Countering distractions to visual detection when driving after dark

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

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Abstract

On main roads, such as motorways and dual carriageways, road lighting is designed to meet the needs of drivers. Well-designed road lighting is intended to support visual performance and visual comfort after dark, and therefore this has been the dominant concentration of previous research. Less attention has been paid to the extent to which lighting can support driver attentiveness, a critical factor for driving since failure to give sufficient attention is a causal factor in many road traffic collisions. Therefore, this thesis reports further investigation of the extent to which light can be used to mitigate drivers' inattention. Two laboratory experiments were conducted to investigate how light can be utilized to counter driver inattention due to sleepiness or distraction.

Experiment 1 investigated the effect of lighting on sleepiness mitigation conducted after dark and three hours before habitual bedtime to simulate driving in the evening. This experiment assessed sleepiness under four lighting conditions with melanopic EDIs ranging from less than half lux to 10 lx. The results did not suggest a significant effect of lighting on sleepiness as measured by salivatory melatonin level, audio reaction time, skin temperature and self-reported sleepiness.

Experiment 2 investigated the visual and non-visual benefits of light in mitigating drivers' distraction using a scale model of a road scene containing three potential hazards: a road surface obstacle, vehicle lane change and a pedestrian. Participants' reaction time to and probability of detection were investigated in the presence of visual or acoustic distraction. The assumption in this experiment was that distraction negatively affects hazard detection, which can be mitigated by higher road surface luminance, in-vehicle short-wavelength blue light, and pedestrian-worn "aids to vision". The results indicate visual distraction impairs hazard detection while acoustic distraction does not. An increment in road surface luminance improved hazard detection but was not enough to overcome the negative impact of visual distraction. In-vehicle short-wavelength blue light improved cognitive performance of distraction tasks but did not transfer into hazard detection. Finally, a flashing LED light has been found to be superior to road lighting in mitigating visual distraction for pedestrian detection.

The findings from these experiments do not suggest that road lighting can be used to effectively mitigate driver sleepiness after dark. While concerns persist about the potential negative effects of road lighting on sleep health, the experimental result of this work did not find melatonin suppression even under the highest light level of current road lighting standards, suggesting no impact on drivers' sleep health. Furthermore, the results did not suggest that in-vehicle short-wavelength blue light mitigates the negative impact of distraction but may also exacerbate visual performance and hazard detection challenges. Future research should investigate potential ocular alterations and pupillary changes which might be induced by the installation of an in-vehicle light system.

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Chapter 1. Introduction: Lighting for Drivers

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1.1. Introduction

The focus of this thesis is lighting for driving. Driving typically involves sitting in the offside front seat of a motorized vehicle and utilizing a steering wheel and foot controls to operate the vehicle safely. It is a complex skill that requires hand and foot coordination to adapt speed and position in response to changes in the road (geometry, lane control, avoiding hazards on the road surface) and to deal with other road users (other motorized vehicles, cyclists, and pedestrians who may be on the carriageway or the pavement but are likely to enter the carriageway). It further requires giving attention to road signs and other relevant sources of information [Land, 2006].

In 2018, there were 1.35 million road traffic deaths globally [World Health Organization, 2018]. In Great Britain, in 2022, there were 153,158 road traffic collisions (RTC) casualties of all severities, including 25,945 severe injuries and 1,752 reported deaths (Table 1.1). The total value of prevention of these collisions is estimated over £43 billion [Department for Transport, 2024].

Table 1.1. Numbers of casualties by type and severity for road traffic crashes in Great Britain in 2022 [Department for Transport, 2023].

Road user	Level of injury	Number
All	Killed	1,752
	Seriously injured	25,945
	Slightly injured	125,461
Car Occupants	Killed	781
Pedestrians	Killed	376

Successfully driving a vehicle in traffic demands driver attention and allocation of significant cognitive resources [Hills, 1980]. However, inattentive drivers are frequently observed engaging in activities such as conversing with another passenger or using mobile phones. Inattention appears to be an inseparable part of everyday driving. Concerns arise from converging evidence linking inattention with impaired driving performance, which contradicts the UK Department for Transport's future aspirations for safer people, vehicles, and roads [Department for Transport, 2019]. While drivers are often blamed for inattention, the human ability to process information is limited, and some sources of inattention are inherent to driving itself, such as checking road signs and navigating routes.

Two primary light sources can help drivers' vision after dark, enabling them to see surrounding objects:

I. Vehicle headlights:
“A large, powerful light at the front of a vehicle, usually one of two” [Cambridge Dictionary, 2023], is used to illuminate the road in front of the vehicle, enabling hazard detection and early reactions.

II. Road lighting:
“A light in or at the side of a road or public area that is usually supported on a tall post” [Cambridge Dictionary, 2023], used primarily to improve safety by increasing the visibility of hazards and by reducing the effects of glare from other light sources (e.g., vehicle headlamps) in the visual environment [Bullough, 2016].

1.2. Road lighting in major roads

Road lighting is installed to offset impairments to vision after dark. Road lighting typically comprises a light source located a few metres above the ground surface at intervals of around 30 m. The light sources are located along the sides of the road or above the centre, either atop a lamp post or suspended by a cable. Figure 1.1 shows an example of road lighting.

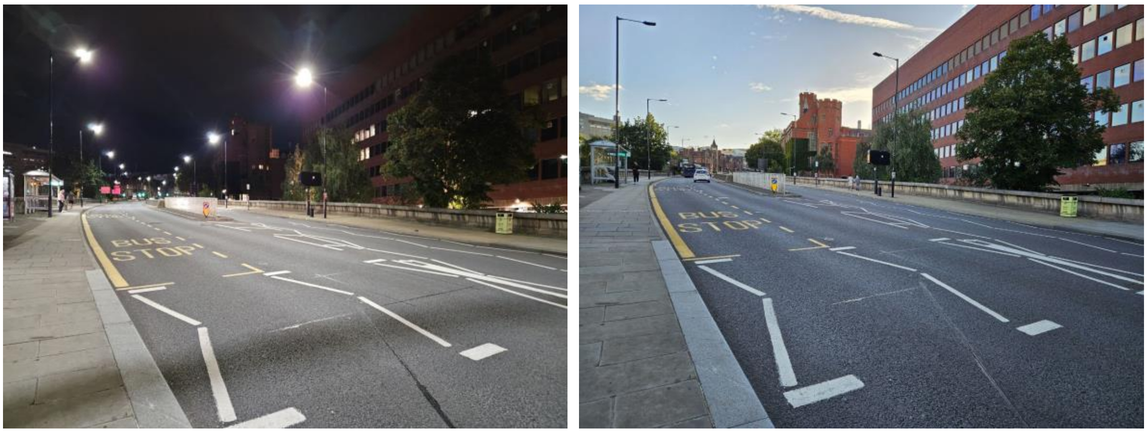


Figure 1.1. Example of road lighting on a main route (left after dark and right daytime), Sheffield, UK.

The three primary purposes of road lighting, as described by the International Commission on Illumination (CIE) [CIE 115-2010], are:

- *"To allow all road users, including operators of motor vehicles, motorcycles, pedal cycles, and animal-drawn vehicles to proceed safely".*
- *"To allow pedestrians to see hazards, orientate themselves, recognize other pedestrians, and give them a sense of security".*
- *"To improve the daytime and night-time appearance of the environment".*

Road lighting must be carefully designed because inadequate lighting is as adequate as or even worse than no lighting at all [Bullough et al., 2009; Van Bommel and Tekelenburg, 1986]. Poor lighting may cause overconfidence, increased speed and reduced concentration [Assum et al., 1999]. Well-designed road lighting should ensure visual performance and comfort while maintaining driver attentiveness [van Bommel, 2014]. Designers follow rules based on road lighting standards to ensure the lighting system is safe, effective, and aesthetically pleasing. These standards guide all aspects of road lighting design, including the type of luminaires, the mounting height and spacing, the illumination level required and other spectral power distribution (SPD) characteristics. The following section discusses the current road lighting standards.

1.3. Current road lighting standards

On main roads, such as motorways and dual carriageways, road lighting is designed to meet the needs of drivers [CIE 115:2010; BS5489-1, 2020]. For main roads, the recommended criteria for road lighting are known as the M-class [CIE 115:2010]. These define light quantity using luminance, with average luminance ranging from 0.3 to 2.0 cd/m^2 (Table 1.2).

Light levels vary across the lit surface due to the luminaire's optical properties and the lamp posts' height and spacing. The light level is determined for each node in an array across the lit surface, with the average being the mean average of these nodes. In the M class, this is controlled by setting minimum values of luminance uniformity throughout the installation's life, which depends on luminaire distribution, luminous flux, the installation's geometry, and the road surface's reflection properties [BS5489-1, 2020].

Table 1.2. Average light levels recommended for M-class [CIE 115:2010, BS EN 13201-2:2015].

Light class	Average luminance (cd/m^2)
M1	2.0
M2	1.5
M3	1.0
M4	0.75
M5	0.50
M6	0.30

British standard [BS5489-1, 2020] uses the following criteria to select between the lighting classes of Table 1.2:

I. Traffic speed, density, and composition (e.g., increased in luminance with higher traffic speed)
II. Task complexity
III. Ambient illuminance
IV. Risk assessment (local specific conditions, local custom and practice, and topography)

While there is evidence that increases in traffic speed and volume are associated with an increase in RTCs, the extent to which different conditions of road lighting offset such risks is not known: in other words, the class-selection factors are not well substantiated and do not appear to be founded in robust empirical evidence [Fotios and Gibbons, 2018, Fotios, 2020]. Moreover, the need to review standards is critical because of ongoing developments in road lighting technology and developments in the understanding of vision and unwanted side effects of road lighting [Fotios and Gibbons, 2018].

1.4. Aim of this thesis

Historically, research into the human-light interaction has focused primarily on the image-forming visual system, investigating the mechanisms underlying light perception and image formation. A recent paradigm shift in research occurred following the discovery of non-visual photoreceptors. These findings laid the groundwork for exploring the broader influence of light on human psychophysiology beyond visual perception – the non-image-forming (NIF) response. Light can modulate various physiological processes, including circadian rhythms, sleep, attention, fatigue, body temperature, neuroendocrine function, and mood. In recent years, there has been a growing interest in understanding methods utilizing light to counter sleepiness and cognitive impairment. For example, a meta-analysis by Figueiro et al. [Figueiro et al., 2017] underscored light's potential to induce a rapid acute attentional response, similar to caffeine consumption (for a comprehensive overview of visual and non-visual light impacts, refer to Chapter 2. Literature Review). These light-modulated responses to human performance offer the potential to develop research in traffic collision prevention and mitigation by targeting the mechanisms through which light influences driver attention.

In line with the United Nations resolution [United Nations General Assembly, 2021] to improve global road safety and reduce road traffic casualties by at least 50% by 2030, this thesis explored the potential of light to support drivers' attention, specifically addressing impairments caused by sleepiness and distraction.

1.5. Structure of the thesis

Chapter 2 presents a literature review, defining vision, the challenges of driving after dark, and the potential of light to overcome these challenges. It provides an overview of the visual and non-visual systems, exploring the challenges of nighttime driving, including the impact of driver sleepiness, distraction, and cognitive impairment on road safety. Chapter 2 concludes by examining the potential of road lighting as a countermeasure to address these issues and outlines the subsequent research hypotheses. Two experiments were conducted to investigate the potential of light to mitigate inattention induced by sleepiness and distraction.

Experiment 1 was conducted to investigate light as a mitigation to sleepiness: Chapter 3 describes the Experiment 1 method which assessed light as a mitigation to sleepiness. This chapter covers the development of independent variables (lighting condition, and posture), dependent variables (melatonin level, audio reaction time, self-reported sleepiness, and skin temperature), apparatus and laboratory setup, step-by-step experimental protocol, and sample demographics. Chapter 4 presents the results of Experiment 1 including data preparation (error cleaning and identifying representative values), distribution testing, statistical analysis and significant testing. Chapter 5 describes synthesis, evaluating the findings of Experiment 1 on the merit of supporting the proposed hypotheses, and questions the validity of the findings by comparing them with previous research. This chapter also discusses the limitations of Experiment 1 and makes suggestions for future research.

Experiment 2 was conducted to investigate light as a mitigation to distraction: Chapter 6 describes the Experiment 2 method which assessed light as a mitigation to distraction. This chapter covers the development of independent variables (lighting condition, distraction tasks and pedestrian model versions), dependent variables (hazard detection tasks, and distraction tasks performance), apparatus and laboratory setup, step-by-step experimental protocol, and sample demographics. Chapter 7 presents the results of Experiment 2 including data preparation (error cleaning, dealing with missing data, and identifying representative values), distribution testing, statistical analysis and significant testing.

Chapter 8 provides synthesis, evaluating the findings of Experiment 2 respectively on the merit of supporting the proposed hypotheses, and questions the validity of the findings by comparing them with previous research. This chapter also discusses the limitations of each experiment and makes suggestions for future research. Finally, the findings of this study and potential recommendations for lighting practice and application are concluded in Chapter 9.

Chapter 2. Literature Review

Chapter 2. Literature Review

2.1. Introduction

Chapter 1 introduces the aim of this study, which is safe driving after dark, as well as current road lighting standards and their limitations. Chapter 2 extends this by defining and reviewing the visual and non-visual systems, challenges of driving after dark, human cognitive performance, and its impairment due to sleepiness and distraction, which can lead to RTCs. This chapter then discusses road lighting in previous research and the potential of lighting as a countermeasure to inattention. The chapter concludes with the research hypotheses.

2.2. Visual and non-visual systems

This section describes the fundamentals of human vision. It discusses how light affects our perception and understanding of the environment through the visual system and how it could affect our daily life and activities beyond vision through non-visual systems.

2.2.1. Human vision

Vision is the ability to see [Cambridge Dictionary, 2023]. It is a complex process that involves the eyes, the optic nerve, and the brain. The eyes are spherical organs in the face used for seeing, with a diameter of about 2.5 cm [Tovée, 1996]. They collect light from the environment and convert it into electrical signals. The optic nerves are a group of nerve fibres (structures like threads) that pass signals from the retina at the back of each eye to the brain and serve as a bridge between the eyes and the brain [Willoughby et al., 2010]. Finally, the visual cortex, the primary cortical region of the brain, receives, integrates, and processes visual information relayed from the retinas and perceives the electrical signals collected from the environment [Huff et al., 2018]. As visual information travels through the brain, it becomes more processed and specialized, forming images. It is theorized that there are specialized cells or groups of cells that learn to respond to specific features of objects, allowing us to immediately recognize things we have seen before [Fournier et al., 2018].

Light is the brightness that comes from the sun, fire, etc., and from electrical devices that allow things to be seen [Cambridge Dictionary, 2023]. CIE defines light as radiation that is considered from the point of view of its ability to excite the visual system [CIE S 017:2020]. The captured light from the environment is focused onto the retina, a membrane situated inside the back of the eye that is sensitive to light stimuli [CIE S 017:2020], and the lens. When an image is focused on the retina, the light pattern must be converted into a neural signal that accurately represents that image. This transformation is carried out by the light-sensitive receptors in the retina, called photoreceptors [Tovée, 1996]. Photoreceptors absorb light and release electrical signals. There are three types of photoreceptors: rods, cones, and intrinsically photosensitive retinal ganglion cells (ipRGC). These photoreceptors each have different photopigments and shape the two main visual and non-visual systems. The visual system is responsible for visual responses to light (also known as image-forming responses). At the same time, the non-visual system is accountable for non-visual responses to light (also known as non-image-forming responses (NIF)) (Figure 2.1).

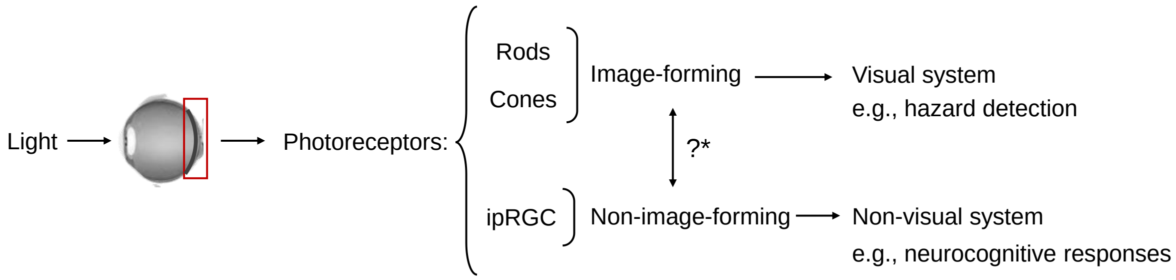


Figure 2.1. Visual and non-visual systems. The “?*” indicates a still-to-be-defined interrelation between image and non-image-forming systems, which requires further research.

2.2.2. Image-forming responses

There are three states of vision (photopic, mesopic, and scotopic), characterised by the dominant photoreceptor or the adaptation luminance (Table 2.1).

Table 2.1. Definitions of photopic, mesopic, and scotopic vision according to adaptation luminance and photoreceptor activity [CIE 191:2010].

State of vision	Photopic	Mesopic	Scotopic
Adaptation luminance (L)	> 5 cd/m^2	0.005 < L <5 cd/m^2	< 0.005 cd/m^2
Dominant photoreceptors	Cones	Cones and rods	Rods

Image-forming photoreceptors are the rods and the cones. All rods have the same photopigment (rhodopsin). Rods are dominant and responsible for vision under low lighting conditions, known as scotopic (< 0.005 cd/m^2). Cones, which include three types (short, medium, and long wavelength), each with different photopigments, are responsible for colour vision and vision under higher light levels of daylight (> 5 cd/m^2). Under mesopic vision ($0.005 < L < 5$ cd/m^2), both rods and cones are active, with each relative contribution depending on adaptation level and light source spectrum. As the light level reduces from the upper to lower boundaries of the mesopic range, the cone contribution decreases, and the rod contribution increases [CIE 191:2010].

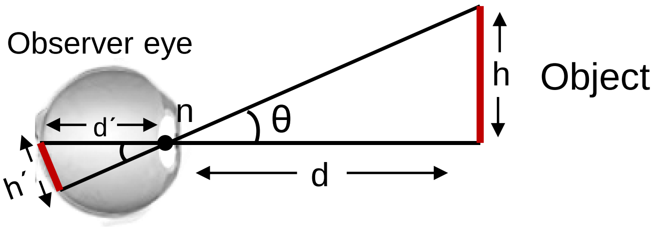
The cone photoreceptors are primarily positioned in and around an area of the retina called "fovea", a pit of approximately 2° diameter that contains only cones but no rods. When we deliberately fixate on an object, that object is projected onto the fovea, where the high density of cones permits high-resolution vision. With increasing distance from the fovea, the number of cone photoreceptors decreases sharply, and the number of rod photoreceptors increases with a maximum concentration of around 15° from the fixation point direction. This results in rods being the dominant receptor of peripheral vision. Humans use peripheral vision to scan the visual field to identify potential targets of interest. Then, if necessary, head and eyes will be moved toward the hazard so that the fovea (central vision) can be directed to that hazard for further inspection [Boyce, 2014].

Central vision in humans, empowered by cone photoreceptors, provides a colourful and sharp image due to the characteristics of cone photoreceptors and their individual nerve connection into magnocellular and parvocellular pathways, which in turn feed into the brain. On the other hand, most rods are interconnected, which means the signal sent into the brain toward rods loses some information and makes peripheral vision blurry rather than sharp [Tovée, 1996].

The visual system's capabilities, like other physiological systems, are limited. The extent to which the visual system can perform is defined as visual performance. Visual performance, the ability to see and process visual information, is a complex process that involves many different parts of the eye and brain. Visual performance while performing a task depends on [Boyce, 2014]:

I. Visual size
II. Luminance contrast,
III. Colour difference
IV. Retinal image quality
V. Retinal illuminance.

Visual size in degrees, which is the size of an object as it appears to the eye, is determined by the physical size of the object (actual size in the real world) relative to the distance of the object (how far is the object) from the observer [Konkle and Oliva, 2011]. Figure 2.2 shows an observer's eye looking at an object with a height of h. Visual angle (θ) is created by drawing rays from each side of the object into the nodal point (n). The continuation of these lines represents the image formed on the retina at the back of the eye. The nodal distance of the eye (d′) is constant (≈17 mm) [Katz and Kruger 2013]. Therefore, when an object is closer to the observer, it appears larger than when it is farther away, as the image created on the retina by closer objects takes up more space on the retina. Visual size is essential for our understanding of the world around us. It helps us judge the distance of objects and avoid obstacles. The larger the visual size of an object, the easier it is to see the details of that stimulus.



$$\tan\theta = \frac{h}{d} = \frac{h'}{d'}$$

Figure 2.2. Visual size in degrees of an observed object according to height and distance.

CIE defines luminance contrast (C) as “*quantity relating to the difference in luminance between two surfaces”* [CIE S 017:2020]. In other words, it is the object's luminance relative to its immediate background. Luminance contrast is measured using Equation 2.1. The higher the luminance contrast of an object, the easier it is to be detected [Boyce, 2014].

$$C = \frac{L_1 - L_2}{L_1}$$

Equation 2.1. Luminance contrast calculated from L_1 (object luminance) and L_2 (background luminance) [CIE S 017:2020].

An object's colour difference and appearance are related to the wavelength emitted by a specific light rather than its luminance. We can detect an object with zero luminance contrast as far as its colour differs from its background [Boyce, 2014].

Retinal image quality, the relative sharpness of a stimulus, can be measured by its spatial frequency distribution. High spatial frequencies signify a highly detailed, sharp image, while low frequencies characterize a blurry one. Both the characteristics of the object itself and the limitations of the visual system influence perceived sharpness. Light plays a slight effect on the sharpness of a stimulus. However, under the same luminance, short wavelength light, by producing smaller pupil sizes, could result in a better-quality retinal image as it provides a greater depth of field [Boyce, 2014].

Finally, retinal illuminance, which determines the state of eye adaptation, affects the visual system's performance by affecting the dominant photoreceptors and image processing. The visual system can process images under a wide range of luminance, from very dark (0.0001 cd/m^2) to very bright (20,000 cd/m^2). However, it cannot process information across this range all at once. The visual system constantly fine-tunes its sensitivity and accuracy to the amount of light available, becoming less sensitive and more discerning when there is plenty of light and more sensitive and less discerning when light is scarce [Boyce, 2014]. This process is known as “Adaptation”. The CIE defines it as: *“process by which the state of the visual system is modified by previous and present exposure to stimuli that can have various luminance values, spectral distributions and angular subtense”* [CIE S 017:2020].

Adaptation contains three mechanisms: change in pupil size, neural adaptation, and photochemical adaptation. The first two stages are fast and can be completed in less than a second. These mechanisms benefit more minor changes in retinal illumination (2 to 3 log units). However, more significant changes in retinal illumination would require the photochemical adaptation of cones and rods.

Cone photoreceptors are faster in adaptation than rods. It takes 10 to 12 minutes for cones to reach maximum sensitivity. Conversely, Rods may require 60 minutes or longer to achieve this [Boyce, 2014]. Therefore, in higher lighting conditions (photopic), the human eye adapts much faster than in lower lighting conditions (Scotopic).

As discussed, adaptation is not an immediate process. Therefore, a sudden change in luminance or contrast in luminance could cause glare. Glare is unpleasantly bright or strong light that usually occurs under a light source much brighter than its surroundings (e.g., oncoming vehicle headlights after dark). Glare can impair vision by reducing the ability to see details or objects. Until the visual system reaches complete adaptation, its capabilities are limited, and visual performance deteriorates [Boynton and Miller, 1963].

