 (0.72)	3.77 (0.81)	0.12	$p = 0.68$

Figures 6.17 and 6.18 show the mean daylight and mean after-dark composite reassurance scores plotted against arithmetic mean horizontal illuminance in the corresponding locations, for male and female participants separately. Overall, male and female ratings exhibited small differences. Daylight ratings, as shown in Figure 6.16, displayed minimal variation across the 12 locations, which is attributable to the uniform ambient lighting for all evaluations. Conversely, Figure 6.17 indicates that differences in after-dark ratings were slightly higher in the three locations with the lowest illuminance levels compared to the locations with higher illuminance. This hints that higher illuminances may mitigate the increased fear experienced by females.

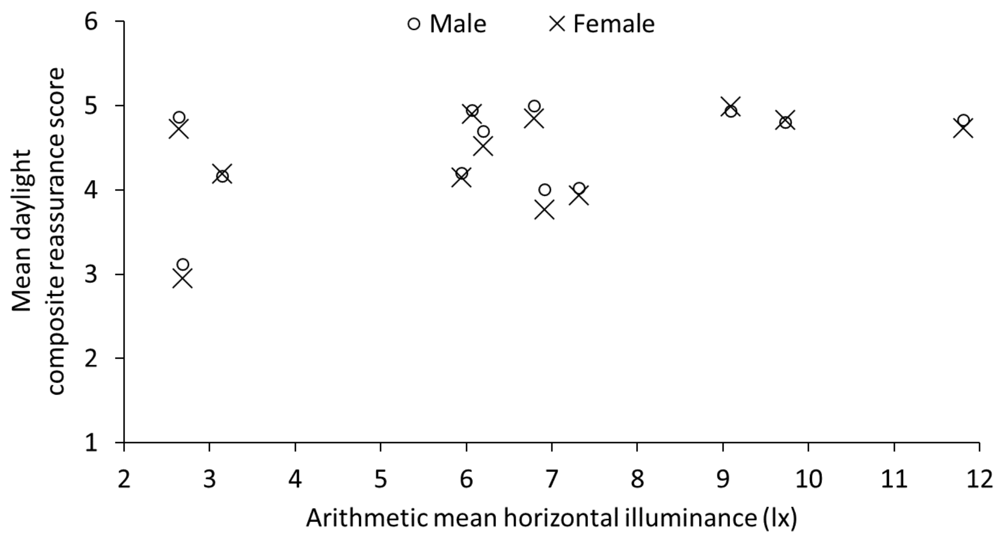


Figure 6.16. Mean daylight composite reassurance scores plotted against arithmetic mean horizontal illuminance in the 12 test locations, for male and female participants separately.

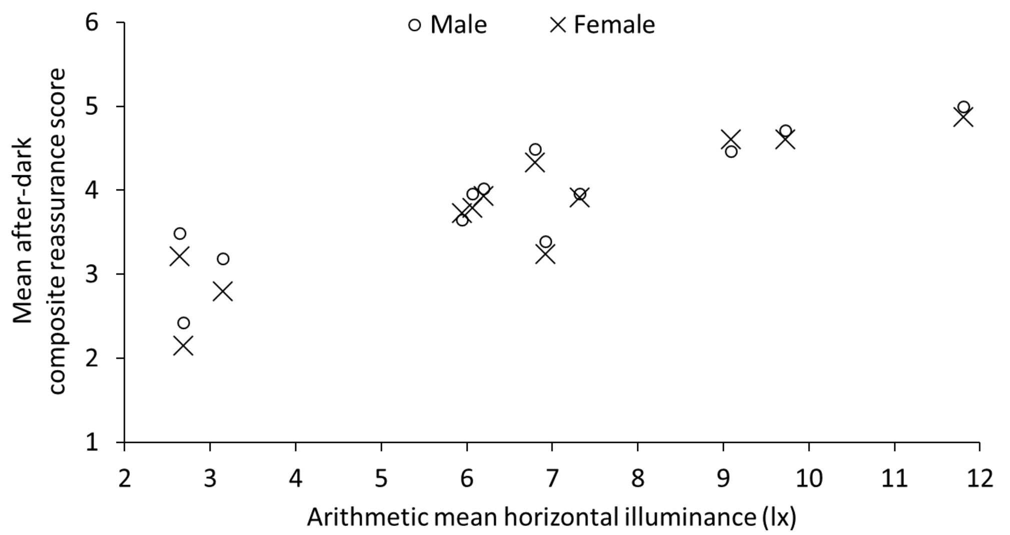


Figure 6.17. Mean after-dark composite reassurance scores plotted against arithmetic mean horizontal illuminance in the 12 test locations, for male and female participants separately.

To analyse the effects of gender and light condition on mean composite reassurance scores, a repeated measures ANOVA was performed. Gender was treated as a between-subjects factor and light condition (daylight or after dark) as a within-subjects factor. The mean composite reassurance score served as the dependent variable. The findings indicated that participants experienced a statistically significant increase in reassurance during daylight hours (mean = 4.42, SD = 0.63) compared to after dark (mean = 3.81, SD = 0.70, $p < 0.001$). Although females had slightly lower mean reassurance ratings (mean = 4.05, SD = 0.62) than males (mean = 4.19, SD = 0.61) across the daylight and after-dark evaluations, this difference was not statistically significant ($p = 0.202$). No significant interaction was found between gender and lighting condition (daylight or after-dark) ($p = 0.422$), indicating that the effect of lighting condition on reassurance did not differ between males and females.

Figures 6.18 plots the differences between mean male after-dark composite reassurance scores and mean female after-dark composite reassurance scores at each location, against the arithmetic mean horizontal illuminance. The linear best-fit line suggests a statistically significant relationship ($R^2 = 0.36$, $p = 0.033$) between the male-female difference and illuminance, indicating that higher illuminances decrease the disparity in male and female ratings.

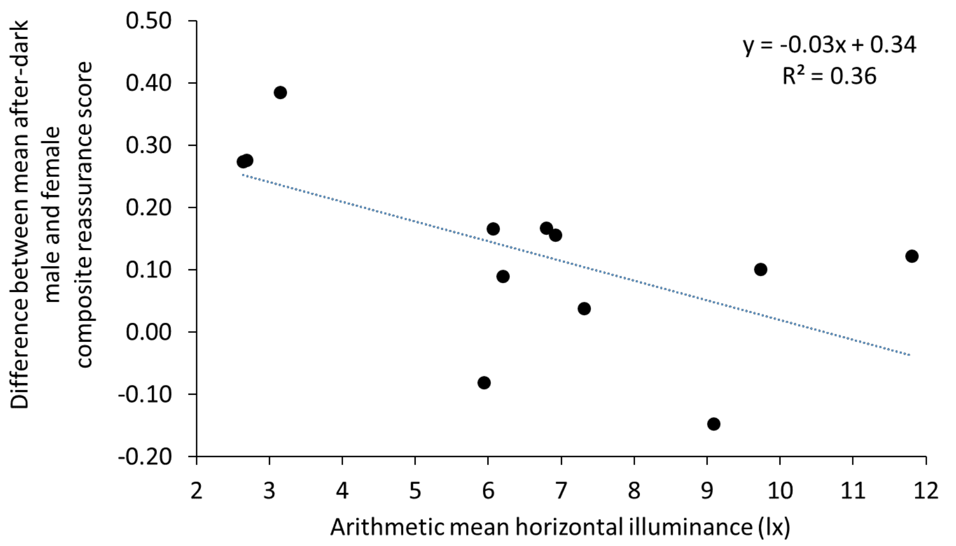


Figure 6.18. The difference between mean after-dark male and mean after-dark female composite reassurance scores, plotted against arithmetic mean horizontal illuminance in the 12 test locations. Regression line uses a linear function.

6.7 Summary

This chapter presented the results of Experiment 2, a field study to investigate the influence of different illuminances on pedestrian reassurance. It was found that roads with higher mean illuminance enhanced pedestrian reassurance, and that higher illuminances significantly reduced the gender gap in reassurance after dark. However, within the illuminance range tested in Experiment 2, the difference between male and female after-dark reassurance ratings was not found to be statistically significant. The variations between solo and group responses were small and unimportant, and lacked a predictable trend. The next chapter outlines the methods used in Experiment 3.

CHAPTER 7. EXPERIMENT 3 – TRAVEL COUNTS: METHOD

7.1 Introduction

Experiments 1 and 2 investigated subjective perceptions of reassurance through self-reported assessments. The literature review (Chapter 2) revealed that such evaluations have limitations; subjective evaluations are prone to influence by stimulus range bias, location specific environmental differences, or socially desirable responding, and, as stated preferences, it is unknown whether they are reflective of real-world behaviour of pedestrians (i.e. revealed preference).

Behavioural measurements offer an alternative approach to assessing reassurance. This includes recording gait characteristics like walking speed, physiological responses such as heart rate or pupil dilation, pedestrian route selection, and travel counts of the number of people walking in daylight and darkness. Experiment 3 uses one of these methods, travel counts, by comparing the numbers of people walking in daylight and after dark in different lighting conditions, to assess the influence of lighting conditions on the number of pedestrians walking. This will enable comparison of the results with the subjective evaluations reported in Experiment 2 (Hypothesis H6).

Experiment 3 was conducted on two occasions. The first, in Spring 2021 (referred to hereafter as *Spring 2021 experiment/period*), was done to explore the travel count method. The second was conducted in Spring 2024 (referred to hereafter as *Spring 2024 experiment/period*), using the same procedure as the Spring 2021 experiment but using, instead, some of the locations used in Experiment 2 to enable a direct comparison of the results. The Spring 2021 experiment took place during a two-week period in the months of March and April 2021, centred on the Spring 2021 daylight savings clock change. The Spring 2024 experiment took place during a two-week period in the months of March and April 2024, centred on the Spring 2024 clock change. Compared with analyses using data from automated counters collated over many years (e.g. Fotios et al. (2019b)), both travel count experiments used on-street counts to gain additional information (in particular, pedestrian gender) but at the expense of a smaller sample and only one combination of case and control hour.

This chapter explains the method used in Experiment 3. The experiment received ethical approval from the University of Sheffield Research Ethics Committee (Spring 2021 experiment: reference number 007204; Spring 2024 experiment: reference number 046126).

7.2 Test locations

7.2.1 Spring 2021 experiment locations

The choices of locations for the Spring 2021 experiment were based on three considerations:

(1) To include a diverse range of roads, including main and subsidiary roads in residential areas, office/commercial areas, and parks, to ensure the generalisability of findings.

(2) To include a diverse range of path types, including a range of different pedestrian pathways (footpaths along the road, footpath in park, and no footpaths).

(3) To consider accessibility and observer safety: choosing locations which were accessible to the observers (close to their residences), were safe for observers to stand alone (avoiding areas with high crime rates based on crime rate data (CrimeRate, 2024), or hazardous conditions such as with road works), and provided a suitable shelter for the observers (e.g. a nearby tree, bus stop, or store front) in case of adverse weather conditions.

(4) To include only those locations which were anticipated to have a non-zero flow of pedestrian traffic.

Eight urban locations in Sheffield, England, were used in the Spring 2021 experiment (Figure 7.1). This number of locations was limited by the resources available, i.e. the number of observers that could be recruited. The eight locations are labelled hereafter as R3.1 to R3.8. Images and characteristics of each location can be found in Figure 7.2 and Table 7.1.

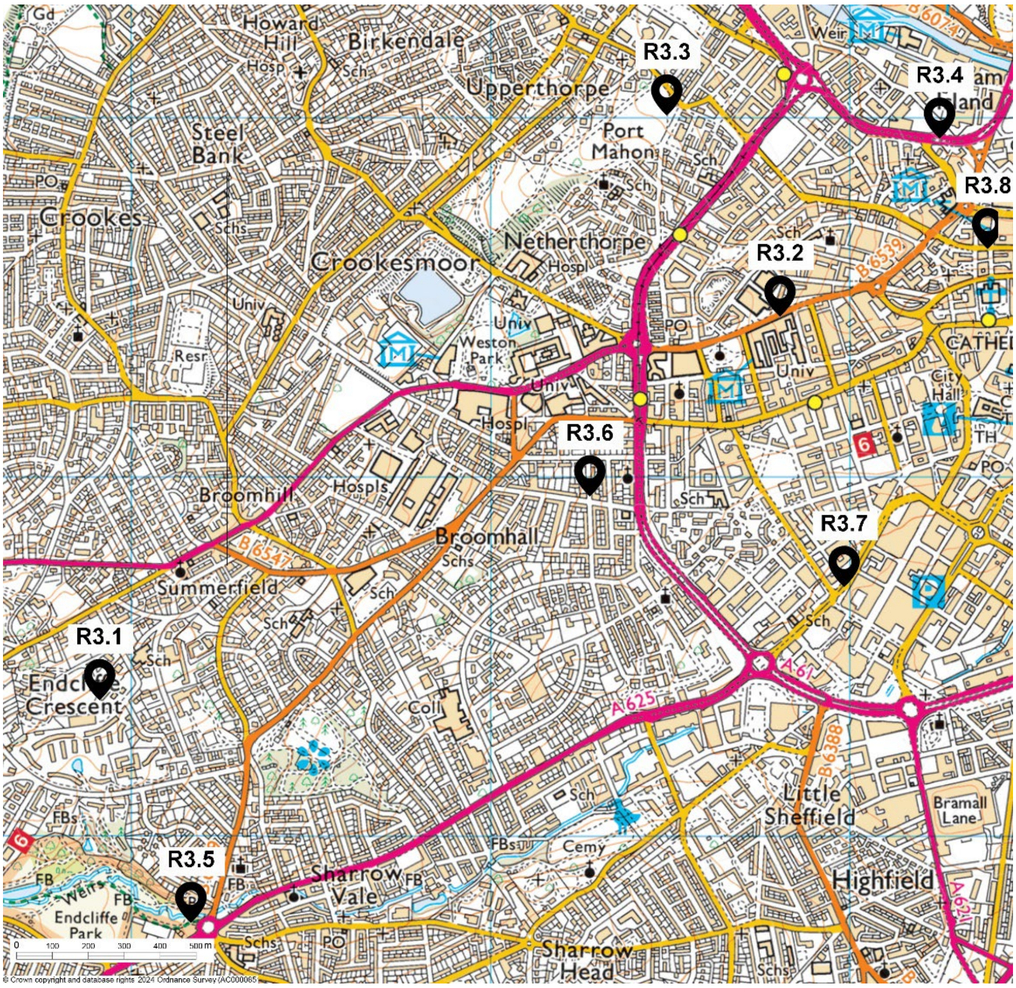


Figure 7.1. Map of the eight locations in the Spring 2021 experiment (background map from Digimap (digimap.edina.ac.uk/roam/map/os) and locations added by author).

R3.1

R3.2

R3.3

R3.4

R3.5

R3.6

R3.7

R3.8

Figure 7.2. Daylight images of the eight test locations in the Spring 2021 experiment (image R3.3 by author and the remainder from Google Maps Street View (www.google.com/maps)).

Table 7.1. Characteristics of the eight locations in the Spring 2021 experiment. The light source was LED in all locations.

Location ref.	Location coordinates	Path type*	Lighting configuration
R3.1	53°22'24.0"N 1°30'24.2"W	C	Single sided
R3.2	53°22'58.8"N 1°28'38.7"W	A	Staggered
R3.3	53°23'16.0"N 1°28'58.3"W	B	Single sided
R3.4	53°23'14.1"N 1°28'16.3"W	A	Staggered
R3.5	53°22'03.8"N 1°30'10.6"W	B	No lighting (spill over light from the nearby roundabout).
R3.6	53°22'41.8"N 1°29'10.5"W	A	Single sided
R3.7	53°22'33.2"N 1°28'32.6"W	A	Staggered
R3.8	53°23'04.0"N 1°28'08.8"W	A	Single sided

* A = Footpath along the road, B = Footpath in a park, C = no footpath

7.2.2 Spring 2024 experiment locations

For the Spring 2024 experiment, nine of the 12 locations used in Experiment 2 were chosen (Figure 7.3 and Table 7.2), with the selection made to include variety of day-dark differences from the results of Experiment 2 (See Table 6.16). The initial selection included three locations from each of the low (R2.5, R2.10, and R2.11), medium (R2.2, R2.3, and R2.12), and high (R2.1, R2.4, and R2.8) day-dark differences. However, location R2.10 from the low category was replaced with R2.6 from the medium category, as it was anticipated that R2.10 would have a low flow of pedestrian traffic due to being a cul-de-sac to four houses with no dedicated pedestrian footpath. Photographs of the selected locations can be found in Chapter 5 - Figure 5.5.

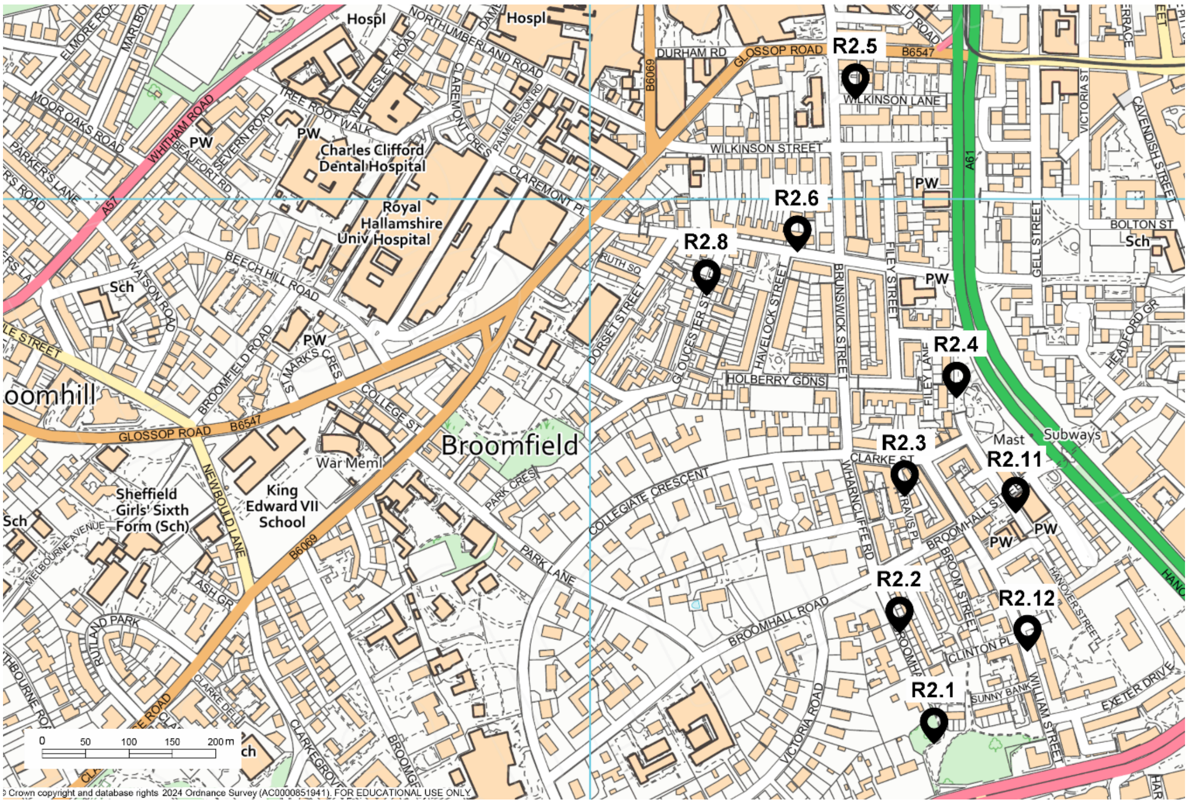


Figure 7.3. Map of the nine locations in the Spring 2024 experiment (background map from Digimap (digimap.edina.ac.uk/roam/map/os) and locations added by author).

Table 7.2. The mean day-dark difference (from lowest to highest) for the 12 locations in Experiment 2, and the selected locations for Spring 2024 experiment.

Road ref.	Mean day-dark composite reassurance score*	Category of day-dark difference**	Selected for Spring 2024 experiment
R2.5	-0.15	Low	×
R2.11	0.05	Low	×
R2.10	0.16	Low	
R2.6	0.44	Medium	×
R2.12	0.49	Medium	×
R2.3	0.51	Medium	×
R2.9	0.57	Medium	
R2.2	0.64	Medium	×
R2.7	0.75	Medium	
R2.8	1.05	High	×
R2.1	1.18	High	×
R2.4	1.44	High	×

* From Table 6.16.

** Low: day-dark differences below 0.4, Medium: day-dark differences between 0.4 and 0.8, High: day-dark differences above 0.8.

7.3 Light measurements

The focus of the Spring 2021 experiment was not illuminance, but rather exploration of the case-control method (see section 7.6) to refine the method used in the Spring 2024 experiment. Therefore, illuminance measurements were not carried out for the Spring 2021 experiment locations.

One of the aims of the Spring 2024 experiment was to assess the relationship between road lighting and changes in pedestrian counts. The light measurements in Experiment 2 were assumed to be sufficiently close in time to the Spring 2024 experiment to make it reasonable to assume no or trivial change in illuminances. Hence, the same light measurements from Experiment 2 (see Table 5.2 and section 5.3) were used for the Spring 2024 experiment.

7.4 Pedestrian count observers

The counts were recorded in-situ by on-road observers (Figure 7.4). For Spring 2021 period, there was eight observers, one for each location. For Spring 2024 period, the observation procedure was improved by assigning observers in pairs to each location. Pairs were used to provide mutual support, ensure coverage if one observer was absent or delayed, and enhanced safety of observers, particularly during after-dark sessions. Sixteen observers were used in the Spring 2024 period: one observer each, for locations R2.5 and R2.6, and two observers each, for the rest of the locations. There was no need for pairing the observers in locations R2.5 and R2.6, as they were experienced members (researchers) from the Lighting Research Group, who were familiar with Sheffield and had access to support from the Lighting Research Group, if needed.

Figure 7.4. Observers recording pedestrian traffic counts in Location R2.4.

All observers were University of Sheffield students, and were researchers from the Lighting Research Group, University of Sheffield master students using the experiment data as part of their dissertations, and University of Sheffield students who were recruited using the university's job vacancies website. The author was also an observer for the Spring 2021 experiment. Some observers received a monetary reimbursement for their time. Table 7.3 shows information about the observers in Experiment 3.

Table 7.3. The observers in Experiment 3.

Experiment period	Type of observer	No. of observers	Received financial payment?
Spring 2021	Author	1	No
	University of Sheffield master student who was using the data as part of their dissertation	4	No
	University of Sheffield student recruited through the university's job vacancy website	3	Yes (£16.40/hr for 26 hours)
Spring 2024	University of Sheffield master student using the experiment data as part of their dissertation	3	No
	Researchers from the University of Sheffield Lighting Research Group	2	Yes (£16.71/hr for 26 hours)
	University of Sheffield student recruited through the university's job vacancy website	11	Yes (£16.71/hr for 26 hours)

7.5 Test times

The Spring 2021 experiment was carried out during the six days before and the six days after the Spring 2021 clock change (Sunday 28 March 2021). The Spring 2024 experiment was carried out during the six days before and the six days after the Spring 2024 clock change (Sunday 31 March 2024) (Table 7.4). The biannual clock change was used as it provides a convenient way to get a clear distinction between daylight and darkness for a specific hour of the day, and enables counting pedestrians in the same time of the day but under daylight or darkness. The Spring 2021 experiment included one public holiday (Friday 2 April), and the Spring 2024 experiment included two public holidays (Friday 29 March, and Monday 1 April).

Table 7.4. The test times in Experiment 3.

Survey date	Week 1 of experiment	Clock change date	Week 2 of experiment
Spring 2021*	Monday 22 March 2021 to Saturday 27 March 2021	Sunday 28 March 2021	Monday 29 March 2021 to Saturday 3 April 2021
Spring 2024**	Monday 25 March 2024 to Saturday 30 March 2024	Sunday 31 March 2024	Monday 1 April 2024 to Saturday 6 April 2024

* Friday the 2 April 2021 was a public holiday.
** Friday 29 March 2024 and Monday 1 April 2024 were public holidays.