2.2.3. Non-image-forming responses

In addition to supporting image-forming responses, light exposure contributes to NIF responses [CIE S 026/E:2018]. NIF responses are mainly driven by ipRGCs' photoreceptors, with their photopigment known as melanopsin [Kumbalasiri and Provencio, 2005]. Melanopsin is highly sensitive to short-wavelength light [Berson, 2007], which is characterised by Melanopic Equivalent Daylight Illuminance (EDI), the circadian metric adopted by the CIE [CIE S 026/E:2018]. These photoreceptors feed signals directly to suprachiasmatic nuclei (SCN) in the brain, which serves as the central pacemaker, coordinating the timing of numerous physiological processes, ranging from cell division and hormone production to basic physiology and changes in behaviour [Boyce, 2014]. For example, light modulates circadian rhythm, sleep, attention, fatigue, body temperature, neuroendocrine function, neurocognitive responses, and mood [Vetter et al., 2021].

The circadian system and its rhythm are biological cycles associated with physical, mental, and behavioural changes throughout a day (24-hour) [Vitaterna et al., 2001]. The circadian system, which plays a crucial role in sleep regulation (circles of wakefulness and sleepiness), is essential for the body's systems to function properly. Insufficient or disrupted sleep significantly impairs vital daily functions such as memory consolidation and the assimilation of complex motor systems and affects the ability to perform everyday tasks properly and accurately [Reddy et al., 2018].

The circadian system is synchronized by the master clock, located in the SCN [Moore, 1997] and entrained to the 24-hour light-dark cycle via light exposure [Prayag et al., 2019].

The NIF responses to light are influenced by various factors, including intensity, duration, timing, temporal pattern, spatial distribution, light wavelengths, and prior light exposure history [Prayag et al., 2019]. Determining the exact impact of each factor is challenging due to the interrelatedness of these factors. For example, it has been shown that NIF responses can be obtained from lower levels of short-wavelength light compared to other tested wavelengths, and prior light history has been shown to affect these responses by decreasing or increasing photic sensitivity of neurons in the SCN [Vetter et al., 2021].

Regarding intensity, *"density of photon flux with respect to solid angle in a specified direction"* [CIE S 017:2020], there are two crucial dose-response boundaries: 'threshold' and 'maximum response'. The 'threshold' represents the intensity at which a noticeable change in NIF responses is induced. The 'maximum response' is the intensity of light at which saturation is achieved [Vetter et al., 2021].

Previous work has demonstrated a non-linear relationship between intensity and NIF responses, with a steep increase in these responses as intensity increases until reaching a saturation point where further increases in light intensity do not further increase NIF responses [Vetter et al., 2021]. Half saturation (ED_{50}) has been shown to be obtained from the range 3.47×10^{13} to 1.0×10^{14} (photons $cm^{-2}s^{-1}$), depending on the level of pupil dilation [Vetter et al., 2021].

Photic exposure duration was shown to have a non-linear relationship with intensity, where shorter durations of exposure were found to be more effective in inducing NIF responses per minute of exposure than longer durations [Vetter et al., 2021].

The timing of photic administration, in other words, when the lighting exposure occurs throughout the day, is of importance. More significant effects on NIF responses were noticed during the biological night. However, further studies must be conducted to investigate these effects during daylight [Vetter et al., 2021].

Regarding wavelength, both short and long wavelengths have been shown to induce NIF responses [Phipps-Nelson et al., 2009]. These responses were found to be positively correlated with melatonin suppression when exposed to short-wavelength blue light (peak sensitivity at around 460 nm) [Cajochen et al., 2000]. However, melatonin suppression is not the only mechanism underlying light-induced NIF responses. Daytime exposure to light (melatonin levels are undetectable) has also been found to be effective [Rahman et al., 2014], and exposure to red light (630 nm), with no impact on melatonin levels, has also been shown to induce NIF responses as identified by self-reports and changes in EEG spectrum [Plitnick et al., 2010; Papamichael et al., 2012].

To summarize, NIF responses induced by light are embodied in complex physical, physiological, and psychological routes [Lin et al., 2020], and the exact pathways by which light influences these responses are not yet thoroughly known [Boyce, 2014]. Further research is needed to determine the optimal NIF responses and to explore the exact underlying mechanisms.

The following section explores the importance of vision for drivers after dark. It discusses the challenges that may arise due to limitations of human vision while driving in low-light conditions after dark.

2.3. Driving after dark

Vision plays a key role for drivers. Among the traditional five primary human senses (vision, hearing, smell, taste, and tactile kinaesthetic (touch, movement, and doing)), vehicles are designed to filter out these primary human senses. The vehicle cabin (e.g., steel, glass, etc.) blocks out most odours and tastes (filter of smell and taste senses), the suspension system absorbs bumps and vibrations (reduces tactile and kinaesthetic sensation), and hearing sense is attenuated by noise barriers. However, light for vision is only slightly limited by passing through the windshield.

A reliable claim, supported by evidence, would emphasize the critical importance of visual information and give some importance to kinesthetic and auditory sensory input for driving [Sivak, 1996]. Whatever the exact figure is, undoubtedly, vision plays a key role for drivers.

The key visual tasks for drivers include scanning and monitoring the road ahead for potential hazards, identifying and recognizing motions and objects on and aside the road, lane control, reading traffic signs, and estimating distance and speed. In summary, a driver's task is to extract information from the environment, make decisions, and take action [Boyce, 2014].

While driving, visual stimulus changes rapidly and unexpectedly, making it crucial for drivers to recognize and anticipate potential hazards quickly [Durso et al., 2007]. These hazards must first be detected by peripheral vision (visual field that extends beyond the central four to five degree of gaze [Larson and Loschky, 2009]), which then redirects central vision toward that hazard, enabling the capture and processing of detailed information necessary for appropriate reactions [Crundall et al., 1999]. As a result, drivers relied on their peripheral vision as an initial source of information, highlighting the reliance of drivers' visual performance on rod photoreceptors. Moreover, drivers' reliance on rod photoreceptors for visual responses increases further in the hours of darkness with reduced surrounding luminance.

The mentioned reliance of drivers' visual system on rod photoreceptors after dark could affect the key visual tasks of drivers due to the limitation on rod photoreceptors' capabilities discussed in section 2.2, including lower resolution and no colour discrimination. Poor performance on these key visual tasks after dark might increase the risk of being involved in an RTC. This could be the result of decreased visibility, difficulty with colour and contrast in poor light (affecting drivers' ability to perform critical reactions to detect hazards while driving), poor detectability of vulnerable road users, especially in dark clothing, and difficulty with speed and distance judgment [Royal Society for the Prevention of Accidents, 2017]. Table 2.2 summarises visual challenges after dark with the decrement of luminance from photopic toward mesopic and scotopic ranges according to previous studies.

These challenges tend to get worse with ageing because of normal changes in the structure of visual system including deteriorating visual acuity, contrast sensitivity, colour discrimination, visual field size, etc. [Boyce, 2014]. As a result, ageing could lead to reduced driving performance and safety, particularly when performing manoeuvres in which visibility is restricted, such as detecting and avoiding low-contrast road hazards after dark [Boyce, 2014].

Surprisingly, it is not uncommon for drivers to misjudge these visual challenges after dark and fail to compensate for these limitations [Owens et al., 2007]. For instance, reducing driving speed after dark could decrease the likelihood and severity of an RTC caused by poor visibility [Leibowitz et al., 1998]. Nevertheless, previous studies have demonstrated that drivers do not typically reduce their speed after dark [e.g., Jägerbrand and Sjöbergh, 2016]. Even when they do so, the reduction is often insufficient to offset the impaired visual performance in low-lighting conditions [Owens et al., 2007]. In other words, drivers generally do not tend to notice the gradual decline in their vision while driving.

Table 2.2. Visual challenges after dark from photopic luminance to mesopic and scotopic luminance.

Visual challenge	**Reference**
Increased reaction time	Walkey et al., 2006; He et al., 1997
Increased search time	Walkey et al., 2006
Decreased visual acuity of central vision	Sturr et al., 1990
Decreased visual acuity of peripheral vision	Bedell, 1987
Decreased contrast sensitivity	Wood and Alfred, 2005
Impaired motion perception	Gegenfurtner et al., 1999, Yoshimoto et al., 2016
Impaired motion direction judgment	Takeuchi et al., 2001
Decreased velocity perception	Gegenfurtner et al., 2000
Errors in distance and depth estimation	Bourdy et al., 1991
Reduced colour vision and hue perception	Zele and Cao, 2015; Pokorny et al., 2006

Considering the limitations of vision after dark and the reasons they might impair driving performance, the following section (section 2.4) discusses the other main factor that impairs driving performance: Inattention. The section argues the fundamentals of driver attention and the factors affecting this.

2.4. Inattention

Attention is the state of watching, listening to, or thinking about something carefully or with interest [Cambridge Dictionary, 2023]. Attention refers to the operation of selection mechanisms in the brain and how those are involved in processes of decision-making and consciousness [Chun et al., 2011].

Studies on attention, commonly consider four dimensions based on two factors for attention [Nideffer, 1976]:

I. Width, which concerns how wide (awareness) or narrow (focus) the attention is.
II. Direction, which concerns whether the attention is sourced externally (environmental) or internally (thoughts and feelings).

Accordingly, proper task performance depends on using the attentional processing of the most important cues, which can differ greatly depending on the task nature itself. For instance, planning and analysis might benefit from a broad-internal attentional mode, allowing the consideration of various possibilities. In contrast, efficiently scanning your surroundings requires a broad-external attentional mode. Alternatively, specific tasks might demand a narrow and intense focus on certain stimuli, leaving everything else temporarily out of your awareness [Nideffer, 2021].

Driving a vehicle is a complex task that requires drivers' attention, specifically visual attention. Visual information plays a crucial role in driver decision-making [Sivak, 1996]. This is further supported by research showing that road traffic crashes (RTCs) can often occur when drivers fail to attend to critical visual cues at the appropriate time [Victor et al., 2015]. Drivers constantly scan the environment, taking in information from various points: the road ahead for potential hazards, the sides for pedestrians and cyclists, and lane markings to keep the vehicle within a lane and safe distance of the vehicles ahead. On top of this, they need to maintain control of the vehicle, adhere to traffic regulations, and interpret signs and signals. Navigation adds another layer, requiring occasional glances at guiding signs or in-vehicle displays. Furthermore, manoeuvrers like lane changes, turns, and avoiding obstacles all necessitate shifting our gaze to different areas around the visual field [Kotseruba and Tsotsos, 2021]. In addition to the demands of the driving task and occurrence of unexpected events in the road environment, a driver's visual attention is also influenced by their physical and emotional state, which can impact their overall driving skills and susceptibility to distractions [Kotseruba and Tsotsos, 2021].

Drivers’ visual attention can be categorized into overt, covert and divided attention. Overt attention refers to movement of the eye to bring new targets into the central visual field. Covert attention enables planning future eye movement and refers to changing the focus of attention without explicit gaze change. Finally, divided attention argues the theory that while attentional resources are limited, drivers are often required to divide their attention between several tasks (e.g., steering, adjusting gear, reading road signs, etc.) and performance can be worsened when these tasks compete for the same resources [Recarte et al., 2000]. Dividing and diverting attention may result in a phenomenon known as inattention blindness and result in failure to notice an event or object. For example, previous research suggests that divided or diverted attention while driving, especially on familiar roads, leads to drivers missing crucial visual cues like road signs [Charlton and Starkey, 2013], and failing to see hazards because of conversing with a passenger [White and Caird, 2010].

Visual attention and changes in gaze location are controlled by attentional control mechanisms which are divided into the bottom-up and top-down [Yantis, 2016]. Bottom-up is a process that is guided primarily by the properties of the scene and depends on the saliency of objects which attract gaze, unlike featureless areas [Treisman and Gelade, 1980; Itti et al., 1998]. On the other hand, top-down attention is driven by the demands of the task at hand [Yarbus and Yarbus, 1967]. In other words, even salient stimuli may fail to attract attention if they are irrelevant to the task.

Inattention, failure to give attention [Cambridge Dictionary, 2023], while driving is defined as *"insufficient or no attention to activities critical for safe driving"* [Regan et al., 2011] (e.g., mobile phone conversation). Regan et al., 2011 classified different mechanisms that could cause driver inattention into five main categories:

I. Driver Restricted Attention (DRA):
   Biological factors (e.g., saccades, sleepiness, microsleeps, and blinks) that physically prevent drivers from attending to activities critical for safe driving (e.g., closing the eye while sneezing and microsleeps while driving).
II. Driver Misprioritised Attention (DMPA):
   Mis/prioritizing between activities that are equally (or almost equally) critical for safe driving (e.g., a driver is trying to avoid a pedestrian and fails to see a merging car).
III. Driver Neglected Attention (DNA):
   Faulty expectations of a driving scene (e.g., approaching a signalized intersection with the right of way and ignoring to check for conflicting redlight runner vehicles).
IV. Driver Cursory attention (DCA):
   Careless and rushed attention (e.g., taking over without checking the rear-view or wing mirror).
V. Driver Diverted Attention (DDA):
   Equivalent to "distraction", defined as *"diversion of attention away from activities critical for safe driving toward a competing activity"* [Regan et al., 2008].

The current thesis focuses on utilizing light-based responses (visual and non-visual) to mitigate sleepiness, a type of driver restricted attention, and distraction (driver diverted attention). Both factors lead to increased cognitive workload and impaired driver cognitive performance, consequently reducing the likelihood of safe driving. A conceptual framework illustrating how light-based responses (visual and non-visual) can influence driving performance is summarized in Figure 2.3.

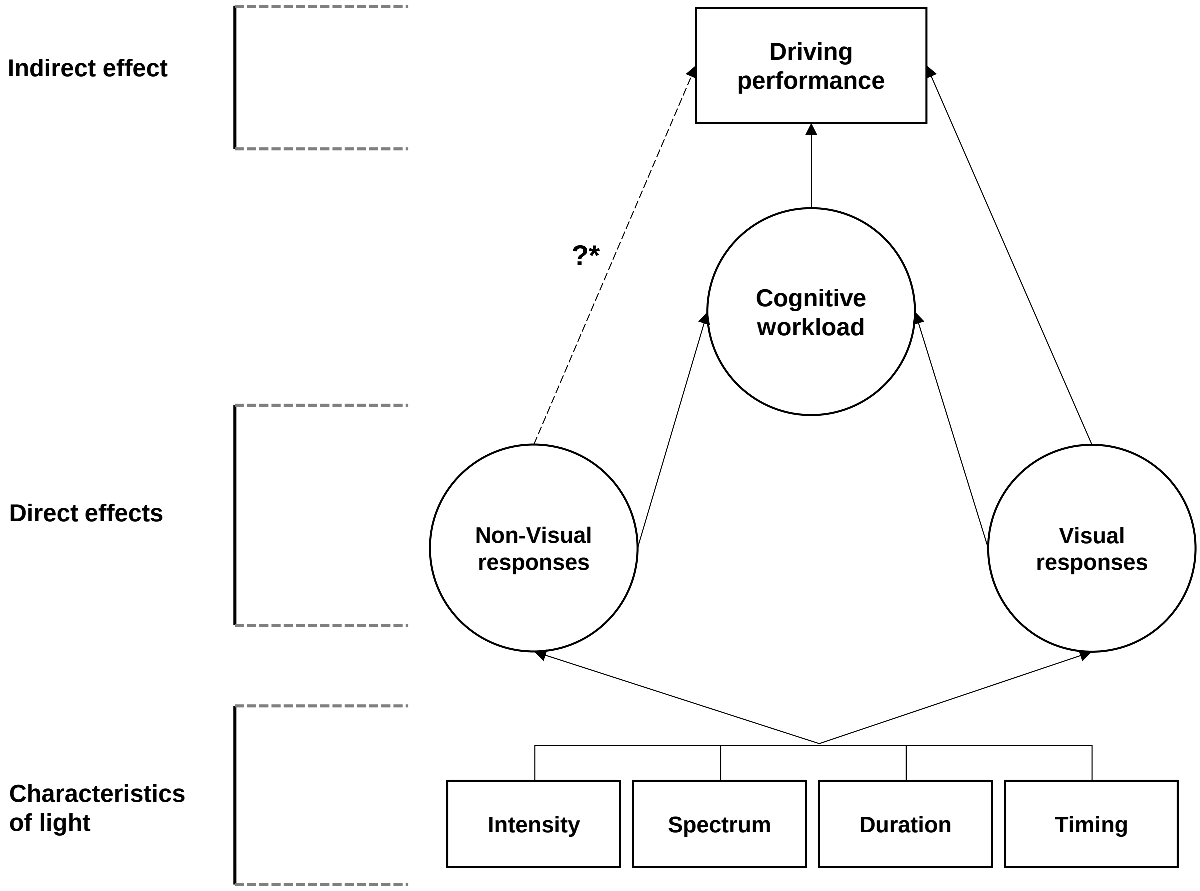


Figure 2.3. Conceptual framework of how responses to light (visual and non-visual) can be measured. The "?*" indicates a still-to-be-defined interrelation between image and non-image-forming systems, which requires further research.

The subsequent sections argue cognitive workload, exploring its relationship to restricted and diverted attention. The methodologies employed to measure cognitive workload are detailed, followed by their critical role in ensuring road safety.

2.5. Cognitive workload

Cognitive workload is the dynamic interplay between resources required to perform a task and an operator's ability to supply those resources [Young et al., 2015]. In other words, it is the physiological response to the interplay between cognitive capacity and task complexity [Oviatt et al., 2018]. Within this context, workload is the amount of information processing resources employed per unit of time for task execution [Wickens et al., 2021].

The concept of cognitive workload is something that people can relate to; however, it is not clear if all people have the same exact meaning for it. As a concept, it is fairly understood, but it is not always clear if everybody has the same exact meaning in mind. Frequently, task difficulty is equated with mental workload, which serves as a reasonable representation given the inherent subjectivity of difficulty. Infect, like physical workload, cognitive workload depends on both the task and the individual. In other words, mental workload can vary significantly between people and even for the same person at different times [de Waard and Van Nes, 2021].

The concept of quantifying cognitive workload likely stems from its analogy to physical workload. In a physical task, workload is readily defined by the force required to move an object. However, defining cognitive workload is not quite the same. While information processing demands (e.g., number of calculations needed to solve a mathematical problem) offer a starting point for quantification, individual capacity for such operations remains crucial. This applies to physical workload as well; a 60kg weight is easier to be lifted by a physically fit person than a small child. Nevertheless, physical workload tends to focus on task demands, while cognitive workload acknowledges the interaction between task demands and individual capacity (mental resources). Mental resources, further linked to operator state (background state of an individual), are subject to both inter- and intra-individual variability. A novice may find a task demanding significant resources, while an experienced person finds it effortless. Similarly, a bad night's sleep can elevate the perceived difficulty of a routine task. This highlights another key concept: effort. Effort, a voluntary process akin to exerting extra mental force, can maintain performance despite increased internal costs (energy expenditure). Two types of effort exist: computational (task-related) effort to address heightened task demands; and compensatory (state-related) effort to offset a deteriorated state [de Waard and Van Nes, 2021].

Successful task performance necessitates cognitive control, which enables an individual to focus on the current task while suppressing irrelevant stimuli [Miller and Cohen, 2001]. Cognitive control is a brain function primarily subserved by the prefrontal cortex [Miller and Cohen, 2001], which comprises three core components [Miyake et al., 2000]:

I. Inhibition:

Crucial function in preventing interference with ongoing tasks by employing cognitive inhibition (limiting thoughts), selective attention (focusing on relevant features by suppressing irrelevant ones), and response inhibition (inhibiting unwanted actions).

II. Working memory:

The simultaneous cognitive processes of information retention and manipulation create a dynamic framework for effectively integrating new data while maintaining goal-directed focus.

III. Cognitive flexibility:

Ability to shift from one mental set to another.

These components are linked together. For example, inhibitory control removes irrelevant thoughts and frees up the mental workspace for working memory operation [Diamond, 2013].

Previous research has demonstrated that mental activities share the same resources [Ryu and Myung, 2005]. Moreover, individual working memory has a limited capacity [Wickens, 1987], restricting the ability to process all information simultaneously.

Cognitive control is mediated by task demands, external support, and experience [Karwowski, 2006]. Suboptimal cognitive control can stem from cognitive overload or underload, which can lead to slow and impaired performance [McKendrick et al., 2019]. Cognitive overload, or task saturation, is associated with a decline in overall performance, particularly for tasks that share cognitive resources [Young et al., 2015]. Conversely, cognitive underload, an elusive yet detrimental state, adversely affects performance to an extent comparable to cognitive overload. This state often goes unnoticed, rendering it even more insidious than cognitive overload [Hancock et al., 1995].

The following section delves into the fundamental relationship between cognitive workload and driving, exploring the potential impact of driving complexity, sleepiness, and distraction on cognitive performance impairment.

2.6. Cognitive workload and driving

Driving is a cognitively demanding task that imposes a significant cognitive workload. Drivers must continuously monitor the road environment, make split-second decisions about speed and direction, and maintain precise control over the vehicle. Additionally, drivers must remain attentive and prepared to respond to unexpected events, such as sudden manoeuvres by other drivers or pedestrians crossing the road.

2.6.1. Fundamentals

Driving, the human-machine system environment [Paxion et al., 2014], contains a hierarchy of tasks on three levels [Michon, 1985]:

I. Strategic and constitutes the decision-making (e.g., choosing to follow a route)
II. Tactical which includes reaction or manoeuvres faced to the situation (e.g., response to other driver manoeuvres to follow the road)
III. Operational which concerns vehicle control (e.g., managing the trajectory)

Drivers process the mentioned information and respond accordingly, either automatically or through a more controlled mechanism. Controlled processing demands greater cognitive resources than automatic processing. Automatic responses, developed through repeated exposure to consistent stimulus-response mapping, are generally effortless and unconscious. Controlled processing is necessary for handling novel, non-routine, or inherently challenging tasks that require attentional effort, drawing upon executive cognitive functions such as working memory [Schneider and Shiffrin, 1977]. Driver information processing depends on the task complexity and the driver's experience. For instance, decision-making typically involves a high level of controlled processing, while maintaining the vehicle on a specific path is primarily an automatic task [Paxion et al., 2014].

Obtaining most of the information crucial for safe driving necessitates engagement with the immediate physical environment. Therefore, successfully driving a vehicle in traffic demands a significant allocation of driver attention and cognitive resources [Hills, 1980]. Within a naturalistic driving setting, attention selection stems from a dynamic interplay between four overarching modes of attention [Trick and Enns, 2009]:

I. Reflex (automatic)
II. Habit (automatic)
III. Exploration (controlled)
IV. Deliberation (controlled)

Reflexes generally involve less complex automatic responses, such as visual orienting towards the sudden appearance of a braking lead vehicle. In contrast, habit encompasses more intricate goal-directed behaviours that become effortless and unconscious through practice (e.g., vehicle lateral and longitudinal control). Exploration refers to the actively controlled investigation of surrounding events without a specific goal, such as scanning for potentially interesting roadside objects. Finally, deliberation occurs in challenging or novel conditions that demand momentary planning and flexible adaptation of different strategies (e.g., negotiating a complex intersection) [Trick and Enns, 2009].

Attention, a crucial factor for determining driving safety [Patten et al., 2004], is directly linked to the varying levels of driver cognitive workload [Wickens et al., 2021]. For instance, allocating attention to a task that demands high perceptual processing can significantly reduce the ability to detect peripheral stimuli [Lavie, 2005; Lavie and Fockert, 2006]. This impairment in peripheral detection could lead to the failure to detect salient stimuli appearing right before the driver's eyes [Simons and Chabris, 1999], a phenomenon known as "looked but failed to see", where victims claimed to have looked in the direction of the colliding object, but without consciously perceiving it [Brown, 2005].

Cognitive workload while driving can be affected by:

I. Driving complexity
II. Sleepiness (The circadian rhythm and sleep homeostasis)
III. Distraction (e.g., talking on the phone)

2.6.2. Driving complexity

Driving complexity is defined by the characteristics of the traffic situations and the demands they place on driver's information processing and vehicle handling capabilities [Patten et al., 2004]. Consequently, it is influenced by both driver's experience and situational complexity. The cognitive control hypothesis suggests that the impact of cognitive workload on driving will vary greatly between drivers. This is because individual driving history shapes a driver's "automatic toolbox" of responses to common situations. In general, novice drivers will likely struggle more with driving complexity under a high workload compared to experienced drivers. However, experience is not just about the amount of time spent driving. The type of experience matters too. Factors like typical road layouts and cultural norms influence the kinds of automatic behaviours a driver develops. Interestingly, even experiences outside of driving might play a role. For example, basic steering skills learned from walking, cycling, or toy cars could influence how someone later acquires automatic driving skills [Engström et al., 2017].

Theoretical models in human behaviour argue that training and practice result in a transition from knowledge or rule-based levels toward the skill-based level [Rasmussen, 1987]. These models suggest that how quickly drivers learn automatic skills depends on two things: how often they encounter a task, and how predictable the task is. Simple tasks done often, like staying in your lane, become automatic faster. Trickier tasks done less often, like scanning intersections, take much longer to learn. This means the effect of cognitive workload on driving will depend heavily on the specific task. For instance, keeping in your lane might be automatic even for new drivers, while scanning intersections might not be [Engström et al., 2017].

Experience level could modulate the mode of information processing (controlled vs. automatic) where novice drivers have a low level of task automation [Patten et al., 2006]. Novice drivers would experience higher levels of cognitive workload when operating machine systems [Wickens et al., 2021], especially under demanding situations and in terms of visual search patterns [Chapman et al., 2002].

Novice drivers frequently make incorrect assessments and tend to implement compensatory strategies (e.g., reduction of speed, taking a break) when it is too late [De Craen et al., 2008]. This group tends to overestimate their ability and underestimate the risk they are taking [McKenna, 1993].

On the other hand, experienced drivers demonstrate superior scene memory recall compared to novice drivers, due to the expansion of information sampling scope within the immediate traffic environment, encompassing a wider range of spatial locations [Underwood et al., 2003]. Moreover, experience helps drivers to adapt their strategy appropriately by increasing their horizontal search [Patten et al., 2006]. Experience allows drivers to process more information and consequently maintain a reasonable level of performance even under conditions of high cognitive workload [Paxion et al., 2014]. However, the exact relationship between cognitive workload, experience, and task difficulty has not been fully explored yet, and that is a great area for future research [Engström et al., 2017].

To sum up, increased driving experience reduces the cognitive workload associated with driving tasks, allowing drivers to allocate more attentional resources to other tasks or operations under complex situations [Patten et al., 2006].

Complexity while driving is influenced by several factors, including road design, layout, and traffic flow. Additionally, hazardous events, such as unexpected pedestrians crossing the road directly in front of the car, can introduce high temporal pressure for reaction, further increasing the complexity of driving situations and decision-making [Paxion et al., 2014]. Consequently, situation complexity can be categorized into four main types [Patten et al., 2004]:

I. High demand for both information processing and vehicle handling (e.g., driving in a crowded city centre)
II. High demand for information processing and low demand for vehicle handling (e.g., intersections regulated by road signs when the driver has the right of way)
III. Low demands on information processing and high demand on vehicle handling (e.g., driving on curvy rural roads)
IV. Low demand for information processing and low demand for vehicle handling (e.g., driving in a motorway)

Low-complexity (e.g., highways) and high-complexity situations (e.g., urban areas) can induce poor cognitive control, leading to increased cognitive workload and impaired driver performance. The extent of this cognitive impairment is nuanced by driving experience. Therefore, the same driving situations can elicit lower or higher mental workloads depending on the driver's experience level [Paxion et al., 2014].

Under low-demanding situations (monotonous environments), the driving task primarily focuses on trajectory maintenance, with information processing occurring automatically. Low-demanding situations can lead to a decrease in alertness and situational awareness. As a result, maintaining attention while driving under such conditions requires greater effort [Paxion et al., 2014]. Prolonged driving in monotonous environments causes a steady decline in vigilance. Drivers often fail to recognize this decline in their attention [Schmidt et al., 2009].

Driving in monotonous situations can have a more pronounced impact on experienced drivers as the skills acquired through practice reduce their mental workload [Patten et al., 2006]. Consequently, under monotonous conditions, the cognitive workload of experienced drivers can drop significantly [Schneider and Shiffrin, 1977], and therefore, automatic processing induced by the driving task should be more observed for experienced drivers than for novice ones [Paxion et al., 2014].

On the other hand, high-complexity situations, such as manoeuvring at a crowded intersection after dark, require specific strategies and manoeuvres [Michon, 1985], necessitating more controlled information processing. These situations pose a greater challenge for novice drivers as experienced drivers can leverage their experience to anticipate and plan accordingly, a crucial ability for efficient decision-making, especially under complex situations. This ability is called cognitive readiness [Cegarra and van Wezel, 2012].

2.6.3. Sleepiness

Sleepiness is tiredness and wanting to sleep [Cambridge Dictionary, 2023]. It can result from various factors, including sleep disorders [Ellen et al., 2006], behavioural issues such as sleep deprivation [Carter et al., 2003], and engagement in shift work [Drake et al, 2004]. Sleepiness is derived from circadian rhythm and sleep homeostasis.

Circadian rhythm, influenced by the light-dark cycle, is a 24-hour biological clock that regulates various physiological processes, including sleep-wake cycles, body temperature fluctuations, and cognitive functions [Rogers et al., 2003]. On the other hand, sleep homeostasis is a regulatory mechanism corresponding to sleep pressure and periods of wakefulness. As sleep homeostasis increases, attentiveness declines and sleepiness levels rise [Maire et al., 2013].

The ability to maintain optimal attention and vigilance fluctuates throughout the day. It typically diminishes during prolonged driving at non-optimal times [Rodríguez-Morilla et al., 2017], with the most significant impairment observed after midnight (2 am), in the early morning (6 am), and early afternoon (2 pm) [Lenné et al., 1997].

Working memory, a crucial component of cognitive control, is significantly impaired by sleepiness [Chengyang et al., 2017]. The cumulative effects of sleep deprivation can severely disrupt cognitive functions and impair behaviour [Jarraya et al., 2013]. Furthermore, sleepiness can potentially diminish an individual's visual processing ability [Chee, 2015]. Sleepiness at the wheel, characterized by the inability to maintain attention, can significantly interfere with driving skills and has been linked to an increased risk of RTCs [Bioulac et al., 2017]. Additionally, sleepiness can impair neurobehavioral performance [Roehrs et al., 2003], which ultimately reduces the driver's ability to operate a motor vehicle safely [Powel et al., 2001; Lee et al., 2016].

2.6.4. Distraction

Driving is a complex and demanding task requiring visual and cognitive attention. The lack of drivers' focused attention on the primary task (driving) puts them at risk of slow and less appropriate responses to road changes that demand full attention [Anttila and Luoma, 2005].

Driver distraction, engagement in activities not critical for safe driving, is a form of driver inattention [Engström et al., 2013]. Drivers tend to participate in tasks that are not primarily relevant to the driving task, which results in a diversion of attention that would otherwise be needed for driving safely [Patten et al., 2006].

Two prominent theoretical frameworks within cognitive psychology argue around driver distraction: resource-based models and dynamic attention models. The former perspective posits that attention is a limited pool of cognitive resources that can be depleted by competing demands. Distraction, in this view, arises from a situation where the combined demands of the driving task and the distracting activity exceed the driver's available resources, leading to performance decrements. While resource-based models have provided a valuable foundation for understanding distraction, they may not fully capture the complex dynamics of attention allocation in real-world driving scenarios. On the other hand, dynamic attention models, define distraction within a framework which breakdowns in interruption management and makes it a critical contributor to driver distraction. This framework reconceptualizes distraction as a consequence of failures in three core executive functions: task timing, task switching, and task prioritization. These failures disrupt the efficient allocation of attentional resources between the driving task and secondary tasks. Furthermore, distraction dynamics acknowledges disengagement from driving, such as mind wandering, as a substantial challenge. Distractive tasks can either exacerbate or potentially mitigate this disengagement, depending on the specific demands of both the driving task and the distraction task [Lee, 2014].

Distractive activities while driving could be related to something (a task, object, or person) both inside and outside the vehicle, including texting, eating, and drinking, looking at billboards, conversing on the mobile phone or with passenger, and interacting with the onboard system (e.g., navigation devices) [Engström et al., 2017]. However, checking your mirrors before passing or scanning an intersection is still important for safe driving and may not be considered a distraction.

There are three main types of distractions drivers can face:

I. Visual: These distractions take your eyes off the road, like looking at a phone or a billboard.
II. Manual: These distractions take your hands off the wheel, like eating or adjusting the radio.
III. Cognitive: These distractions take your mind off driving entirely, like having a deep conversation on a hands-free phone ("mind off road").

Majority of activities while driving involve a mix of these. The first two types refer to modality-specific interference in the perceptual and motor processes. In contrast, cognitive distraction encompasses a broader phenomenon of attentional disengagement from the driving task [Victor, 2005] and diversion of attention toward a competing activity [Regan et al., 2013], which can result in decrement in mental concentration [Anderson & Crawford, 1980]. Cognitive distraction refers to anything that pulls your attention away from driving, like a phone call or even daydreaming (mind wandering) [Lee et al., 2009; Martens & Brouwer, 2013].

Driver distraction poses a significant challenge due to the limitation of human attentional resources and the brain's tendency to prioritize specific tasks over others [Patten et al., 2006]. Notably, driver reaction time does not immediately return to the baseline levels after engaging in a secondary (distractive) task [Winzer et al., 2017]. Reestablishing driver focus can take up to 27 and 15 seconds for high and moderate distractions, respectively [Strayer et al., 2015, 2017]. Furthermore, while engaged in a secondary task, drivers often struggle to accurately assess their driving performance [Horrey et al., 2008], leading to underestimating the risks associated with their actions. Regardless of these challenges, drivers engage in distractive activities due to motivations for distraction.

A process-based approach to driver distraction necessitates examining the factors that motivate and influence engagement in distractive tasks, alongside the factors that lead to disengagement from the primary driving task. In this context, Fuller's [Fuller, 1991] concept of "safety traps" provides a valuable framework for understanding the dynamics of driver distraction and the self-regulation process [Lee, 2014].

The concept of safety traps describes three distinct scenarios that can lead drivers to disengage from the primary driving task and engage in distractive tasks [Lee, 2014]:

I. Contingency Traps: These traps arise when drivers fail to adequately monitor the driving environment due to poorly perceived hazards or low roadway demands. Novice drivers are particularly susceptible to contingency traps due to their limited experience in identifying potential threats [Fisher et al., 2006]. This is particularly relevant for novice drivers who may underestimate the risks associated with distraction. Previous work reported that a significantly higher proportion of (approximately 32%) young adult drivers (18-24 years old) compared to older adults (>25 years old) overestimated their ability to safely divert visual attention away from the roadway for extended durations (3-10 seconds) [Tison et al., 2011].

II. Consequence Traps: These traps occur when drivers are aware of driving demands but choose to prioritize secondary tasks. This prioritization can be driven by the perceived rewards associated with the secondary task (e.g., gratification from using infotainment) outweighing the anticipated consequences of neglecting the road. Seo & Torabi [Seo & Torabi, 2004] surveyed 1,291 college students and found that among those who drove and owned mobile phones (87%), a high number (86%) admitted to using their phones at least occasionally while driving. Worryingly, the study linked mobile phone use to potentially unsafe driving behaviours. Participants reported over 750 crashes or near-crashes, with 21% attributed to mobile phone use. These findings align with those of Pöysti et al. [Pöysti et al, 2005] who identified a link between younger driver age and increased mobile phone use behind the wheel. Their study also suggested a connection between phone use and experiencing dangerous situations on the road for younger drivers compared to more experienced ones. Finally, Olsen et al. [Olsen et al., 2005] investigated motivations for driver distraction with in-vehicle infotainment systems. Their findings showed drivers prioritized entertainment over safety considerations when interacting with these systems. Interestingly, participants reported similar willingness to engage in distracting tasks regardless of road type (highways, arterials, two-lane roads). The study also found a significant age effect, with younger drivers exhibiting a greater tendency to use technology while driving compared to older age groups.

III. Conditioning Traps: These traps emerge from a history of encountering similar situations without negative consequences. Experienced drivers are more likely to fall into conditioning traps as they may develop a sense of complacency based on past experiences. This can lead to disengagement from driving despite the potential risks. Bayer and Campbell [Bayer and Campbell, 2012] highlight the concerning role of habit in texting while driving. Their study suggests that texting can become automatic, occurring unconsciously and without deliberate intention. This automaticity may be a stronger explanation for the prevalence of texting while driving compared to factors like social norms or attitudes towards the danger.

There is a crucial need for accurate evaluation and measurement of cognitive workload to address the challenges posed by cognitive load while driving. A diverse range of objective and subjective measures can be employed to assess cognitive load. The following section discusses these measurement techniques and identifies the most practical approaches within the field of driving research.

2.7. Cognitive workload measurement techniques

Measuring cognitive workload enables maximizing safety, efficiency, performance, and well-being by allowing to accurately monitor and support one's cognitive performance [McKendrick et al., 2019]. Cognitive workload can be measured directly by assessing changes in cognitive performance or assessing factors impairing cognitive performance, such as sleepiness.

Cognitive workload can be measured either directly or by measuring factors that indirectly could impair cognitive workload such as sleepiness. The following sections will delve into these methods in detail, exploring their strengths, limitations, and applications within the context of driving performance.

2.7.1. Direct measure of cognitive workload

Direct measures are divided into:

I. Self-assessment or subjective rating scales
II. Performance measures (containing subdivisions of primary and secondary tasks)
III. Psychophysiological measures

2.7.1.1. Self-assessment or subjective rating scales

Rating scales represent subjective self-reports. The National Aeronautics and Space Association Task Load Index (NASA TLX) is the most widely used subjective measure of cognitive workload and has become synonymous with the concept [de Winter, 2014]. Subjective methods are more commonly employed than other methods due to their ease of administration and lower costs [McKendrick et al., 2019]. However, operators can be unreliable and invalid measuring instruments [Gopher and Donchin, 1986]. Therefore, self-reports are often combined with performance or psychophysiological measures [McKendrick et al., 2019].

2.7.1.2. Performance measures

Performance measures indicate cognitive workload directly (primary task measure) or indirectly (secondary task measures).

Primary task measures are valuable tools with good generalization, as they directly assess operator performance on the task of interest. This measure is beneficial when a task is already quite demanding, and performance deteriorates from baseline or ideal levels, as evidenced by changes in speed, accuracy, reaction or response time, and error rates during task execution. In the field of driving research, the following parameters have been used as primary measures of cognitive performance [Engström et al., 2017]:

I. Object/event detection response
II. Lateral control performance
III. Longitudinal control performance
IV. Decision-making

Secondary task measures assess performance on tasks that may not be directly relevant to the primary tasks and serve only to impose or gauge cognitive load on the operator [Cain, 2007]. These measures evaluate reaction time (RT), time estimation variance, accuracy and response time, signal detection rates, performance level, the number of concurrent tasks handled within a specific interval, and the percentage of time occupied by the secondary task. To ensure minimal interference with the primary task, secondary tasks should be quickly learned and self-paced (easily interrupted or delayed). There are several reasons why cognitive measurement tasks used in the context of driver distraction research might benefit from being self-paced:

I. Ecological Validity: Self-paced tasks better mimic real-world driving situations. Drivers encounter information and make decisions at their own pace while navigating traffic. A forced-pace task would not accurately reflect this variability in processing speed and information intake.
II. Reduced Stress and Anxiety: Timed tasks can create unnecessary stress and anxiety in participants, potentially impacting their cognitive performance. Self-paced tasks allow participants to complete the task at a comfortable pace, reducing the influence of these factors on the results.
III. Individual Differences in Processing Speed: People naturally have different processing speeds. Self-paced tasks allow participants to allocate time-based on their individual needs for understanding and responding to the task demands. This can lead to more reliable and generalizable data.
IV. Focus on Cognitive Load: Self-paced tasks can be used to assess cognitive load by measuring the time participants take to complete them. This would not be possible with timed tasks, where speed is prioritized over the internal effort involved.
V. Understanding Attention Allocation: Self-paced tasks, particularly those with multiple stimuli or tasks, can provide insights into how participants allocate their attention. By observing how participants choose to focus and take breaks, researchers can gain valuable information about the cognitive demands of driving and the impact of distractions.

Self-paced tasks are not without limitations. They can be more time-consuming to administer and analyse compared to timed tasks. The specific design of the self-paced task needs to be carefully considered to ensure it is engaging and provides meaningful data.

Examples of secondary tasks include but are not limited to rhythmic tapping, random number generation, verbal shadowing, spatial reasoning, time estimation and production, critical instability tracking tasks, and compensatory or pursuit tracking tasks [Cain, 2007]. When selecting a secondary task to measure cognitive workload, it is essential to carefully consider the pairing with its primary counterpart, as a poorly chosen secondary task can artificially impair performance on the primary task [Young and Stanton, 2007].

The secondary task performance metrics specifically employed to assess driver cognitive performance include the peripheral detection task (PDT), tactile detection task (TDT), Sternberg method, and working memory tasks such as n-back [van der Horst, 2010; Rupp, 2010; Engström et al., 2005; Sternberg, 1996; Angell et al., 2006; Mehler et al., 2011].

During PDT, a driver must respond to the onset of peripherally presented stimulus within a specific timeframe. For instance, a red square or LED might appear on the driver's periphery every four seconds [Rupp, 2010]. As the task demand increases, drivers tend to miss more peripheral cues, and their response time may become longer. This decline in response accuracy and speed indicates peaks in driver objective workload. This happens because driving requires a significant investment of cognitive resources, including attention, memory, and processing speed and these resources are like a pool of mental energy used to manage all driving tasks. When a driver is distracted by a secondary task like texting or interacting with the infotainment system, these resources are diverted away from the primary driving task. This depletion of resources leads to a higher cognitive workload. Since Response accuracy and speed are objective measures of a driver's performance. When workload increases due to distraction, these measures suffer and as cognitive resources become stretched thin, drivers take longer to process information and make decisions (slower response speed) which can lead to missed cues, delayed reactions, and ultimately, an increased likelihood of errors (decreased response accuracy).

TDT was explicitly developed as a non-visual version of the PDT [Engström et al., 2005]. This method utilizes vibrators attached to the skin to address the limitation of PDT, which can be affected by varying light conditions and background contrast [Rupp, 2010].

The Sternberg method was developed to study human short-term memory [Sternberg, 1996]. It involves presenting participants with a series of general numbers or visual signs to remember and then asking them to recall. The modified version of the Sternberg method [Angell et al., 2006] has been shown to be superior to PDT and offers the most robust criterion validity across the broadest set of conditions for on-road event detection [Rupp, 2010]. However, it is important to note that each one of these tasks requires different modalities and tapping into different resources.

Finally, the n-back task [Mehler et al., 2011] measures the load on working memory in different degrees by generally generating stimuli (e.g., numbers or letters) with brief pauses in between to allow the participants to repeat the stimuli given n steps before [von Janczewski et al., 2021]. Table 2.3 shows an example of n = 0, n = 1, and n = 2 back tasks with alphabet letter stimuli. During this task, participants must continuously retain information in their working memory while adding new information and comparing it with each other [Peck et al., 2014]. Auditory attention and memory performance while performing the n-back task demand resources similar to those required to perform in-vehicle infotainment systems while driving [Mehler et al., 2011]. The n-back task has been shown to fulfil the criteria for use as a cognitive workload measure while driving [Mehler et al., 2011], as it minimally interacts with the primary task (driving itself), requires minimal equipment and time, and is easy to score [Janczewski et al., 2021].

Table 2.3. Example of alphabet letter stimulus n-back task with n = 0, n = 1, and n = 2.

Stimulus or response	n-back delay	Letter sequence							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Stimulus (as presented to the participant)	-	*A*	*B*	*C*	*F*	*G*	*H*	*I*	*K*
Response expected from the participant	n = 0	A	B	C	F	G	H	I	K
	n = 1	-	A	B	C	F	G	H	I
	n = 2	-	-	A	B	C	F	G	H

2.7.1.3. Psychological measures

Psychophysiological measures, developed based on cognitive neuroscience, cognitive psychology, and human factors, utilize non-invasive neurophysiological tools to measure the known correlations of mental effort and assess workload during a task [McKendrick et al., 2019]. These measures can be recorded simultaneously with the task of interest and are sensitive to cognitive workload changes even before they are evident in actual task performance [Foy and Chapman, 2018]. The main psychophysiological measures include electroencephalogram (EEG), ocular measures, cardiac measures, and respiration.

Brain activity measurement using EEG can reveal different aspects of cognitive load, such as movement-related readiness potential and preparatory slow brain potentials, which have been shown to be sensitive to attention, demand, and decision-making [Freude and Ullsperger, 2000]. The EEG spectrum reveals workload according to the power within different frequency bands or the time shifts of events related to potentials. However, the EEG is less often used in field studies since its data proneness to artefacts, complexity, and the requirement for sophisticated signal processing equipment [Cain, 2007].

Ocular measures are sensitive to cognitive demands but dependent on the task type. For example, the blink rate declined with increased workload from processing visual stimuli. Still, it increased with an increment of load resulting from a memory task [Castor et al., 2003].

Currently used ocular measures are:

I. Eyelid and Blink movements (duration, latency and frequency)
   Concerning the link between blink rate and workload, previous studies reported inconsistent results which seem to stem from the difference between cognitive workload and visual workload [Marquart et al., 2015]. A review by Kramer [Kramer, 1990]

highlighted this very issue and reported studies which showed both increases and decreases in blink rate with workload, depending on the visual demands of the task [Kramer, 1990]. Further studies have not fully resolved the issue. A car driving study (1998) found blink rates decreasing with sharper road curves, suggesting a link to visual difficulty [Huger, 1998]. However, a later study (2008) observed the opposite for cognitive tasks [Recarte et al., 2008], where blink rates increased when listening, talking, or calculating compared to a control condition, suggesting a connection to mental effort. Interestingly, the Recarte et al. [Recarte et al., 2008] study also saw a decrease in blink rate for more visually demanding tasks compared to less demanding ones and concluded that blink rate reflects these two kinds of workload in opposing ways: less blinking for high visual demand, and more blinking for high mental demand.

Concerning the blink duration, previous research suggests a decrease in duration as workload increases, both mentally and visually [Marquart et al., 2015]. The researchers suggest this "blink duration inhibition" might be a way to avoid missing crucial visual information which aligns with Kramer's earlier work proposing that blinks are delayed until enough visual data is acquired [Kramer, 1990]. In essence, while blink duration decreases with workload, how this conclude might depend on the specific demands of the task and the need to maintain visual awareness [Marquart et al., 2015].

Concerning the time between blinks (latency), previous reviews highlight that an increase in latency is noticed with higher cognitive workload [Eggemeier et al., 1990; Carmody, 1994]. This is suggested to be because of delaying blinking until enough visual information is gathered to complete the task effectively [Kramer, 1990].

Finally concerning the percentage of eyelid closure (PERCLOS), a positive correlation was noticed, where people tend to report feeling sleepier, perform worse on tasks, and experience more lapses in attention, especially in visual reaction time tasks [Dinges and Grace, 1998; Friedrichs and Yang, 2010; Kozak et al., 2005].

II. Visual fixation (duration, gaze variation)

Studies consistently show that as mental workload increases, our eyes dwell longer on specific points (fixation duration) and explore a narrower area (gaze concentration). This suggests we spend more time processing information when facing demanding tasks [Marquart et al., 2015]. This is particularly evident in driving scenarios. Drivers fixate for longer periods during hazardous situations, likely to extract crucial information [Reimer and Mehler, 2010]. Additionally, research shows that even mentally demanding tasks, like listening to instructions, lead to a narrower gaze focus while driving [Recarte and Nunes, 2000; Reimer, 2009; Reimer and Mehler, 2010, Victor et al., 2005]. Interestingly, drivers seem to adjust their gaze behaviour before their driving performance suffers [Reimer, 2009].

III. Pupillometry

Concerning pupil size, previous research has shown an increase in pupil size with increased workload in both on-road and simulator driving studies which consistently showed larger pupil diameters during tasks like mental imagery and verbal instructions [Recarte and Nunes, 2000; Recarte and Nunes, 2003, Palinko et al., 2010].