Pedestrian counts were recorded during two periods for each day of the experiment: once during a one-hour period from 19:00 to 20:00 (the case hour), and once during a one-hour period from 16:00 to 17:00 (the control hour) (Figure 7.5). The case hour was a transitional period in which ambient light level changed following the clock change; the case hour was predominantly in darkness before the clock change (latest onset of civil twilight was 19:07), and was in daylight after the clock change (earliest onset of civil twilight was 20:09). The control hour was an hour which remained daylight during the entire period of the experiment, this helping to account for potentially confounding variables, such as weather, which may also vary.

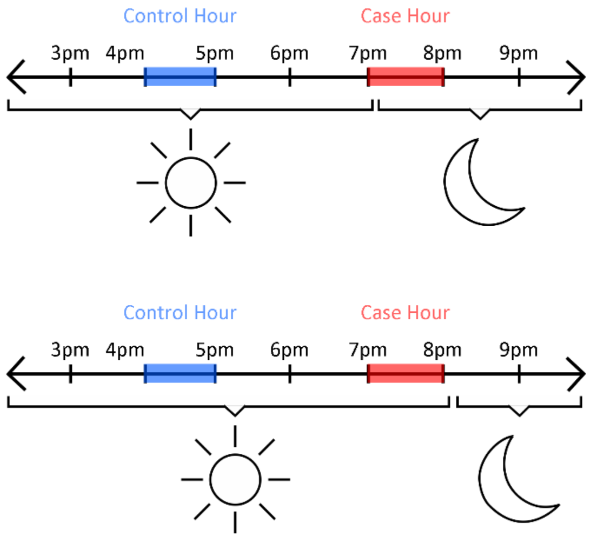


Figure 7.5. The test sessions before the clock change (top) and after the clock change (bottom) for the Spring 2021 and Spring 2024 experiments.

7.6 Procedure

7.6.1 Observer briefing session

To ensure consistency of approach across locations, the observers attended a briefing session with the author prior to data collection. During this session, the observers received information about the experiment design and how to conduct counts at each location. Using example images, the observers were trained to classify pedestrians' apparent age group (below 30 years, 30 to 59 years, and 60 years and above) and apparent gender (male or female) (Figure 7.6). The Spring 2021 experiment highlighted some ambiguity among observers in distinguishing pedestrians from non-pedestrians. For example, it was unclear whether someone using a wheelchair should be classified as a pedestrian. To address this ambiguity, the Spring 2024 briefing session provided more detailed guidance on differentiating pedestrians from non-pedestrians; observers were instructed to classify anyone on foot as a pedestrian (e.g. someone pushing a bicycle was counted as a pedestrian, not a cyclist). At the end of the briefing session, observers were offered the chance to ask questions. A WhatsApp group chat was created for all observers, for coordination and to ensure safety during the experiment.

Figure 7.6. Example images used in the observer briefing session, for identifying the apparent age group of pedestrians.

7.6.2 Observation sheet and booklet

Observers were given printed observation sheets, to help record pedestrian counts during the test sessions (Figure 7.7). The observation sheet also included a space to record the weather conditions at the start of, midway through, and end of each test session. Observers were also instructed to write down the number of lampposts, visible from their observation point, which were turned on or off.

Observation recording sheet - PEDESTRIANS

Date: **Hour:** **Location:** **Observer name:**

PEDESTRIAN						Notes
Young (<30 years)		Middle age (30-59 years)		Older (60+ years)		
Male	Female	Male	Female	Male	Female	
						Weather condition - start:
						Weather condition - mid:
						Weather condition - end:
						street lights on/off: / Comment:
						Total:

Figure 7.7. The observation sheet used in Experiment 3. to record the number of pedestrians passing the observation line.

Building on the experience of the Spring 2021 experiment, observers in the Spring 2024 experiment also received a printed instruction booklet, to achieve consistency and ensure accurate adherence to the experimental protocol:

(1) The booklet's first page contained experiment instructions and contact information of the author, university security, and emergency services, in case observers required assistance (Figure 7.8).

(2) A map of the observation locations was provided on the second page, to assist observers in finding their assigned location (Figure 7.9).

(3) The third page provided a detailed map of each observer's assigned location, including a photograph of the test location, the designated observation point, and an imaginary observation line (Figure 7.10). At each location, the imaginary observation line was drawn between two successive lampposts, and perpendicular to the direction of travel. For the Spring 2024 experiment, these were the same lampposts used in Experiment 2. The observers recorded the number of pedestrians passing this imaginary observation line in either direction and on either side of the road, whilst also recording the pedestrians' apparent age group and apparent gender. If the same pedestrian crossed the line, they were counted again. To

minimise the likelihood of confusion or double counting, the imaginary line avoided junctions or corners.

How to carry out the fieldwork:

- **Step 1:**
  Walk to your specific observation point (highlighted in the map overleaf). Please arrive **a few minutes earlier** to get prepared.

- **Step 2:**
  Message the WhatsApp group to inform Shahab you have arrived at the observation point. Shahab will send a **count down** in the WhatsApp group when it is time to start the recording. It is therefore important that everyone is at their location on time.

- **Step 3:**
  Record the number of pedestrians passing the imaginary observation line (highlighted in the map overleaf).

  1. You should count pedestrians passing the line in **either direction**, and on **either side of the path**. This includes any pedestrian you think has been recorded before.

  The following should **NOT** be counted as a pedestrian:
     - Scooters (including e-scooters or mobility scooters) being ridden

  The following **should be** counted as a pedestrian:
     - Scooters (including e-scooters or mobility scooters) being pushed
     - Bicycles being pushed

  2. You should also record the apparent **gender** and **age group** of pedestrians.

- **Step 4:**
  Shahab will send a message to the WhatsApp group **when it is time to stop** the recording.

Important Information / Contact details:

- Please have with you a charged mobile phone with data access.
- Please have a pen/pencil on you for marking the observation sheet.
- Message Shahab on WhatsApp in case of any issues: 07908442767
- University security services: 0114 222 4444 & Police: 999
- You are advised to install the SafeZone app (https://www.sheffield.ac.uk/security/safezone) on your phone in case of an emergency.

Figure 7.8. The first page of the instruction booklet given to observers in the Spring 2024 experiment, showing instructions for carrying out observations and important contact details.

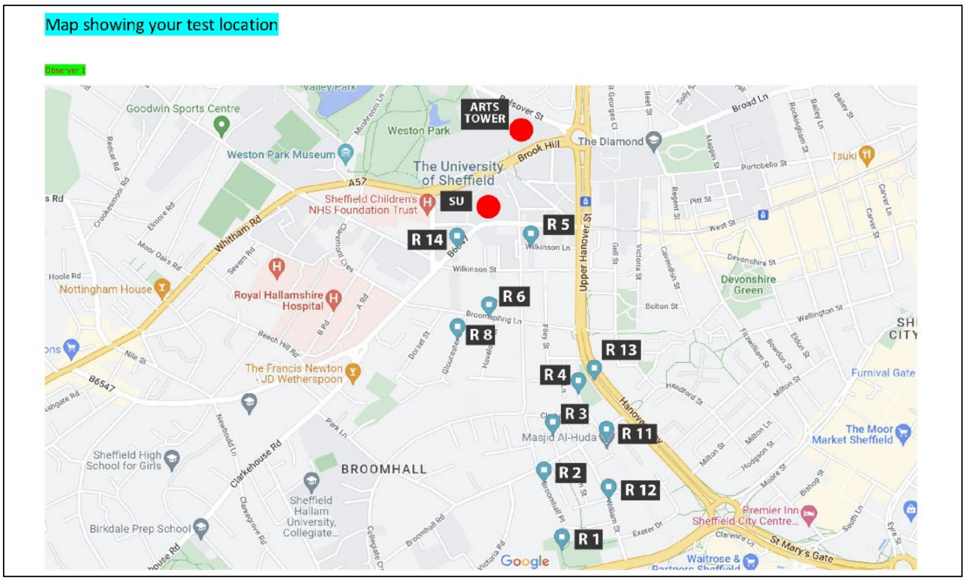


Figure 7.9. The second page of the instruction booklet in the Spring 2024 experiment, showing a map of the test locations.

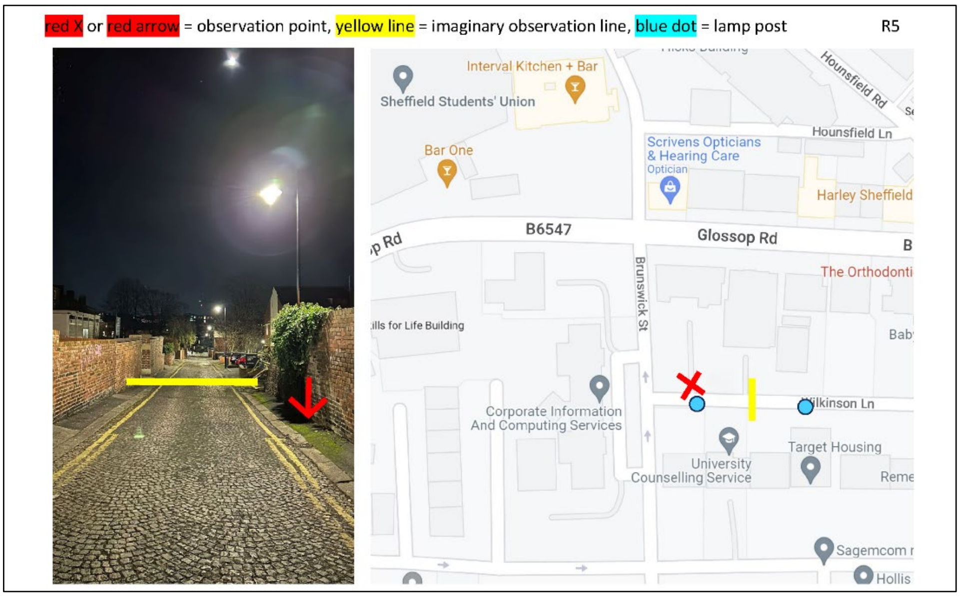


Figure 7.10. An example third page of the instruction booklet in the Spring 2024 experiment, showing location R2.5.

7.6.3 Recording pedestrian counts

In the Spring 2021 experiment, observers arrived at their assigned locations a few minutes before the start time to prepare. They were all instructed to start and end counts at the exact start and end time of each session, for example, beginning the count precisely at 4:00 PM and concluding at 5:00 PM. At the end of the experiment, observers entered their data into a spreadsheet.

For the Spring 2024 experiment, the procedure was refined, to enhance consistency in observations and data collection. Observers were asked to arrive at their assigned locations a few minutes prior to each session's start time to prepare, and to notify the author via the WhatsApp group chat upon arrival. To synchronize observations across all locations, the author initiated a countdown in the group chat at both the beginning and end of each test session. During each test session, the author made unannounced visits to all locations in a randomised order, to check on observers' adherence to instructions and ensure they were correctly positioned. After each test session, observers uploaded a scanned copy of their observation sheet to a shared Google Drive. The data from these sheets was then compiled into a spreadsheet at the conclusion of the experiment.

7.7 Odds ratio

Odds ratio is a statistic used to quantify the strength and direction of association between an exposure and an outcome. It is a ratio of two sets of odds: the odds that an outcome will occur given a particular exposure, compared to the odds of the outcome occurring in the absence of that exposure (Persoskie and Ferrer, 2017; Sackett et al., 1996). In Experiment 3, the aim was to investigate the effect of daylight (the exposure) on walking by comparing the odds of people walking during daylight to the odds of them walking after dark (i.e. absence of daylight). The use of the control hour helped to account for confounding factors, such as variation in weather or purpose of travel.

The odds ratio (*OR*) was calculated using equation 1 (Johansson et al., 2009).

$$OR = \frac{odds\ of\ the\ otcome\ in\ the\ presense\ of\ the\ exposure}{odds\ of\ the\ otcome\ in\ the\ absense\ of\ the\ exposure} = \frac{\frac{Case\ Day}{Control\ Day}}{\frac{Case\ Dark}{Control\ Dark}} = \frac{\frac{Case\ Day}{Case\ Dark}}{\frac{Control\ Day}{Control\ Dark}} \quad (1)$$

where $Case\ Day$ is the number of pedestrians during the case hour after the clock change when it was daylight, $Case\ Dark$ is the number of pedestrians during the case hour before the clock change when it was dark, $Control\ Day$ is the number of pedestrians during the control hour after the clock change (i.e. the days when the case hour would be in daylight), and $Control\ Dark$ is the number of pedestrians during the control hour before the clock change (i.e. the days when the case hour would be in darkness).

An odds ratio of 1 indicates that the exposure does not affect the odds of the outcome (i.e. the odds of the outcome is the same, with or without the exposure), an odds ratio of below 1 shows the exposure is associated with lower odds of the outcome, and an odds ratio of above 1 shows the exposure is associated with higher odds of the outcome; the larger the odds ratio above 1, the higher odds that the outcome will occur with exposure (Field, 2018). In Experiment 3, an odds ratio of 1 indicates that the number of pedestrians walking is not associated with the presence or absence of daylight. A ratio below 1 suggests that daylight is associated with a decrease in pedestrian traffic. Conversely, a ratio greater than 1 implies that daylight is associated with increased pedestrian traffic, and the larger the odds ratio above 1, the stronger the association (and, we assume, the lower the reassurance).

The significance of the odds ratio is assessed by calculating the confidence interval (Sedgwick, 2015), which estimates the range within which the true odds ratio for the entire population is likely to fall. A 95% confidence is traditionally chosen in the literature (Szumilas, 2010). A confidence interval containing the value 1 indicates a lack of statistical significance, as the expected true odds ratio for the population could be either greater or less than 1.

The 95% confidence intervals (*95%CI*) were calculated using equation 2 (Johansson et al., 2009).

$$95\%CI = \exp\left(Ln(OR) \pm 1.96 \times \sqrt{\frac{1}{CaseDay} + \frac{1}{CaseDark} + \frac{1}{ControlDay} + \frac{1}{ControlDark}}\right) \quad (2)$$

Where OR is the odds ratio, and $Case\ Day$, $Case\ Dark$, $Control\ Day$, and $Control\ Dark$ are the number of pedestrians during each of the respective periods.

7.8 Summary

This chapter described the method used in Experiment 3, conducted on two occasions. The first, was a study to explore the travel count method, and the second, used travel counts as an objective method to test the effect of darkness on the number of pedestrians. The results of Experiment 3 are described in Chapter 8.

CHAPTER 8. EXPERIMENT 3 – TRAVEL COUNTS: RESULTS

8.1 Introduction

This chapter presents the results of Experiment 3, a field study in which the numbers of pedestrians were counted in daylight and after-dark to investigate the deterrent effect of darkness. This objective approach to measuring pedestrian reassurance was carried out to enable comparison with the subjective evaluations reported in Experiment 2. The first step of the analysis was to determine if the data were normally distributed, as this dictates the choice of statistical tests for examining significant differences, and how to report the data. The results of the studies in Spring 2021 and Spring 2024 were then explored to assess the effect of darkness on pedestrian traffic, by calculating the odds ratios (OR) of change in number of pedestrians. For the spring 2024 data, the relationship between ORs and illuminance, and ORs and reassurance ratings from Experiment 2 were explored (Hypothesis H6).

8.2 Distribution normality

Following the same procedure outlined in chapter 4 (see section 4.3) the results of the travel count field studies were assessed to determine if they were drawn from a normally distributed population This was done for the Spring 2021 and Spring 2024 experiments separately.

It was revealed that the data exhibited a normal distribution. An example normality test for location R2.1 in a daylight session of the Spring 2024 experiment is shown in Table 8.1 and Figure 8.1. The distribution is considered to be normal because two of the three tests report a normal distribution: (1) the graphical test is near normal (the histogram approximates the bell-curve shape for normally distributed data; the box plot is normally distributed, as the median line is central within the box and the whiskers above and below the box are almost of similar length; the Q-Q plot is not normal as the data points form an s-shape around the straight diagonal line); (2) the skewness and kurtosis values are inside the normal ranges of ±0.5 and ±1 respectively; and (3) the median falls within the 95% confidence interval of the mean.

Table 8.1. The normality test for location R2.1 - daylight session in the Spring 2024 experiment.

Normality Test													
Graphical				Dispersion			Central Tendency						Ov
Histogram	Box Plot	Q-Q Plot	**Normal?**	Skewness	Kurtosis	**Normal?**	Mean	Lower 95% CI	Upper 95% CI	Median	**Normal?**		
Yes	Yes	No	**Near**	-0.27	-0.51	**Yes**	4.30	13.22	16.39	14.00	**Yes**		**Yes**

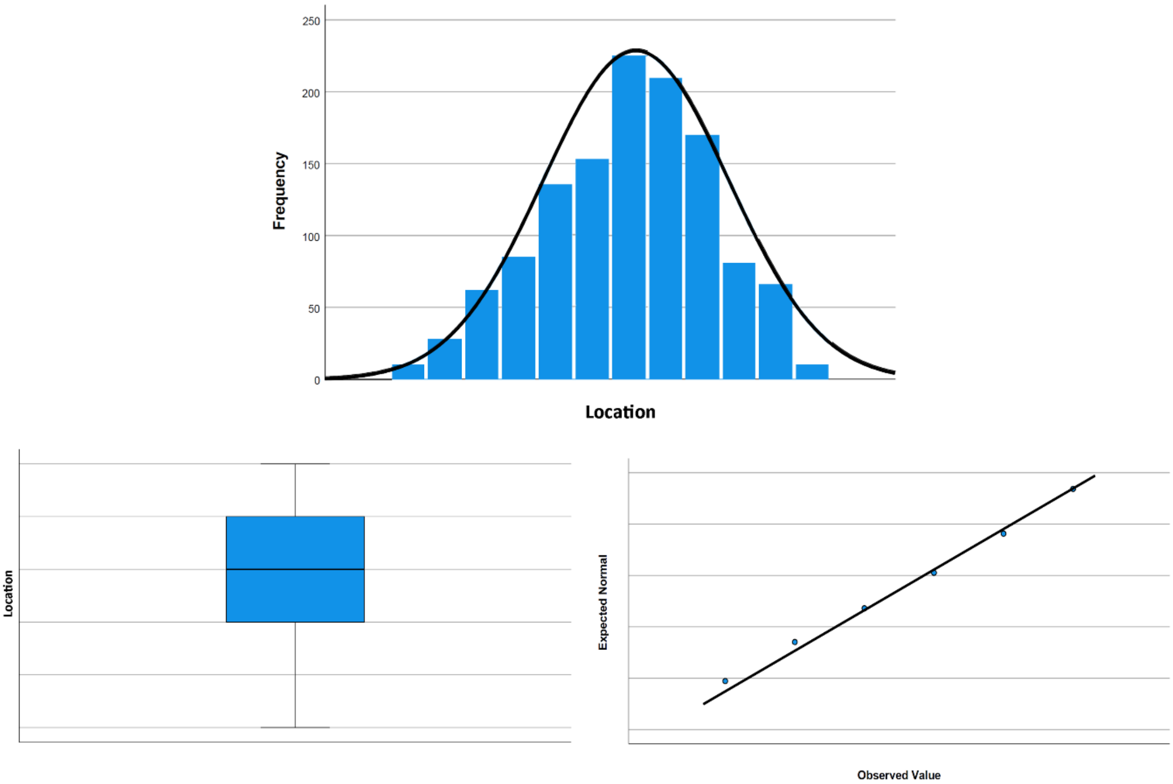


Figure 8.1. Box plot (top), histogram (middle), and Q-Q plot (bottom) of pedestrian counts for location R2.1 - daylight session in the Spring 2024 experiment.

8.3 Results

8.3.1 Odds ratio

The overall impact of darkness on pedestrian traffic was evaluated by combining travel counts from all locations. Odds ratios (ORs), 95% confidence intervals (95%CIs), and p-values were then calculated for this aggregated data. This was done for the Spring 2021 and Spring 2024 experiments separately, and for the combined data of both experiments (Table 8.2). ORs are a measure of effect size on their own (Field, 2018), and the strength of the effects observed were categorised using Olivier and Bell's (2013) thresholds: an OR of 1.22 was considered a small effect, 1.86 a medium effect, and 3.00 a large effect. Statistical comparisons of ORs were conducted between subgroups (males vs females, younger vs older) to determine if differences were significant. This involved calculating z-scores and converting them to p-values. The level of significance was established at α = 0.05.

Table 8.2. Travel counts and associated odds ratios and 95%CIs for all locations combined, in the Spring 2021 and Spring 2024 experiments separately, and both experiments combined.

Period	Pedestrian category	No. of travellers				OR	95%CI	p-value	Effect size
		Case Day	Case Dark	Control Day	Control Dark				
Spring 2021	Overall	6,686	3,739	11,881	10,394	**1.56**	1.49-1.64	p<0.001	Small-medium
	Male	3,793	2,194	5,897	5,300	**1.55**	1.46-1.66	p<0.001	Small-medium
	Female	2,893	1,545	5,984	5,094	**1.59**	1.48-1.71	p<0.001	Small-medium
	Young	5,452	2,841	9,135	7,499	**1.58**	1.49-1.66	p<0.001	Small-medium
	Old	129	36	499	471	**3.38**	2.29-5.00	p<0.001	Large
Spring 2024	Overall	1694	1645	2200	2944	**1.38**	1.26-1.50	*p*<0.001	Small-medium
	Male	1140	1139	1285	1823	**1.42**	1.27-1.58	*p*<0.001	Small-medium
	Female	554	506	915	1121	**1.34**	1.16-1.56	*p*<0.001	Small-medium
	Young	889	849	1070	1460	**1.43**	1.26-1.62	p<0.001	Small-medium
	Old	120	121	134	180	**1.33**	0.95-1.87	*p* = 0.09	Small-medium
combined	Overall	8380	5384	14081	13338	**1.47**	1.41-1.54	p<0.001	Small-medium
	Male	4933	3333	7182	7123	**1.47**	1.39-1.55	p<0.001	Small-medium
	Female	3447	2051	6899	6215	**1.51**	1.42-1.61	p<0.001	Small-medium
	Young	6341	3690	10205	8959	**1.51**	1.44-1.59	p<0.001	Small-medium
	Old	249	157	633	651	**1.63**	1.30-2.05	p<0.001	Small-medium

The overall OR across all genders and age groups, were suggested to be significantly greater than 1.00 (Combined: 1.47, Spring 2021 OR = 1.56, Sping 2024 OR = 1.38, p<0.001), indicating fewer number of pedestrians in darkness compared to daylight, to an extent that exceeded the threshold for a small effect size. Differences between the ORs for males and females were not suggested to be significant (Spring 2021: male OR = 1.55, female OR = 1.59, z = 0.518, p = 0.302; Spring 2024: male OR = 1.42, female OR = 1.34, z = 0.318, p = 0.375). The ORs for younger and older pedestrians for the Spring 2021 experiment were indicated to be significantly different (young OR = 1.58, old OR = 3.38, z = 3.800, p<0.001), showing that darkness has a greater deterrent effect on old pedestrians than on young pedestrians. For Spring 2024, this difference was also significant (young OR = 1.43, old OR = 1.33, z = 2.900, p<0.01). However, the odds ratios for old pedestrians did not reach statistical significance (p =

0.09). All effect sizes for the Spring 2021 experiment were small to medium, and increase to large effects for old pedestrians. For the Spring 2024 experiment, the effect sizes were small to medium in all cases.

8.3.2 The effect of illuminance

Figures 8.2 to 8.4 show the overall OR at each location plotted against the arithmetic mean horizontal illuminance, minimum horizontal illuminance, and horizontal uniformity, for the Spring 2024 data. The initial analysis included all nine locations (n=9). Upon visual inspection, one data point (R2.5) was identified as a potential outlier. To determine the effect of this outlier, the analysis was repeated without the outlier (n=8). A linear function provided the best fit for the relationships for both n=9 and n=8.