Cardiac measures are sensitive to task complexity and cognitive workload. Cardiac measurement offers advantages in that the measurement devices are relatively cheaper than EEG, require little to no training for researchers for data collection, and are less susceptible to noise from participant movements [Wallen et al., 2016]. Measurement of cardiac activity includes heart period, also known as interbit interval (average time in milliseconds (ms) between heartbeats), heart rate (number of heart contractions measured per unit of time), and heart rate variability (variation in pattern between interbeat interval calculated using time and frequency domain indices). Heart rate often rises with a higher cognitive workload as the body demands more oxygen and energy delivery [Hughes et al., 2019]. Concerning heart rate variability, some studies show a decrease in HRV with workload, suggesting the heart's activity becomes less adaptable [Hughes et al., 2019]. However, the interpretation of HRV can be tricky and depends on factors like stress response and individual differences. A meta-analysis comparing different cardiac measurements suggests heart rate variability, heart rate, blood pressure, and heart period are sensitive to task demands and elicit the level of cognitive workload, with no measure being more sensitive than others [Hughes et al., 2019].

Heart Rate Variability (HRV): This reflects the variation between heartbeats and can be a more nuanced indicator. Some studies show a decrease in HRV with workload, suggesting the heart's activity becomes less adaptable. However, the interpretation of HRV can be tricky and depends on factors like stress response and individual differences.

Respiration rate has been observed to increase with a decrease in respiration volume as the mental workload increases. Other respiration measures recorded for cognitive workload assessment are time for inspiration or expiration, the complete cycle time, the volume, and the flow rate [Cain, 2007].

In the field of simulation-based studies, the following batteries of cognitive workload measurement techniques have been recommended [Farmer and Brownson, 2003]: modified Cooper-Harper (subjective), instantaneous self-assessment (subjective), primary and secondary tasks performance (objective), heart rate (psychophysiological), heart rate variability (psychophysiological), NASA TLX (subjective), and blink rate (psychophysiological)

2.7.2. Sleepiness measurement techniques

There are two primary methodologies for measuring sleepiness:

I. Subjective measures
II. Objective measures

Subjective measures are methods of quantifying individuals' self-reported sleepiness. These methods primarily rely on self-reports, such as rating scales (e.g., Karolinska sleepiness scale (KSS)). These tests are known for being inexpensive, straightforward, and less time-consuming compared to objective measurement techniques [Cluydts et al., 2002]. However, these tests have some drawbacks, including unintended bias and purposeful falsification [Shahid et al., 2010]. Sleepiness rating scales can either assess state sleepiness, which measures short-term fluctuations in sleepiness (e.g., Stanford Sleepiness Scale (SSS), KSS) or measure a global level of sleepiness (e.g., Epworth Sleepiness Scale, Sleep-wake activity inventory) [Shahid et al., 2010].

KSS is a one-dimensional measure of situational attention that was developed and validated against objective measures of sleepiness, including Electroencephalogram (EEG), slow eye movements (SEM) [Åkerstedt and Gillberg, 1990], and performance measures [Kaida et al., 2006]. The KSS contains a nine-point Likert scale where participants report their psychophysical state experienced in the last 10 minutes. Its score is strongly correlated with the time of day [Kecklund and Åkerstedt, 1993] and increases with increased periods of sleepiness. The KSS has been reported as a valuable tool in assessing changes in response to environmental factors, circadian rhythm, and the effects of drugs [Shahid et al., 2010].

There are two versions of the KSS: the original version with word labels on every second (uneven) step (1,3,5,7 and 9), and the version developed by Baulk et al., 2001 where word labels are added to the remaining four (even) steps as well. These two versions have been shown to be highly correlated across time, and no significant difference concerning the labelled and unlabelled parts of the scales was found [Miley et al., 2016].

Self-reported sleepiness and self-assessed performance capability are unreliable predictors of task performance decrements [Frey et al., 2004]. Therefore, Objective measures have been developed to provide quantifiable outcomes. Objective measures of sleepiness include but are not limited to, hormone levels (e.g., nocturnal melatonin levels), psychomotor vigilance test (PVT), and body temperature.

Hormone melatonin (5-methoxy-N-acetyltryptamine), known as the sleep hormone, is secreted at high levels during the night and low levels during the day [Arendt, 1995]. Melatonin is not stored anywhere systematically in the body. It will rapidly be cleared in the liver with a half-life of around 10 minutes in plasma [Iguchi et al., 1982]; therefore, measuring changes in melatonin levels in response to different stimuli, such as environmental darkness, has proven to be a very efficient way of investigating effects throughout all tissues and organs of the body [Bhagavathula et al., 2021]. It has been proposed that melatonin does not make us sleepy by directly activating brain structures that promote sleep. Instead, it works by suppressing the activity of brain structures that inhibit wakefulness by inhibiting the SCN wakefulness-generating mechanisms (e.g., Orexins, Acetylcholine signals) [Skocbat et al., 1998].

There are three primary methods of melatonin sampling: salivary, urinary, and blood sampling [Benloucif et al., 2008]. Salivary sampling is a non-invasive measurement method with good practicality and reliability for field studies and research trials, with samples taken every 30 to 60 minutes. Samples are typically collected using a salivary gland stimulator, such as a plastic strip or a small cotton swab. The stimulator is placed in the mouth for a few minutes to stimulate saliva and is then stored in a small tube.

Urine sampling, another non-invasive melatonin collection method, can be used to track changes in melatonin secretion over time. Urine samples are collected every two to eight hours over a one-day or two-day period. Urine sampling is a relatively inexpensive and easy-to-perform method that can be applied in various research designs and settings. However, urine melatonin levels are lower than salivary levels, resulting in lower resolution and sensitivity when comparing and analysing results.

Blood sampling is a more invasive method, where samples are obtained through a blood draw from a vein in the arm. While invasive, it provides higher accuracy than saliva or urine sampling and reflects the overall melatonin in the body. Plasma melatonin levels are approximately three times higher than salivary melatonin levels. Therefore, plasma sampling can detect even small changes in melatonin levels, particularly beneficial for individuals with low melatonin levels. This method also provides a larger effect size, higher resolution, and sensitivity during statistical comparison and analysis [Benloucif et al., 2008].

The psychomotor vigilance test (PVT) is an objective measure of sustained attention and psychomotor speed which assesses an individual's ability to detect and respond quickly to infrequent and unpredictable stimuli over a prolonged period. This test tracks the temporally dynamic changes induced by the interaction of the homeostatic drive for sleep and the endogenous circadian pacemaker. The original version of the PVT was a 10-minute simple visual reaction time test to stimuli occurring at random intervals [Dinges and Powel, 1985]. The test focuses on measuring the ability to sustain attention and respond promptly. It is one of the most sensitive tests to sleep restriction, the most reliable with no evidence of learning over repeated administration, and the most practical test to use in an operational environment [Balkin et al., 2004]. The PVT is highly sensitive to total sleep deprivation [Jewett et al., 1999; Doran et al., 2001], partial sleep deprivation [Belenky et al., 2003; Van Dongen et al., 2003], sleep homeostatic and circadian drives [Cohen et al., 2010], and inter-participant variability in the response to sleep loss [Van Dongen et al., 2004].

The outcome measures of PVT reported by Basner et al., 2018 are:

I. The number of lapses
II. Response speed
III. Reaction time (mean, median, fastest and slowest 10%, standard deviation)
IV. False starts, minimum, and maximum reaction time

The visual version of PVT using computer screens or tablets is undesirable in studies investigating the impact of lighting on sustained attention as it exposes participants to additional light [Gabel et al., 2019]. Therefore, an auditory version of the PVT (aPVT) was developed for such studies. While the visual version of the PVT requires the participant to respond to a visual stimulus on a screen, the auditory version requires participants to react to a tone delivered at a constant volume and random intervals through headphones [Gabel et al., 2019]. A comparison of the visual and auditory PVT results shows that sleep deprivation affects the general pattern of change in attention similarly among different modalities of sensory-motor behavioural response [Jung et al., 2011]. In general, reaction measured using auditory attention was found to be faster and less variable than visual attention [Jung et al., 2011].

Body temperature, another factor regulating the sleep-wake cycle, strongly correlates with sleepiness. As the core body temperature, the temperature inside the body, falls, the likelihood of feeling sleepy will increase. Core body temperature is controlled by SCN and follows a natural rhythm throughout the day, with a peak in the afternoon and early morning. As the SCN starts the melatonin secretion in the evening, the core body temperature begins to fall. This drop is one of the triggers of sleepiness.

Skin temperature, the temperature on the skin's surface, is related to core body temperature by a link of blood vessels that carry heat from the core to the skin and vice versa. When the core body temperature is high, blood vessels near the skin dilate, which allows heat to escape from the body, and when the core body temperature is low, these vessels constrict to help with heat conservation. Unlike core body temperature, skin temperature's relation to sleepiness and circadian rhythm follows an inverse trend [Marotte and Timbal, 1981], where higher skin temperature is related to higher sleepiness.

Both attentiveness (vigilance) and sleepiness are related to core body and skin temperatures. Higher core body temperature (daytime) and lower skin temperature are associated with optimal attentiveness.

On the other hand, lower core body temperature (night-time) and higher skin temperature are associated with optimal sleep [Wright et al., 2002; Kleitman and Jackson, 1950; Hull et al., 2003].

Several techniques for measuring skin temperature exist, including contact and non-contact thermometry. Contact thermometry, a direct measure of skin temperature, involves using a probe or sensor attached to the skin, such as an iButton temperature sensor. Contact thermometry is cheaper, easier to use than non-contact methods, and generally provides higher accuracy. However, these methods can be invasive and only apply to small skin areas.

Contact thermometry has been employed using both wired and wireless sensors. The extensive wiring of wired sensors makes them more complicated and less practical for use in everyday situations, as they can disrupt daily activities. Wireless peripheral thermometry devices like iButtons address the limitations of wired thermometers. An iButton is a wireless data logger capable of directly measuring human pointwise skin temperature (Figure 2.4). This device typically consists of a semiconductor temperature sensor, an embedded computer chip integrating a 1-Wire transmitter/receiver, a clock/calendar, a thermal history log, and memory storage, all enclosed in a stainless steel can (16×6 mm^2) and powered by a lithium battery. A systematic review has shown that iButtons can provide valid measurements of skin temperature and its changes over time, allowing researchers to obtain accurate, continuous skin temperature measurements over extended periods without interfering with participants' daily activities [Hasselberg et al., 2013].

Figure 2.4. iButton thermometer device.

Non-contact thermometry includes non-invasive techniques like infrared thermography and thermal imaging, which can measure temperature over large areas. However, these methods are more expensive and less accurate than contact thermometry for small skin areas.

Section 2.7 described different ways to measure cognitive load, including direct and indirect measurement techniques. The following section discusses how cognitive load can impair driving performance and increase the risk of RTCs.

2.8. Cognitive workload and impaired driving performance

The challenges associated with cognitive workload have intensified in recent decades as driving becomes increasingly complex due to the rise in traffic congestion and the introduction of sophisticated information technologies inside the vehicle [da Silva, 2014]. Establishing a direct link between cognitive workload and RTCs is a complex task, as measuring a driver's mental state is often indirect [Brookhuis and De Waard, 2010], and cognitive workload elements such as distraction often leave no physical evidence at the scene of a crash [Strayer and Cooper, 2015]. However, the undeniable impact on driving task performance has led researchers to consistently assume a strong association between RTC risks and driver cognitive workload [Kantowitz & Simsek, 2000], with loss of life in the field of air and ground transportation, often attributed to mental overload or task saturation [Sumwalt et al., 2019].

2.8.1. Cognitive load-induced driving impairment

One viable approach to investigate the relation between cognitive load and impaired driving performance is to examine the impairments that emerge in situations that induce cognitive workload while driving. Safe driving requires a compelling performance of cognitive tasks, including visual scanning, hazard prediction, identification, decision-making, response execution, situational awareness, and self-regulation.

Driver's visual scanning patterns are significantly influenced by cognitive load. When experiencing higher levels of cognitive workload, drivers tend to fixate more on the centre of the roadway and less on the side or rear-view mirrors or peripheral objects [Reimer et al., 2012; He et al., 2011]. Consequently, alterations in the gaze pattern can lead to lateral lane position variation and adversely affect drivers' situational awareness. This is the result of:

I. Shorter Fixations and Saccades: When cognitive workload increases, drivers may exhibit shorter fixations on key points (like the road ahead) and make more frequent, smaller saccades (eye jumps). This rapid scanning can lead to a less complete picture of the surrounding environment, making it harder to detect lane markings or potential hazards at the periphery.

II. Attentional tunnelling and narrowed Gaze Focus: As workload rises, drivers might focus their gaze more narrowly on the area directly in front of the vehicle. This "tunnel vision" effect reduces awareness of what is happening on the sides of the road, making it difficult to judge lane position relative to the edges.
III. Delayed processing and increased fixation durations: in some cases, drivers might show longer fixation durations on specific points. While this might indicate an attempt to process complex information, it can also lead to delayed reactions if they miss lane markers or drifting tendencies while fixated elsewhere.
IV. Reduced peripheral monitoring and less frequent glances: When workload increases, drivers might make fewer glances to check their blind spots or mirrors. This reduced peripheral monitoring can make them less aware of vehicles approaching from the side, potentially leading to lane swerves to avoid last-minute manoeuvres.

These alterations in gaze patterns can create a domino effect. Reduced awareness due to faster scanning or tunnel vision can lead to drivers unconsciously drifting out of their lane. This, in turn, might increase workload as they try to correct their position, potentially creating a cycle of gaze changes and lane variation.

Anticipation and prediction of hazards are negatively affected by an increase in cognitive workload. Drivers tend to make anticipatory glances towards locations where potential hazards might appear in the visual scene. This anticipatory glance is impaired when the cognitive workload increases. For instance, a study found that drivers not distracted by a secondary task were 50% more likely to make anticipatory glances toward potential hazards than those talking on their mobile phones [Taylor et al., 2015].

Inattentional blindness, also known as the “looked but failed to see” phenomenon, is the impairment of event identification while performing a cognitively demanding secondary task. This phenomenon impairs the identification of objects in the line of sight [Strayer and Drews, 2007] and is widely recognized as a significant threat to traffic safety [Herslund and Jørgensen, 2003].

Effective decision-making during driving manoeuvres necessitates the evaluation of multiple information sources. However, secondary task performance hinders dynamic decision-making [Horswill and McKenna, 1999]. Furthermore, divided attention (higher cognitive load) leads to unsafe decision-making, increasing the crash risk. For instance, using a mobile phone while driving has been shown to increase the likelihood of unsafe lane changes by 11%, and this risk further escalates as driving demands intensify (e.g., in higher traffic density) [Cooper et al., 2009].

Timely execution of a response is critical for safe driving. Delayed reaction time while driving, induced by high cognitive workload, elevates the probability and severity of RTCs [Brown et al., 2001]. This delay can manifest while performing a secondary task, such as conversing on a mobile phone [Caird et al., 2008]. It can worsen as the perceptual demands of the driving environment increase (e.g., in higher traffic density) [Strayer et al., 2003].

Situation awareness refers to one's ability to grasp what's happening around and can be broken down into three key components [Endsley, 1988]:

I. Perception: Perception involves picking up on important cues in one's environment. If these crucial details are missed, the understanding of the situation (mental picture) is much more likely to be wrong.
II. Comprehension: Situational awareness is not just about noticing things. It is about understanding what those things mean. While perceiving cues (perception) is crucial, true situational awareness requires more (e.g., high reading comprehension compared to just reading words). Comprehension argues the ability to integrate and make sense of information.
III. Projection: This is the most advanced level of situational awareness. Projection argues the ability to project from current events to anticipate future events and their implications for timely decision-making.

Situation awareness facilitates expectancy-based processing of the driving scene [Strayer and Fisher, 2016] and is mediated by working memory [Heenan et al., 2014]. Drivers must be aware of the objects in the driving scene (e.g., bicycles, vehicles, etc.) and update this information as relative positions change over time. Even minor lapses in situation awareness can lead to poor performance [Endsley, 1995]. Higher cognitive workload due to placing demand on working memory (e.g., conversing on a mobile phone while driving) degrade driver situation awareness [Heenan et al., 2014].

To summarize drivers with higher levels of cognitive workload:

I. Increase the duration of fixations on the central visual field while scanning the periphery less
II. Limited in their capacity to recognize and react to unforeseen hazards
III. Experiences challenges perceiving objects within their visual field
IV. Make poor decisions
V. Have slower reaction time in critical situations

The following two sections explore the relationship between sleepiness and distraction as the two primary drivers of cognitive impairment and how they can impair driving performance.

2.8.2. Sleepiness and impaired driving performance

Sleepiness is a major contributor to impaired cognitive performance [Desai and Haque, 2006]. Failure to adequately monitor the driving environment is the primary cause of most crashes. However, at the last moment, drivers typically attempt some evasive manoeuvres (e.g., braking, turning, etc.). The likelihood of such actions being taken by sleepy drivers is low or delayed, rendering the effect undetectable or disorganized. Delayed or no reactions increase the severity of such collisions, as it has been observed that sleeping-driver crashes result in disproportionately more fatalities [Johns, 2000]. The relationship between sleepiness, driving performance, and RTCs has been investigated using subjective and objective methods in real-life and simulated driving conditions.

Real-life subjective studies, such as questionnaire-based [Abe et al., 2011; BaHammam et al., 2014] or case-control studies [Philip et al., 2014], rely on self-reported information from drivers and/or police after a collision to investigate the association between sleepiness and the occurrence of real or near-miss RTCs. Objective studies conducted in real-life settings examine the impact of sleepiness on measurable parameters such as the frequency of inappropriate line crossings or hazard detection ability while driving [Philip et al., 2005; Davenne et al., 2012]. Simulation studies investigate how changes in drivers' sleepiness affect hazard perception latencies [Smith et al., 2009; Johns et al., 2008] and provide a safe virtual environment to assess driving behaviour under controlled conditions [Davenne et al., 2012]. Compared to driving simulators, real-world driving induces more stimulation than simulators, improving the result's generalizability [Philip et al., 2005]. However, driving simulators provide a safe environment for studying a wide range of driving scenarios, facilitate easy recording of test results, enable strict control of experimental setups, and could be more time and cost-effective than real-world driving studies.

Sleepiness while driving elevates the risk of unintentional speed fluctuations and jerking motions, and sleep-related crashes are more likely to result in severe injuries or fatalities compared to other types of crashes [Akerstedt, 2000; Bunn et al., 2005]. Furthermore, sleepy drivers are more prone to lane drifting and react slower to on-road events [Lenné et al., 1998; Philip et al., 2005].

Table 2.4 summarizes performance decrements associated with insufficient sleep. The extent of impairment caused by sleepiness while driving is considered to be comparable to that of alcohol intoxication [Roehrs et al., 2003; Powell et al., 2001].

Table 2.4. Performance decrement factors related to sleepiness.

Performance issue	References
Delayed reaction	Cajochen et al., 1999 ; Anderson et al., 2010.
Impaired visual perception	Anderson et al., 2010 ; Russo et al., 2005
Higher likelihood of distraction	Anderson et al., 2010; Anderson and Horne, 2006.
Diminished cognitive focus	Anderson et al., 2010 ; Turner et al., 2007.
Increased likelihood of eyelid closure, potentially leading to momentary lapses in situational awareness despite open eyes.	Anderson et al., 2010.
Impaired cognitive processing.	Durmer and Dinges, 2005; Ratcliff and Van Dongen, 2009.
Memory impairment.	Turner et al., 2007.
Deterioration in vigilance with time-on-ask.	Lee et al., 2016; Banks and Dinges, 2007.

Sleep-deprived individuals often underestimate their level of impairment and tend to increase their speed, even at the expense of making more mistakes and taking greater risks [Horowitz et al., 2003; Killgore et al., 2012]. A meta-analysis suggests that driver sleepiness doubles the risk of RTCs [Bioulac et al., 2017].

2.8.3. Distraction and impaired driving performance

Distraction impairs the driver's ability to utilize cognitive resources effectively, which hinders the safe and adequate performance of the driving task [Salvucci, 2002]. The relationship between distraction-impaired driving performance and RTCs can be explored through two main approaches: direct investigation linking RTCs and casualties to drivers' distraction (e.g., mobile phone use by the driver prior to the crash) and indirect assessment by highlighting the detrimental effects of distraction on critical driving tasks (e.g., increased reaction time due to engagement in distractive activities).

In previous studies, direct investigation was implemented using two main approaches:

I. After crash investigation, including crash studies based on police reports and in-depth crash reviews (e.g., Beanland et al., 2013)
II. Naturalistic observational crash studies (NDSs) (e.g., Dingus et al., 2015)

A review of studies used after-crash investigation reported that distraction contributed to 10-12% of RTCs [Regan et al., 2008]. A recent in-depth study of 186 fatal and injury crashes in Australia from

2014 to 2018 [Wundersitz, 2019] reported a slightly higher distraction contribution rate of 13.8%. However, these types of studies have certain limitations:

I. Different ways to classify distraction (what activity should be considered distraction?)
II. Retrospective nature (e.g., unknown or missing information)
III. Subjectivity and relying on the driver (individuals might offer what they believe to be valid justifications, or they could be dishonest)
IV. Different levels of training of the investigating personnel (e.g., the level of training in crash scene investigation varies among police departments, leading to subjectivity and inferential weaknesses in police reports)
V. Lack of proper information on exposure (e.g., frequency and duration of a distractive task)

An alternative approach to overcoming some of these limitations is naturalistic observational crash studies. These studies investigate driver state, behaviour, and performance in real life by equipping vehicles with advanced instruments (e.g., radars and sensors) [Dingus et al., 2016]. Real-time monitoring helps researchers investigate the drivers' exact actions in minutes or seconds leading to an RTC and near-crash events (events that could lead to a crash but were prevented by a timely manoeuvre by the driver) [Dingus et al., 2011].

An analysis of the findings from the most extensive and most recent naturalistic observational crash study, which captured over 35 million miles of naturalistic driving from more than 3500 participants (Strategic Highway Research Program Naturalistic Driving Study [Dingus et al., 2015]), highlights that drivers engaged in distracting activities more than 50% of the time, which result in RTC risk two times higher than those associated with model driving (alert, attentive and sober) [Dingus et al., 2016]. They have concluded that observable distraction (use of an in-vehicle handheld device, interaction with passengers, and outside distraction) was present in 68.3% of RTCs (but not confirmed as a causal factor). Such a rate of distraction presence highlights the potential to prevent four million of the 11 million crashes that occur annually in the United States if distraction can be mitigated [Dingus et al., 2016]. It is essential to mention that these conclusions and estimations are based on only observable distraction and do not include internal or cognitive distraction (e.g., daydreaming). Therefore, the actual contribution of distraction in RTCs may be even higher. Naturalistic driving studies also have some limitations, including:

I. Some types of distraction (e.g., internal/cognitive) cannot be identified
II. Ethical and privacy concerns regarding installing cameras in cars and recording conversations
III. Expensive in terms of conduction and big data analysis after the study

In contrast, indirect investigations focus on assessing the impairment caused by each type of distraction (visual and cognitive (e.g., auditory)) while driving. These studies can involve real cars or test tracks in laboratory or field settings. Typical performance measures in these studies include vehicle longitudinal and lateral control and drivers' reaction time to potential hazards.

A meta-analysis by Yusoff et al. 2017 found that exposure to visual and cognitive distractions can lead to both increases and decreases in speed. Furthermore, they reported that visual distraction increased lane position variability in some studies, while others found no significant difference. None of the reviewed studies found a significant impairment in lateral control due to cognitive distraction. Finally, they found no studies that investigated the effect of visual distraction on reaction time, while cognitive distraction studies found increased reaction time and miss rate while detecting hazards.

Section 2.8. described various ways in which impaired cognitive performance, and its primary components (sleepiness and distraction) can negatively impact driving performance, potentially leading to an increased risk of RTCs. The subsequent sections first discuss previous studies on the impact of road lighting on drivers and its already known and explored potential benefits. This is followed by a discussion of general strategies employed to mitigate sleepiness and distraction, the main elements of impaired cognitive performance. The extent to which light can be utilized to mitigate these challenges is then discussed. Finally, an evaluation of previous research on implementing light as a mitigation strategy for impaired driver cognitive performance, along with their findings and limitations, is presented.

2.9. Road lighting and driving in previous research

The impact of road lighting on driving performance (e.g., visual performance, vehicle longitudinal and lateral control, etc.) has been the subject of prior investigations employing field studies and laboratory experiments. Field studies are conducted in real roads, where researchers measure and observe driving performance either in a controlled road environment by implementing actual driving scenarios (using a test track and a real car) or directly from naturalistic driving scenarios where drivers' behaviour is observed in the real world [e.g., Gibbons et al., 2012].

In contrast, Laboratory studies employ either driving simulators (a computer-based system that replicates real-world driving scenarios in a simulated environment) or road scenes (scale models that stimulate a driver's view of a road) [e.g., Fotios et al., 2019]. Table 2.5 summarises the existing research on road lighting and driving performance. These studies varied in terms of location of conduct (field vs. laboratory), lighting interventions, participant demographics (e.g., different age groups), cognitive workload levels (driver vs. passenger, changes in speed and driving task difficulties), and surrounding brightness. Additionally, The studies employed different techniques to measure driving performance, including hazard reaction time and its performance rate, crash frequency, variation in vehicle lateral and longitudinal control, and changes in drivers' visual performance (e.g., visual acuity).

Concerning target detection after dark, an increase in road surface luminance and visibility level has been shown to improve target detection distance [Van Bommel and Tekelenburg, 1986; Mayeur et al., 2010; Gibbons et al., 2012]. Similar improvements have been observed in reaction time and relative performance rates to hazard detection [Bullough and Rea, 2000; Alferdinck, 2006; Easa et al., 2010; Fotios et al., 2019; Chen et al., 2019].

Concerning vehicle speed after dark, Bullough and Rea, 2000 demonstrated a positive correlation between higher luminance and increased driving speed, while no significant variation in speed was observed with changes in SPD. Similar findings were noticed in the work of Easa et al., 2010, who found that higher light levels led to increased vehicle speed, improved driving confidence, and reduced attention. In support, a reduction in vehicle speed was also noticed due to a reduction in road surface luminance [Pritchard and Hammett, 2012].

Finally, concerning vehicle lateral control, Brooks et al., 2005 found no impact even under severe blur or extremely low luminance in healthy young adults, as evidenced by constant steering performance. On the other hand, Alferdinck, 2006 reported an impairment of vehicle lateral control with decreasing background luminance, as indicated by variation in the standard deviation of lateral position, percentage of time outside lane, time of line crossing, the standard deviation of steering wheel position, its reversal rate, and high-frequency area.

The findings of these studies can be summed up as follows:

I. Visual performance in relation to light level (luminance) tends to exhibit a plateau-escarpment relationship. At low light levels, an increase in luminance significantly improves visual performance (the escarpment). However, there is a point where further increases in luminance no longer yield additional improvements in visual performance (the plateau).
II. Peripheral target detection highly depends on luminance and SPD (improved detection with increased S/P ratio of SPD).
III. Higher luminance provides additional time for a driver to make safe manoeuvres.

In conclusion, strategically designed road lighting can positively impact driver behaviour on the roadway and promote safer driving behaviours. This can be evidenced by improved visibility, better speed control, proper lane guidance, improved intersection safety, and increased pedestrian safety.

Table 2.5. Previous research on road lighting and driving performance. Studies are presented in chronological order.

Reference	Method	Independent variables	Dependent variables
Van Bommel and Tekelenburg, 1986	Field (Controlled road)	• Average Luminance (0.3, 1, 1.1, 3.4 cd/m^2) • Surroundings (Bright vs. dark)	• Target detection (distance)
He et al., 1997	Laboratory (View chamber)	• Background luminance (0.003, 0.03, 0.1, 0.3, 1, 3, 10 cd/m^2) • Light source (MH vs. HPS) • Target location (on-axis vs. off-axis)	• Target detection (RT)
Bullough and Rea, 2000	Laboratory (Simulator)	• Background luminance (0.1, 0.3, 1, 3 cd/m^2) • SPD_S/P ratio (HPS_0.64; Red_1.35; MH_1.78; Blue_3.77)	• Target detection • Vehicle speed • Crash frequency • Brightness ratings
Brooks et al., 2005	Laboratory (Simulator)	• Average Luminance (0.003, 0.03, 1.0, 16.7 cd/m^2) • Induced blur (0, +1, +2, +5, +10 dioptre) • Visual field size	• Target detection • Vehicle lateral control • Visual acuity • Vehicle speed
Alferdinck, 2006	Laboratory (Simulator)	• Driving speed (70 km/h vs. 100 km/h) • Background luminance (0.01, 0.1, 1, 10 cd/m^2) • Background colour (white, yellow, red, blue) • Target eccentricity (-15, -10, …, +10, +15 degree)	• Target detection (RT and PR) • Vehicle lateral control
Easa et al., 2010	Laboratory (Simulator)	• Average luminance (0.6, 2.5 cd/m^2) • Age (19-27; 37-56; 63-84) • Road type (highway, transition, rural)	• Target detection (RT) • Vehicle lateral control • Vehicle speed
Mayeur et al., 2010	Field (Controlled road)	• VL (3.4, 16.9, 0.5, 1.7, 9.8, 3.0, 13.9, 7.1) • Driver vs. passenger • Speed	• Target detection (distance)
Pritchard and Hammett, 2012	Laboratory (Simulator)	• Average Luminance (0.42, 4.87, 59.95 cd/m^2)	• Vehicle Speed

Reference	Method	Independent variables	Dependent variables
Gibbons et al., 2012	Field (Controlled road)	• Age (18-34; >65) • Overhead lighting (on vs. off) • Signage (two types at varying locations) • Target object (pedestrian/car/bicycle) • Glare (yes vs. no) • Pavement markings (waterborne paint vs. type II beads)	• Target detection (distance)
Fotios et al., 2019	Laboratory (Road scene)	• Age (18-30 vs. 40-70) • SPD (low and high S/P_1 cd/m2, High S/P, _0.1 cd/m^2, high S/P_2 cd/m^2) • Overhead light (on vs. off)	• Target detection (RT and PR)
Chen et al., 2019	Laboratory (Simulator)	• Workload (watching a scene vs. driving in the scene) • Target position (left, middle, and right) • Luminance contrast of target (0.1, 0.2, 0.4, 0.8, 1.6, 3.2 cd/m^2)	• Target detection (RT and PR)

2.10. Sleepiness and distraction mitigation strategies

As discussed in section 2.8, driver sleepiness at the wheel can be extremely dangerous and should never be ignored, as it can lead to RTCs due to impaired cognitive performance and reaction times. Drivers employ various measures to combat sleepiness with varying degrees of effectiveness. Table 2.6 summarizes the most commonly used countermeasures to sleepiness and their effectiveness:

Table 2.6. Countermeasures to sleepiness.

Countermeasure	Effectiveness	Reference
Rest brake	• Reduce physiological sleepiness • Reduce subjective sleepiness • Improve simulated driving performance	Phipps-Nelson et al., 2011
Nap brake (15-20 min)	• Reduce physiological sleepiness • Reduce subjective sleepiness • Improve simulated driving performance	Horne and Reyner, 1996; Leger et al., 2009
Caffeine consumption	• Reduce physiological sleepiness • Reduce subjective sleepiness • Reduce indices of lane drifting	De Valck and Cluydts, 2001; Horne and Reyner, 1996
Listening to music	• Very small to no effect	Schwarz et al., 2012
Use of air conditioning or window opening	• Very small subjective sleepiness • Negligible on physiological sleepiness and driving performance	Schwarz et al., 2012

Of the above countermeasures, nap brakes are the most effective and long-lasting strategy to mitigate sleepiness while driving.

Driver distraction, which diverts driver attention away from the critical task of driving, can lead to delayed reaction times, impaired decision-making, and a loss of situational awareness, significantly elevating the risk of collisions. This makes distraction a serious road safety concern, contributing to RTCs, injuries, and even fatalities. Existing countermeasures to address distraction include but are not limited to, legislation and enforcement, vehicle fleet management, education and training, and the design of vehicles, technology, and roads [Regan et al., 2008].

2.11. Light as a mitigation strategy

Light possesses the potential to be employed as an effective countermeasure against sleepiness and distraction as a means here, which is called "aids to vision". The term "aids to vision" is defined and used in this thesis as any support to driver vision which includes but is not limited to solutions that support visual responses (e.g., higher levels of road lighting, pedestrian high-visibility clothing, …) and non-visual responses (e.g., short-wavelength blue-enriched light to mitigate sleepiness). Poorly designed road lighting diminishes visibility and increases the likelihood of perceptual errors (e.g., distraction) and sleepiness [Boyce, 2014]. As previously mentioned, both sleepiness and distraction can elevate cognitive load and delay reaction times to potential hazards.

2.11.1. Visual responses to light as the mitigation strategy

Regarding visual responses, proper usage of lighting has the potential to:

I. Enhance visibility of the objects and users on and aside the roads. Improved visibility lets drivers anticipate the road ahead and potential hazards, including pedestrians and other road users. This early anticipation and detection can help compensate for a proportion of the delayed reaction times caused by sleepiness and distraction.
II. Simplifying driver detection tasks by reducing the cognitive workload imposed by visual processing. In other words, by making the detection task easier through proper road lighting, the demand for visual processing is reduced, allowing for more cognitive resources to compensate for the negative effects of sleepiness and distraction.
III. Reduce glare from oncoming vehicle headlights, which could significantly contribute to driver discomfort and fatigue and increase driver sleepiness [Madvari et al., 2023].

An example of "aids to vision" for hazard detectability and conspicuity is the use of high-visibility clothing or worn self-luminance devices by pedestrians. Pedestrian conspicuity is defined by Tyrrell et al. [Tyrrell et al., 2016] as "*the ability to be recognised by a driver as a pedestrian, without prior knowledge of their presence in the driving scene*". The clothing typically worn by pedestrians is of low reflectance, typically 0.10 or less, comparable to dark grey [Bhise et al., 1977], giving a low contrast and a low conspicuity. Rather than rely only on road lighting to improve their conspicuity, pedestrians can choose to use on-person devices.

A first improvement is to wear instead clothing of higher reflectance, such as the high-visibility vest more commonly worn by cyclists: the higher reflection of incident light leads to a greater luminance contrast between the clothing and its background. However, the geometry between the observer, the reflective surface, and the light source must be correct to be effective. A further improvement is to use instead a self-luminous device – a source of light. This is likely to create a higher luminance than a high-visibility vest and, therefore, create a higher contrast against the background. Being self-luminous, it does not need to be lit by an external light source to be effective. The self-luminous device can be improved in two ways: it can flash, and/or it can be worn on the moving limbs to mark bio-motion.

The effectiveness of "aids to vision" is frequently characterised by the distance at which the target (e.g., a pedestrian) is detected, with a larger distance indicating a more effective aid. Sayer and Mefford [Sayer and Mefford, 2004] found that adding retroreflective material to a dark-clad pedestrian increased the detection distance. However, the amount of retroreflective material did not have an effect. Fekety et al. [Fekety et al., 2016] found that adding self-luminous material (electroluminescent in their study) to retroreflective clothing enabled pedestrian detection at a greater distance than retroreflective clothing alone did. Blomberg et al. [Blomberg et al., 1986] found pedestrians were recognised at greater distances when wearing retroreflective bands around the wrists and ankles than when wearing a high-visibility vest (a fluorescent vest with retroreflective material) and these at a greater distance than the baseline pedestrian wearing a white tee shirt.

2.11.2. Non-visual responses to light as the mitigation strategy

Regarding non-visual responses, exposure to lighting with higher levels of melanopic EDI has been shown to reduce attentional lapses significantly, decrease subjective sleepiness, improve attention, and improve performance on neurocognitive tests [Rahman et al., 2014; Souman et al., 2018].

Moreover, NIF responses that are independent of visual perception could improve saccadic eye movements and attentional disengagement [Lee et al., 2021], facilitate cognitive flexibility, and decrease switch cost (reaction time of switching mental sets) [Ferlazzo et al., 2014], and improve performance on cognitive tasks [Alkozei et al., 2016]. It has been shown that tasks requiring psychomotor functioning exposure to light can be superior to caffeine for sustaining performance [Beaven and Ekström, 2013].

Lee et al. [Lee et al., 2021], studied the effect of short wavelength blue light on saccade latency of 26 young male participants (age range: 18-30 years old). Two experiments were conducted that involved both eye movement control (eye tracker) and attention (fixate at a black dot) to separate their contributions from each other. Experiment 1 provided evidence for a facilitatory effect of blue light on saccadic eye movements. Experiment 2 further revealed a nuanced interaction, demonstrating that blue light only expedited saccade latency when attention and the oculomotor system operated concurrently. A critical assumption underlying this study was that participants' ability to detect the target (a small black dot) remained constant across the two lighting conditions (blue and orange). This assumption is crucial because differences in detection thresholds could have influenced saccade latencies independent of any oculomotor or attentional effects. However, the findings revealed a more complex pattern. Experiment 1 did show a main effect of colour, suggesting faster saccades under blue light. However, both experiments also revealed a significant interaction effect between colour and the gap condition. This pattern of results suggests that the influence of blue light on saccade latency cannot be solely attributed to differences in target detectability under the two lighting conditions. The observed interaction implies that blue light exerts its influence through a mechanism that is contingent upon the specific task demands, such as the presence or absence of a gap in the fixation cue.

Ferlazzo et al. [Ferlazzo et al., 2014], studied the effects of short-wavelength blue-enriched LED light sources on higher-order cognitive functions like visuospatial abilities and executive functions. In this study 44 healthy participants (22 males; mean age range 25 years old) performed tasks designed to assess visuospatial processing (mental rotation of 3D objects) and executive function (inhibitory control and task switching) within a controlled light environment. The results suggest that exposure to short wavelength light enhances the cognitive system's ability to manage multiple task representations simultaneously, leading to reduced interference and improved performance. Additionally, short wavelength light appears to benefit visuospatial processing, as evidenced by fewer errors in the 3D mental rotation task.

Alkozei et al. [Alkozei et al., 2016], investigated the post-exposure effects of blue light on working memory performance and associated neural correlates. Thirthy-five healthy participants (18 females) were exposed to either blue (469 nm) or amber (578 nm) light for 30 minutes in a darkened room. Immediately following exposure, participants performed an N-back working memory task while undergoing functional magnetic resonance imaging (fMRI). Participants in the blue light condition exhibited significantly faster response times on the N-back task compared to the amber light control group. Furthermore, the blue light group displayed increased activation within the dorsolateral prefrontal cortex (DLPFC) and ventrolateral prefrontal cortex (VLPFC) compared to the amber light group. Notably, a positive correlation emerged between greater activation in the VLPFC and faster N-back response times.

The prefrontal cortex (PFC) is a critical brain region involved in working memory [Cohen et al., 1997], decision-making [Figner et al., 2010], and executive control [Badre and Wagner, 2007]. Improved working memory performance has been associated with increased activation of PFC [Owen et al., 2005].

The decision-making process is a trade-off between speed and accuracy ("safe and slow" or "fast but risky") [Bogacz et al., 2010], suggesting that changes in baseline activation levels in the prefrontal cortex are opposed to changes in the decision threshold itself. This increment in baseline activation, elicited by lighting containing higher levels of melanopic EDI (short-wavelength blue light), was observed by cortical responses to cognitive tasks [Perrin et al., 2004]. This increase was demonstrated in functional magnetic resonance imaging studies [Vandewalle et al., 2006]. This activation induced measurable functional brain responses within prefrontal regions associated with executive functions, positively impacting working memory performance [Alkozei et al., 2016]. This impact was found to be independent of exposure duration as even short bursts of short-wavelength blue light, as little as one minute, have been shown to activate prefrontal cortex regions effectively during auditory working memory tasks [Vandewalle et al., 2011]. This light-induced alteration in brain responses, associated with improved performance, persisted for at least 30 minutes after termination of the light exposure [Alkozei et al., 2016].

While the circadian effect of light on sleep and attention is well established [Fisk et al., 2018], the acute stimulating effects of light on immediate brain function and cognition remain less understood. The potential of short-wavelength blue light to effectively modulate higher-level cognitive processes has not been explored [Killgore et al., 2020]. While short-wavelength blue light could potentially influence behaviour by modulating cortical activity, its potential could be limited as conscious experience can only occur after relative neurons have been activated to a certain extent [Sergent et al., 2004]. Most existing studies on light-induced cognitive enhancements have been conducted under highly controlled conditions, highlighting the need to investigate these effects in real-world settings.

2.12. Previous studies on the use of short-wavelength light as the mitigation strategy

To our knowledge, there is scant empirical research exploring the impact of lighting as a countermeasure to sleepiness and distraction after dark.

Bhagavathula et al., 2021 investigated the impact of blue-rich LEDs containing higher levels of melanopic EDI on circadian rhythms under dim lighting conditions on the roads. They lit a closed-loop road after dark using each of five lighting conditions (Tables 2.7 and 2.8) with their test participants (10 people with age range between 18 to 30) first spending a two-hour adaptation period (23:00 to 01:00) under normal home-indoor lighting levels (Table 2.8) and then driving for two hours (the test period; 01:00 to 03:00) in a closed-loop road.

Table 2.7. Lighting conditions used by Bhagavathula et al., 2021 - general characteristics.

Light source	Correlated colour temperature (K)	Intensity (cd/m^2)	Corneal irradiance (lx)
Test period			
HPS	2100	1.5	1.8
	4000	1.5	1.9
LED	4000	1	1.4
	4000	0.7	1.1
No roadway lighting	-	< 0.05	0.8
Adaptation period			
LED	4000	-	200

Table 2.8. Lighting conditions used by Bhagavathula et al., 2021 - photometric values at eye level. Equivalent daylight illuminance values from CIE S 026/E:2018 for each experimental light condition.

Light condition	Alpha-opic equivalent daylight (D65) illuminance, lx				
	s-cone-opic	M-cone-opic	L-cone-opic	Rhodopic	Melanopic
Test period					
2100 K HPS-1.5lx	0.3	1.2	1.9	0.5	0.3
4000 K LED-1.5lx	0.6	1.6	1.8	1.1	0.8
4000 K LED-1lx	0.5	1.2	1.4	0.8	0.6
4000 K LED-0.7lx	0.4	1	1.1	0.6	0.5
Adaptation period					
4000 K LED-200lx	66.4	173.0	194.5	112.4	87.1

They measured salivary melatonin, objective, and subjective attention at 30-minute intervals. Their findings did not suggest a significant impact of lighting conditions on melatonin suppression or attention.

Rodríguez-Morilla et al., 2017 investigated the impact of in-vehicle blue-enriched and orange lighting conditions (Table 2.9, 2.10) on nocturnal subjective, physiological, and cognitive measures of sleepiness during simulator driving. Their outcome metrics were simulator driving performance as examined by lane and speed deviations, auditory reaction time test (PVT), Kronowise ambulatory circadian monitoring, and skin temperature. Their samples contained 36 healthy participants (18 to 25 years). Participants arrived in a lab at 21:00 and stayed under control conditions (<1 lx) for 45 minutes (answered the KSS questionnaire, performed PVT, and drove in a simulator). After adaptation, participants drove for 60 minutes in the simulator while exposed to one of the lighting conditions. After completing the driving task, participants again answered the questionnaires and performed the PVT.

Table 2.9. Lighting conditions used by Rodríguez-Morilla et al., 2017 - general characteristics.

Light condition - Spectral wavelength (nm)	Luminance at the eye* (lx)	Intensity (µw/m^2)
Blue light - 440	469	141
Orange light - 595	410	114
Lights off	< 1	-

* Measured at the horizontal angel of gaze.

Table 2.10. Lighting conditions used by Rodríguez-Morilla et al., 2017 - photometric values at eye level. Equivalent daylight illuminance values from CIE S 026/E:2018 for each experimental light condition.

Light condition	Alpha-opic equivalent daylight (D65) illuminance, lx				
	Cyanopic	Melanopic	Rhodopic	Choloropic	Erythropic
Blue light	323	224	294	401	444
Orange light	4	26	81	271	424
Lights off	-	-	-	-	-

Their result indicates that exposure to blue-enriched light, containing higher levels of melanopic EDI, decreased distal-proximal temperature gradient and produced larger driving errors when compared with orange light. They concluded that physiological arousal due to exposure to light does not always lead to improved cognitive performance, and excessive arousal can impair accuracy in complex tasks such as driving, which require precision. This can be potentially justified by the Yerkes-Dodson principle [Broadbent, 1965] which suggests an optimal arousal level for tasks. While moderate arousal enhances focus, exceeding this threshold can impair performance. The impact of light-induced arousal hinges on task complexity. While simple tasks might benefit from moderate brain activation, intricate tasks requiring precision, like driving, could suffer from overarousal. This excessive arousal depletes cognitive resources needed for focused attention and decision-making, leading to errors. Furthermore, excessive arousal can narrow attention [Thayer, 1978], hindering the ability to process peripheral information critical for tasks like driving. In conclusion, light exposure can improve attention, but its effect on cognitive performance may depend on the task.

Taillard et al., 2012 Investigated the impact of in-vehicle monochromatic blue light (spectral wavelength: 468 nm; luminance at the eye: 20 lx; intensity: 7.4 µw/m^2) on nocturnal driving performance as measured by inappropriate lane crossing (ILC) and standard deviation of the vehicle lateral position (SDLP), in 48 healthy participants (aged 20-50 years) who drove 400 km on a motorway at night (01:00 – 05:00). They have found that this nocturnal exposure to blue light, rich in melanopic EDI, reduced the number of ILC and SDLP events, suggesting that this intervention could be employed to mitigate sleepiness while driving after dark.

Phipps-Nelson et al., 2009 examined the effects of red and blue in-vehicle lighting conditions (Table 2.11) on nocturnal subjective and objective indices of sleepiness during simulator driving. Their outcome measures included simulator driving performance as evaluated by lane and speed deviations, auditory reaction time test (PVT), subjective sleepiness (KSS), salivary melatonin, and brain activity (EEG). Their samples comprised eight experienced and healthy drivers (aged 20-43 years). Participants were exposed to ambient dim light (< 1 lx) from 18:00 (adaptation period), and the main experiment was conducted between 21:00 and 9:00 in the morning, performing three-hour sessions.

Table 2.11. Lighting conditions used by Phipps-Nelson et al., 2009 - general characteristics.

Light condition - Spectral wavelength (nm)	Luminance at the eye* (lx)	Intensity (μw/m^2)
Test period		
Blue light - 460	1.12 – 1.15	2.05 – 2.07
Red light - 620	1.13 – 1.18	0.57 – 0.69
Adaptation period		
Broad spectrum with peaks at 430 and 620	0.02 – 0.2	0.05 – 0.17

* Measured at the horizontal angle of gaze.

Their findings demonstrate that blue light exposure with higher melanopic EDI led to suppressed EEG activity, a reduced occurrence of slow eye movements, and faster PVT reaction time compared to ambient light exposure. However, blue light exposure did not significantly influence simulator driving performance, KSS scoring, or salivary melatonin levels compared to ambient light exposure. The authors conclude that low-intensity blue light exposure can enhance attention during prolonged nighttime performance testing and could be employed to improve attention in situations where bright light is impractical, such as driving after dark.

Regarding distraction, none of the previous studies reported in section 2.9 implemented a source of distraction or investigated the impact of road lighting on its mitigation as a means of changes in driving performance.

There is a need to further investigate the impact of lighting as a means of “aids to vision” on the mitigation of sleepiness and distraction both under visual and non-visual responses to light. The research hypotheses for this thesis are presented in the following section.