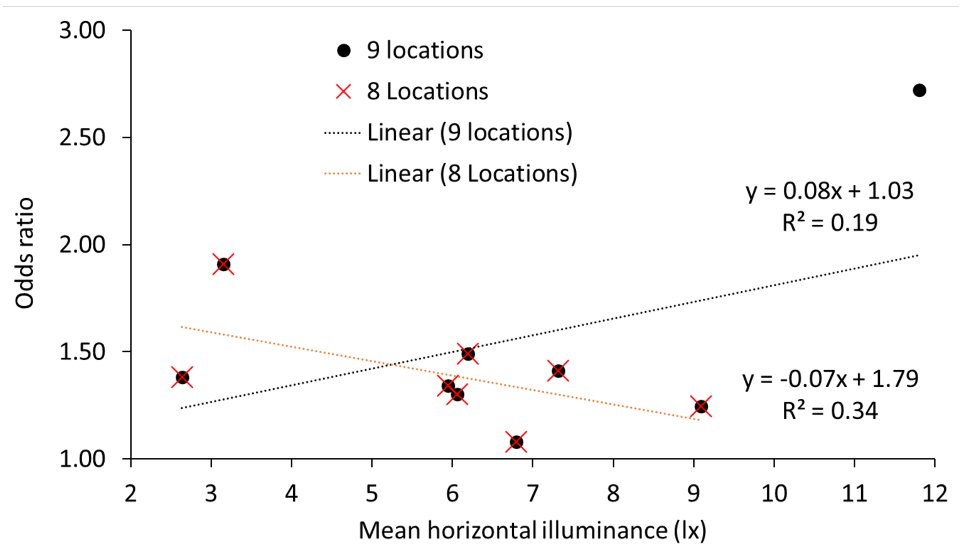


Figure 8.2. Odds ratios plotted against arithmetic mean horizontal illuminance in Spring 2024 experiment, for n=8 and n=9. Regression line uses a linear function.

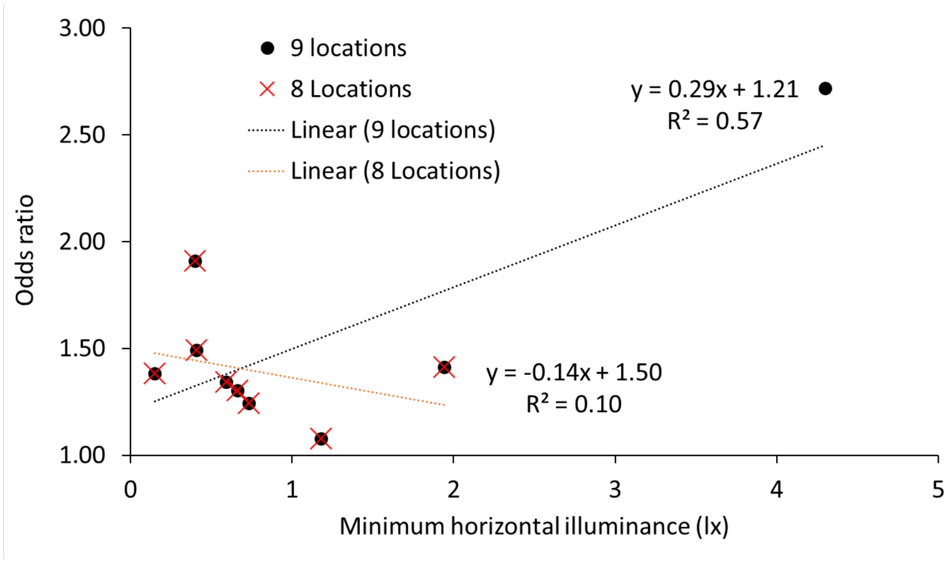


Figure 8.3. Odds ratios plotted against minimum horizontal illuminance in Spring 2024 experiment, for n=8 and n=9. Regression line uses a linear function.

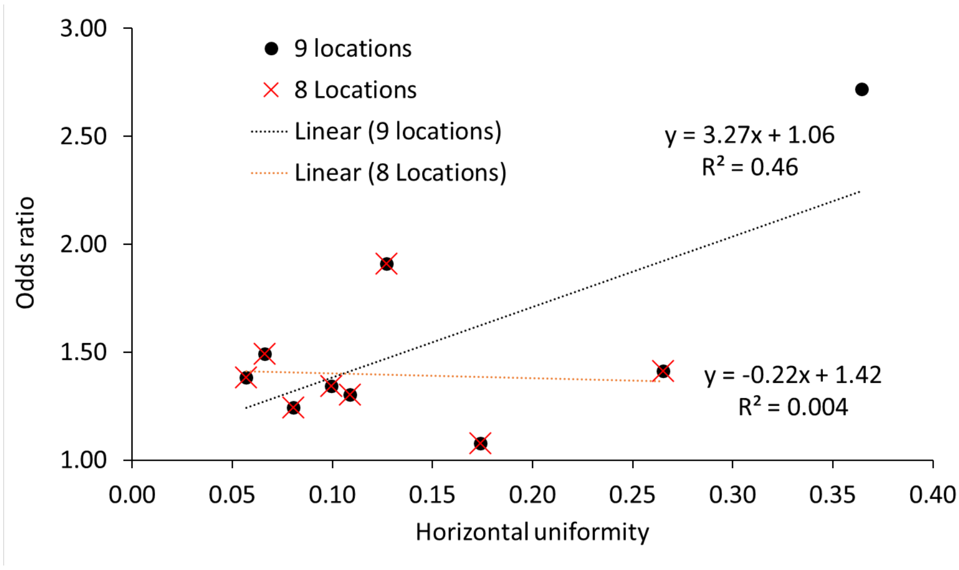


Figure 8.4. Odds ratios plotted against horizontal uniformity in Spring 2024 experiment, for n=8 and n=9. Regression line uses a linear function.

The results suggested that excluding the outlier (n=8) produced a better representation of the trend than including it (n=9). For n=8, arithmetic mean horizontal illuminance had a stronger association with the ORs (R^2= 0.34, n=8, p<0.01) than minimum horizontal illuminance (R^2= 0.10, n=8, p=0.07) or horizontal uniformity (R^2= 0.004, n=8, p=0.11). For n=8, the higher R-squared for mean illuminance suggests that this model better fits the observed data, and provides the strongest explanation for the findings. The plots (for n=8) show lower odds ratios in locations with higher arithmetic mean illuminances, indicating that the deterrent effect of darkness on number of people walking (i.e. the ORs) reduces with higher arithmetic mean illuminances.

8.3.3 Travel counts versus reassurance surveys

Hypothesis H6 proposed that ORs determined using travel counts are associated with reassurance ratings from subjective evaluations. To test this hypothesis, ORs in the Spring 2024 experiment were plotted against the relevant mean after dark and mean day-dark composite reassurance scores from Experiment 2 (see Table 8.3 and Figures 8.5 and 8.6). As in section 8.3.2, the Spring 2024 experiment was initially analysed using data from all nine locations (n=9). Upon visual inspection, the same data point as before, R2.5, was identified as a potential outlier. To determine the effect of this outlier, the analysis was repeated without the outlier (n=8). A linear function provided the best fit for the relationships for both n=9 and n=8.

Table 8.3. Travel counts and associated odds ratios in Experiment 3: Spring 2024, and mean after-dark and day-dark composite scores in Experiment 2, for each location separately.

	Travel count method (Experiment 3 – Spring 2024)						**Survey method (Experiment 2)***	
Location ref.	**No. of travellers**				**OR**	**95% CI**	**Mean after-dark composite reassurance score**	**Mean day-dark composite reassurance score**
	Case day	**Case dark**	**Control day**	**Control dark**				
R2.1	174	151	248	411	1.91	1.46-2.50	3.00	1.18
R2.2	198	181	346	472	1.49	1.17-1.91	3.98	0.64
R2.3	47	40	61	56	1.08	0.62-1.88	4.41	0.51
R2.4	276	239	309	370	1.38	1.10-1.74	3.35	1.44
R2.5	21	11	40	57	2.72	1.18-6.26	4.94	- 0.15
R2.6	323	300	607	702	1.25	1.03-1.51	4.53	0.44
R2.8	84	69	115	123	1.30	0.87-1.96	3.88	1.05
R2.11	397	452	284	457	1.41	1.16-1.73	3.94	0.05
R2.12	174	202	190	296	1.34	1.02-1.76	3.69	0.49

* Values from Table 6.16.

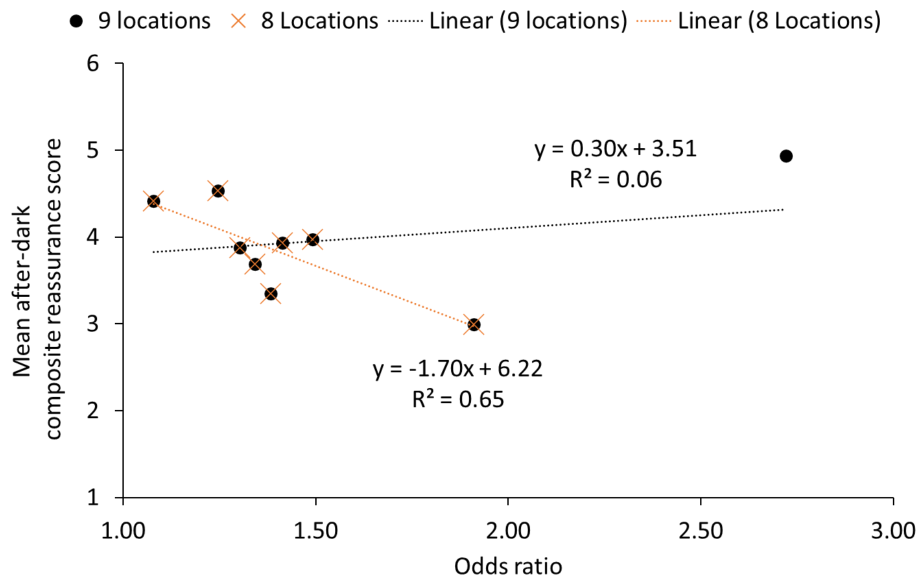


Figure 8.5. Mean after-dark composite reassurance scores (Experiment 2) plotted against odds ratios (Experiment 3: Spring 2024) for n=8 and n=9.

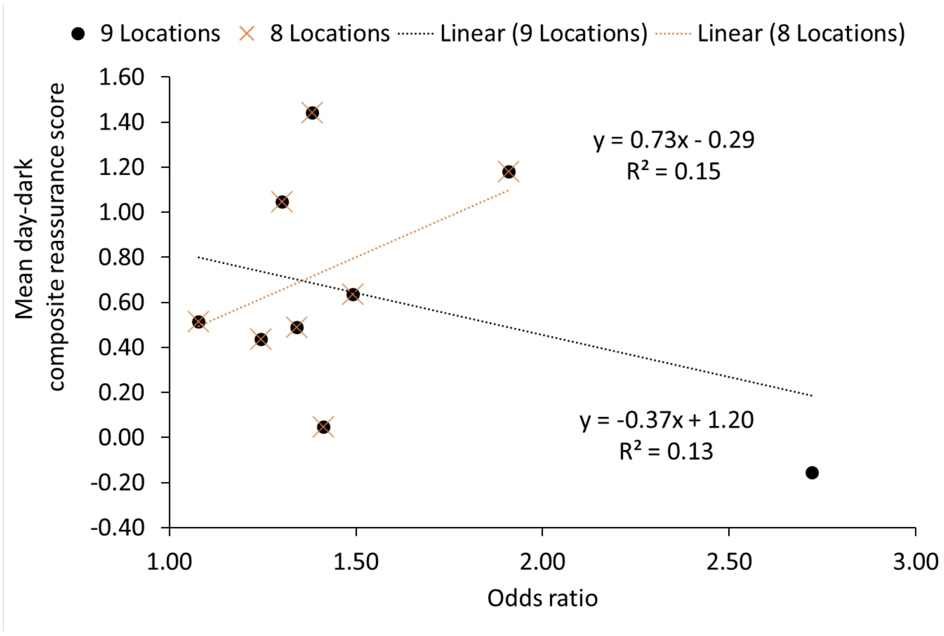


Figure 8.6. Mean day-dark composite reassurance scores (Experiment 2) plotted against odds ratios (Experiment 3: Spring 2024) for n=8 and n=9.

The results suggested that excluding the outlier (n=8) produced a better representation of the trend than including it (n=9). For n=8, ORs had a stronger association with the mean after-dark composite reassurance scores (R^2= 0.65, n=8, p<0.01) than mean day-dark composite reassurance scores (R^2= 0.15, n=8, p=0.08). The plots reveal that locations with greater day-dark differences also have a higher odds ratio, suggesting that where pedestrian reassurance is lower, darkness has a stronger deterrent effect on pedestrian traffic.

8.4 Summary

This chapter presented the results of Experiment 3, which used the travel count method to compare the numbers of pedestrians during daylight and after dark. The results suggested that pedestrian numbers were significantly reduced in darkness compared to daylight, and that higher illuminance reduced the deterrence effect of darkness on pedestrian traffic. This deterrence effect was not suggested to be significantly different between males and females. It was also found that ORs were highly associated with after-dark reassurance ratings. In the next chapter, the findings of Experiments 1, 2 and 3 are discussed to evaluate whether they support the proposed hypotheses of this thesis.

CHAPTER 9. DISCUSSION

9.1 Introduction

This thesis investigated the road lighting illuminance necessary for pedestrian reassurance. Six hypotheses were raised from the literature review:

H1: Higher illuminance enhances pedestrian reassurance after dark.

H2: Illuminance has a stronger association with the day-dark difference than after-dark ratings.

H3: Day-dark difference in reassurance ratings obtained at the same time of day is different from day-dark difference in reassurance ratings obtained at different times of day.

H4: Evaluations from groups of participants will suggest higher reassurance than evaluations from solo participants for the same lighting conditions.

H5: Higher illuminances reduce the disparity between male and female reassurance after dark.

H6: Odds ratios determined using travel counts are consistent with reassurance ratings from subjective evaluations.

Three experiments were conducted to test the hypotheses:

Experiment 1 (Chapters 3 and 4), was a pilot study to refine the day-dark method for measuring pedestrian reassurance, by investigating the potential confound of time-of-day. This confound is that in previous studies, daylight and after-dark evaluations were carried out at different times of day. To investigate this, daylight evaluations in Experiment 1 were carried out at two different times of day: once at a different time of day to the after dark evaluations (noon daylight), and once at the same time of day as the after dark evaluations (evening daylight). The day-dark differences obtained using each of the noon daylight and evening daylight sessions were then compared to assess the impact of time of day on the daylight evaluations (Hypothesis H3).

Experiment 2 (Chapters 5 and 6), was a field study carried out to investigate whether pedestrian reassurance was affected by a change in illuminance (Hypothesis H1), and whether the gender difference in reassurance could be mitigated with higher illuminances (Hypothesis

H5). Experiment 2 was conducted using the same day-dark method as used in Experiment 1, but with two main changes: following the findings of Experiment 1 only one daylight session was used (noon daylight), and participants were allocated to either solo or group evaluations to assess how participant accompaniment affected the results (Hypothesis H4). The association between illuminance and the after-dark ratings, and illuminance and day-dark differences were assessed to explore the ability to define an optimal illuminance (Hypothesis H2).

Experiment 3 (Chapters 7 and 8), used the travel count method to enable comparison with the subjective evaluations reported in Experiment 2 (Hypothesis H6). This involved comparing the numbers of people walking in daylight with the number of people walking after dark under different lighting conditions, to evaluate the influence of these conditions on pedestrian traffic.

This chapter discusses the findings from Experiments 1, 2, and 3 to determine their support for the proposed hypotheses. It also discusses the internal and external validity of the results, the implications of the research, limitations of the work, and suggestions for future research.

9.2 Internal validity

The internal validity of Experiments 1, 2, and 3 was addressed through the following measures.

9.2.1 Experiments 1, 2, and 3

For all three experiments, standardisation of procedures was used to ensure internal validity. This was achieved by ensuring that the experiment conditions, instructions, and measurement procedures were consistent across all participants and groups. This also included training researchers on assessment procedures. For Experiments 1 and 2, a briefing session was held to inform participants how the experiment would be conducted, and solo participants in Experiment 2 received instruction booklets so they all followed the same procedure, and to ensure that this procedure was similar to that of group evaluations. In Experiments 1 and 2, the same instructions were given to participants in all sessions, and the same questionnaire was used in all sessions. For Experiment 3, a training session was held for observers where they were briefed on how to carry out the travel counts, and trained on age and gender identification. All observers in Experiment 3 also received instruction booklets to ensure consistency.

9.2.2 Experiments 1 and 2

Participants in Experiments 1 and 2 were randomly selected from those who expressed interest in the experiments, and, for Experiment 2, were randomly assigned to the evaluation mode (solo or group). This helped control and account for internal threats to the validity in Experiments 1 and 2; random selection helped minimise selection bias, and random assignment of participants to evaluation modes prevented systematic differences between the solo participants and group participants (Taylor, 2013).

In experiments 1 and 2 the test participants each conducted two evaluations, one in daylight and one after dark. The order in which the daylight or after-dark evaluation was carried out first, was balanced. The test participants repeated these evaluations at multiple locations: in Experiment 1 the order in which the six locations were visited was randomised, while in Experiment 2 the order was counter balanced.

A bogus question was included in Experiments 1 and 2 to identify inattentive respondents, for example, those who ticked a response without carefully reading the question and/or response options. This helped reduce threats to internal validity, primarily by addressing participant-related biases that could confound results (Taylor, 2013). A strict 20% threshold, higher than the 50% recommended by literature (Curran, 2016), was used for excluding participants with invalid responses to the bogus questions. This resulted in the exclusion of one participant from Experiment 1, and five participants from Experiment 2.

To ensure solo participants in Experiment 2 followed instructions, their questionnaire responses were reviewed after the completion of the experiment; response timestamps were checked for reasonable completion times, and the order of questionnaire responses were assessed to confirm adherence to the predetermined routes.

9.2.3 Experiment 3

In Experiment 3, the control period was used as a measure of internal validity; by including a control period during daylight hours (i.e. when the ambient lighting is consistent across the day-dark change of the case hour), factors that could influence pedestrian numbers other than the lighting conditions (e.g. weather) were accounted for (Uttley and Fotios, 2017). Without a control period, any observed differences in the number of pedestrians between daylight and after-dark could be attributed to other factors, not just the lighting; the control period allowed the establishment of a baseline for pedestrian numbers, and the effect of lighting was isolated by comparing the pedestrian counts in the case period to this baseline. This approach strengthened internal validity, increasing confidence that the observed effects were genuinely caused by the lighting conditions.

In Experiment 3, the researcher conducted random checks on the onsite observers who were responsible for the travel count, verifying they were fulfilling their duties correctly and stationed in the appropriate locations.

9.3 Assessment of research hypotheses and comparison with previous research

This section examines each hypothesis, determining if the experimental results support or refute it. It also evaluates the alignment of these findings with prior research and road lighting standards, to measure external validity.

9.3.1 Hypothesis H1

H1: Higher illuminance enhances pedestrian reassurance after dark.

This can be tested using the results of Experiment 2. In Experiment 2, a single composite reassurance rating was determined using factor analysis. This was used to assess the impact of variations in illuminance on the mean after-dark reassurance scores, and mean reassurance ratings obtained using the day-dark approach. The plots of mean horizontal illuminance, minimum horizontal illuminance, and horizontal uniformity against after-dark and day-dark composite reassurance scores (Figures 6.8 to 6.13) suggested a positive relationship between illuminance and after-dark ratings of reassurance, and a negative relationship between illuminance and day-dark differences in ratings of reassurance.

Overall, the results from both the after-dark ratings and day-dark differences indicate that roads which were lit to higher illuminances, enhanced pedestrian reassurance. Therefore, the results of Experiment 2 support hypothesis H1.

This finding agrees with that of past studies of pedestrian reassurance and road lighting which have focused on illuminance. A sample of these studies, presented in Table 9.1, consistently demonstrate a positive effect of higher illuminances on reassurance. For example, in a study by Vrij & Winkel (1991), 160 passers-by on a bridge in Netherlands were approached for an interview to evaluate the impact of improved street lighting on fear and subjective victimisation risks. Their results suggested that increases in the level of street lighting, decreased fear of crime and the perceived likelihood of victimisation.

Table 9.1. Sample of past studies looking at the effect of higher illuminances on pedestrian reassurance.

Study	Change in illuminance tested	Reported effect of higher illuminance
Boyce et al. (2000) – Exp. 1	Mean horizontal illuminance (estimated from Figure 2 in that source): 0.5-192 lx	Higher mean illuminances increased reassurance - diminishing returns with higher values.
Boyce et al. (2000) – Exp. 2	Mean horizontal illuminance (estimated from Figure 2 in that source): 0.3-91 lx	Higher mean illuminances increased reassurance - diminishing returns with higher values.
Boyce et al. (2000) – Exp. 3	Median horizontal illuminance (estimated from Figure 5 in that source): 0.5-48.2 lx	Higher median illuminances reduced the difference in perceived safety between day and night - diminishing returns with higher values.
Peña-García et al. (2015)	Mean horizontal illuminance: 14.63 lx to 57.23 lx	Well-illuminated streets with higher illuminances increased perception of safety, especially when lighting was uniform.
Svechkina et al. (2020)	Mean point horizontal Illuminance: 0.47 lx to 199.96 lx, with an average of 18.52 lx	Significant and positive relationship between feeling of safety and higher illuminances.
Vrij & Winkel (1991)	Minimum illuminance: 0.24 lx and 1.31 lx	The higher illuminance led to a reduction in fear of crime and subjective evaluations of victimisation risks.
Wei et al. (2024)	Average horizontal illuminance: 2.5 lx to 17.2 lux	Higher illuminances were associated with improved perceptions of safety and visual comfort, and reduced perceived risk.

The results of Experiment 2 also indicated that mean horizontal illuminance had a stronger correlation with pedestrian reassurance scores (after-dark: R^2= 0.79, n=12, *p*<0.01; day-dark: R^2= 0.72, n=12, *p*<0.01), than did minimum horizontal illuminance or horizontal uniformity, indicating that the mean was a better predictor of reassurance. This finding is in contrast to that of Fotios et al. (2019), who suggested that minimum illuminance and the uniformity of illuminance revealed better association with day-dark differences in reassurance ratings than did mean. One explanation could be the type of locations used in that experiment. For example, one location was an underpass. Residential roads, despite having potential hiding places due to vegetation or building design, lack the extreme features found in underpasses - underpasses are relatively dark during daylight hours, but relatively bright during dark hours. Underpass design significantly hinders the assessment of potential threats and escape routes, factors which Appleton (1996) identifies as anxiety-inducing. The study by Fotios et al. (2019) focuses on a single urban area within a UK city, and the results require validation across diverse settings and different illuminance ranges.

One method for establishing an optimal illuminance is to find the illuminance associated with a small day-dark difference. Past research (Fotios et al., 2019; Wei et al., 2019) has suggested that a day-dark difference of 0.5 or 1.0 units is small enough to consider the lighting adequate, as this small difference means that reassurance levels after dark are only slightly lower than those experienced during the day. For a day-dark difference of 0.5 units, the plot and the associated regression equation of day-dark differences against mean illuminances in Experiment 2 (see Figure 6.11), suggest an optimal mean illuminance of approximately 7.2 lx (between 7 and 8 lx). This value is approximately the same as the P3 lighting classification, and roughly 50% lower than the maximum recommendation of 15 lx (i.e. the P1 lighting class). This finding suggests that P3 is a better choice for pedestrian reassurance. Two previous studies [Fotios et al., 2019a; Wei et al., 2024] have determined illuminances for a similar 0.5 day-dark difference, suggesting a minimum illuminance of 2 lx or 1.8 lx to be optimum. This agrees with the findings of Experiment 2 which suggested an optimal mean illuminance of 7 to 8 lx for the same day-dark difference, which was equivalent to a minimum illuminance between 1 and 2 lx in the observed plots of Experiment 2 (see Figure 6.12). Mean illuminance is used in this thesis rather than minimum, as it was a better predicter of reassurance (as explained in the previous paragraph). Lighting design guidelines in some countries also suggest a similar optimal mean illuminance. For example, the average illuminance values suggested in Australia and New Zealand for roads in local areas, detailed in AS/NZS 1158.3.1:2020 (Standards Australia/Standards New Zealand, 2020), range from 0.85 to 7.0 lx. This range is lower than that specified in EN 13201-2:2015 (BSI, 2015a). Notably, the upper limit of 7 lx aligns with this research's finding of an optimal mean illuminance between 7 and 8 lx.