2.13. Research Hypotheses

This work aims to determine the extent to which “aids to vision” and conspicuity can mitigate sleepiness and distraction when driving. Two experiments were performed to test the following hypotheses:

> H1: An increase in melanopic EDI (lx) leads to a decrease in sleepiness when driving in the evening after dark.
>
> H2: Distraction (via acoustic or visual stimuli) leads to a deterioration in hazard detection, as indicated by an increase in reaction time from onset of the hazard stimulus to its detection or a decrease in detection rate.
>
> H3: An increase in road surface luminance leads to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.
>
> H4: In-vehicle short-wavelength blue light (increment in melanopic EDI exposure) leads to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.
>
> H5: Pedestrian-worn “aids to vision” lead to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.

Two distinct experiments were conducted to test the formulated hypotheses. Experiment 1 was designed to evaluate Hypothesis H1, while Experiment 2 focused on Hypotheses H2 to H5. A summary overview of the research design is presented in Figure 2.5.

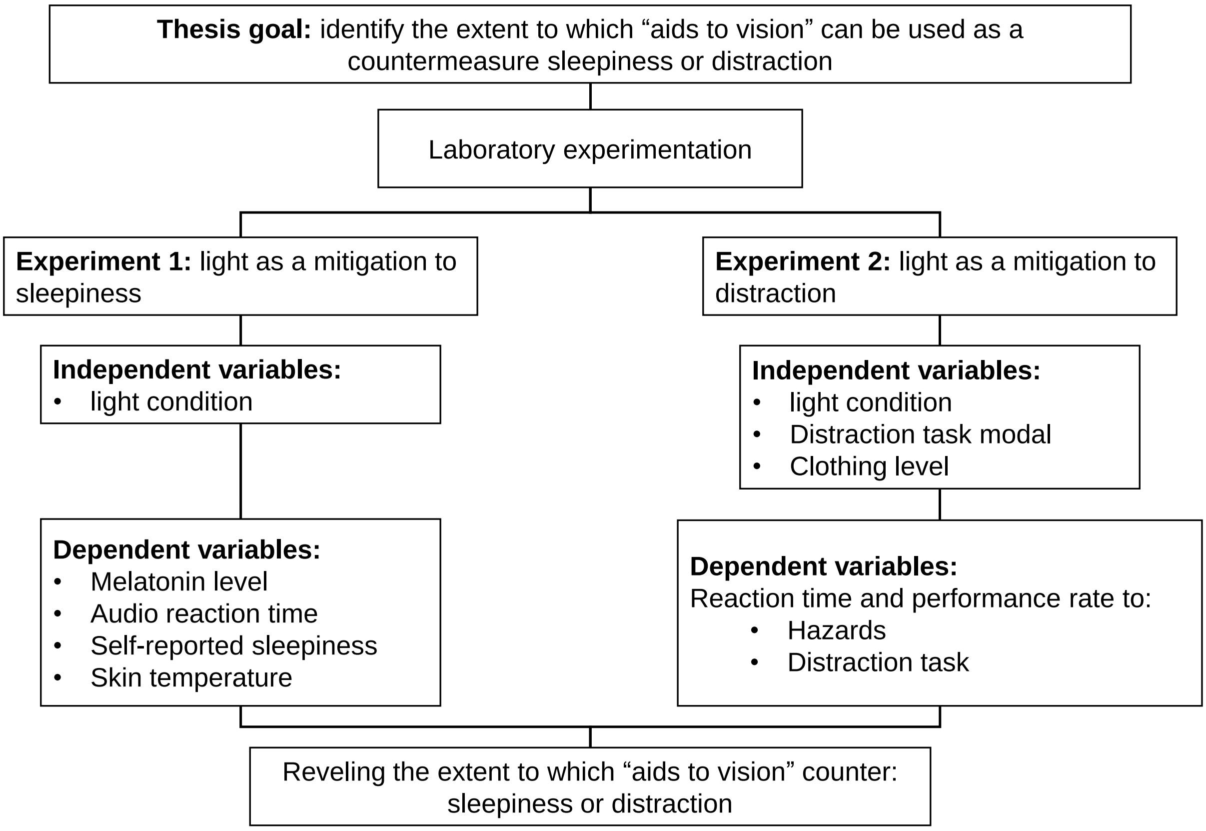


Figure 2.5. Summary of the thesis methodological structure.

2.14. Summary

This chapter defined and discussed key literature concerning human vision and its visual and non-visual responses to light. It explored the risks associated with driving after dark, driver inattention and its contributing factors, and the challenges of nighttime driving. The chapter continues to examine cognitive workload, its relationship to driving performance, and how sleepiness and distraction could impair driver's cognitive performance, potentially leading to road traffic collisions (RTCs). Finally, the chapter reviewed previous research on road lighting and its potential as a countermeasure to inattention. The chapter concluded with the research hypotheses. The next chapter provides an in-depth description of the method used in Experiment 1.

Chapter 3. Method: Experiment 1

Chapter 3. Method: Experiment 1

3.1. Introduction

Chapter 2, literature review, establishes that lighting conditions might affect sleepiness when driving after dark. However, there is a lack of conclusive evidence to support the generalization of these findings to outdoor lighting practices specifically designed for drivers. Existing studies have primarily examined the impact of non-visual responses to light on sleepiness mitigation, employing higher light intensities than those of typical road environments. Additionally, these studies have incorporated dark adaptation periods, contrasting with real-world scenarios where individuals are exposed to artificial lighting in their nighttime living environments. Consequently, further research is required to investigate the potential of light to mitigate sleepiness in natural settings, considering brighter adaptation periods and lighting levels that more closely resemble actual outdoor lighting conditions that drivers are exposed to after dark.

An experiment was conducted to test if:

H1: An increase in melanopic EDI (lx) leads to a decrease in sleepiness when driving in the evening after dark.

This chapter details the method used in Experiment 1. This experiment aimed to explore the extent of the benefits of lighting on driver sleepiness during typical journeys under specific lighting conditions achievable on roads. This experiment was reviewed by the University of Sheffield ethics board and gained approval prior to conduction (reference number 042711, dated the ninth of September 2022).

3.2. Apparatus

The effects of change in light level and spectrum on attention were investigated in a laboratory study. The light levels and test participant posture were selected to resemble driving and walking. The context of this experiment was a person seated at home for two hours (adaptation period (AD)) followed by a one-hour test period (T) representing a drive or walk. Two participants attended each test session.

The test environment (Figure 3.1, and 3.2) was one end of a room of dimensions of 3.45 m length, 2.43 m width, and 2.80 m height. The wall surfaces visible to participants were painted white, of approximate reflectance: 0.81.

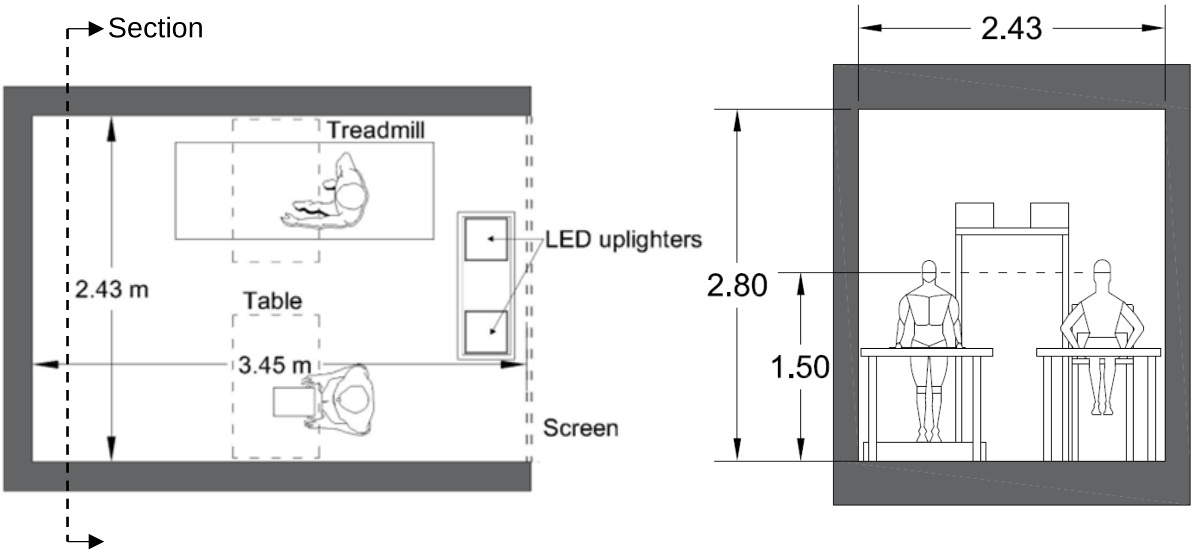


Figure 3.1. Plan layout (left) and front section (right) of the test environment (not to scale).

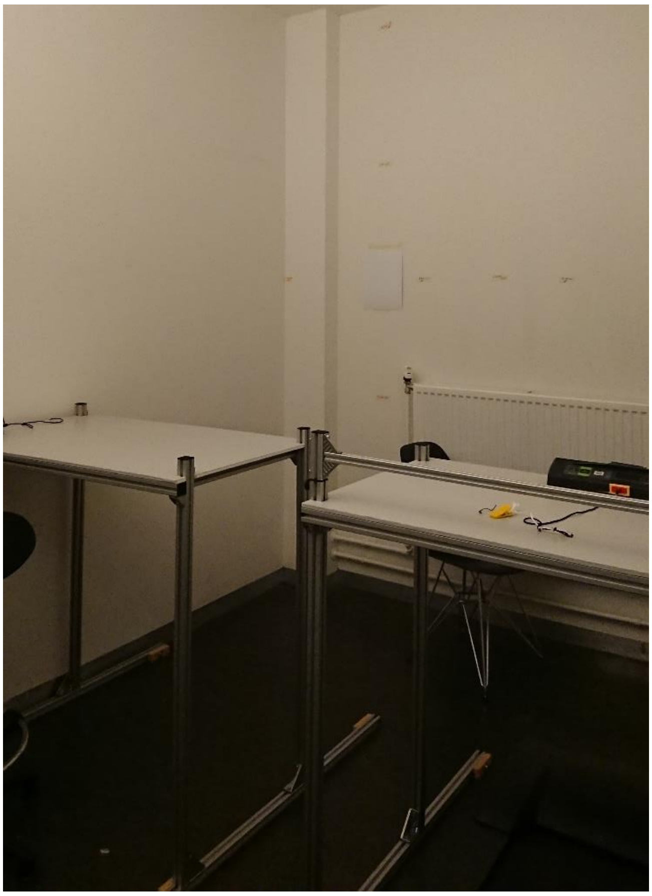


Figure 3.2. Test environment setup (photo was taken from behind the participant position)

Electric lighting in the room was switched off during the experiment, and the test environment was lit using a pair of LED uplighters (THOUSLITE LED Cubes) (Figure 3.3). Each LED array (Dimensions: 300 mm length, 300 mm width, 210 mm height; emitting size: 270*270 mm) was equipped with 11 different LED channels, allowing a tuneable spectral range of 400-700 nm and CCT range of 2000-20000K (Duv tolerance < ± 0.003) with maximum illuminance of 850 lx (D65: 1 metre) and 1250 lx (D50: 1 metre). The lighting conditions are set and controlled using LEDNavigator software.

Figure 3.3. THOUSLITE LED Cube-11 (model no: R27).

3.3. Independent variables

The independent variables used in the test period were:

I. Lighting condition (combinations of vertical illuminance at the eye (height: 1.5 m), and SPD)
II. Posture (walking vs. seated)

3.3.1. Lighting conditions

The lighting conditions are shown in Table 3.1. The reported illuminances are vertical at the height of 1.5 m above the floor, facing the participants' direction of view. To ensure the uniformity of the light levels within the experiment area, the light sources located behind the participants (Figure 3.1) directed to the ceiling and a grid of measurements was investigated the SPD, illuminance and luminance on the front wall (the end wall in front of the participants) and the tables top (Appendix A).

Adjustable seats were used to keep the eye height of participants at approximately 1.5 m when seated or walking. The lighting condition during AD was chosen to represent the luminous conditions of a typical residential setting as recommended by the Society of Light and Lighting [Society of Light, Lighting, Chartered Institution of Building Services Engineers, 2002], which recommends a range of 5 lx to 50 lx for corridors and TV lounge rooms in quasi-domestic buildings (residential).

Participants were exposed to one of the four test conditions during the test period. The first lighting condition (L1) used an illuminance of 8 lx, which is within the range of subsidiary roads [British Standard Institution, 2020] and P-classes for the pedestrian environment [CIE: 115:2010], providing a lower illuminance but the same SPD as that for the AD. For outdoor environments, CIE [CIE TN 007:2017] has suggested that adaption illuminances are estimated as the average horizontal illuminance for P-class roads ranging from 2.0 lx to 15.0 lx [British Standard Institution, 2016]. A small survey of vertical illuminance measurement on minor and major urban roads in Sheffield, United Kingdom, revealed a range of 0.5 lx to 30 lx, which confirmed that 8 lx was within the range of likely experience (Appendix B).

The second lighting condition (L2) used the same photopic illuminance as L1 but changed the SPD to increase the melanopic EDI from 3.4 lx to 10.4 lx. This value was chosen to see if an increase in melanopic EDI would result in sleepiness mitigation and because a melanopic EDI of 10 lx is the maximum recommended for unavoidable activities for (at least) three hours before bedtime to avoid melatonin suppression, which would affect sleep quality [Brown et al., 2022] and represent a level which might be used in practice. The third lighting condition (L3) used the same SPD as L1 but with the illuminance increased to offer similar melanopic EDI as L2. The purpose of lighting condition L3 is to determine if the increase in melatonin suppression observed in L2 (if any), due to the higher melanopic EDI, directly caused mitigated sleepiness and alternatively to highlight whether other factors beyond melanopic EDI, inherent to the light spectrum, might influence sleepiness. Lighting condition L3 is the same lighting condition used in the adaptation period. The fourth lighting condition (L4) was a benchmark condition representing an outdoor setting with no road lighting.

Table 3.1. Light settings (illuminance and SPD-derived metrics) used in the adaptation and test conditions.

Lighting condition	**Ev* (lx)**	**CCT (K)**	**Alpha-opic equivalent daylight (D65) illuminance (lx)****				
			S-cone	**M-cone**	**L-cone**	**Rhodopic**	**Melanopic**
Adaptation							
AD	25 lx	2700 K	8.2	19.5	25.6	12.7	10.7
Test							
L1	8 lx	2700 K	2.6	6.1	8.0	4.0	3.4
L2	8 lx	5800 K	9.2	8.2	8.6	9.4	10.4
L3	25 lx	2700 K	8.2	19.5	25.6	12.7	10.7
L4	<0.5	2700 K	<0.5	<0.5	<0.5	<0.5	< 0.5

* Vertical illuminances at eye level (1.5 m above the floor).

** Alpha-opic equivalent daylight illuminance calculated using luox calculator (https://luox.app/) [Spitschan et al.].

3.3.2. Posture

Regarding posture, during the first two hours (AD), both participants remained seated, but for the following one hour (test period), one remained seated to resemble a driver while the other walked on a treadmill with a comfortable speed (as chosen by the participant; ranged between 1.2 km/h and 2 km/h) to resemble a pedestrian (inducing higher levels of cognitive workload compared to a seated position).

3.4. Dependent variables

The effect of changes in lighting and posture was measured using four dependent variables:

I. Melatonin level
II. Audio reaction time
III. Self-reported sleepiness
IV. Skin temperature.

3.4.1 Melatonin level

Melatonin levels were determined from saliva samples collected using salivettes with a cotton swab and cap from SARSTEDT at intervals of approximately 30 minutes during the adaptation and test periods. Participants were required to chew a cotton swab for one to two minutes and then place it into a tube (Figure 3.4). The tubes were labelled and stored in a freezer set to -20 °C, as recommended to keep the saliva sample stable until the time of melatonin level analysis [Middleton, 2013].

Upon completion of all trials, the samples were packaged in dry ice to reduce degradation and transported to the Chorono@work laboratory at the University of Groningen (the Netherlands) for analysis using radioimmunoassay. This technique works by mixing a known amount of radioactive melatonin (2-1-iodomelatonin or H-melatonin) with a fixed amount of antibody raised against melatonin [De Almeida et al., 2011]. The Chorono@work laboratory was selected upon the suggestion of Dr. Vikki Revell (Lecturer in Translational Sleep and Circadian Physiology at the University of Surrey). This laboratory was also used previously by other members of the LIGHTCAP-MSCA ITN project (European Union’s Horizon 2020 research and innovation programme) for their melatonin analysis.

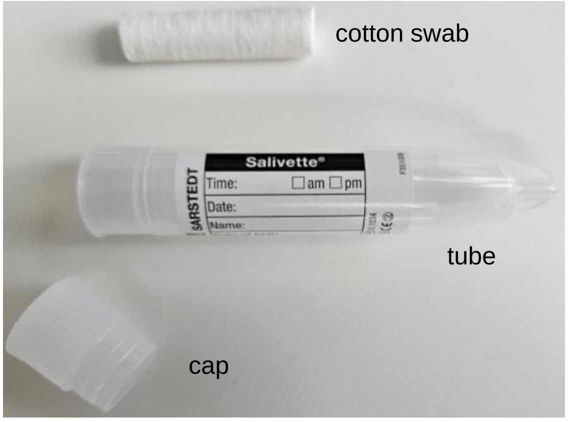


Figure 3.4. Salivettes with cotton swab and a cap for salvia collection (melatonin sampling).

3.4.2. Audio reaction time

Attention was measured using an auditory version of the PVT test, which measured reaction time from onset to detection of an acoustic stimulus (a 1000 Hz tone). In this experiment, a version of aPVT-B, initially developed by [Basner et al., 2018], was used. However, the inter-stimulus interval was modified to range from two to six seconds instead of the original two to five seconds. This slight difference was expected to reduce the predictability of the stimulus by the participants and, consequently, improve the test's sensitivity.

The loudness of this signal was established at the start of each experiment session to be near the audibility threshold for each test participant. Adjusting the loudness to the audibility threshold maximizes response delay differences between different experimental conditions [Kohfeld et al., 1981]. Each participant's signal loudness was estimated as associated with a 50% detection rate. This threshold was measured twice: once when both participants were seated, once when one was seated and the other was walking on the treadmill. This was done to include the noise created by the treadmill and walking into the threshold calculation. Accordingly, two different thresholds were set for each participant: one for the adaptation period and one for the test period. For the PVT test, the loudness of the tone played to a test participant was their estimated hearing threshold (50% detection rate), which was increased by 10 dB. This increase is perceived to be about twice as loud [Stevens, 1957], ensuring the audibility of every stimulus. Headphones were worn for this threshold assessment and subsequently for the PVT performance. The signal was played for half a second at randomised intervals ranging from two to six seconds. Test participants wore headphones and were instructed to press a desk-mounted response button as soon as they heard a stimulus. Trials were conducted in pairs. Different stimulus patterns were delivered to each participant to prevent the other participant's mechanical actions from being used as a cue.

3.4.3. Self-reported sleepiness

Self-report of sleepiness was assessed using the KSS. This is a 9-point category response scale with the categories labelled from 1 (very sleepy) to 9 (extremely alert) (Table 3.2). Participants were asked to state their sleepiness level at 30-minute intervals throughout the adaptation and test periods.

Table 3.2. Response categories of the 9-point Karolinska Sleepiness Scale.

Rating	Description
9	Extremely alert
8	Very alert
7	Alert
6	Rather alert
5	Neither alert nor sleepy
4	Some signs of sleepiness
3	Sleepy, but no effort to keep awake
2	Sleepy, some effort to keep awake
1	Very sleepy, great effort to keep awake

3.4.4. Skin temperature

Skin temperature was measured using temperature sensors (iButtons, DS1922L) attached to each participant at four locations: the neck, wrists, and shin. After being attached before the start of the adaptation period, these sensors subsequently measured temperatures and recorded them at three-second intervals throughout the three-hour experiment. As in previous work [Te Kulve et al., 2018], room temperature was also measured using an iButton, here with one suspended at a height of approximately one metre above the floor beside the test participants.

3.5. Procedure

The experiment was conducted between 13 October 2021 and 16 November 2021. The adaptation period started at 21:00, which was chosen to be around three hours before the usual sleep time of the recruited participants. Participants (two per session) were asked to arrive 45 minutes before the adaptation period to enable preparation, with the lighting condition of this preparation period being the same as that for the adaptation period. They wore their normal clothing and were asked to bring paper-based reading material for the intervals between tests. Several tasks were undertaken before the adaptation period started:

I. Participants were invited to sign the consent form in accordance with ethical approval.
II. Visual acuity was checked using a Landolt C chart to ensure an acuity of at least 6/12 (the minimum standard for driving in the UK [Government Digital Service, 2012]), with participants wearing their normal corrective lenses.
III. Colour blindness was evaluated using Ishihara colour plates illuminated by a D65-simulating source.
IV. The four temperature sensors (iButton) were fixed onto the skin with adhesive tape.
V. The participants were seated in their chairs for the adaptation period. The choice of seated or walking for the test period was initially assigned randomly by drawing lots from a sealed bag, but toward the end of the experiment, the experimenter assigned this to ensure a gender-balanced participant assignment.
VI. Each participant's hearing threshold was measured by presenting a series of tones of different loudness in random order, with the participant instructed to press a button upon detection.

Figure 3.4. summarizes the protocol of this experiment. The dependent variables were recorded at regular intervals within the adaptation and test period. Saliva samples, PVT, and KSS were recorded at intervals of approximately 30 minutes (Figure 3.5). The PVT test was split into two three-minute blocks, one immediately before and one immediately after the interval point at which saliva samples and the KSS evaluation were taken. The results of both three-minute blocks were considered as one six-minute test, having responses to typically approximately 60 stimuli altogether (no significant difference was noticed between first and second block of the PVT test (Appendix B)).

The measurement points for the KSS, the saliva samples and the PVT were centred on minutes 5, 30, 60, 90 and 110 in the adaptation phase and minutes 10, 30 and 60 in the test phase. The selection of these intervals is upon the suggestion of Doctor Vikki Revell (Lecturer in Translational Sleep and Circadian Physiology at the University of Surrey) and other sleepiness psychophysiological experts within the LIGHTCAP consortium (https://lightcap.eu/) to enable a proper evaluation of changes in melatonin levels. The intervals were labelled AD1 to AD5 in the adaptation phase and T1, T2 and T3 in the test phase. In the adaptation phase, at minutes 30 (AD2) and 90 (AD4), the KSS and saliva samples were recorded, but the PVT test was not conducted. Skin temperature was recorded continuously and subsequently interpolated for the two minutes centred on those same points.

Two hours from the start of the adaptation period, the light setting changed to one of the four test conditions (Table 3.1), and one participant transitioned from being seated to walking on the treadmill, while the other participant remained seated. The treadmill was set to a comfortable walking speed (as chosen by the participant, ranging between 1.2 km/h and 2 km/h. This threshold was set prior to the start of the experiment). The measurement schedule in the adaptation period was set so that the second part of the final PVT test was completed just before the change in lighting conditions.