Two steps are necessary to translate the findings of this research about optimal illuminance into actionable changes for road lighting design guidelines, necessitating the need for further research:

1. The proposed illuminance reduction to 7-8 lx requires validation through broader, large-scale studies across diverse urban and rural environments with a wider demographic of participants.

2. While reassurance is a key aspect (Fotios et al., 2015), future guideline revisions must consider the purpose of application. For pedestrians, in addition to reassurance, this includes the mitigation of crime against people and property (BSI, 2020), as well as critical visual tasks such as obstacle and hazard detection, wayfinding, and interpersonal evaluations (CIE, 2010). For example, research suggests that pedestrians typically detect obstacles at a distance of about 3.4 meters (Uttley 2015). The study by Fotios and Uttley (2018) found that the minimum horizontal illuminance needed for a pedestrian to detect a 10mm obstacle at this distance varies between 0.22 lx and 0.93 lx, influenced by the pedestrian's age and the Scotopic/Photopic ratio. However, it appears that increasing light levels beyond 2 lx does not significantly improve obstacle detection (Uttley et al. 2017)). Furthermore, it is important to consider the distinct needs of other road users such as cyclists and drivers. For example, for drivers, this can include the need to detect pedestrians or the need for safe passage (Fotios and Gibbons, 2018). Meeting these needs may necessitate higher horizontal illuminances than observed in the current study. It may also be necessary to provide recommendations for other lighting metrics, such as vertical illuminance for interpersonal evaluations. Optimal lighting conditions for these specific tasks can be investigated through empirical research, such as experiments (e.g., Rea et al. (2009) and Uttley et al. (2017)) or computational modelling (e.g., Rea et al. (2010)); through collaborative work of researchers, urban planners, policymakers, and public safety experts; and via public engagement.

9.3.2 Hypothesis H2

H2: Illuminance has a stronger association with the day-dark difference than after-dark ratings.

This hypothesis was tested using the results from Experiment 2. The day-dark method aims to eliminate the influence of environmental factors other than lighting, by using daytime ratings as a baseline to normalise the inherent level of reassurance in an area. If this principle holds true, it would be anticipated that the day-dark difference would have a stronger association with illuminance than the after-dark ratings. This would manifest as a higher coefficient of determination (R^2) value in the regression models. Therefore, the degree of association of after-dark composite reassurance scores and day-dark differences in composite reassurance scores with mean horizontal illuminance, minimum horizontal illuminance, and horizontal uniformity was assessed by analysing the R^2 values in Table 6.17.

While a statistically significant relationship was found between mean illuminance and either after-dark ratings or the day-dark differences in ratings, the association was slightly stronger for the after-dark ratings (R^2= 0.79, n=12, p<0.01) than for the day-dark difference (R^2= 0.72, n=12, p<0.01). Minimum horizontal illuminance and horizontal uniformity also demonstrated a stronger association with day-dark scores (minimum: R^2= 0.43, n=12, p<0.01; uniformity: R^2= 0.30, n=12, p<0.05), and this relationship was significant in both cases. Given that not all three measures of horizontal illuminance yielded a higher R^2 with the day-dark method, and the R^2 values for mean illuminance were very similar for both after-dark and day-dark ratings, the findings support hypothesis 2, but with caution. One reason for this result could be the small number of locations used in Experiment 2.

Past research also indicates that the day-dark difference in reassurance is more strongly associated with illuminance than after-dark ratings (Table 9.2). For example, Fotios et al. (2019) found that while mean horizontal illuminance was not significantly associated with after-dark reassurance, it did show a strong association with the day-dark difference. They also noted that minimum illuminance and illuminance uniformity were better predictors of this difference than mean illuminance. Similarly, Wei et al. (2024) observed that minimum illuminance was a more effective predictor of pedestrian reassurance when using the day-dark approach, compared to mean illuminance or illuminance uniformity. However, Wei et al. did not specifically assess the association between illuminance and either after-dark or the day-dark difference in reassurance.

Table 9.2. Comparison of Experiment 2 findings about the association between illuminance and either after-dark or day-dark reassurance ratings, with previous studies.

Study	**Association between illuminance and after-dark reassurance or day-dark reassurance**	
	Overall	**Lighting characteristic with higher R^2**
Fotios et al. (2019)	Day-dark difference showed a stronger association with illuminance.	Minimum illuminance; illuminance uniformity
Wei et al. (2024)	Not assessed	Minimum illuminance
Experiment 2	Day-dark difference showed a stronger association with illuminance, but with caution.	Mean illuminance

The discrepancy of these findings with that of Experiment 2 could stem from several factors, including the different set of locations (the study by Fotios et al. included distinct locations such as an underpass), and a larger sample size in Experiment 2 compared to Fotios et al. (2019) and Wei at al. (2024).

9.3.3 Hypothesis H3

H3: Day-dark difference in reassurance ratings obtained at the same time of day is different from day-dark difference in reassurance ratings obtained at different times of day.

This hypothesis was tested based on the results of Experiment 1. Two day-dark differences were calculated: one comparing the noon daylight ratings to after-dark ratings (noon daylight – after dark), and another comparing evening daylight ratings to after-dark ratings (evening daylight – after dark). The results (shown in Figure 4.4) indicated that using noon daylight ratings resulted in a larger day-dark difference compared to when using evening daylight ratings. However, despite being statistically significant ($p<0.05$), the effect size was small (0.15 - below Cohen's small effect threshold), rendering the difference practically irrelevant. Figure 4.4 visually reinforced this by showing an obvious overlap between the day-dark differences calculated using noon daylight ratings and the day-dark differences using evening daylight ratings. Therefore, while Hypothesis H3 is supported by the data, its implications are of little practical importance.

Experiment 1 specifically considered the two extremes of daylight: noon daylight and evening daylight. The finding of only a small effect size when comparing these extremes suggests that the noon daylight session would be suitable for Experiment 2, especially given the logistical challenge of collecting the day and after-dark reassurance ratings at the same time of day. The statistical significance of the results in Experiment 1 merely indicates that the observed effect is unlikely to be due to chance. However, it is important to state that even a very small, practically unimportant effect can be statistically significant if the variability is very low. Therefore, it is possible the results would differ if a wider range of locations and light levels were included in Experiment 1. The small effect size observed could also be due to gloomy weather during the experiment, making the actual light levels darker than anticipated.

Previous pedestrian reassurance research using the day-dark method (e.g., Boyce et al. (2000) and Fotios et al. (2019)) has not explicitly explored the effect of time of day of the daylight evaluations on the day-dark difference, but rather recorded the daylight and after-dark ratings of reassurance at different times of the day. For example, Fotios et al. (2019) state that the daylight sessions typically commenced at 10.30 am. However, they do not discuss whether varying this 10:30 am start time within the daylight period would have influenced the outcome of the day-dark difference. The result of Experiment 1 supports the validity of such research that has used the day-dark method without controlling for the specific time of day of daylight evaluations.

9.3.4 Hypothesis H4

H4: Evaluations from groups of participants will suggest higher reassurance than evaluations from solo participants for the same lighting conditions.

This hypothesis was tested using the results of Experiment 2. Test participants in Experiment 2 were allocated to one of two solo and group evaluation types, with solo participants taking part in the surveys on their own, and group participants being accompanied by other participants and researchers. It was revealed that the difference between solo and group evaluations was not statistically significant, when using either the after-dark method or the day-dark approach (as shown in section 6.5). The results, therefore, do not support hypothesis H4.

This contradicts previous research, which generally suggests walking alone can heighten perceived danger (Fyhri et al., 2011), and that the presence of other people can create a sense of safety (Cohen and Felson, 1979). For example, in a pilot reassurance study, Unwin and Fotios (2011) found that the presence of other people was a frequently mentioned reason (44%) for feeling happy or unhappy to walk on a street alone at night. Koga et al. (2003) also observed that well-lit, busy streets increased feelings of security, suggesting that the presence of other people offers reassurance, and Okuda et al. (2007) identified empty roads as a significant factor contributing to feelings of insecurity. Furthermore, research has shown that people feel less fear when they feel supported by other users (Greene and Greene, 2003), and when in the presence of individuals or groups, as busy environments are generally seen as deterring potential attacks (Nasar and Jones, 1997). The qualitative and quantitative analyses by Khachatryn et al. (2024) also found that "*a significant amount of reassurance is built through the presence of others and walking with others*" (p. 8). Interestingly, one study [Forde, 1993] found that concerns about an increase in crime were not associated with the rates of individuals walking alone at night. In this Canadian study, respondents were asked about their perceptions of crime level (increased, stayed the same, or decreased) in three specific locations: their neighbourhood, the city, and across Canada. Analysis suggested that perceived crime in the city and across Canada were not associated with walking alone at night. The study also found that perceived crime in respondents' neighbourhoods showed only a weak association with walking alone at night; while respondents expressed high concern for increasing crime rates, a large majority of them continued to feel safe and regularly walked alone at night in their neighbourhoods. It is important to note that this study did not compare these perceptions between solo individuals and groups of people.

Although the definition of reassurance given in CIE 236:2019 (CIE, 2019) specifically refers to walking alone, many pedestrian reassurance studies involve participants who are not alone. The findings of

Experiment 2 do not provide evidence that the inclusion of accompanied participants compromises the ability of the experiment to characterise the effect of lighting on pedestrian reassurance. Therefore, Experiment 2 results support the validity of previous research in which participants were accompanied by other participants and/or researchers. With this said, it is important to note that the conclusion that solo and group assessments are not different holds true only as long as the solo and group settings do not confer - as long as they do not introduce unmeasured effects that influence participant's perceptions or their responses to the questionnaire. For example, there might have been unmeasured variables within the solo and group settings of Experiment 2 that influenced the results, leading to no significant difference. These unmeasured effects could potentially relate to the subtle dynamics of being accompanied by other participants and researchers as opposed to just other people in a natural setting. The nature of the accompaniment (researchers versus peers) might also be a factor, given that individuals tend to conform more to socially desirable responses when authority figures are present (Sutton and Farrall, 2005), a role the researchers could have inadvertently filled. Another reason for this outcome could be that the number of test locations or the specific ranges of light levels used in Experiment 2 were not diverse or extreme enough to elicit a differential response between solo and group participants. It could also be that other aspects of the environment, such as refuge and prospect, had more impact on participants' reassurance, compared to being alone or accompanied.

9.3.5 Hypothesis H5

H5: Higher illuminances reduce the disparity between male and female reassurance after dark.

This hypothesis was tested using the results of Experiment 2. A balanced gender sample was recruited in Experiment 2 to test the effect of different illuminances on the gender disparity in reassurance. The results (shown in Figure 6.18) suggested that higher illuminances significantly decreased the difference in male and female feelings of reassurance, indicating that it benefited females more than males. This finding supports hypothesis H5.

Past studies (e.g., Atkins et al. (1991), Boyce et al. (2000), Haans and de Kort (2012), Gover et al. (2011), Moran et al. (2014), and Unwin and Fotios (2011)) provide insight into gender differences in reassurance, suggesting that females generally feel less safe than males after dark or in low-lit environments, and that increased lighting improves reassurance for both genders. However, these studies did not directly analyse the effect of higher illuminances on the gender disparity in reassurance. For example, after improvements to street lighting (a four-fold increase in illuminance), Atkins et al.

(1991) found that with higher light levels, there was a significant increase in safety amongst females, but they did not find a general increase in feelings of safety for males and females combined. This might imply a reduction in the gender disparity of reassurance with higher light levels, but the study had insufficient data to support statistics. Furthermore, Boyce et al. (2000) assessed the perceived safety of groups of participants in daylight and after dark in 24 different parking lots in USA. They found that females required higher illuminances (60 lx) than males (35 lx) for a *good example of security lighting*. Although not specifically analysed, Figure 3 in that source suggested that higher median horizontal illuminances were associated with smaller day-dark differences in perceived safety. However, the figure is not of enough clarity for a definitive conclusion. Haans and de Kort (2012) also found that female participants generally had lower perceived personal safety than males. Their second experiment showed a "marginally significant gender by light distribution interaction" (p. 350), which suggests that the effect of light distribution might differ between genders. Additionally, they noted that lighting was "more important for individuals who deem themselves attractive targets" (p. 351), which could indirectly relate to how certain groups, including women, perceive their vulnerability.

Studies of pedestrian route choice behaviour also offer some insight into gender disparity in reassurance. For example, utilising GPS data from smartphone travel surveys in Chicago, Lieu and Guhathakurta (2025) found that the presence of amenities, including well-lit spaces, was more strongly preferred by females in route choice. With this said, they did not quantify light levels or explicitly state that increased lighting reduced the disparity in reassurance between the two genders. Bernhoft and Carstensen (2008) also investigated the risk perception and behaviour of pedestrians and cyclists in Danish cities in relation to route choice. The data was collected from two age groups: those 70 and older, and a younger group aged 40-49. Their findings revealed a notable gender difference within the younger age group: women valued good street lighting more than younger men when choosing a walking route. However, the study didn't specify what *good* lighting entailed, such as particular illuminance levels or other lighting characteristics, or whether more lighting led to a reduction in the gender disparity of reassurance.

Some urban planning strategies in street design, such as *gender mainstreaming* (a strategy that involves adopting female-friendly plans to promote gender equity), also advocate for additional street lighting after dark to address female's specific needs and perception of safety (Damyanovic, 2013; Park and Garcia, 2020). While these studies strongly indicate that street lighting enhances overall reassurance after dark, and acknowledge the significant gender disparity in reassurance, they do not directly present empirical data or specific findings that quantify the reduction of the disparity between male and female reassurance with higher illuminances.

Finally, studies investigating active travel behaviour also hint at the greater positive effect of road lighting on female pedestrians compared to their male counterparts. For example, van Cauwenberg et al. (2012a) investigated the relationship between the physical environment and physical activity, specifically walking and cycling, in older adults. Considering the moderation effects of area of residence, age, and gender, the results indicated that the presence of road lighting was positively related to walking for transportation in females, but not in males. This differential impact suggests that lighting interventions have a greater positive effect on females' active travel behaviours, which is likely mediated by an increased reassurance.

Another finding of Experiment 2 was that the effect of lighting condition on reassurance did not significantly differ between males and females (see Section 6.6). This unexpected result might stem from the limited range of illuminances examined in Experiment 2. In real-world scenarios, pedestrians encounter a much wider array of lighting conditions. Some of these, particularly those at the extremes, could elicit more distinct gender-based perceptions of safety. For example, females might report feeling less safe than men in specific, dimly lit, or highly non-uniform areas — conditions that were not included in Experiment 2. Furthermore, the locations in Experiment 2 generally had good uniformity, largely because the streets adhered to lighting guidelines. This might have obscured how non-uniform lighting, such as harsh shadows, dark corners, or bright spots adjacent to darkness, differentially affect reassurance between genders. Research frequently indicates that females are sensitive to environments that could conceal threats (Jorgensen et al., 2013). Since non-uniform lighting can create such areas, the limited range of uniformities in Experiment 2 might not have captured these nuances. This highlights a need for further research.

9.3.6 Hypothesis H6

> H6: Odds ratios determined using travel counts are consistent with reassurance ratings from subjective evaluations.

This hypothesis was tested using the results from Experiment 3. The results from the Spring 2024 experiment (shown in Figures 8.5 and 8.6) revealed that odds ratios had a stronger and significant association with the after-dark reassurance ratings (R^2= 0.65, n=8, p<0.01) than day-dark reassurance ratings (R^2= 0.15, n=8, p=0.08). The R^2 values show the after-dark method is highly associated with the odds ratio method whilst the day-dark method shows a weak relationship. Therefore, the findings support hypothesis H6.

It was anticipated, however, that the day-dark method would correlate better with the odds ratio method than the after-dark method. This is because the day-dark method specifically isolates the effect of darkness on reassurance by comparing perceptions of safety during daylight to those in darkness, thereby highlighting the impact of darkness. This approach is similar to the odds ratio method, which also focuses on the difference between daylight and after-dark conditions to assess the influence of darkness on travel counts. In contrast, the after-dark method only captures reassurance after-dark, without directly accounting for the baseline daylight reassurance. For example, if a pedestrian gives an after-dark rating of 6 to Street A and 3 to Street B, considering lower ratings represented less reassurance, this would not necessarily mean darkness had a greater impact on Street B. Street B might have been perceived as very unsafe even in daylight; the after-dark rating does not provide the crucial comparison to daylight conditions to determine the isolated effect of darkness. One explanation for the unexpected results of Experiment 3, is that the odds ratios in Experiment 3 might be weak due to the low number of observations, compared to studies which have used automated counters (see Table 9.2). A larger sample of locations with a diverse range of illuminances might yield more reliable results, and warrants further research.

In Experiment 3, Odds ratios (ORs) of changes in pedestrian traffic also helped with assessing the effect of darkness on the number of pedestrians compared to daylight. The results (shown in Table 8.2) indicated that, overall, darkness had a deterrence effect on pedestrian traffic. It was inferred that the reason could be because darkness reduces pedestrian reassurance (Uttley and Fotios, 2017). This aligns with the findings of previous research shown in Table 9.3. In this table, the overall pedestrian ORs from Experiment 3 are compared with those found in past research that utilised traffic counters across multiple sites. Across all studies, pedestrian traffic is shown to be lower after dark than during daylight. The pedestrian ORs from the current study (Spring 2024: 1.38, Spring 2021: 1.56) are consistent with the range of ORs (1.29-1.93) reported in prior studies. However, compared to previous research, the 95%CIs in Experiment 3 (Spring 2021: 1.26-1.50; Spring 2024: 1.49-1.64) exhibit a wider range. One explanation could be the smaller number of pedestrians observed in Experiment 3 compared to previous studies (see Table 9.3); a larger sample, provided the allocation across case and control periods remains proportional, should result in similar ORs but with a reduction of the confidence interval width.

Table 9.3. Comparison of odds ratios and 95%CIs in Experiment 3 to previous studies comparing pedestrian traffic in daylight and after dak – arranged in ascending order of odds ratios.

Study	Overall sample	OR	95%CI	Significance of difference from OR=1.0	Effect size
Fotios and Robbins (2022)*	89,392	1.29	1.26-1.33	*p*<0.001	Small-medium
Experiment 3: Spring 2024	8,483	1.38	1.26-1.50	*p*<0.001	Small-medium
Experiment 3: Spring 2021	32,700	1.56	1.49-1.64	*p*<0.001	Small-medium
Uttley and Fotios (2017)**	521,316	1.62	1.60-1.63	*p*<0.001	Small-medium
Fotios et al. (2019b)***	1,735,460	1.93	1.92–1.95	*p*<0.001	Medium-large

* Data from 14 counters in Cambridge, UK (from June 2019 to September 2020)
** Data from 11-33 (varying by year) automated counters in Arlington, USA (from 2011 to 2016), for the 13 days before and after Spring and Autumn clock changes
*** Data from 11-32 (varying by year) automated counters in Arlington, USA (from 2012 to 2015), for each entire year.

Differences between the ORs for males and females were not suggested to be significant (Spring 2021: male OR = 1.55, female OR = 1.59, z = 0.518, p = 0.302; Spring 2024: male OR = 1.42, female OR = 1.34, z = 0.318, p = 0.375). The results are in agreement with the self-reported walking behaviour data collected by Foster et al. (2004), whose analysis of interviewees' recollections of walking frequency also found no significant gender difference. However, this contrasts with studies using subjective reassurance evaluations, which demonstrate a greater negative impact of darkness on female reassurance (Gover et al., 2011; Fisher and Nasar, 1992). A possible explanation is socially desirable responding, where men tend to downplay their fear of crime more than women (Sutton and Farrall, 2005). This could lead men to overstate their feelings of reassurance, creating an artificial gender difference, when using subjective evaluations. Therefore, although self-reported data suggests female pedestrians experience greater fear than their male counterparts, this is not corroborated by the observed number of men and women walking after dark in Experiment 3.

The ORs for younger and older pedestrians for Experiment 3, were suggested to be significantly different (Spring 2024: young OR = 1.43, old OR = 1.33, z = 2.900, p<0.01; Spring 2021: young OR = 1.58, old OR = 3.38, z = 3.800, p<0.001). This indicated that darkness had a greater deterrent effect on old pedestrians than on young pedestrians. Greve et al. (2018) also found this age-based variation.

Finally, the results from the Spring 2024 experiment (shown in Figures 8.2 to 8.4) suggested that ORs had a stronger and significant association with mean horizontal illuminance than minimum or uniformity. The results also showed that the deterrent effect of darkness on number of people walking reduced with higher arithmetic mean horizontal illuminances, providing evidence that higher illuminance is beneficial. This aligns with findings from studies on cyclists. For example, Uttley et al. (2020) analysed cyclist counts in Birmingham, UK, assessing its relationship with estimated road brightness from aerial imagery. They found that increased road brightness positively impacted cycling rates, with higher road brightness being associated with a reduction in the ORs of cyclist counts. This relationship was found to be non-linear, reaching a plateau with continued brightness increase. The authors concluded that even minimal lighting can promote after-dark cycling. Previous reassurance studies using the day-dark approach have not yet analysed this specific relationship for other road users, including pedestrians

In Experiment 3, location R2.5 was identified as an outlier and was, therefore, removed from the analysis (sections 8.3.2 and 8.3.3). This was established through visual analysis. First, scatter plots (Figure 8.2 to 8.6) revealed R2.5 as being visually distant from the other eight locations. To further confirm this, each of the nine data points was sequentially removed, and the regression line was redrawn. Only the removal of location R2.5 caused a change in the slope's direction, suggesting that R2.5 had a large error or residual within the overall n=9 linear regression model. Finally, box plots corroborated R2.5 as an outlier, with it appearing as an individual point beyond the whiskers, specifically, outside 1.5 times the Interquartile Range. Experiment 2 also revealed that Location R2.5 contradicted the general finding that higher illuminance leads to greater reassurance; participants in location R2.5 reported feeling more reassured after dark than during daylight, as evidenced by a negative day-dark reassurance rating (see Table 6.16 and Figures 6.11 to 6.13). This suggests that factors beyond just lighting may have influenced reassurance in this specific location. When comparing R2.5 to other test locations, several environmental aspects stand out:

- Poor refuge and high concealment: While the overall prospect in R2.5 appears adequate, the presence of numerous walls and potential hiding spots (see Figure 5.5) means that, compared to other test locations, refuge in R2.5 is poor and concealment for potential offenders is high.
- Wider path and reduced *Eyes on the Street*: The buildings in location R2.5 are set further back from the path than in other locations, making the path seem much wider. This is whilst in the other test locations surrounding buildings are closer or adjacent to the path. This inadvertently creates a disconnection between pedestrians and adjacent buildings, reducing the eyes on the street - a concept first introduced by Jacobs (1962). Jacobs argued that

informal observation by *normal* people, such as residents and passersby, is the most effective way to deter crime and ensure an enhanced sense of safety in public spaces. When potential offenders know they are likely to be seen by other people, they are less likely to commit crimes. This increased visibility also makes people feel safer and more inclined to use public spaces, which in turn creates a positive loop.

- Daylight vs. after-dark discrepancy: During daylight, the open wall layout paradoxically seems to provides more concealment than refuge. However, after dark, the ability to see people inside the houses may lead to a greater sense of surveillance, improving the perception of safety.
- The pedestrian traffic data for location R2.5 also revealed an exceptionally low number of pedestrians compared to other locations, in daylight and during after dark (see Table 8.3). Due to these very low counts, even a slight change in the number of people present could have a significant impact on the odds ratios and, consequently, the conclusion drawn from the data in location R2.5.

Ultimately, location R2.5 seems to be a more complex environment, characterised by broken walls, openings, and numerous opportunities for concealment, compared to the other test locations. This highlights that reassurance is potentially influenced by more than just road lighting, prospect, refuge, or escape. Future research should consider the broader complexities of an environment, including setbacks, and their impact on reassurance.

The Spring 2021 observations in Experiment 3 were conducted during the COVID-19 pandemic. Before the clocks changed, the UK was under lockdown measures. After the clock change, these restrictions were eased. It may be argued that these travel restrictions might have influenced pedestrian counts due to shifts in travel demand, public transport availability, and individual choices. It may also be argued that this might have particularly affected old pedestrians, due to their increased frailty and fear of contracting the virus could which would have led to them to stay home more often compared to young people. However, the odds ratio is only susceptible to these factors if they disproportionately affected the case and control groups, the periods before and after the clock change, or the ambient light-related travel choices of the young pedestrians and old pedestrians. There is no evidence that yields these scenarios probable in Experiment 3.

9.4 Implications of the research and contribution to knowledge

This research contributes to the body of knowledge of road lighting and pedestrian reassurance, and advances the theoretical understanding of pedestrian reassurance. By investigating the impact of illuminance, it provides empirical evidence for the notion that road lighting is a proximal factor influencing pedestrian reassurance. The findings advance existing knowledge by demonstrating the nuanced relationship between reassurance and different lighting metrics (mean, minimum, and uniformity), particularly highlighting the importance of mean horizontal illuminance for the day-dark difference. Furthermore, the findings show that higher illuminance can mitigate gender differences in reassurance by benefiting female pedestrians more than male pedestrians after dark. It further challenges previous assumptions about gender disparity in reassurance, by revealing that despite males stated preference of higher reassurance compared to females, their actual walking behaviour after dark is similar to females.

This research also offers methodological implications for future studies of road lighting and pedestrian reassurance. The findings contribute to improved understanding of the day-dark method for measuring reassurance, showing that the time of day for daylight evaluations has minimal practical impact on the day-dark difference. This finding simplifies research design and allows for greater flexibility in experiments. Furthermore, the finding that the presence of accompanied participants does not significantly alter reassurance ratings compared to when evaluations are carried out alone, allows more diverse participant recruitment strategies for future data collection. Finally, the confirmation of a strong association between travel counts (expressed as odds ratios) and subjective reassurance ratings, establishes an alternative objective approach to assessing pedestrian reassurance. This paves the way for incorporating behavioural observation techniques as a reliable, indirect measure of reassurance, which can be used in conjunction with direct subjective evaluations. Future research can combine these methods to triangulate findings, and provide a more comprehensive and robust understanding of pedestrian reassurance and strengthen the validity and generalisability of the findings. This could include integrating subjective evaluations (such as surveys or interviews) with behavioural observations (such as travel counts or walking speed) and physiological measures (such as gaze patterns, heart rate variability, or skin conductance response).

The practical implications of this research are relevant to urban planners, lighting designers, and policymakers. The findings suggest that current recommendations in road lighting guidelines regarding mean illuminances may be higher than strictly required for pedestrian reassurance. Specifically, there is a potential for reducing the maximum P-class by around 50% to approximately 7-8 lux, if the aim is to enhance pedestrian reassurance. This is a crucial finding because it points towards opportunities for energy savings and associated environmental benefits, for designers who might have otherwise specified higher illuminance levels. For those already utilising lower illuminance levels, this change could lead to an increase in energy consumption, if they were to adopt the new optimal range. This research provides the evidence to justify this increase, as it benefits pedestrian reassurance. By providing empirical evidence that lower illuminances lead to adequate pedestrian reassurance, this research directly informs the development of road lighting guidelines, such as EN 13201-2:2015 (BSI, 2015a). The finding that higher illuminances reduce the gender disparity in reassurance is also a key practical insight. Designing road lighting schemes and developing public safety policies that specifically address this, can lead to more inclusive and equitable public spaces, encouraging more females to walk after dark, and make public spaces feel safer for all pedestrians.

In the United Kingdom, the predominant method for illuminating roadways relies on electricity. This reliance contributes to road lighting's substantial energy footprint, as evidenced by global reports indicating it constitutes approximately 40% of outdoor energy consumption in urban environments (European Commission, 2013). Lower illuminances can reduce operating costs from around 25% to 60% (USAID, 2019), potentially extend the lifespan of installations, and lower carbon emissions depending on the fuel mix used to generate the electricity (Boyce et al., 2009). In the UK, despite the move from fossil fuels towards more renewable and low-carbon sources like hydroelectric, wind, solar, and nuclear power (National Grid, 2025), fossil fuels still play a substantial role, with natural gas accounting for 31.5% of the electricity generation in 2024 (DESNZ, 2025). Therefore, reducing light levels can directly contribute to mitigation of carbon emissions.

Too much artificial light can negatively impact the natural environment by disrupting the ecological integrity of the countryside, creating extensive sky glow that affects vast areas beyond urban centres, and severely disrupting plants by altering their seasonal preparations and flowering cycles. Too much road lighting also significantly impacts wildlife behaviour, including altering nocturnal foraging patterns, confusing natural day-night cues for animals, and increasing their vulnerability to predators (Dick, 2014). One example of the environmental benefit of reduced illuminances is reduction in sky glow, a phenomenon initially discussed as *sky haze* due to street lighting by Waldram (1972). Recent studies including those by Bierman (2012), Duriscoe et al. (2014), and Rea and Bierman (2014), demonstrate that Sky glow diminishes the aesthetic quality of the night sky and hinders the appearance, study, and detection of stars and other celestial bodies. They also discuss the non-visual effects of increased light at night due to sky glow on the circadian rhythms and melatonin production in both humans and wildlife, which can negatively impact human and wildlife health.

9.5 Limitations and suggestions for future research

This section outlines general and experiment-specific limitations of this research, and offers considerations for future work.

9.5.1 The sample of participants

The sample in Experiments 1 and 2 were from the younger age group - between 18 and 39 years. When considering age, differences exist between the preferences and behaviour of old pedestrians and young pedestrians. This is believed to be a result of differences in the physical ability and health of old people compared to their younger counterparts (Bernhoft and Carstensen, 2008). For example, old people have poorer visual abilities and an increased eye sensitivity to adverse conditions (Hengstberger et al., 2011; Haegerstrom-Portnoy et al., 2000). This loss of visual capacity with age means old people may demand higher levels of lighting when walking. Previous research on the effect of age on pedestrian reassurance has shown inconsistent and contradictory results. For example, some studies (e.g. Ghani et al. (2018), Liao et al. (2015), van Cauwenberg et al. (2014) and Yun (2019)) have suggested that safety has a bigger impact on the decision to walk among old people compared to the young age group. This is while, results from a walkability survey by Shigematsu et al. (2009) demonstrated that while there was significant association between safety from crime and walking, there was minimal difference between different age groups (20-39 years to 76+ years). Lagrange and Ferraro (1989) also concluded that many studies have overestimated the fear of crime amongst old people due to the measure of fear used. Most past studies have not differentiated between walking in daylight and after dark. The findings of those which have done so is inconclusive. One study looking at after dark evaluations [Johansson et al., 2011] reported no effect of age. In contrast, results from Greve et al. (2018) suggested darkness had a bigger impact in reducing the number of old people walking than for young people. These discrepancies are likely to be a result of the methodology used to measure fear, such as quantitative versus qualitative (Moran et al., 2014; Greve et al., 2018; Hale, 1996), or the scope of the study and environmental variability (van Dyk et al., 2012). Given the inconsistencies in past findings, future research should incorporate a wider age range of participants to clarify how reassurance varies across different age groups.

The unique characteristics of the participants in Experiment 2 - being young, told not to confer and walking along the route individually - limits the generalisability of the findings. Specifically, the conclusion that there's no difference in reassurance ratings of solo and group participants may not apply to other demographics, such as older individuals, groups who are allowed to interact, or those experiencing the test route between the lampposts together. Future research should therefore include the study of more diverse groups to enable broader applicability of the findings.

Another limitation of the sample in Experiments 1 and 2 was the potential familiarity with the test locations. Given that participants were from the University of Sheffield and the locations were close to campus, some may have had prior exposure to these areas, potentially influencing results. Past research has shown that when considering the overall pedestrian experience, familiarity is an important attribute. For example, in a pilot study, Unwin and Fotios (2011) explored factors influencing pedestrian reassurance at night. Participants were asked to photograph roads where they felt comfortable or uncomfortable walking alone after dark. These photos then served as prompts for interviews designed to understand the factors that made people feel safe (or unsafe). The study identified *familiarity* as one of seven key categories influencing reassurance, accounting for 9% of the reasons participants gave for being happy or not happy to walk alone at night. In another study, van Cauwenberg et al (2012b) investigated environmental factors which influenced older adults' walking for transportation, using walk-along interviews. The results suggested that participants expressed a preference for walking in familiar streets, as these provided them with a sense of safety and even nostalgia. A more recent study by Fotios et al. (2019) included "*How familiar are you with this particular street?*" as one of the questions in their survey measuring environmental and contextual aspects of reassurance. This question was incorporated into a composite reassurance score, and the analysis revealed a weak but statistically significant positive correlation between familiarity and the overall reassurance score. It is, therefore, important that future research also considers the role of familiarity in reassurance.

9.5.2 The sample of test locations and range of lighting characteristics

One other limitation of this study was the restricted number of locations in the three experiments. For instance, in Experiment 1, the narrow 45-minute timeframe of test sessions limited the number of locations that could be assess. One way to extend this limited timeframe is to incorporate a longer test period, such as two weeks before and two weeks after the clock change. Alternatively, the current one-week before and one-week after the clock change could be maintained, but the experiment could be conducted across multiple, geographically separate, parallel groups. These were not possible in the current study due to limited resources. Future studies should explore these alternative approaches, whilst controlling for seasonal influences that might arise during extended testing periods.

A further limitation is the choice of locations. Experiments 1, 2 and 3 were conducted in two relatively safe, urban residential areas of Sheffield, necessitated by ethical constraints. This limits the generalisability of the findings. The perceived safety of an environment is sensitive to its physical qualities (Basu et al., 2021; Fotios and Castleton, 2016; Mukherjee and Kumar, 2024), and while the experiment locations may be representative of Sheffield's residential roads, it is uncertain whether they reflect conditions in less safe environments; in other cities where the walking culture could be different; alternative settings, such as, industrial, commercial, or car parks; urban versus non-urban areas, especially considering the lower perceived risk of crime in suburban areas (Boyce et al. 2000); different countries; or varied path types. For example, whilst this research and other studies on residential environments [Fotios et al., 2019a; and Wei et al., 2024] suggest an optimal illuminance of around 7-8 lx, in other safety studies, such as those investigating parking lots (Bhavagavathula & Gibbons, 2020; Bullough et al., 2020; Narendran et al., 2016), 10 lux has been identified as the optimal. Future research should validate the findings of Experiments 1, 2, and 3 by exploring a broader range of settings.

The limited range of lighting conditions studied, presents another limitation. Specifically, both Experiment 2 and Experiment 3 only included a narrow range of illuminances. This is evident from the day-dark difference range of roughly 2 units in Experiment 2. This is a small range, considering the possible maximum difference of 5 units on a 6-point rating scale (i.e. a daylight rating of 6 compared to an after-dark rating of 1). One solution is to use pre-defined light categories. This was considered in Experiment 2, where the author initially selected locations by visiting all pedestrian paths in the Broomhall area, and self-assessing the level of reassurance and light levels on a three-level scale (low, medium, and high). This method aimed to ensure a representative sample from each category (further details can be found in section 5.2.1). To ensure better representation, future research should include a wider range of lighting conditions, from extremely well-lit to very poorly lit locations.

This thesis primarily focused on the impact of one lighting characteristic, illuminance, on reassurance. Future research should expand on this by exploring the effects of other characteristics such as light distribution and spectrum on reassurance. This is particularly important because current guidelines, such as EN 13201-2:2015 (BSI, 2015a), typically recommend lighting levels based on mean and minimum horizontal illuminance. However, the scientific basis for focusing on these specific lighting characteristics is unclear (Fotios and Gibbons, 2018). A significant limitation of using only mean illuminance is that it doesn't account for how light is distributed; two locations could have the same mean illuminance, but one might have uneven lighting with dark, gloomy spots (low illuminance uniformity), while the other has high illuminance uniformity. Existing literature demonstrates a link between uniformity and reassurance (Bullough et al., 2020; Haans and de Kort, 2012; Narendran et al., 2016; Nasar and Bokharaei, 2017). A notable example comes from Narendran et al. (2016), who showed that improving illuminance uniformity in parking lots (to a 3:1 ratio from 10:1) led to perceptions of *good* lighting and increased feelings of safety, even at significantly lower average light levels. This finding suggests that increasing illuminance uniformity can lead to the same or higher reassurance at much lower mean light levels, leading to lower energy use - up to 75% as evidenced by computer simulations from Narendran et al. (2016). These findings suggests that the spatial distribution of light might be a better indicator of how safe people feel than simply the amount of light. Another study in residential streets [Fotios et al., 2019] also demonstrated that the uniformity of illuminance as well as minimum illuminance exhibited better association with reassurance than did the mean. The concept of moving beyond the mean is important, as it highlights the need for a more dynamic understanding of how light is arranged and perceived across a space, rather than focusing on a single metric. It is, therefore, important for future studies to assess this. With regards to spectrum, an example is that from Knight (2010), who conducted a study in residential streets across the Netherlands, Spain, and the United Kingdom, involving over 300 residents who experienced both high-pressure sodium lamps, which emitted yellowish light, and ceramic metal halide lamps, which provided white light. The results suggested that whiter light enhanced perceptions of safety. Despite these findings, very few studies have explored the relationship between spectral power distribution and reassurance, indicating a clear need for further research.

Experiment 3 relied on in-person observations of pedestrians at a limited number of locations—eight in Spring 2021 and nine in Spring 2024—during a single clock-change period for each of the experiments. This contrasted with methods using automated counters across more extensive number of locations and timeframes. Although this resulted in smaller samples than past research, the observed ORs were consistent with previous studies (Table 9.1). A smaller sample was deemed acceptable to allow detailed demographic information, such as age and gender, to be recorded. Also, only one control period was included in Experiment 3, in comparison to multiple control periods in other studies. The limited choice of case and control hours represent a limitation in Experiment 3, but one which was necessary due to the use of on-road human observers. To address this limitation, future research could use cameras equipped with gender and age recognition capabilities, enabling data collection over a longer period and with more control hours.

The Spring 2024 observations were carried out during a two-week period in residential streets which had low pedestrian traffic. This means that minor fluctuations in pedestrian counts could have disproportionately influenced the findings. This limitation was an unavoidable consequence of resource restrictions in recruiting on-site observers. Future research should aim to mitigate this by extending the observation period, diversifying the range of street types and locations, and integrating automated counters and artificial intelligence to facilitate broader data collection.

9.5.3 The measurement method

The day-dark method used in Experiments 1 and 2 is subject to criticism due to its inherent susceptibility to disproportionate representational variability. For example, considering the suggestion of prior research about reduced reassurance after dark (e.g., Svechkina et al. (2020)), a location assigned a daylight rating of 6 may exhibit a range of after-dark ratings from 1 to 6, while a location assigned a daylight rating of 2 is constrained to an after-dark rating of 1. This disparity results in a 50% reduction in the latter scenario, as opposed to a 15% reduction in the former, thereby highlighting a critical methodological limitation of the day-dark approach. Peña-García et al. (2015) also offer a critical perspective on using daytime conditions as a control in the day-dark method. For example, they indicate that disability glare differs greatly between high luminance daylight conditions, and lower luminance road lighting conditions, making the two situations incomparable. They also note that disability glare increases dramatically with age, making comparisons across age groups problematic if daylight conditions are used as a control. More research is needed to assess how these issues can be mitigated and how the day-dark method can be further refined.

This thesis only focused on two methods for assessing pedestrian reassurance: surveys as a direct measure and travel counts as an indirect measure. However, surveys have a limited ability to capture emotional nuances, such as reassurance, because they rely on self-reporting. This means surveys reveal an individual's conscious interpretation of their feelings, which might not always align with their true emotional state. This may introduce inaccuracies in results. For instance, men often report less fear than women (Gover et al., 2011), possibly reflecting societal expectations rather than actual feelings (Sutton and Farrall, 2005; Farrall et al., 2009). This subjectivity also poses a problem for representation. Each person interprets the questions through their unique lens of experiences and beliefs. This means that even if a survey question is phrased identically, the underlying emotional reality it is attempting to measure can be different from one respondent to the next. When these subjective experiences are aggregated to represent a larger population, the nuances and individual differences can be lost, potentially leading to a skewed or incomplete picture of the emotional landscape being studied. Therefore, to validate the subjective evaluations from Experiments 1 and 2, in addition to the objective travel counts of Experiment 3, alternative methodologies should be employed. One approach is the analyse gait characteristics, such as walking speed. Another is the study of biological signals related to reassurance. Fear, being a primal survival emotion, triggers measurable physiological responses, and the measurement of these involuntary physiological responses such as eye movement, pupil size, and heart rate variability can be used to assess pedestrian reassurance. For example, Castro-Toledo et al. (2017) compared self-report data with physiological measures, specifically heart rate frequency, in parallel. They manipulated illuminances to see if it affected heart rate frequency. The findings suggested that heart rate captured aspects of fear not reflected in self-report questionnaires and that a lack of luminosity in public spaces triggered fear of crime experiences.

While real-world studies are valuable, immersive or virtual reality (VR) offers a promising alternative for studying road lighting and reassurance. VR can create realistic simulated environments, allowing for greater control over variables and the ability to test a larger sample size. For example, Jedon et al. (2025) investigated how different lighting conditions in virtual urban environments (daytime versus nighttime) influenced pedestrian perceived environmental safety, alertness, and arousal. Using a within-subject virtual reality experiment with 62 participants, the researchers found that perceived environmental safety was highest in the daytime virtual environment and significantly lower in the nighttime virtual environment. Kim and Park (2025) also explored the effectiveness of Crime Prevention Through Environmental Design (CPTED) elements, particularly street lighting, in reducing fear of crime within virtual urban settings. Through a study involving 32 participants experiencing three different virtual CPTED environments, it was found that CPTED features generally decreased the fear of crime, with adequate street lighting being identified as especially crucial.

In Experiment 1 each participant took part in three different test sessions, visiting the same locations within a two-week period. There is a risk that participants may experience evaluation boredom, or that they may compromise the validity of their responses by simply recalling previous answers rather than providing independent evaluations. Randomisation of questionnaires, question orders, and location visit sequences was used in this experiment to address these limitations. Future research could further investigate this by employing a parallel-group design, with one group undergoing repeated measures and the other utilising independent samples. Conducting both groups consecutively within the same seasonal period would allow for a direct comparison of the two methodologies and the identification of any resulting differences

It cannot be excluded that observers in Experiment 3 may have made errors in classifying travellers by age and gender. Prior to data collection, observers underwent a training session focusing on age classification to minimise potential errors. Also, the middle age group (30-59 years) was removed from the analysis, to ensure that the young and old age groups were clearly differentiated, even if the observes had misclassified the age category of some pedestrians. Age and gender misclassifications would only skew the overall results if they occurred unevenly across the four observation periods (Case day, Case dark, Control day, and Control dark), and there is no basis to anticipate such asymmetry.

9.5.4 Other limitations

Past research shows reassurance is influenced by distal factors (such as past experiences and social representation of crime) and proximal factors (physical features of the environment such as prospect, refuge, entrapment, and lighting) (Appleton, 1966; Fisher and Nasar, 1992; Skogan and Maxfield, 1981; van Rijswijk, 2016). Given that this research focused solely on road lighting, future studies should investigate the influence of other factors on reassurance, as well as the interaction between road lighting and other physical environmental attributes such as prospect and refuge (van Rijswijk and Haans, 2018).

9.5 Summary

This chapter discussed the results of Experiments 1, 2 and 3. The results supported four hypotheses (H1, H2, H5, and H6), and refuted two hypotheses (H3, and H4). Implications of the findings, limitations of the research, and suggestion for future work were also discussed. The next chapter presents the conclusion.

CHAPTER 10. CONCLUSION

10.1 Introduction

This thesis investigated the role of road lighting in pedestrian reassurance. Building upon the understanding that reassurance is crucial for encouraging walking after dark, this research aimed to inform road lighting guidelines by providing empirical evidence for optimal illuminance for pedestrian reassurance. This concluding chapter begins with a summary of the research and synthesises the key findings from the three experiments conducted; it discusses their implications for methods, theory and practice; acknowledges the limitations of the research; and finally, it proposes directions for future areas of research.

10.2 Summary of experiments and key findings

Three experiments were conducted. Experiment 1 was a pilot study investigating a specific aspect of the day-dark method for evaluating pedestrian reassurance - the effect of time of day on the daylight evaluations. To do this, the daylight evaluations were carried out at two different times: once at around midday, and once at the same time of day as the after-dark evaluations, this being done by taking advantage of the biannual daylight savings clock change. The 55 participants rated their feelings of reassurance on six residential streets using a questionnaire. It was found that within the range of locations and light levels examined, day-dark differences in reassurance ratings obtained from daylight evaluations carried out at different times of day to the after-dark evaluations, were significantly different to those obtained from evaluations at the same time of day as after-dark evaluations. However, the effect size was small, which indicated the difference is of little practical significance.

Experiment 2, then used the day-dark method to investigate whether pedestrian reassurance was affected by a change in illuminance, and whether higher illuminances reduced the gender differences in reassurance. This experiment used 122 participants who each evaluated 12 residential streets. In addition, the influence of participant accompaniment was assessed by allocating the participants to either solo or group evaluations. It was revealed that higher illuminance led to greater perceived reassurance; using a composite reassurance rating, a positive correlation between illuminance and reassurance, and a negative correlation between illuminance and day-dark differences in reassurance ratings were observed. Mean horizontal illuminance was found to be the strongest predictor of reassurance, and an optimal mean horizontal illuminance of approximately 7.2 8 lx was suggested for a day-dark difference of 0.5 in reassurance ratings. Furtehrmore, it was found that increased illuminance, significantly decreased the difference in reassurance between male and female pedestrians. The finding supports the idea that road lighting plays a crucial role in addressing gender disparities in feelings of reassurance, specifically that it benefits females more than males. No statistically significant difference in reassurance levels between solo and group participants, using either the after-dark method or the day-dark method, were found. This indicates that including accompanied participants in reassurance studies does not compromise the validity of the findings, as long as being in a solo or group setting does not introduce unmeasured effects that influence participant's perceptions or their responses to the questionnaire.

Experiment 3 explored the use of travel counts as an objective method for measuring pedestrian reassurance. This was done for nine of the 12 locations used in Experiment 2, to enable comparison of results from subjective and objective measures. The numbers of people walking in daylight and after dark was recorded and compared using an odds ratio, to assess the influence of lighting conditions on pedestrian traffic. Darkness was suggested to have a deterrence effect on pedestrian traffic, with, generally, fewer pedestrians walking after-dark compared to daylight. It was found that this effect was not significantly different between males and females, contrasting with subjective reassurance studies that show females feeling less safe than males. It was also suggested that odds ratios calculated from these data, were associated with reassurance ratings obtained by subjective evaluations in Experiment 2. A stronger correlation between ORs and after-dark reassurance ratings than with day-dark ratings was found. This suggested that after-dark subjective evaluations more closely aligned with odds ratio of pedestrians traffic.

10.3 Implications of the research, limitations, and future research

This research contributions to the body of knowledge concerning road lighting and pedestrian reassurance, encompassing theoretical, methodological, and practical implications.