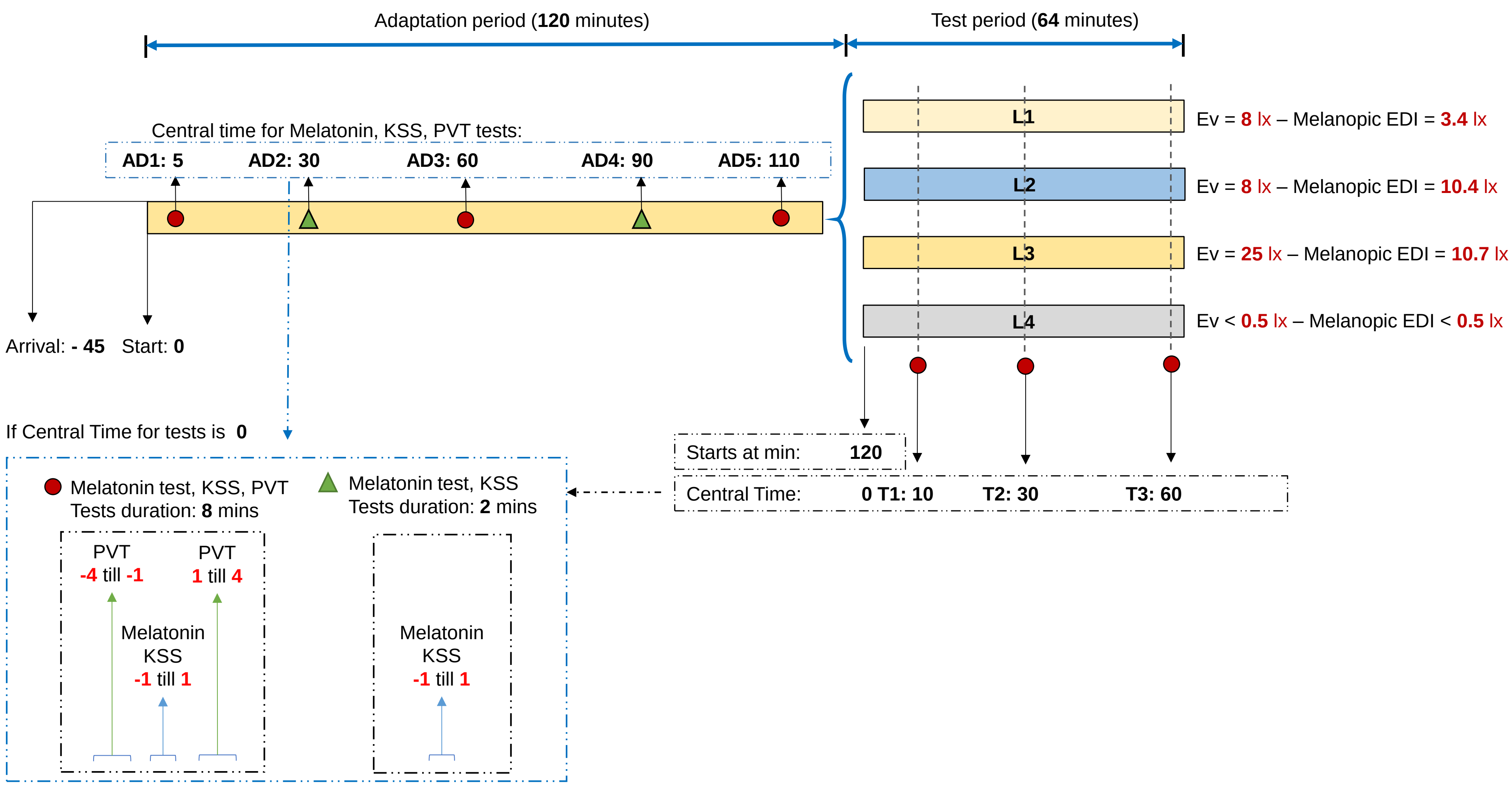


Figure 3.5. The protocol of Experiment 1.

3.6. Sample

Participants were recruited through emails posted on volunteer recruitment lists to the University of Sheffield staff and students. Participants were selected from those meeting the following criteria: aged between 18 and 30 years; healthy (assessed using self-report of no short or long-term medication, regular sleep, non-smoker, no history of mental or physical health issues); habitual bedtime not later than midnight; not employed for night-time shift work in the past year; and not having travelled over a time zone in the past three months.

Forty participants were recruited, with ten (five males and five females) allocated to each of the four lighting conditions shaping a between-subject design. Table 3.3 summarizes the age and gender diversity of the participants according to posture and lighting conditions. Participants were asked to keep a steady sleep-wake schedule for the seven days before the experiment, which was confirmed through a self-reported sleep-wake diary. On the day of their experiment, participants were asked not to eat bananas or chocolate during the day, nor take any medication to avoid consuming substances after midday which contain alcohol or caffeine and refrain from napping; otherwise, these might influence the melatonin analysis [Middleton, 2013]. During the experiment, participants were given a range of snacks, including pure orange juice, nuts, and water. Participants were paid £40 upon completion of the experiment.

Table 3.3. Age and gender characteristics of the participants by lighting condition and posture.

Lighting condition	Posture	Age (years)			Gender (no)	
-	-	Median	Min.	Max.	Male	Female
L1	Seated	19	18	27	2	3
	Walking	23	19	28	3	2
L2	Seated	19	18	26	3	2
	Walking	20	19	30	2	3
L3	Seated	23	18	30	3	2
	Walking	19	19	25	2	3
L4	Seated	19	18	30	2	3
	Walking	23	19	28	3	2

3.7. Summary

Chapter 3 detailed the design of Experiment 1. It described the selection and implementation of independent variables: lighting condition, and posture. Furthermore, the chapter comprehensively described the measurement techniques (melatonin level, audio reaction time, self-reported sleepiness, and skin temperature) used to investigate how changes in independent variables affected the hypothesized aim: sleepiness mitigation. A step-by-step protocol outlining the tasks performed by experimenters and participants before and during the experiment was presented. This chapter concluded with a description of the study sample's demographics and their distribution across different experimental groups. The next chapter focuses on the statistical analysis of Experiment 1 findings.

Chapter 4. Results: Experiment 1

Chapter 4. Results: Experiment 1

4.1. Introduction

Chapter 3 outlines the methodology employed in Experiment 1, which examines the influence of independent variables (lighting conditions and posture) on participants' sleepiness. This chapter presents the result of Experiment 1, including outcomes of the four dependent measures: melatonin level, audio reaction time, self-reported sleepiness, and skin temperature. Analyses were performed using IBM SPSS Statistics version 28.0.0.0. The statistical significance level (alpha) was set at 0.05. When necessary, p-values were adjusted using Bonferroni correction to account for multiple comparisons [Chen et al., 2017].

4.2. Data preparation

Before testing the distribution and selection of the most suitable analysis, the data for each variable should be cleaned of any errors and replaced with representative values, if necessary.

4.2.1. Error cleaning

For audio reaction time, a test participant responded to approximately 60 stimuli in each trial. Each participant has completed six trials per experiment night at different times. Recorded results were initially controlled to exclude any errors. Generally, two types of errors can occur in vigilance tests: errors of omission (lapses of attention) and errors of commission (response without stimuli). The error of omission is defined by the threshold of twice the median and measured by considering all reaction times without excluding any responses. The error of commission is defined as the responses without stimuli or responses faster than 100 ms [Basner and Dinges, 2011]. Therefore, each time the participant presses the responses button without a stimulus in advance or with a stimulus but with a pace faster than 100 ms, it will be counted as one error of commission. The data for audio reaction time was cleaned to include only valid responses for the analysis. No errors existed in the data for melatonin level, self-reported sleepiness, and skin temperature.

4.2.2. Representative values

For the audio reaction time, the 60 responses to acoustic stimuli per participant in a single trial must be condensed into a single value. The most representative of this data might be the mean or median. For the 40 participants, each with six trials of responses per experiment night, there are 240 datasets. To establish whether mean or median is the better representative value, 20 out of these 240 data sets were selected, and the distributions of reaction times were assessed against a normal distribution. The majority (80%) highlighted a non-normal distribution (Appendix C, Table C.1). Therefore, the median amongst the 60 responses of each participant in a single trial was selected as the representative reaction time for a single participant in a specific trial.

For skin temperature, measured at three-second intervals throughout the experiment and at each test location (neck, wrists, and shin), a single representative value for a participant at each test interval must be provided before further analysis. To estimate this representative value, the mean temperature for 60 seconds before and after each test interval was measured for each test location, assuming skin temperature is a continuous value and expected to be normally distributed. To establish a single value, the mean skin temperature at each location was averaged, providing a single value for each test interval. Melatonin level and self-reported sleepiness are already a single value and can be analysed directly.

4.3. Testing the distribution

The data for each dependent variable were first analysed to determine if they were normally distributed. This was done using four methods: comparing measures of central tendency (mean, median, and confidence intervals), graphical representations (box chart and histogram), measures of dispersion (skewness and kurtosis), and statistical tests (Shapiro-Wilks and Kolmogorov-Smirnov tests).

The procedure for normality checks was as follows:

First, the mean and median were compared. If the median was within the range of the mean confidence level (CI 95%), then the data was considered normally distributed. Otherwise, the data was not normally distributed.

Second, graphical representations were used to inspect the data. If the data was normally distributed, the histogram and boxplot should follow normal distribution shapes Figure 4.1. Otherwise, the graphs would be skewed, and the data would not be normally distributed. If one suggests a normal distribution and the other suggests otherwise, the distribution is considered "*near*" normal.

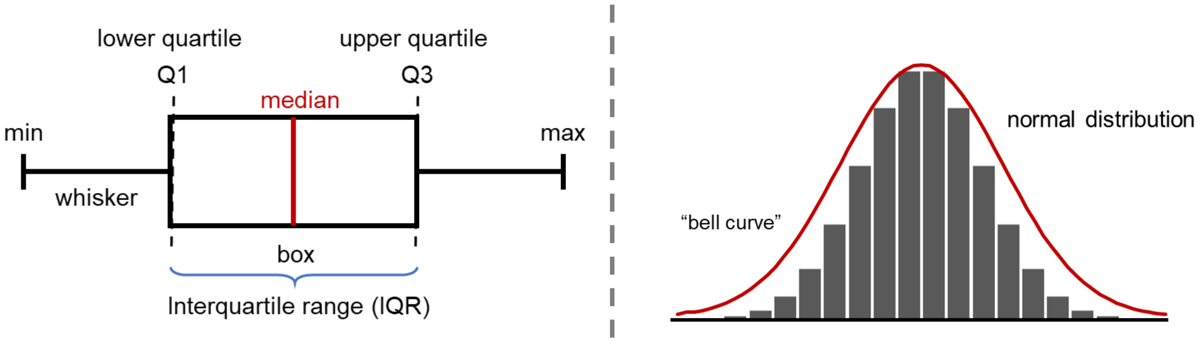


Figure 4.1. Normal distribution graphical representation (box chart left side, histogram right side).

Third, measures of dispersion were used to assess skewness and kurtosis. Skewness measures the asymmetry of a distribution, and kurtosis measures the sharpness of the peak of a distribution. In a normal distribution, skewness and kurtosis should be near zero (skewness: within ±0.5, kurtosis: within ±1.0). If skewness and kurtosis were within the mentioned ranges, then the data is considered normally distributed. Otherwise, the data was not normally distributed. If one suggests a normal distribution and the other one suggests otherwise, the distribution is considered "*near*" normal.

Fourth, two statistical tests were performed: the Kolmogorov-Smirnov and the Shapiro-Wilks tests. These tests are used to determine if a distribution is normally distributed. The significance level for these tests was 0.05. If the p-value for both tests was less than 0.05, then the data was not normally distributed. Otherwise, the data was considered normally distributed.

The final decision about whether the data was normally distributed was made based on the results of all four methods. If the results of at least two of the methods were "*yes*" and the other two were "*near*", then the data was considered normally distributed. Otherwise, the data was not normally distributed.

4.3.1. Melatonin level

For each participant (40 total) at each test interval, eight total (AD1, AD2, AD3, AD4, AD5, T1. T2, T3), there is a single number for melatonin level. The distribution of melatonin levels needs to be checked among the 40 participants to select the suitable statistical method for analysis. Melatonin levels did not follow a normal distribution (Appendix C, Table C.2) and were analysed using nonparametric statistical methods.

4.3.2. Audio reaction time

For each participant (40 total) at each test interval, six total (AD1, AD3, AD5, T1, T2, T3), there is a single value as replaced by the median (section 4.2.2). The distribution of these representative values needs to be checked among the 40 participants. This distribution was normal (Appendix C, Table C.3), so parametric methods have been selected for further analysis.

4.3.3. Self-reported sleepiness (KSS)

For each participant (40 total) at each test interval, eight total (AD1 to T3), there is a single sleepiness score. KSS data are subjective and ordinal; therefore, they must be analysed using non-parametric methods. However, to be extra cautious, these data were also checked against normal distribution and found to be non-normal (Appendix C, Table C.4). Therefore, non-parametric methods were selected to analyse KSS results.

4.3.4. Skin temperature

For each participant (40 total) at each test interval, eight in total (AD1 to T3), there is a single representative as replaced by mean (section 4.2.2). The distribution of these representative values must be checked among the 40 participants. This distribution was normal (Appendix C, Table C.5), so parametric methods have been selected for further analysis.

4.4. Statistical analysis

Statistical tests are mathematical tools for analysing data designed to identify patterns and trends in a dataset. Selection of proper statistical analysis method is of importance as a wrong selection increases the chances of misinterpretation and complete drawing of conclusions. To choose a suitable statistical analysis method, study design (e.g., independent or related samples), number of sample groups which need to be analysed, distribution of each sample (normal, non-normal) and type of data (e.g., ratio, interval, ordinal, etc.) needs to be carefully assessed.

A dataset that follows a normal distribution should be analysed using parametric tests and mean (arithmetic mean for n numbers $= \frac{1}{n}\ (x_1 + x_2 + \cdots + x_n)$), should be used as data representative for comparison. In contrast, a dataset which follows a non-normal distribution needs to be analysed using non-parametric tests [Parab and Bhalerao, 2010] and median (data are arranged in the order of size, and the data in the middle (or the mean of the data in the middle) will be considered as median) should be used as data representative for comparison. In the case of normally distributed variables, repeated measure ANOVA was employed to test the interactions between variables, followed by pairwise comparisons using the t-test when significant differences were observed. For variables that exhibited non-normal distribution, and related samples Friedman's two-way analysis of variance by ranks was employed to examine interactions, followed by pairwise comparisons using the Wilcoxon signed rank test upon detecting significant differences. Independent samples were analysed using the Kruskal-Wallis test.

4.4.1. Melatonin level

Figure 4.2 shows the median melatonin levels for all participants at each test interval (AD1 to T3), which highlights a gradual increase as the test interval progresses closer to participants' habitual bedtime (midnight). The test rendered a Chi-square value, which was significant (Table 4.1).

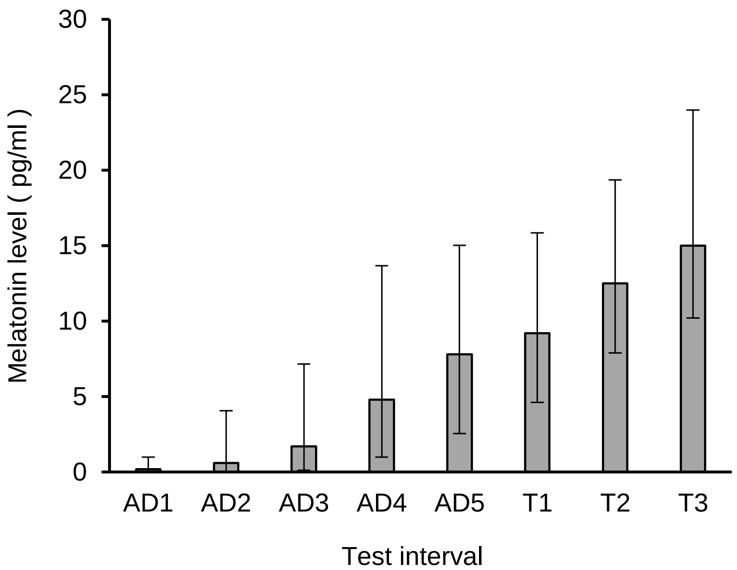


Figure 4.2. Median melatonin level derived from saliva samples collected at each test interval (all participants). Error bars show the interquartile range (IQR).

Table 4.1. Melatonin level derived from saliva sample interaction with time, posture, and lighting condition.

Variables	p			Chi-square
Test interval	< 0.001			221.2
	T1	T2	T3	-
Posture	0.433	0.685	0.543	-
Lighting condition	0.837	0.880	0.989	-

Figure 4.3 illustrates the alterations in melatonin levels associated with posture changes (walking vs. seated) during the test phase. Since posture modifications were only implemented during the test phase, the impact of posture on melatonin levels was assessed by comparing the result between the two groups, walking (n = 20) vs. seated (n = 20), using the Kruskal-Wallis Test. The result did not indicate a statistically significant effect of posture change at any of the test phase intervals (Table 4.1).

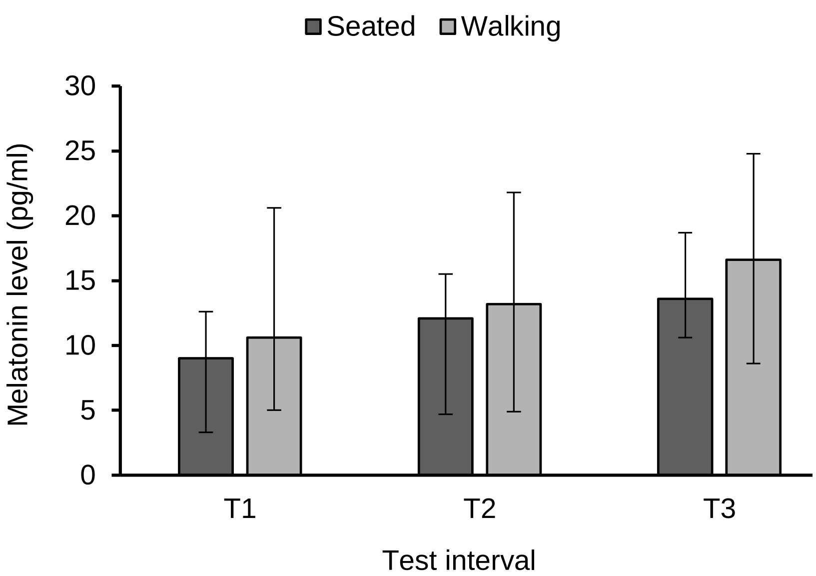


Figure 4.3. Median melatonin levels derived from saliva samples for posture (seated vs. walking) at the test phase. Error bars show the IQR.

The influence of altering lighting conditions (L1-L4) on melatonin levels was explored using two approaches. The first approach compared melatonin levels under the four lighting conditions that were employed during the test phase. This analysis revealed no statistically significant effect of lighting condition changes at any of the test phase intervals (Figure 4.4, Table 4.1).

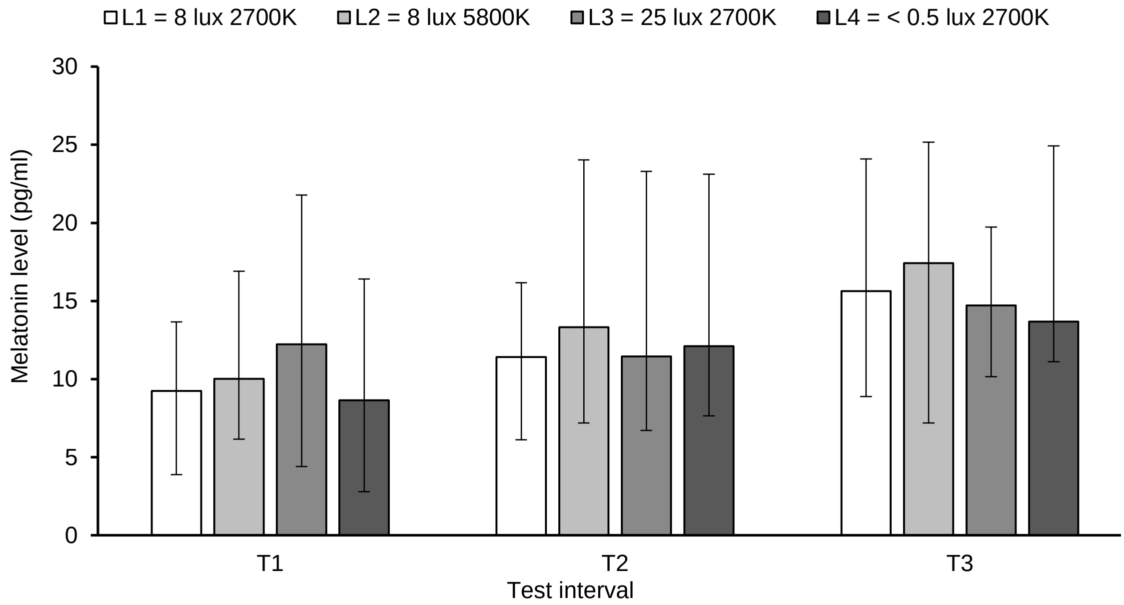


Figure 4.4. Median melatonin levels derived from saliva samples for lighting conditions L1 to L4 at the test phase. Error bars show the IQR.

Alternatively, a second approach can be employed, given the fact that all participants experienced the same lighting intervention (L3) during the adaptation phase. This serves as a control condition for evaluating the effect of lighting conditions on melatonin levels. The effect of lighting conditions was investigated by comparing the last melatonin measurement in the adaptation phase (AD5) for participants ($n = 10$) in each lighting condition with their respective test phase intervals (T1-T3). This effectively controls for the observed gradual increase in melatonin levels across lighting conditions. The general trend was initially examined by comparing melatonin levels between trials AD5, T1, T2, and T3. This analysis revealed Chi-squares (L1=20.937; L2=17.182; L3=20.160; L4= 20.758), which were all significant ($p<0.001$). However, subsequent pairwise comparisons (Table 4.2) did not identify a meaningful trend in melatonin levels attributable to changes in lighting conditions. The observed gradual increase in melatonin levels persisted regardless of any changes in lighting conditions.

To conclude, the result did not suggest a significant effect of any of the lighting interventions on melatonin levels. This implies that melatonin levels exhibited a gradual increase throughout the experiment, irrespective of exposure to different lighting conditions (L1, L2, L3, and L4).

Table 4.2. p-values for pairwise comparison of melatonin level derived from saliva samples interaction between AD5 vs. T1, T2 and T3.

Lighting condition	Trial	T1	T2	T3
L1	AD5	1.000	0.516	0.030
	T1	-	0.846	0.030
	T2	-	-	0.030
L2	AD5	0.444	0.030	0.090
	T1	-	0.030	0.132
	T2	-	-	1.000
L3	AD5	0.03	0.030	0.042
	T1	-	0.168	0.282
	T2	-	-	1.000
L4	AD5	0.132	0.030	0.042
	T1	-	0.054	0.048
	T2	-	-	1.000

* Bonferroni adjusted (significant level < 0.05).

4.4.2. Audio reaction time

Figure 4.5 illustrates the mean audio reaction times at the six intervals where this was measured (AD1 to T3). Regarding test interval, significant differences were found between the trials (Table 4.3). Subsequent pairwise comparison revealed significant differences only between AD1 vs. T1 and AD1 vs. T2 (Table 4.4).

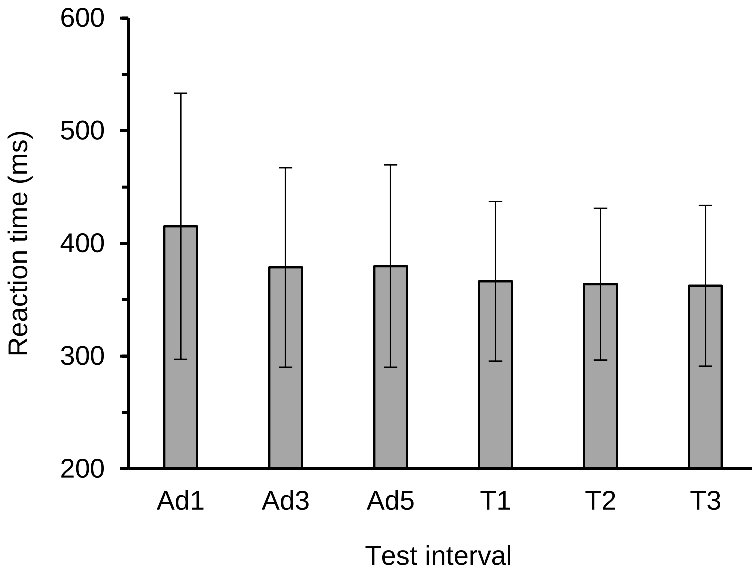


Figure 4.5. Mean reaction times at each test interval as measured using the acoustic PVT. Error bars show one standard deviation above and below the mean.