It provides empirical evidence that road lighting is a influential factor in pedestrian reassurance, offering insight into how different illuminance metrics impact reassurance. Furthermore, it demonstrates that higher illuminances can mitigate gender disparities in reassurance, specifically benefitting female pedestrians more than male pedestrians. It also shows that despite males stated preference of higher reassurance compared to females, their actual walking behaviour after dark is similar to females.

The findings also contribute to improved understanding of the day-dark method for measuring reassurance, showing that the time of day for daylight evaluations has minimal impact, and that the presence of accompanied participants does not significantly alter reassurance ratings. Furthermore, the strong association between travel counts and subjective reassurance ratings introduces an objective approach to assessment, allowing for the incorporation of behavioural observation techniques alongside direct subjective evaluations.

Finally, the findings have significant implications for road lighting guidelines and public safety policy. The suggested optimal illuminance of 7 to 8 lx, hints at a potential 50% reduction in the maximum 15lx recommendation of the current UK guidelines, indicating that current recommendations may be higher than necessary for pedestrian reassurance. This reduction would primarily benefit designers who might have otherwise specified higher illuminance levels, offering an opportunity for energy savings and environmental benefits. For designers currently utilising lower illuminance levels, this change could result in an increase in energy consumption. For this group, this research provides evidence that 7 to 8 lx is an optimal and beneficial choice, as it enhances reassurance. This ensures that any associated increase in energy use is justified and purposeful. This empirical evidence provides a strong basis for re-evaluating existing standards, such as EN 13201-2:2015 (BSI, 2015a), and informs public safety policies enabling the design of more inclusive and equitable public spaces for everyone.

This research is subject to several limitations that warrant consideration for future research. Primarily, the restricted demographic of participants, limited choice of locations, and lighting conditions studied. This limits the generalisability of findings to other populations, such as older people, who display different walking behaviours and visual requirements. It also constrains the application of findings to other settings and environments, such as non-urban locations. The ability of this research to capture the broader range of light conditions in the real-world in relation to reassurance is also limited. Future studies should expand the scope of participant demographics, environmental settings, and lighting conditions examined, to validate the proposed optimal illuminance of 7 to 8 lx.

This thesis only considered illuminance. Future research should look at the broader scope of lighting design metrics, such as vertical illuminance which supports interpersonal evaluations. Exploring the distinct needs of other road users, such as cyclists and drivers, which may necessitate different light levels than observed in this study, is also important.

The day-dark approach employed in this thesis is limited by its susceptibility to disproportionate representational variability; the range of possible after-dark ratings is disproportionately limited for locations with lower daylight ratings, artificially restricting how much change can be observed for these locations compared to locations with higher daylight ratings. This creates a biased representation of the true impact of darkness on reassurance, as locations starting with lower reassurance levels appear to experience larger proportional reductions simply due to the constrained available ratings. The failure of the day-dark approach to account for significant differences between daylight and after-dark vision and glare, and its potential to introduce confounding variables due to the complex interplay of non-visual, social, economic, cultural, and behavioural factors is another limitation of this method. More research is needed to assess how these issues can be mitigated and how the day-dark method can be further refined. To enhance validity and reliability, future research should also explore alternative methods for measuring reassurance, such as gait analysis and involuntary physiological response measurements. Finally, investigating the interaction between reassurance and other environmental factors, such as prospect and refuge, is crucial for a comprehensive understanding of reassurance. This could involve multi-factorial studies that systematically vary both road lighting and other environmental factors.

10.4 Summary

The diverse needs of pedestrians, cyclists, and drivers create complex challenges for optimal road lighting design. Optimal road lighting must be both sufficient, to meet the needs of different road users, and energy-efficient. While achieving this balance is difficult, it is vital for the environment and society. This thesis contributes to knowledge by providing empirical evidence for establishing optimal road lighting illuminance for pedestrian reassurance. By suggesting that the current recommendations of road lighting guidelines for mean illuminance may be higher than required, this thesis provides crucial insights for revising road lighting guidelines, such as EN 13201-2:2015, and improving public safety policies. The impact of such a revision on the environment is substantial. It paves the way for significant energy savings, and a more cost-effective, environmentally friendly public lighting design that promotes reassurance for all pedestrians. Any future revision of lighting guidelines and policies would require collaboration among researchers, urban planners, policymakers, and public safety experts, to ensure comprehensive recommendations and effective implementation.

APPENDICES

Appendix A. Screenshots of SPSS configurations for factor analysis in Experiment 2

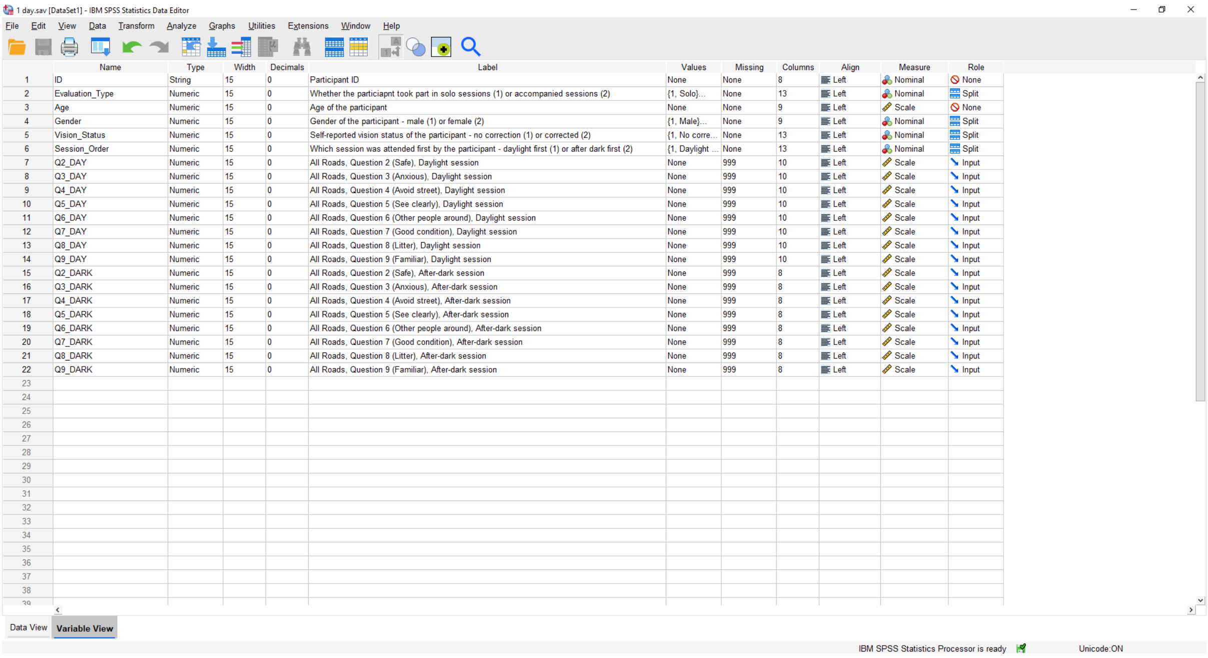


Figure A.1. Variable View tab in IBM SPSS version 27. Eight questions were used in the factor analysis (The bogus question and the question ‘‘*How risky do you think it would be to walk alone here at night*?’ were removed). Responses to each question across all 12 roads was combined in one column of SPSS.

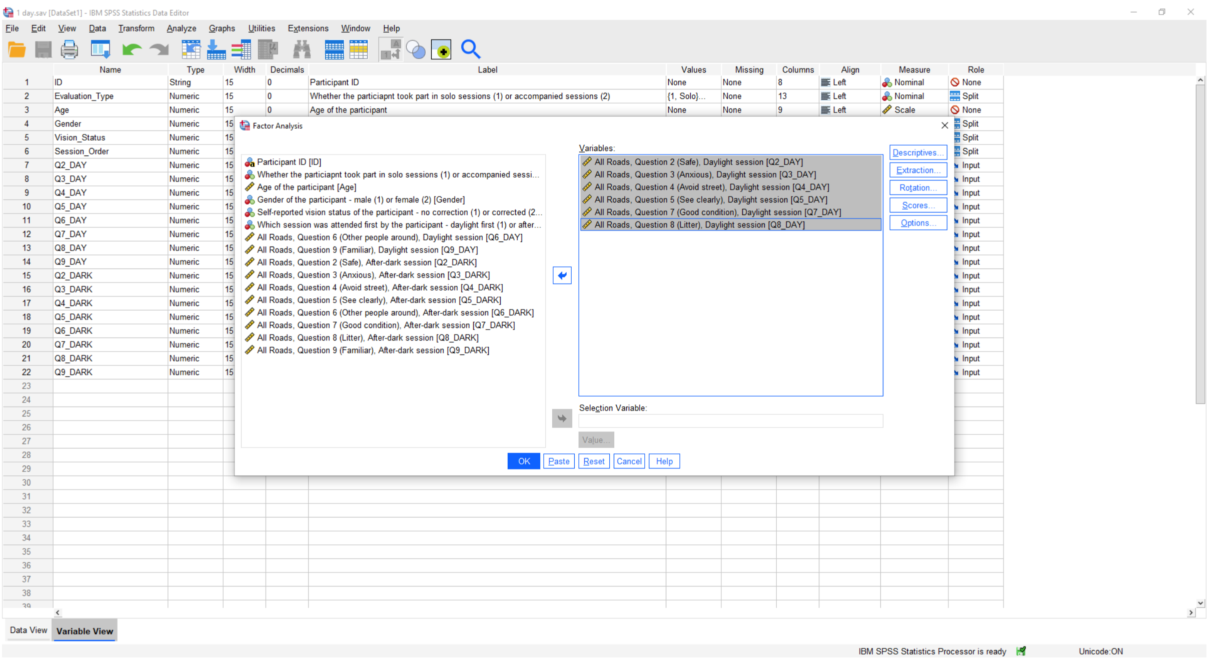


Figure A.2. The variables used in an example factor analysis of the six-question sample.

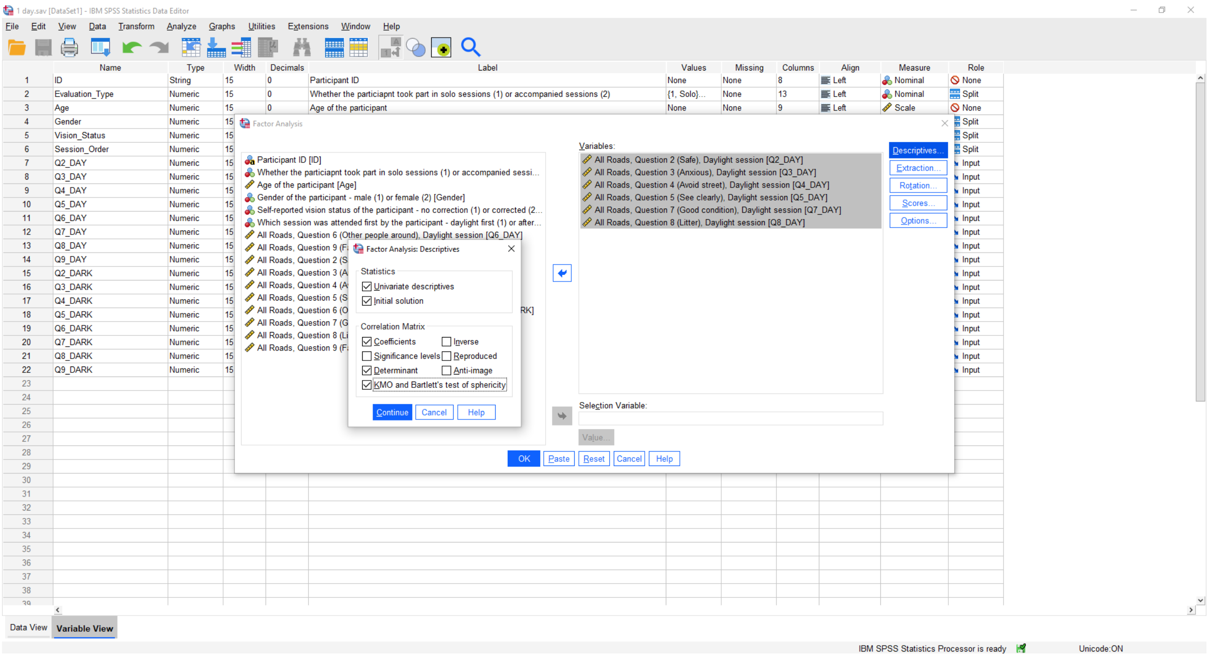


Figure A.3. Descriptive settings for an example factor analysis.

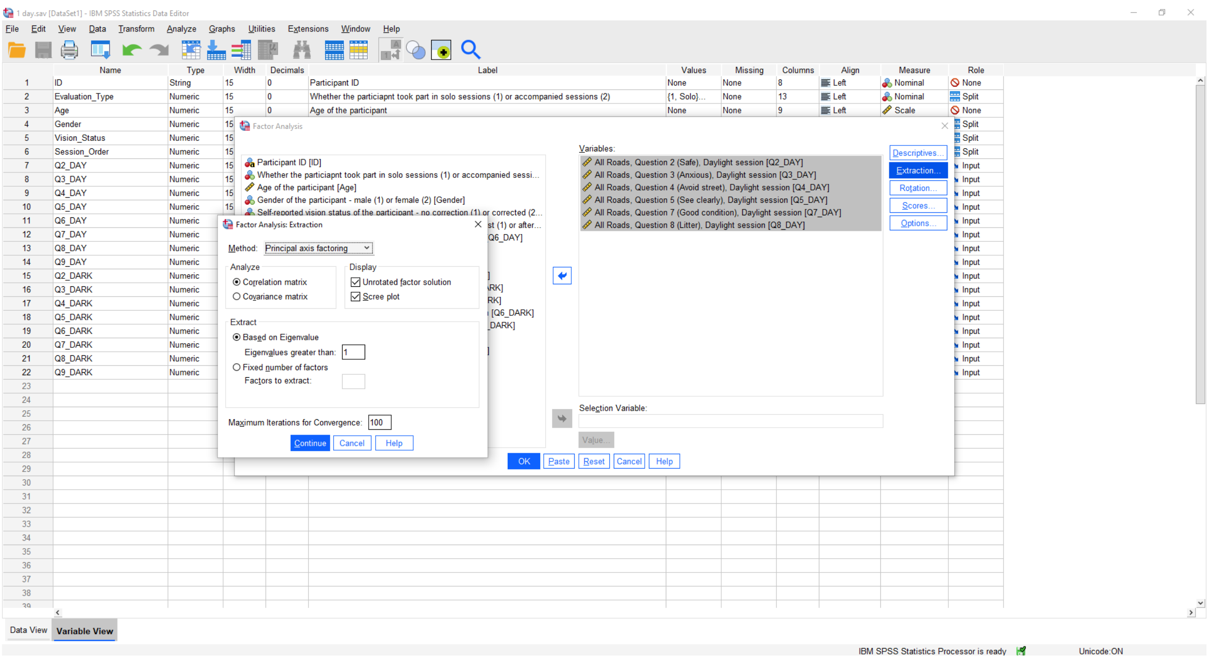


Figure A.4. Extraction settings for an example factor analysis.

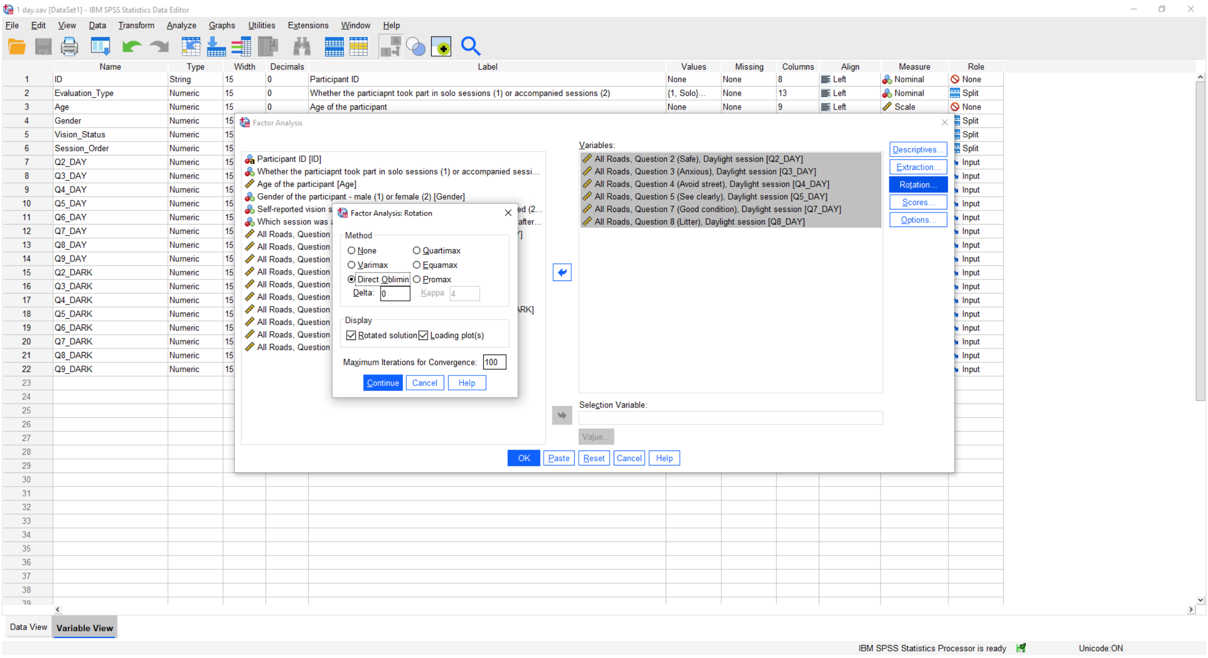


Figure A.5. Rotation settings for an example factor analysis.

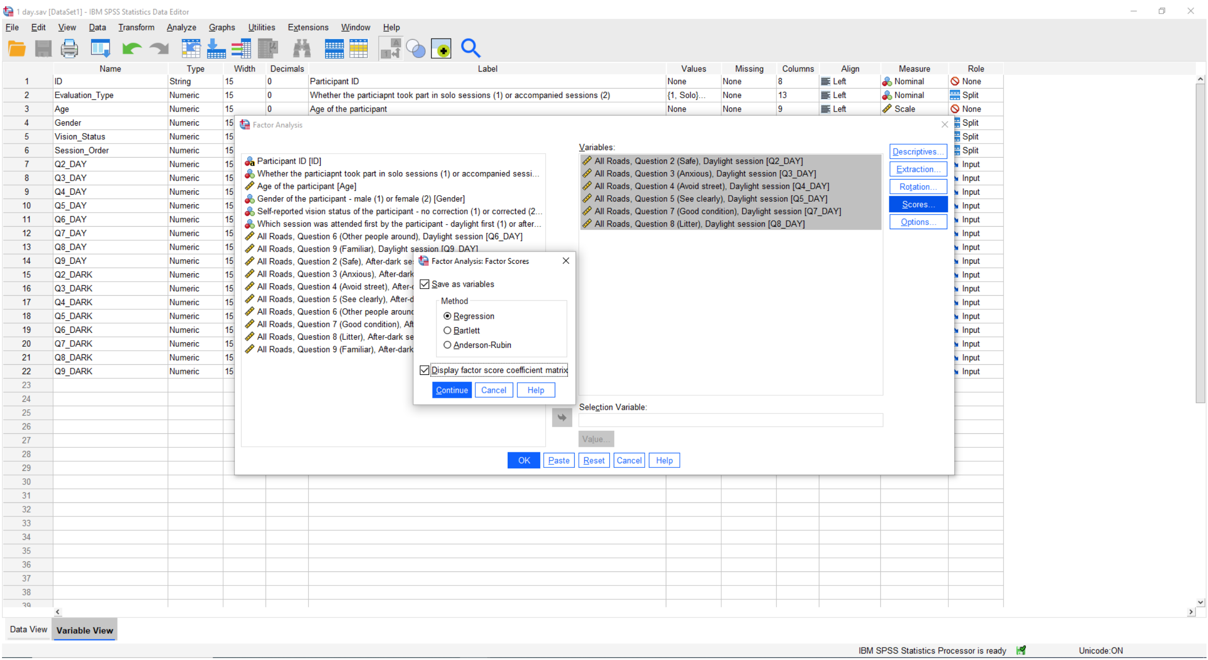


Figure A.6. Scores settings for an example factor analysis.

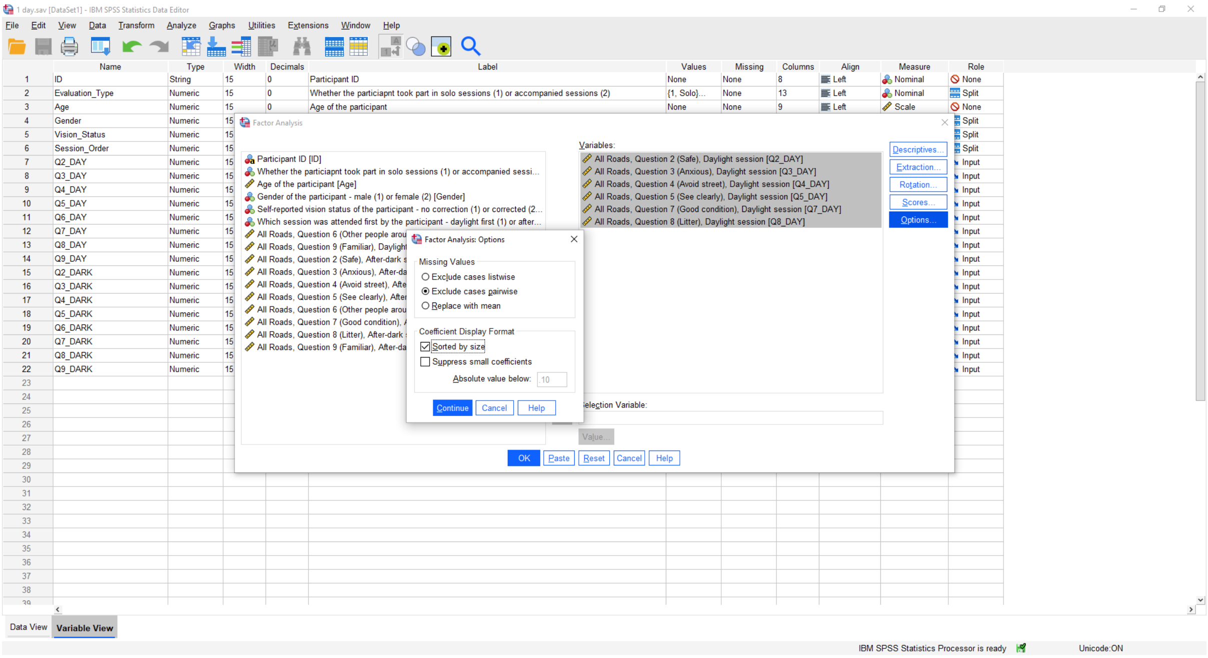


Figure A.7. Options settings for an example factor analysis.

REFERENCES

Aarts, L. and van Schagen, I. (2006) 'Driving speed and the risk of road crashes: A review', *Accident Analysis and Prevention*, 38(2), pp. 215–224.

Acuña-Rivera, M., Uzzell, D. and Brown, J. (2011) 'Perceptions of disorder, risk and safety: The method and framing effects', *Journal of Environmental Psychology*, 2(2), pp. 167–177.

Akashi Y, Rea M, Morante P. (2004) *Progress Report: Improving Acceptance and Use of Energy-Efficient Lighting. Unified Photometry: An Energy-Efficient Street Lighting Demonstration in Easthampton, MA*. Troy, NY: Lighting Research Center.

Alfonzo, M.A. (2005) 'To walk or not to walk? The hierarchy of walking needs', *Environment and Behavior*, 37(6), pp. 808–836.

Appleton, J. (1996) *The experience of landscape*. Rev. ed. Chichester, United Kingdom: Wiley.

Arrindell, W. A., and van der Ende, J. (1985) 'An empirical test of the utility of the observer-to-variables ratio in factor and components analysis', *Applied Psychological Measurement*, 9, pp. 165–178.

Atkins, S., Husain, S. and Storey, A. (1991) *The Influence of Street Lighting on Crime and Fear of Crime. Crime Prevention Unit, Paper No. 28.* London: Home Office.

Aultman-Hall, L., Lane, D. and Lambert, R. (2009) 'Assessing impact of weather and season on pedestrian traffic volumes', *Transportation Research Record: Journal of the Transportation Research Board*, 2140, pp. 35–43.

Austin, D.M. and Sanders, C. (2007) 'Graffiti and perceptions of safety: A pilot study using photographs and survey data', *Journal of Criminal Justice and Popular Culture*, 14(4), pp. 292–316.

Banister, D. (2008) 'The sustainable mobility paradigm', *Transport Policy*, 15(2), pp. 73–80.

Banister, D. and Bowling, A. (2004) 'Quality of life for the elderly: the transport dimension', *Transport Policy*, 11(2), pp. 105–115.

Bartholomew, D. J., Knott, M. and Moustaki, I. (2011) *Latent variable models and factor analysis: a unified approach*. 3rd ed. Hoboken, N.J.: Wiley.

Bartlett, M. S. (1954) 'A note on the multiplying factors for various chi square approximations', *Journal of the Royal Statistical Society*, 16 (Series B), pp. 296– 298.

Basu, N., Haque, M.M., King, M., Kamruzzaman, M. and Oviedo-Trespalacios, O. (2021) 'The unequal gender effects of the suburban built environment on perceptions of security', *Journal of transport & health*, 23. p.101243.

Basu, N., Haque, M.M., King, M., Kamruzzaman, M. and Oviedo-Trespalacios, O. (2022) 'A systematic review of the factors associated with pedestrian route choice', *Transport Reviews*, *42*(5), pp. 672–694.

Beach, D. A. (1989) 'Identifying the random responder', *The Journal of Psychology*, 123(1), pp. 101–103.

Bierman, A. (2012) 'Will switching to LED outdoor lighting increase sky glow?', *Lighting Research & Technology*, 44(4), pp. 449–458.

Bernhoft, I.M. and Carstensen, G. (2008) 'Preferences and behaviour of pedestrians and cyclists by age and gender', *Transportation Research. Part F, Traffic Psychology and Behaviour*, 11(2), pp. 83–95.

Bhagavathula, R. and Gibbons, R.B. (2020) 'Light levels for parking facilities based on empirical evaluation of visual performance and user perceptions', *Leukos*, 16 (2), pp. 115–136.

Bierman, A. (2012) 'Will switching to LED outdoor lighting increase sky glow?', *Lighting Research & Technology*, 44(4), pp. 449–458.

Bishop, I.D. and Rohrmann, B. (2003) 'Subjective responses to simulated and real environments: A comparison', *Landscape and Urban Planning*, 65(4), pp. 261–277.

Bland, J. M. and Altman, D. G. (1997) 'Statistics notes: Cronbach's alpha', *BMJ*, 314(7080), pp. 572–572.

Blobaum, A. and Hunecke, M. (2005) 'Perceived danger in urban public space: The impact of physical features and personal factors', *Environment and Behavior*, 37(4), pp. 465–486.

de Boer, J.B. (1961) 'The application of sodium lamps to public lighting', *Journal of the Illuminating Engineering Society*, 56(4), pp. 293–312.

Boomsma, A. (1985) 'Nonconvergence, improper solutions, and starting values in LISREL maximum likelihood estimation', *Psychometrika, 50*(2), pp. 229–242.

Boomsma, C. and Steg, L. (2014) 'Feeling safe in the dark: Examining the effect of entrapment, lighting levels, and gender on feelings of safety and lighting policy acceptability', *Environment and Behavior*, 46(2), pp. 193–212.

Borst, H.C., Miedema, H.M.E., de Vries, S.I., Graham, J.M.A. and van Dongen, J.E.F. (2008) 'Relationships between street characteristics and perceived attractiveness for walking reported by elderly people', *Journal of Environmental Psychology*, 28, pp. 353–361.

Boyce, P. R. (1996) 'Illuminance Selection Based on Visual Performance-and other Fairy Stories', *Journal of the Illuminating Engineering Society*, 25(2), pp. 41–49.

Boyce, P.R. (2014) Human factors in lighting. Third edition. Boca Raton: CRC Press, Taylor & Francis Group.

Boyce, P.R. and Gutkowski, J.M. (1995) 'The if, why and what of street lighting and crime: A review', *Lighting Research & Technology'*, 27(2), pp. 103–112.

Boyce, P.R., Eklund, N.H., Hamilton, B.J. and Bruno, L.D. (2000) 'Perceptions of safety at night in different lighting conditions', *Lighting Research & Technology*, 32(2), pp. 79–91.

Boyce, P.R., Fotios, S. and Richards, M. (2009) 'Road lighting and energy saving', *Lighting Research & Technology*, 41(3), pp. 245–260.

(BSI) British Standards Institution. (2014) *PD CEN/TR 13201-1:2014. Road lighting - Part 1: Guidelines on selection of lighting classes*. London: BSI.

(BSI) British Standards Institution. (2015a) *EN 13201-2:2015. Road lighting - Part 2: Performance requirements*. London: BSI.

(BSI) British Standards Institution. (2015b) *EN 13201-3:2015. Road lighting - Part 3: Calculation of performance*. London: BSI.

(BSI) British Standards Institution. (2020) EN 5489-1: 2020. *Design of Road Lighting. Part 1: Lighting of roads and public amenity areas – Code of practice*. London: BSI.

Bullough, J.D. and Rea, M.S. (2011) 'Intelligent control of roadway lighting to optimize safety benefits per overall costs', in *14th Institute of Electrical and Electronic Engineers Conference on Intelligent Transportation Systems*, Washington DC, USA, 5-7 October 2011. Piscataway, NJ: IEEE, pp. 968-972.

Bullough, J. D., Donnell, E. T. and Rea, M. S. (2013) 'To illuminate or not to illuminate: Roadway lighting as it affects traffic safety at intersections', *Accident Analysis and Prevention*, 53, pp. 65–77.

Bullough, J.D., Snyder, J.D. and Kiefer, K. (2020) 'Impacts of average illuminance, spectral distribution, and uniformity on brightness and safety perceptions under parking lot lighting', *Lighting Research & Technology*, 52 (2), pp. 626–640.

'Reassure' (2024) in *Cambridge Dictionary Online.* Available at: https://dictionary.cambridge.org/dictionary/english/reassure (Accessed: 25 January 2024)

Caminada, J. F. and Van Bommel, W. J. M. (1980) 'New lighting considerations for residential areas', *International Lighting Review, 3,* pp. 69–75.

Cattell, R.B., 1966. The meaning and strategic use of factor analysis. In R. B. Cattell (Ed.), *Handbook of Multivariate Experimental Psychology* (pp. 174–243). Chicago: Rand McNally.

van Cauwenberg, J., Clarys, P., De Bourdeaudhuij, I., Van Holle, V., Verté, D., De Witte, N., De Donder, L., Buffel, T., Dury, S. and Deforche, B. (2012a) 'Physical environmental factors related to walking and cycling in older adults: the Belgian ageing studies', *Public Health*, 12(1), pp. 142–142.

van Cauwenberg, J., van Holle, V., Simons, D., Deridder, R., Clarys, P., Goubert, L., Nasar, J., Salmon, J., de Bourdeaudhuij, I. and Deforche, B. (2012b) 'Environmental factors influencing older adults' walking for transportation: a study using walk-along interviews', *The International Journal of Behavioral Nutrition and Physical Activity*, 9(1).

van Cauwenberg, J., Van Holle, V., De Bourdeaudhuij, I., Clarys, P., Nasar, J. Salmon, J., … (2014) 'Physical environmental factors that invite older adults to walk for transportation', *Journal of Environmental Psychology*, 38, pp. 94–103

Chataway, M.L. and Hart, T.C. (2019) 'A Social Psychological Process of Fear of Crime for Men and Women. Revisiting Gender Differences from a New Perspective', *Victims & Offenders*, 14(2), pp. 143–164.

Clark, L. A. and Watson, D. (2019) 'Constructing Validity: New Developments in Creating Objective Measuring Instruments', *Psychological Assessment*, 31(12), pp. 1412–1427.

Cohen, J. (1988) *Statistical power analysis for the behavioral sciences* (2nd ed.). New York: Academic Press.

Cohen, J. (1992) 'Statistical Power Analysis', *Current directions in psychological science: a journal of the American Psychological Society*, 1(3), pp. 98–101.

Cohen, L. E., and Felson, M. (1979) 'Social Change and Crime Rate Trends: A Routine Activity Approach', *American Sociological Review,* 44(4), pp. 588–608.

(CIE) Commission Internationale de l'Eclairage (2010) *CIE 115:2010. Technical Report. Lighting of Roads for Motor and Pedestrian Traffic*. 2nd edn. Vienna: Austria.

(CIE) Commission Internationale de l'Eclairage (2019) *CIE 236:2019. Technical Report. Lighting for Pedestrians: A summary of Empirical Data*. Vienna: Austria.

(CIE) Commission Internationale de l'Eclairage (2020) *CIE S 017/E:2020. ILV: international lighting vocabulary*. 2nd edn. Vienna: Austria.

Comrey, A. L., & Lee, H. B. (1992). *A first course in factor analysis* (2nd. ed.). Hillsdale, NJ: Erlbaum.

Corrine, G. (2011) *Becoming Qualitative Researchers: An Introduction*. 4th edn. Boston: Pearson.

CrimeRate (2024) *Crime and safety in Sheffield*. Available at: https://crimerate.co.uk/south-yorkshire/sheffield/ (Accessed: 2 November 2022)

Curran, P. G. (2016) 'Methods for the detection of carelessly invalid responses in survey data', *Journal of Experimental Social Psychology*, 66, pp. 4–19.

Damyanovic, D. (2016) 'Gender mainstreaming as a strategy for sustainable urban planning', in *Fair Shared Cities: The Impact of Gender Planning in Europe*, pp. 177–192. London: Routledge.

Daston, L. and Galison, P. (2007) *Objectivity*. Brooklyn, NY: Zone Books.

(DfT) Department for Transport. (2017) Cycling and Walking Investment Strategy [online]. London: Department for Transport. [Viewed 16 October 2023]. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/918442/cycling-walking-investment-strategy.pdf

Dick, R. (2014) 'Applied scotobiology in luminaire design', *Lighting Research & Technology*, 46(1), pp. 50–66.

(DESNZ) Department for Energy Security and Net Zero (2025) *Energy Trends March 2025*. Available at: https://www.gov.uk/government/statistics/energy-trends-march-2025 (Accessed: 24 January 2025).

Doleac, J. L. and Sanders, N. J. (2015) 'Under the cover of darkness: how ambient light influences criminal activity', *The review of economics and statistics*, 97(5), pp. 1093–1103.

Dosen, A. S. and Ostwald, M. J. (2013) 'Prospect and refuge theory: Constructing a critical definition for architecture and design', *International Journal of Design in Society*, 6(1), pp. 9–23.

Dravitzki, V.K., Cleland, B.S., Walton, D., Laing, J.N. (2003) *Measuring commuting pedestrians' concerns for personal safety and the influence of lighting on these concerns: Proceedings of the 26th Australasian Transport Research Forum*. Wellington, New Zealand, Oct 1–3: 2003.

Duriscoe, D., Luginbuhl, C. and Elvidge, C. (2014) 'The relation of outdoor lighting characteristics to sky glow from distant cities', *Lighting Research & Technology*, 46(1), pp. 35–49.

Van Dyck, D. *et al.* (2012) 'Perceived neighborhood environmental attributes associated with adults' transport-related walking and cycling: Findings from the USA, Australia and Belgium', *The International Journal of Behavioral Nutrition and Physical Activity*, 9(1), pp. 70–70.

European Commission (2013) *Lighting the Cities 2013*. Available at: https://op.europa.eu/en/publication-detail/-/publication/b92b6103-00b3-473a-95c0-dcfc8834b56d (Accessed: 24 January 2025).

Esterberg, K. G. (2002) *Qualitative methods in social research*. Boston, Massachusetts: McGraw-Hill.

Everitt, B. S. (1975) 'Multivariate Analysis: The Need for Data, and other Problems', *British Journal of Psychiatry*, 126(3), pp. 237–240.

Fabrigar, L. R., Wegener, D.T., MacCallum, R.C., and Strahan, E.J. (1999) 'Evaluating the use of exploratory factor analysis in psychological research', *Psychological Methods, 4*(3), pp. 272–299.

Farrall, S., Bannister, J., Ditton, J. and Gilchrist, E. (1997) 'Questioning the measurement of the fear of crime: Findings from a major methodological study', *British Journal of Criminology*, 37, pp. 657–678.

Farrall S., Jackson J. and Gray E. (2009) *Social order and the fear of crime in contemporary times*. Oxford: Oxford University Press.

Fava, J. L., and Velicer, W. F. (1992) 'The effects of overextraction on factor and component analysis', *Multivariate Behavioral Research*, 27 , pp. 387– 415.

Fewster, J. (2004) 'Walking-social, health and economic benefits, and the law', *Proceedings of the Institution of Civil Engineers. Municipal engineer*, 157(2), pp. 111–115.

Field, A. P. (2018) *Discovering statistics using IBM SPSS statistics*. Fifth edition. Los Angeles: SAGE.

Fisher, B.S. and Nasar, J.L. (1992) 'Fear of crime in relation to three exterior site features: prospect, refuge, and escape', *Environment and Behavior*, 24(1), pp. 35–65.

Forde, D.R. (1993) 'Perceived Crime, Fear of Crime, and Walking Alone at Night', *Psychological Reports*, 73(2), pp. 403–407.

Ford, L. R. and Scandura, T. A. (2023) *The Sage handbook of survey development and application*. London: Sage.

Foster, C., Hillsdon, M. and Thorogood, M. (2004) 'Environmental perceptions and walking in English adults', *Journal of Epidemiology & Community Health*, 58(11), pp. 924–928.

Foster S., Hooper, P., Knuiman, M., Christian, H., Bull, F. and Giles-Corti, B. (2016) 'Safe residential environments? A longitudinal analysis of the influence of crime-related safety on walking', *International Journal of Behavioural Nutrition and Physical Activity*, 13(1), pp. 1–9.

Fotios, S. (2020) 'A review of design recommendations for P-class road lighting in European and CIE documents - part 1: parameters for choosing a lighting class', *Lighting Research & Technol*ogy, 52(5), pp. 607–625.

Fotios, S. and Goodman, T. (2012) 'Proposed UK guidance for lighting in residential roads', *Lighting Research & Technology*, 44(1), pp. 69–83.

Fotios, S., Unwin, J. and Farrall, S. (2015) 'Road lighting and pedestrian reassurance after dark: a review', *Lighting Research & Technology*, 47(4), pp. 449–469.

Fotios, S. and Castleton, H. (2016) 'Specifying enough light to feel reassured on pedestrian footpaths', *LEUKOS, The Journal of Illuminating Engineering Society of North America*, 12(4), pp. 235–243.

Fotios, S. and Gibbons, R. (2018) 'Road lighting research for drivers and pedestrians: The basis of luminance and illuminance recommendations', *Lighting Research & Technology*, 50(1), pp. 154–186.

Fotios, S. and Uttley, J. (2018) 'Illuminance required to detect a pavement obstacle of critical size', *Lighting Research & Technology*, 50(3), pp. 390–404.

Fotios, S., Liachenko Monterio, A. and Uttley, J. (2019a) ‘Evaluation of pedestrian reassurance gained by higher illuminances in residential streets using the day-dark approach’, *Lighting Research & Technology*, 51, pp. 557–575.

Fotios S., Uttley, J. and Fox, S. (2019b) ‘A whole-year approach showing that ambient light level influences walking and cycling’, *Lighting Research & Technology*, 51(1), pp. 55–64.

Fotios, S., Robbins, C.J. and Uttley, J. (2021a) ‘A comparison of approaches for investigating the impact of ambient light on road traffic collisions’, *Lighting Research & Technology*, 53(3), pp. 249–261.

Fotios, S., Robbins, C.J.and Farrall, S. (2021b) ‘The effect of lighting on crime counts’, *Energies*; 14: 4099.

Fotios, S. and Robbins, CJ. (2022) ‘Effect of ambient light on the numbers of motorized vehicles, cyclists and pedestrians’, *Transportation Research Record*, 2676(2), pp. 593–605.

Fotios S, Mao Y, Hamoodh K and Cheal, C. (2024) ‘Using relative visual performance to predict performance of an interpersonal evaluation task with variation in adaptation luminance, observer age, skin tone, pavement reflection and interpersonal distance’, *Lighting Research & Technology*, 56(3), pp. 283–294.

Franek, M. (2013) ‘Environmental Factors Influencing Pedestrian Walking Speed’, *Perceptual and Motor Skills*, 116(3), pp. 992–1019.

Fyhri, A., Hof, T., Simonova, Z., and Jong, M. (2010). The influence of perceived safety and security on walking. In: Methorst R, Monterde-i-Bort H, Risser R, Sauter D, Tight & Walker (eds) Pedestrians’ quality needs. Final report of the COST project 358, Cheltenham: Walk21, part B.2 Perceived Needs, pp. 49–69

Gabriel, U. and Greve, W. (2003) ‘The Psychology of Fear of Crime. Conceptual and Methodological Perspectives’, *British Journal of Criminology*, 43(3), pp. 600–614.

Ghani, F., Rachele, J.N., Loh V.H.Y, Washington, S. and Turrell, G. (2018) ‘Do differences in built environments explain age differences in transport walking across neighbourhoods?’, *Journal of Transport & Health*, 9, pp. 83–95.

Gorsuch, R. L. (1983). *Factor analysis*. Hillsdale, NJ: Erlbaum.

Gover, A.R., Tomsich, E.A., Jennings, W.G. and Higgins, GE. (2011) ‘An exploratory study on perceptions of safety, fear of crime, and victimization experiences among faculty and staff at an urban university: A focus on gender’, *Criminal Justice Studies*, 24(1), pp. 37–55.

Greene, M. and Greene, R., 2003, June. Urban safety in residential areas: Global spatial impact and local self-organising processes. In *Proceedings of 4th International Space Syntax Symposium, Londonm2003* (Vol. 52, pp. 52.1–52.8).

Greve, W., Leipold, B. and Kappes, C. (2018) ‘Fear of Crime in Old Age: A Sample Case of Resilience?’, *Journals of Gerontology: Psychological Sciences*, 73(7), pp. 1224–1232.

Guadagnoli, E. and Velicer, W. F. (1988) ‘Relation of sample size to the stability of component patterns’, *Psychological Bulletin*, 103(2), pp. 265–275.

Haans, A. and de Kort, Y.A.W. (2012) 'Light distribution in dynamic street lighting: Two experimental studies on its effect on perceived safety, prospect, concealment, and escape', *Journal of Environmental Psychology*, 32(4), pp. 342–352.

Haegerstrom-Portnoy, G., Schneck, M.E., Lott, L.A. and Brabyn, J.A. (2000) 'The relation between visual acuity and other spatial vision measures', *Optometry and Vision Science*, 77(12), pp. 653–662.

Hale, C. (1996) 'Fear of crime: A review of the literature', *International Review of Victimology*, 4, pp. 79–150.

Hanyu, K. (1997) 'Visual properties and affective appraisals in residential areas after dark', *Journal of Environmental Psychology*, 17(4), pp. 301–315.

Hassinger, J. (1985) 'Fear of crime in public environments', *Journal of Architectural and Planning Research*, 2(4), pp. 289–300.

Hatem, G., Zeidan, J., Goossens, M. and Moreira, C. (2022). Normality testing methods and the importance of skewness and kurtosis in statistical analysis, *BAU Journal. Science and Technology. 3(2).*

Heath, L. and Gilbert, K. (1996) 'Mass Media and Fear of Crime', *The American Behavioral Scientist*, 39(4), pp. 379–386.

Hengstberger, F., Pollard, N., Sagawa, K., Bouma, H., Halonen, L., Iwai, W., Werner, J., Cook, G. and Akashi, Y. (2011) *CIE Technical Report: CIE guide to increasing accessibility in light and lighting. CIE 196:2011*. Vienna: CIE.

(HEPA) European network for the promotion of health-enhancing physical activity. (ca. 2006) *Promotion of transport walking and cycling in Europe: strategy directions* [online]. EU: HEPA. [Viewed 17 October 2020]. Available from: http://www.panh.ch/hepaeurope/materials/HEPA%20Walking%s 20and%20Cycling%20Strate gy%20.pdf

Herbert, D. and Davidson, N. (1994) 'Modifying the built environment: the impact of improved street lighting', *Geoforum*, 25, pp. 339–350.

Hillinski, C.M., Pentecost Neeson, K.E. and Andrews, H. (2011) 'Explaining fear of crime among college women, in their own words', *Southwest Journal of Criminal Justice*, 8(1), pp. 112–127.

Honig, F., Batliner, A., & Noth, E. (2007). Real-time recognition of the affective user state with physiological signals. *Proceedings of the Doctoral Consortium, Affective Computing and Intelligent Interaction* (2007).

I-Meen, L. and Buchner, D.M. (2008) 'The importance of walking to public health', *Medicine and Science in Sports and Exercise*, 40, S512–S518.

Jacobs, J. (1962) *The death and life of great American cities*. London: Cape.

Japanese Standards Association (1988). *Lighting of Roads*. Japanese Industrial Standard, JIS Z 9111:1988. Tokyo: Japanese Standards Association.

Jedon, R., Haans, A. and de Kort, Y. (2025) 'Perceived environmental safety and alertness in virtual urban environments', *Journal of Transport & Health*, 44, p.102138.

Johansson, Ö., Wanvik, P.O. and Elvik, R. (2009) 'A new method for assessing the risk of accident associated with darkness', *Accident Analysis & Prevention*, 41(4), pp. 809–815.

Johansson, M., Rosén, M. and Küller, R. (2011) 'Individual factors influencing the assessment of the outdoor lighting of an urban footpath', *Lighting Research & Technology*, 43(1), pp. 31–43.

Jorgensen, L.J., Ellis, G.D. and Ruddell, E. (2013) 'Fear Perceptions in Public Parks: Interactions of Environmental Concealment, the Presence of People Recreating, and Gender', *Environment and Behavior*, 45(7), pp. 803–820.

Kaiser, H. F. (1970) 'A second-generation little jiffy', *Psychometrika*, 35, pp. 401–415.

Kaiser, H.F. and Rice, J. (1974) 'Little jiffy, mark 4', *Educational and Psychological Measurement*, 34(1), pp. 111–117.

Kass, R. A., and Tinsley, H. E. A. (1979) 'Factor analysis', *Journal of Leisure Research*, 11, pp. 120–188.

Kerlinger, F.N. (1986). *Foundations of behavioral research* (3rd Ed.). Philadelphia: Harcourt Brace College Publishers.

Kerr, J., Emond, J.A., Badland, H., Reis, R., Sarmiento, O., Carlson, J., … and Schofield, G. (2016) 'Perceived neighborhood environmental attributes associated with walking and cycling for transport among adult residents of 17 cities in 12 countries: The IPEN study', *Environmental Health Perspectives*, 124(3), 290.

Khachatryan, A. *et al.* (2024) 'Understanding the behavioural determinants of active travel among older adults: A mixed methods study', *Journal of Transport & Health*, 39.

Killias, M. (1990) 'Vulnerability: Towards a better understanding of a key variable in the genesis of fear of crime', *Violence and Victims*, 5(2), pp. 97–108.

Kim, J. and Mueller, C. W. (1978) *Introduction to factor analysis: what it is and how to do it*. Beverly Hills, Calif.: SAGE.

Kim, D.H. and Noh, K.B. (2018) 'Perceived adequacy of illumination and pedestrians' night-time experiences in urban obscured spaces: A case of London', *Indoor and Built Environment,* 27(8), pp. 1134–1148

Kim, W. and Park, J. (2025) 'Illuminating Safety: The Impact of Street Lighting on Reducing Fear of Crime in a Virtual Environment', *International Journal of Human-Computer Interaction*, pp. 1–15.

Kim, S. K., and Kang, H. B. (2018) 'An analysis of fear of crime using multimodal measurement', *Biomedical Signal Processing and Control*, 41, pp. 186–197.

Kline, P. (1994). *An easy guide to factor analysis*. New York: Routledge.

Knight, C. (2010) 'Field surveys investigating the effect of lamp spectrum on the perception of safety and comfort at night', *Lighting Research & Technology*, 42, pp. 313–330.

Kostic, A. and Djokic, L. (2014) 'Subjective impressions under LED and metal halide lighting', *Lighting Research & Technology*, 46(3), pp. 293–307.

Kwak, S. G. and Kim, J. H. (2017) 'Central limit theorem: The cornerstone of modern statistics', *Korean Jjournal of Anesthesiology*, 70(2), pp. 144–156.

LaBoeuf, R.A. and Shafir, E. (2006) 'The long and short of it: Physical anchoring effects', *Journal of Behavioural Decision Making*, 19(4), pp. 393–406.

LaGrange, R.L., and Ferraro, K.F. (1989) 'Assessing age and gender differences in perceived risk and fear of crime', *Criminology*, 27(4), pp. 697–720.

Lampard, R. and Pole, C. J. (2013) *Practical social investigation: qualitative and quantitative methods in social research*. London; Routledge: Taylor & Francis Group.

Lee, I. M. and Buchner, D. M. (2008) 'The importance of walking to public health', *Medicine and Science in Sports and Exercise*, 40(7), pp. S512–S518.

Liachenko Monteiro, A. (2021) *Road lighting for pedestrian reassurance: consideration of methods and new metrics*. PhD Thesis, University of Sheffield

Liao, Y., Wang, I., Hsu, H. and Chang, S. (2015) 'Perceived environmental and personal factors associated with walking and cycling for transportation in Taiwanese adults', *International Journal of Environmental Research and Public Health*, 12(2), pp. 2105–2119.

Litman, T. A. (2003) 'Economic Value of Walkability', *Transportation Research Record*, 1828(1), pp. 3–11.

Loewen, L.J., Steel, G.D. and Suedfeld, P. (1993) 'Perceived safety from crime in the urban environment', *Journal of Environmental Psychology*, 13(4), pp. 323–331.

Lorenc, T., Petticrew, M., Whitehead, M., Neary, D., Clayton, S., Wright, K., Thomson, H., Cummins, S., Sowden, A. and Renton, A. (2013) 'Environmental interventions to reduce fear of crime: Systematic review of effectiveness', *Systematic Reviews*, 2(1), pp. 30–40.

Lucas RJ, Peirson SN, Berson DM, Brown TM, Cooper HM, Czeisler CA, Figueiro MG, Gamlin PD, Lockley SW, O'Hagan JB, Price LLA, Provencio I, Skene D, Brainard GC. (2014) 'Measuring and using light in the melanopsin age', *Trends in Neurosciences*, 37(1), pp. 1–9

Lumley, T., Diehr, P., Emerson, S., & Chen, L. (2002) 'The importance of the normality assumption in large public health data sets', *Annual Review of Public Health*, 23, pp. 151–169.

MacCallum, R.C., Widaman, K.F., Zhang, S. and Hong, S. (1999) 'Sample size in factor analysis', *Psychological Methods, 4*(1), pp. 84–99.

MacCallum, R. C.,Widaman, K. F., Preacher, K. J., and Hong S. (2001) 'Sample size in factor analysis: The role of model error', *Multivariate Behavioral Research*, 36, pp. 611–637.

Mason, P., Kearns, A., and Livingston, M. (2013) '"Safe Going": The influence of crime rates and perceived crime and safety on walking in deprived neighbourhoods', *Social Science & Medicine (1982)*, *91*, pp. 15–24

Mattoni B, Burattini C, Bisegna F, Fotios S. (2017) The Pedestrian's Perspective: How do illuminance variations affect reassurance? *Proceedings of the 2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe* (EEEIC / I&CPS Europe), 6-9 June 2017, Milan, Italy.

McCambridge, J., de Bruin, M. and Witton, J. (2012) 'The effects of demand characteristics on research participant behaviours in non-laboratory settings: A systematic review', *PLOS One*, 7(6), pp. e39116–e39116.

McCluskey, A. and Lalkhen, AG. (2007) 'Statistics II: Central tendency and spread of data. Continuing Education in Anaesthesia', *Critical Care & Pain* 2007, 7(4), pp. 127–130.

Meade, A. W. and Craig, S. (2012) 'Identifying careless responses in survey data', *Psychological Methods*, 17(3), pp. 437–455.

Menold, N. and Tausch, A. (2016) 'Measurement of Latent Variables With Different Rating Scales: Testing Reliability and Measurement Equivalence by Varying the Verbalization and Number of Categories', *Sociological Methods & Research*, 45(4), pp. 678–699.

'Reassure' (2024) in *Merriam Webster Online.* Available at: https://www.merriam-webster.com/dictionary/reassure (Accessed: 25 January 2024)

Mesch, G. S. (2000) 'Perceptions of risk, lifestyle activities, and fear of crime', *Deviant Behavior*, 21(1), pp. 47–62.

Moran, M., Van Cauwenberg, J., Hercky-Linnewiel, R., Cerin, E., Deforche, B. and Plaut, P. (2014) 'Understanding the relationships between the physical environment and physical activity in older adults', *The International Journal of Behavioral Nutrition and Physical Activity*, 11(1), p. 79.

Morante, P. (2008) *Mesopic Street Lighting Demonstration and Evaluation: Final Report for Groton Utilities, Groton, CT*. Troy, NY: Lighting Research Center.

Mukherjee, D. and Kumar, A. (2024) 'Identification of Factors Influencing Pedestrian Perceived Safety and Satisfaction Level Using Ordered Logit Models in an Indian Midsized City', *International Journal of Transport Development and Integration*, 8(2), pp. 283–299.

Mundfrom, D. J., Shaw, D. G. and Ke, T. L. (2005) 'Minimum Sample Size Recommendations for Conducting Factor Analyses', *International Journal of Testing*, 5(2), pp. 159–168.

Nair, G., Ditton, J. and Phillips, S. (1993) 'Environmental improvements and the fear of crime: The sad case of the 'pond' area in Glasgow', *British Journal of Criminology*, 33(4), pp. 555–561.

Narendran, N., Freyssinier, J. and Zhu, Y. (2016) 'Energy and user acceptability benefits of improved illuminance uniformity in parking lot illumination', *Lighting Research & Technology*, 48(7), pp. 789–809.

Nasar, J. L., Fisher, B. and Grannis, M. (1993) 'Proximate physical cues to fear of crime', *Landscape and Urban Planning*, 26(1), pp. 161–178.

Nasar, J. L. and Jones, K. M. (1997) 'Landscapes of Fear and Stress', *Environment and Behavior*, 29(3), pp. 291–323.

National Grid (2025) *How is the UK's electricity grid being transformed?* Available at: https://www.nationalgrid.com/the-great-grid-upgrade/how-uk-electricity-grid-being-transformed (Accessed: 24 January 2025).

Neter, J., Kutner, M. H., Nachtsheim, C. J., & asserman, W. (2005). *Applied Linear Statistical Models*. (5th ed.). New York: McGraw-Hill Education.

Nasar, J.L. and Jones, K.M. (1997) 'Landscapes of Fear and Stress', *Environment and Behavior*, 29(3), pp. 291–323.

Nasar, J.L. and Bokharaei, S. (2017) 'Impressions of Lighting in Public Squares After Dark', *Environment and Behavior*, 49(3), pp. 227–254.

Noble, H. and Heale, R. (2019) ‘Triangulation in research, with examples’, *Evidence Based Nursing*, 22, pp. 67-68.

Nunnally, J. C. (1978). *Psychometric theory*. New York: McGraw-Hill.

Olivier, J. and Bell, M. L. (2013) ‘Effect Sizes for 2×2 Contingency Tables’, *PLOS one*, 8(3), pp. e58777–e58777.

Oppong, F.B. and Agbedra, S.Y. (2016) ‘Assessing univariate and multivariate normality. a guide for non-statisticians’, *Mathematical Theory and Modelling*, 6(2), pp. 26–33.

Orcan, F. (2020) ‘Parametric or Non-parametric: Skewness to Test Normality for Mean Comparison’, *International Journal of Assessment Tools in Education*, 7 (2), pp. 255–265.

’Reassurance’ (2024) in *Oxford Learner’s Dictionaries Online.* Available at: https://www.oxfordlearnersdictionaries.com/definition/english/reassurance (Accessed: 15 January 2024)

Painter, K. (1994) ‘The impact of street lighting on crime, fear and pedestrian street use’, *Security Journal*, 5(3), pp. 116–124.

Park, Y. and Garcia, M. (2020) ‘Pedestrian safety perception and urban street settings’, *International Journal of Sustainable Transportation*, 14(11), pp. 860–871

Pedhazur, E., and Schmelkin, L. (1991). *Measurement, design and analysis: An integrated approach*. Hillsdale, NJ: Erlbaum.

Peña-García, A., Hurtado, A. and Aguilar-Luzón, M. C. (2015) ‘Impact of public lighting on pedestrians’ perception of safety and well-being’, *Safety Science*, 78, pp. 142–148.

Persoskie, A. and Ferrer, R. A. (2017) ‘A Most Odd Ratio: Interpreting and Describing Odds Ratios’, *American Journal of Preventive Medicine*, 52(2), pp. 224–228.

Piatkowski, D.P., Krizek, K.J. and Handy, S.L. (2015) ‘Accounting for the short term substitution effects of walking and cycling in sustainable transportation’, *Travel, Behaviour & Society*, 2(1), pp. 32–41.

Plainis, S., Murray, I. J. and Charman, W. N. (2005) ‘The role of retinal adaptation in night driving’, *Optometry and Vision Science*, 82(8), pp. 682–688.

Pollard, N. E. (1994) ‘Sky-glow conscious lighting design’, *Lighting Research & Technology (London, England : 2001)*, 26(3), pp. 151–156.

Portnov, B. *et al.* (2024) ‘Establishing optimal illuminance for pedestrian reassurance using segmented regression’, *Lighting Research & Technology*, 56(3), pp. 260–273.

Poulton, E.C. (1977) ‘Quantitative subjective assessments are almost always biased, sometimes completely misleading’, *British Journal of Psychology*, 68(4), pp. 409–425.

Poulton, E.C. (1982). ‘Biases in quantitative judgements’, *Applied Ergonomics*, 13(1), pp. 31–42.

Poulton, E.C. (1989) *Bias in Quantifying Judgements*. Hove, UK: Lawrence Erlbaum Associates.

Pucher, J. and Dijkstra, L. (2003) ‘Promoting safe walking and cycling to improve public health: lessons from the Netherlands and Germany’, *American Journal of Public Health*, 93(9), pp. 1509–1516.

Rader, N. E. (2004) ‘The threat of victimization: A theoretical reconceptualization of fear of crime’, *Sociological Spectrum*, 24(6), pp. 689–704.

Rader, N. E., May, D. C. and Goodrum, S. (2007) 'An empirical assessment of the "threat of victimization": Considering fear of crime, perceived risk, avoidance, and defensive behaviors', *Sociological Spectrum*, 27(5), pp. 475–505.

Ramsay, M. and Newton, R. (1991) *The Effect of Better Street Lighting on Crime and Fear: A Review*. *Crime Prevention Unit paper No. 29*. London: The Home Office.

Rea, M., Bullough, J. and Akashi, Y. (2009) 'Several views of metal halide and high-pressure sodium lighting for outdoor applications', *Lighting Research & Technology*, 41(4), pp. 297–320.

Rea, M., Bullough, J. and Zhou, Y. (2010) 'A method for assessing the visibility benefits of roadway lighting', *Lighting Research & Technology*, 42(2), pp. 215–241.

Rea, M. and Bierman, A. (2015) 'Spectral considerations for outdoor lighting: Consequences for sky glow', *Lighting Research & Technology*, 47(8), pp. 920–930.

van Rijswijk, L. (2016) *Shedding light on safety perceptions: environmental information processing and the role of lighting*. PhD thesis. Eindhoven University of Technology.

van Rijswijk, L., Rooks, G. and Haans, A. (2016) 'Safety in the eye of the beholder: Individual susceptibility to safety-related characteristics of nocturnal urban scenes', *Journal of Environmental Psychology*, 45, pp. 103–115.

van Rijswijk, L. and Haans, A. (2018) 'Illuminating for Safety: Investigating the Role of Lighting Appraisals on the Perception of Safety in the Urban Environment', *Environment and Behavior*, 50(8), pp. 889–912.

Robinson, D. (2019) *Principles of Building Physics: Post Occupancy Evaluation (POE)*. Sheffield: s.n.

Roe, J. and Aspinall, P. (2011) 'The restorative benefits of walking in urban and rural settings in adults with good and poor mental health', *Health & Place*, 17(1), pp. 103–113.

Roman, C. G., and Chalfin, A. (2008) 'Fear of Walking Outdoors. A Multilevel Ecologic Analysis of Crime and Disorder', *American Journal of Preventive Medicine*, *34*(4), pp. 306–312.

Rosenthal, R. (1976). Experimenter effects in behavioral research. United Kingdom: Irvington Publishers.

Rosenthal, R., Rosnow, R. L. (2009). Artifacts in Behavioral Research: Robert Rosenthal and Ralph L. Rosnow's Classic Books. Italy: Oxford University Press, USA.

Rummel, R. J. (1988). *Applied factor analysis*. Evanston, IL: Northwestern University Press.

Sackett, D. L., Deeks, J. J. and Altman, D. G. (1996) 'Down with odds ratios', *Evidence-based Medicine*, 1(6), pp. 164–166.

Schaller, M., Park, J., and Mueller, A. (2003) 'Fear of the Dark: Interactive Effects of Beliefs About Danger and Ambient Darkness on Ethnic Stereotypes', *Personality and Social Psychology Bulletin*, 29(5), pp. 637–649.

Schulman AI. (1967) 'Asch conformity studies: Conformity to the experimenter and/or to the group?', *Sociometry*, 30(1), pp. 26–40.

Schwarz, N. (1999) 'How the questions shape the answers', *American Psychologist*, 54(2), pp. 93–105.

Sedgwick, P. (2015) ‘Confidence intervals, P values, and statistical significance’, *BMJ*, 350, pp. h1113–h1113.

Sheffield City Council (2024) *Ward profiles*. Available at: https://www.sheffield.gov.uk/your-city-council/ward-profiles/ (Accessed: 2 November 2022)

Shigematsu, R., Sallis, J.F., Conway, T.L., Saelens, B.E., Frank, L.D., Cain, K.L., Chapman, J.E. and King, A.C. (2009) ‘Age differences in the relation of perceived neighborhood environment to walking’, *Medicine & Science in Sports & Exercise*, 41(2), pp. 314–321.

de Silva, C.S., Warusavitharana, E.J. and Ratnayake, R. (2017) ‘An examination of the temporal effects of environmental cues on pedestrians' feelings of safety’, *Computers, Environment and Urban Systems*, *64*, pp.266–274.

Simons, R., Hargroves, R., Pollard, N., and Simpson, M. (1987) ‘Lighting criteria for residential roads and areas’, *CIE, Venice*, *53*, pp. 35–39.

Skogan, W. G., and Maxfield, M. G. (1981) *Coping with crime: Individual and neighbourhood reactions*. Beverly Hills: Sage Publications.

Smith, W.R. and Torstensson, M. (1997) ‘Fear of crime, gender differences in risk perception and neutralising fear of crime: Toward resolving the paradoxes’, *The British Journal of Criminology*, 37(4), pp. 608–634.

Standards Australia/Standards New Zealand. (2020) *AS/NZS 1158.3.1:2020: Lighting for roads and public spaces, Part 3.1: Pedestrian area (Category P) lighting – Performance and design requirements*. Sydney, NSW: Standards Australia. (Includes Amendment No. 1:2024).

Stevens, J. P. (2002). *Applied multivariate statistics for the social sciences* (4th ed.). Hillsdale, NJ: Erlbaum.

Sullivan, J.M. and Flannagan, M.J. (2002) ‘The role of ambient light level in fatal crashes: inferences from daylight saving time transitions’, *Accident Analysis and Prevention*, 34(4), pp. 487–498.

Sutton, RM. and Farrall, S. (2005) ‘Gender, socially desirable responding and the fear of crime’, *British Journal of Criminology*, 45(2), pp. 212–224.

Svechkina, A., Portnov, B. A. and Trop, T. (2020) ‘The impact of artificial light at night on human and ecosystem health: a systematic literature review’, *Landscape Ecology*, 35(8), pp. 1725–1742.

Svechkina, A., Trop, T. and Portnov, BA. (2020) ‘How much lighting is required to feel safe when walking through the streets at night?’ *Sustainability*, 12, p. 3133.

Szumilas, M. (2010) ‘Explaining odds ratios’, *Journal of the Canadian Academy of Child and Adolescent Psychiatry*, 19(3), pp. 227–229

Tabachnick, B. G., Fidell, L. S. and Ullman, J. B. (2019) *Using multivariate statistics*. Seventh edition. Boston: Pearson.

Taylor, C. S. (2013) *Validity and validation*. 1st ed. Oxford: Oxford University Press.

Tien, J.M. (1979). *Street lighting projects* (No. 21). Department of Justice, Law Enforcement Assistance Administration, National Institute of Law Enforcement and Criminal Justice.

Toet, A. and van Schaik, M.G. (2012) ‘Effects of signals of disorder on fear of crime in real and virtual environments’, *Journal of Environmental Psychology*, 32(3), pp. 260–276.

Tourangeau, R., Rips, L.J. and Rasinski, K. (2000) *The Psychology of Survey Response.* Cambridge: Cambridge University Press.

Tsolkas, D., Liotou, E., Passas, N. and Merakos, L. (2017) ‘A survey on parametric QoE estimation for popular services’, *Journal of network and computer applications*, 77, pp. 1–17.

Uchikawa, K. and Ikeda, M. (1986) ‘Accuracy of memory for brightness of colored lights measured with successive comparison method’, *Journal of the Optical Society of America. A, Optics, image science, and vision*, 3(1), pp. 34–39.

Unwin, J. (2015) *An investigation of the effect of street lighting on pedestrian reassurance in residential environments*. PhD Thesis. The University of Sheffield.

Unwin, J. and Fotios, S. (2011) ‘Does lighting contribute to the reassurance of pedestrians at night-time in residential roads?’, *Ingineria Iluminatului*, *2*(13), pp. 29–44.

USAID (2009) *Energy Efficient Street Lighting: Guidelines*. New Delhi, India: USAID.

Uttley, J. (2015) *Investigating the visual tasks of pedestrians and how one of these tasks, obstacle detection, is influenced by lighting*. PhD thesis. University of Sheffield.

Uttley, J. (2019) ‘Power Analysis, Sample Size, and Assessment of Statistical Assumptions-Improving the Evidential Value of Lighting Research’, *Leukos*, 15(2-3), pp. 143–162.

Uttley, J. and Fotios, S. (2017) ‘Using the daylight savings clock change to show ambient light conditions significantly influence active travel’, *Journal of Environmental Psychology*, 53, pp. 1–10.

Uttley, J., Fotios, S. and Cheal, C. (2017) ‘Effect of illuminance and spectrum on peripheral obstacle detection by pedestrians’, *Lighting Research & Technology*, 49(2), pp. 211–227.

Uttley, J., Fotios, S., Robbins, C.J. and Moscoso, C., (2023) ‘The effect of changes in light level on the numbers of cyclists’, *Lighting Research & Technology*, *55*(4-5), pp. 366-376.

Uttley, J., Canwell, R., Smith, J., Falconer, S., Mao, Y., Fotios, S. A. and Spitschan, M. (2024) ‘Does darkness increase the risk of certain types of crime? A registered report protocol’, *PLOS one*, 19(1), pp. e0291971–e0291971.

Valera, S., & Guardia, J. (2014). Perceived insecurity and fear of crime in a city with low crime rates. *Journal of Environmental Psychology*, 38, pp. 195–205.

Velicer,W. F., Peacock, A. C. and Jackson, D. N. (1982) ‘A comparison of component and factor pattern: A Monte Carlo approach’, *Multivariate Behavioral Research*, 17, pp. 371–388.

Velicer, W. F., and Jackson, D. N. (1990) ‘Component analysis versus common factor analysis: Some issues in selecting an appropriate procedure’, *Multivariate Behavioral Research*, 25, pp.1– 28.

Viliunas, H., Vaitkevicius, R., Stanikunas, P., Vitta, R., Bliumas, A., Auskalnyte, A., Tuzikas, A., Petrulis, L., Dabasinskas, Z. and Zukauskas, A. (2013) ‘Subjective evaluation of luminance distribution for intelligent outdoor lighting’, *Lighting Research & Technology*, 46(4), pp. 421–433.

Vrij, A. and Winkel, FW. (1991) ‘Characteristics of the built environment and fear of crime: A research note on interventions in unsafe locations’, *Deviant Behavior*, 12(2), pp. 203–215.

Waldram, J. M. (1972) ‘The calculation of sky haze luminance from street lighting’, *Lighting Research & Technology*, 4(1), pp. 21–26.

Walliman, N. (2011) *Research Methods: The Basics*. London: Routledge.

Ward, M. K. and Meade, A. W. (2023) ‘Dealing with Careless Responding in Survey Data: Prevention, Identification, and Recommended Best Practices’, *Annual review of psychology*, 74(1), pp. 577–596.

Warr, M. (1990) ‘Dangerous Situations: Social Context and Fear of Victimization’, *Social Forces*, 68(3), pp. 891–907.

Wei, L., Bizjak, G. and Kobav, M.B. (2024) ‘Evaluating the impact of road lighting on pedestrian reassurance through the day-dark approach’, *Lighting Research & Technology*. Online First DOI:10.1177/14771535241269699

Weijters, B., Cabooter, E. and Schillewaert, N. (2010) ‘The effect of rating scale format on response styles: The number of response categories and response category labels’, *International Journal of Research in Marketing*, 27(3), pp. 236–247.

Weiss, N. A. (2012) *Introductory statistics*. 10th ed. United Kingdom: Pearson Education.

Welsh, B. C. and Farrington, D. P. (2008) ‘Effects of Improved Street Lighting on Crime’, *Campbell Systematic Review*, 4(1), pp. 1–51.

Widdershoven, P. (2023) *The role of arousal on alertness and perceived safety of pedestrians*. Master

Wilcox, R. R. (2010). Fundamentals of modern statistical methods: Substantially improving power and accuracy (2nd ed.). New York: Springer.

de Winter, J. C. F., & Dodou, D., and Wieringa, P. A. (2009) ‘Exploratory factor analysis with small sample sizes’, *Multivariate Behavioral Research, 44*, pp. 147–181.

Wyant, B. R. (2008) ‘Multilevel Impacts of Perceived Incivilities and Perceptions of Crime Risk on Fear of Crime: Isolating Endogenous Impacts’, *The Journal of Research in Crime and Delinquency*, 45(1), pp. 39–64.

Yao, Q., Wang, H., Uttley, J. and Zhuang, X. (2018) ‘Illuminance reconstruction of road lighting in urban areas for efficient and healthy lighting performance evaluation’, *Applied Sciences*, 8(9), p. 1646.

Yun, H.Y. (2019) ‘Environmental factors associated with older adult's walking behaviors: A systematic review of quantitative studies’, *Sustainability*, 11(12), p. 3253.

Zwick, W. R. and Velicer, W. F. (1986) ‘Comparison of five rules for determining the number of components to retain’, *Psychological Bulletin*, 99, pp. 432– 442.

Zygmont, C. and Smith, M.R., (2014) ‘Robust factor analysis in the presence of normality violations, missing data, and outliers: Empirical questions and possible solutions’, *The Quantitative Methods for Psychology*, *10*(1), pp. 40–55.