In contrast, regarding posture and lighting condition, the interactions (reaction time vs. posture and reaction time vs. lighting condition) resulted in no significant differences (Table 4.3).

Table 4.3. Audio reaction time interaction with time, posture, and lighting condition.

Variables	F (df between, df within)	p-value*	Effect size**
Test interval	(2.299, 73.560) = 5.947	0.003	0.157
Test interval*Lighting condition	(6.896, 73.560) = 0.783	0.602	0.068
Test interval*Posture	(2.299, 73.560) = 1.331	0.271	0.298

* Greenhouse–Geisser correction.
** Effect size thresholds: small = 0.20; medium = 0.50; large = 0.80 [Lipsey and Wilson, 2001].

Table 4.4. p-values for pairwise comparison of audio reaction time according to the test interval.

Test interval	AD2	AD3	T1	T2	T3
AD1	0.104	0.562	0.05	0.036	0.086
AD2	-	1.000	1.000	1.000	1.000
AD3	-	-	0.903	1.000	1.000
T1	-	-	-	1.000	1.000
T2	-	-	-	-	1.000

* Bonferroni adjusted (significant level < 0.05).

Furthermore, the analysis was repeated for only the three test sessions (T1, T2 and T3), where lighting conditions and posture were varied. This analysis did not reveal any significant main effects of lighting conditions or posture (Table 4.5). Figures 4.6 and 4.7, respectively, show the mean reaction time according to posture (walking vs. seated) and lighting condition (L1 to L4) for trials T1 to T3 (test period).

Table 4.5. Audio reaction time interaction with posture and lighting condition (Test phase only).

Variables	F	p-value	Effect size
Lighting condition	1.896	0.15	0.151
Posture	0.301	0.587	0.009

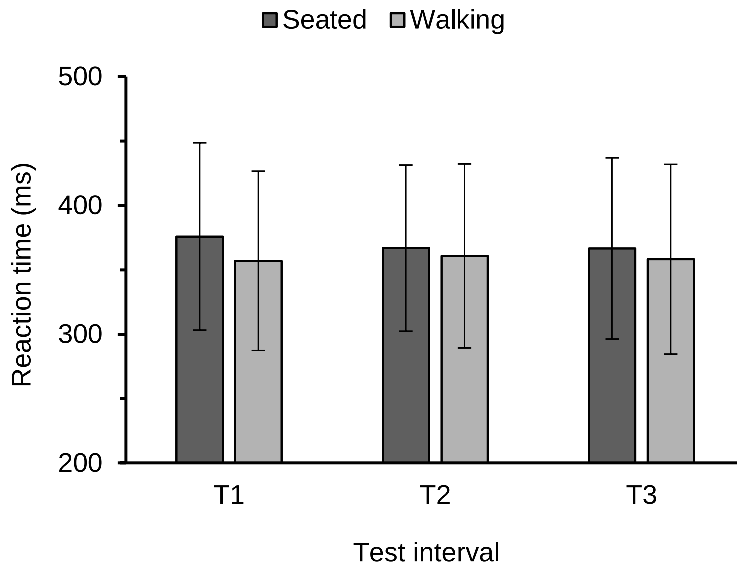


Figure 4.6. Mean reaction time for posture (seated vs. walking) at the test phase. Error bars show one standard deviation above and below the mean.

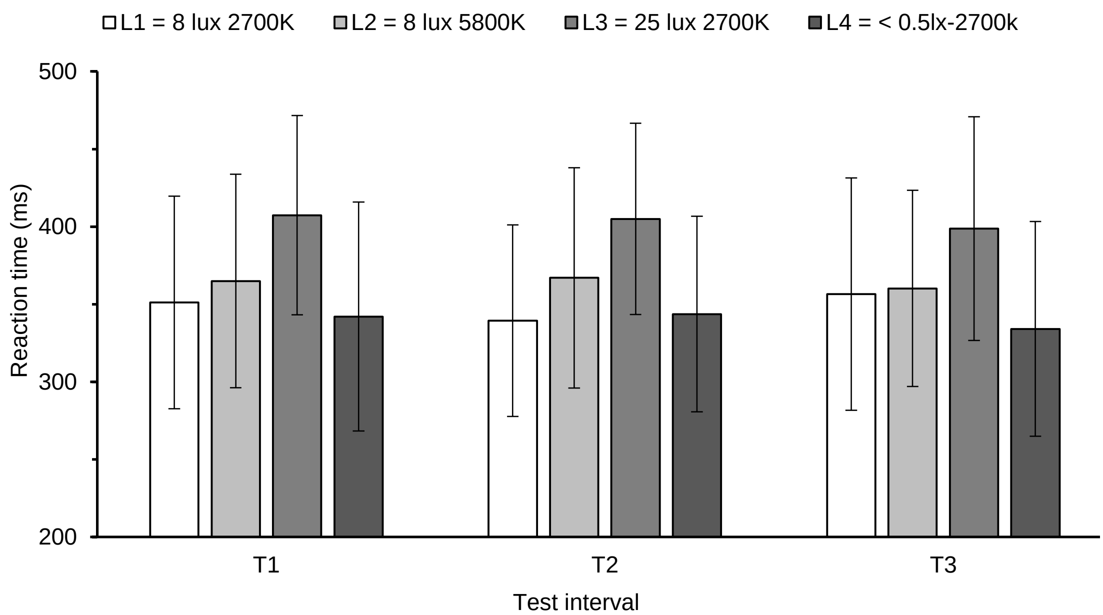


Figure 4.7. Mean reaction time for lighting conditions L1 to L4 at the test phase. Error bars show one standard deviation above and below the mean.

4.4.3. Self-reported sleepiness

Figure 4.8 illustrates the median sleepiness scores at each interval (AD1 to T3), which highlights a gradual decrease as it gets closer to participants' habitual bedtime. The test rendered a Chi-square value, which was significant (Table 4.6).

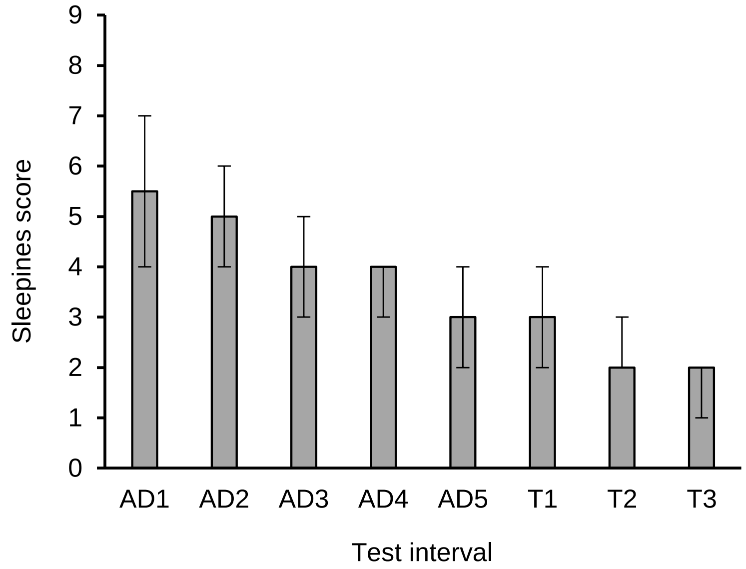


Figure 4.8. Median self-reported sleepiness score at each test interval. Error bars show the IQR (sleepiness score: 1 = very sleep, 9 = extremely alert)

Since the posture change (walking vs. seated) occurred at the test phase, the effect of posture on sleepiness score was assessed by comparing the results between the two groups of walking (n = 20) vs. seated (n = 20) in the test phase. The analysis revealed near statistically significant effects at T1 and T2 but not at T3 (Table 4.6). As shown in Figure 4.9, this suggests a tendency for the seated participants to report being sleepier than the walking participants. During the adaptation phase, the test did not suggest a significant effect at any interval ($p \geqslant 0.244$ in each case).

Table 4.6. Self-reported sleepiness score interaction with time, posture, and lighting condition.

Variables	**p-value**			**Chi-square**
Test interval	< 0.001			179.5
	T1	T2	T3	-
Posture	0.056	0.091	0.208	-
Lighting condition	0.662	0.808	0.787	-

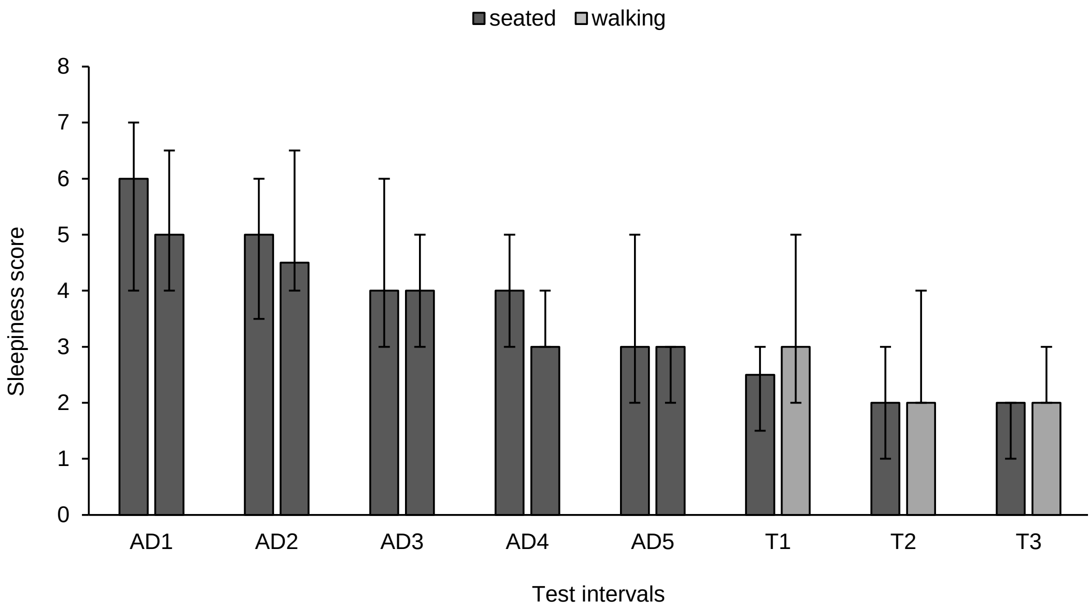


Figure 4.9. Median self-reported sleepiness scores reported at each test interval according to whether the test participant was seated or walking during the test phase. Error bars show the IQR. Note: During the adaptation phase, all participants were seated.

The potential influence of lighting condition changes (L1 to L4) on sleepiness score was evaluated using two approaches. The first approach compared sleepiness scores under the four lighting conditions employed in the test phase. This test suggested no significant effect of change in lighting condition at any of the test phase intervals (Figure 4.10 and Table 4.6).

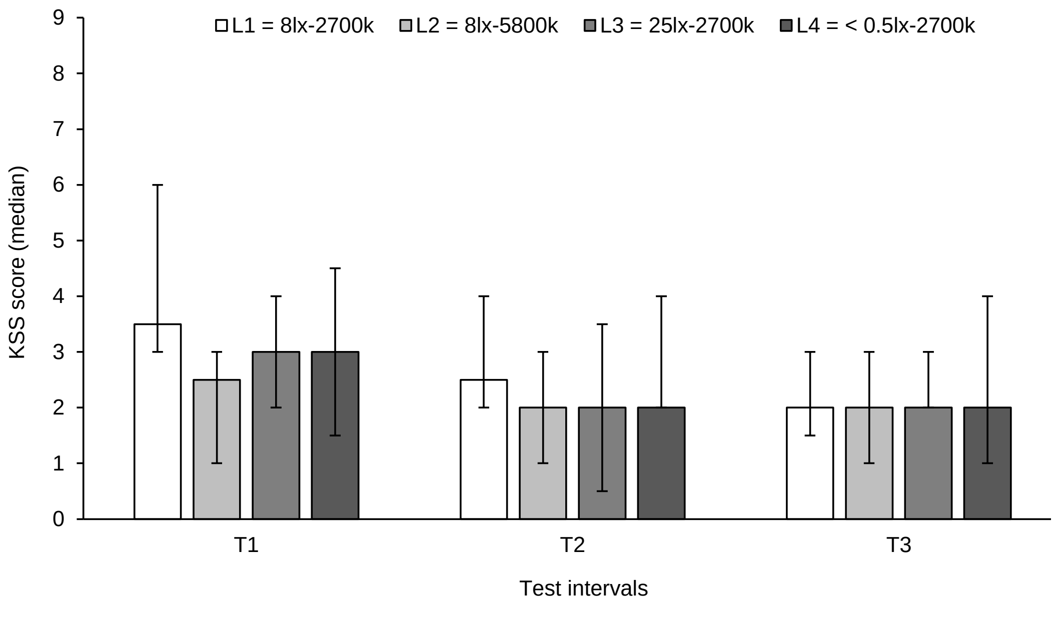


Figure 4.10. Median self-reported sleepiness score for lighting conditions L1 to L4 at the test phase. Error bars show the IQR.

Alternatively, a second approach can be employed, given the fact that all participants experienced the same lighting intervention (L3) during the adaptation phase. This serves as a control condition for evaluating the effect of lighting conditions on sleepiness scores. The effect of lighting condition was investigated by comparing the last sleepiness score in the adaptation phase (AD5) for participants (n = 10) in each lighting condition with their respective reported test phase intervals (T1-T3). This effectively controls the changes in sleepiness score according to the changes in lighting conditions. The general trend was initially examined by comparing sleepiness scores between trials AD5, T1, T2, and T3. This analysis revealed Chi-squares (L1=10.273; L2=10.273; L3=12.689; L4=10.329), which were all significant ($p \leq 0.016$). However, subsequent pairwise comparison (Table 4.7) did not identify a meaningful trend in sleepiness scores attributable to changes in lighting conditions.

To conclude, the result did not suggest a significant effect of any of the lighting interventions on reported sleepiness scores. This implies that participants reported higher levels of sleepiness irrespective of exposure to different lighting conditions (L1, L2, L3, and L4).

Table 4.7. p-values for pairwise comparison of melatonin level derived from saliva samples interaction between AD5 vs. T1, T2 and T3.

Lighting condition	**Trial**	T1	T2	T3
L1	AD5	1.000	1.000	0.240
	T1	-	0.204	0.156
	T2	-	-	0.354
L2	AD5	1.000	0.576	0.084
	T1	-	0.942	0.138
	T2	-	-	0.276
L3	AD5	1.000	0.588	0.510
	T1	-	0.150	0.504
	T2	-	-	1.000
L4	AD5	1.000	1.000	0.240
	T1	-	0.204	0.156
	T2	-	-	0.354

* Bonferroni adjusted (significant level < 0.05).

4.4.4. Skin temperature

Figure 4.11 illustrates the mean skin temperature at each of the eight test intervals. Regarding test interval, significant differences were observed among the trials (Table 4.8). These differences were investigated further using a pairwise comparison, revealing significant differences only between AD2 vs. T1 and AD5 vs. T1 (Table 4.9).

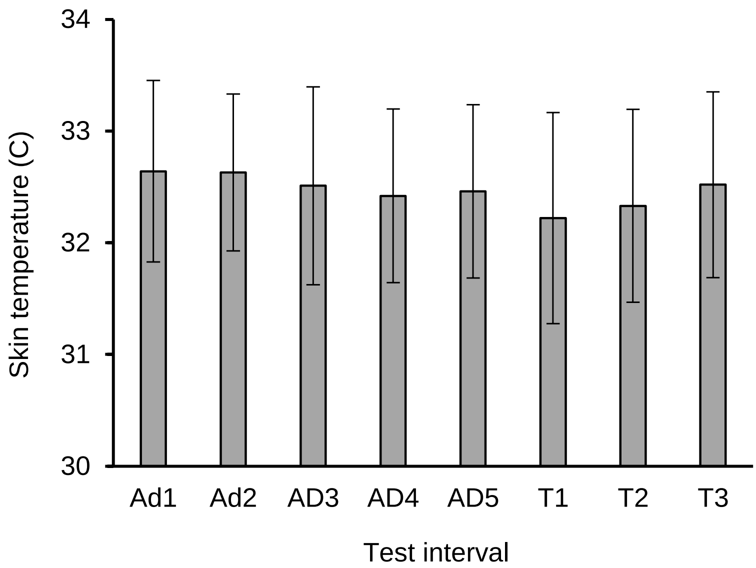


Figure 4.11. Mean skin temperature at each test interval. Error bars show one standard deviation above and below the mean.

In contrast, regarding posture and lighting condition, the interactions (skin temperature vs. posture and skin temperature vs. lighting condition) resulted in no significant differences (Table 4.8).

Table 4.8. Skin temperature interaction with time, posture, and lighting condition.

Variables	**F** (df between, df within)	**p-value***	**Effect size**
Test interval	(3.924, 125.553) = 4.427	0.002	0.122
Test interval*Lighting condition	(11.771, 125.553) = 1.963	0.627	0.155
Test interval*Posture	(3.924, 125.553) = 2.003	0.639	0.059

* Greenhouse–Geisser correction.

Table 4.9. p-values for pairwise comparison skin temperature according to test interval.

Test interval	AD2	AD3	AD4	AD5	T1	T2	T3
AD1	1.000	1.000	1.000	1.000	0.074	0.311	1.000
AD2	-	1.000	1.000	1.000	0.015	0.09	1.000
AD3	-	-	1.000	1.000	0.067	1.000	1.000
AD4	-	-	-	1.000	0.927	1.000	1.000
AD5	-	-	-	-	0.042	1.000	1.000
T1	-	-	-	-	-	1.000	0.084
T2	-	-	-	-	-	-	0.605

* Bonferroni adjusted (significant level < 0.05).

Furthermore, the analysis was repeated for only the three test sessions (T1, T2 and T3), where lighting conditions and posture were varied. This analysis did not reveal any significant main effects of posture (Table 4.10). However, a significant difference was observed for lighting conditions (Table 4.10). Subsequent pairwise comparisons highlighted this significant difference only between lighting conditions L1 and L3 and L1 and L4 (Table 4.11). Figures 4.12 and 4.13, respectively, show the mean reaction time according to posture (walking vs. seated) and lighting condition (L1 to L4) for trials T1 to T3 (test period).

Table 4.10. Skin temperature interaction with posture and lighting condition (Test phase only).

Variables	F	p-value	Effect size
Lighting condition	4.523	0.009	0.297
Posture	0.076	0.785	0.002

Table 4.11. p-values for pairwise comparison of skin temperature according to lighting condition.

Test interval	L2	L3	L4
L1	0.385	0.041	0.011
L2	-	1.000	0.865
L3	-	-	1.000

* Bonferroni adjusted (significant level < 0.05).

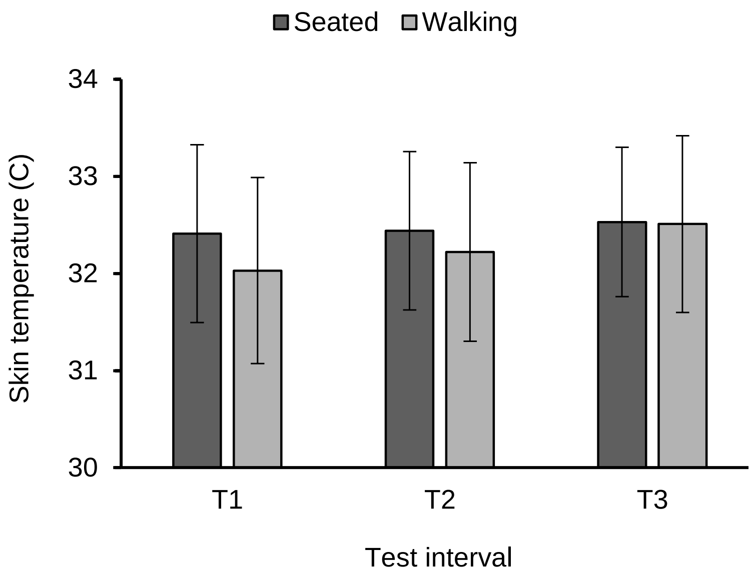


Figure 4.12. Mean skin temperature according to posture (seated vs. walking) at the test phase. Error bars show one standard deviation above and below the mean.

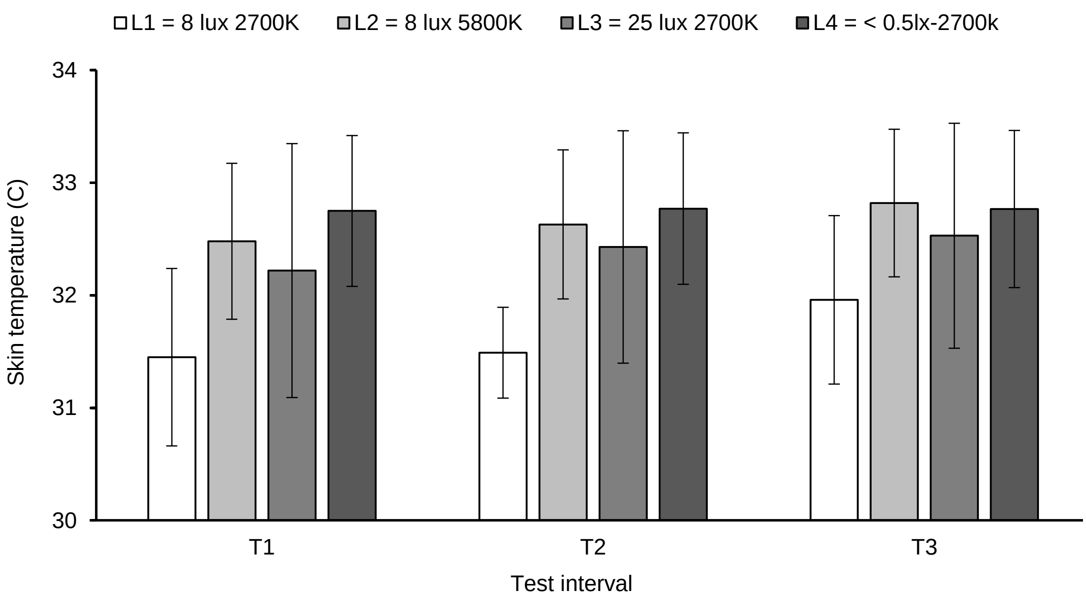


Figure 4.13. Mean skin temperature according to lighting conditions L1 to L4 at the test phase. Error bars show one standard deviation above and below the mean.

4.5. Summary

The aim of Experiment 1 was to explore and examine the effect of different lighting interventions delivering different melanopic EDIs on sleepiness-related measures. The four test conditions presented melanopic EDIs of approximately less than half lux to 10 lx, which was insufficient to reveal meaningful differences in reaction time to an acoustic stimulus, melatonin levels derived from saliva samples, self-reported sleepiness, and skin temperature. These results do not suggest that road lighting levels that are accessible and currently practical to use in an application are sufficient to decrease drivers' sleepiness after dark.

The subsequent section will discuss the findings of Experiment 1 and compare them with similar previous work. This chapter will further highlight current limitations to the experimental setup and suggest potential areas for further research.

Chapter 5. Discussion: Experiment 1

Chapter 5. Discussion: Experiment 1

5.1. Introduction

The current chapter initially evaluates whether the experimental findings support the hypotheses. It then proceeds to critically examine the validity of the current findings by comparison with previous research, identifies the limitations of the study, and makes suggestions for further research.

Experiment 1 investigated hypothesis H1 (An increase in melanopic EDI (lx) leads to a decrease in sleepiness when driving in the evening after dark) using four different measures of sleepiness (melatonin level, audio reaction time, self-reported sleepiness, and skin temperature) in a laboratory setting. The experiment commenced after dark and three hours before the participants' habitual bedtime. Previous research suggests that as the time approaches an individual habitual bedtime, he/she would experience increased levels of sleepiness as indicated by higher melatonin levels, slower audio reaction time and higher error rates, increased self-reported sleepiness, and higher skin temperature. Experiment 1 aimed to determine whether exposure to a light intervention with higher melanopic EDI (lx) than typically used in road lighting could mitigate sleepiness. The interaction between lighting conditions (L1 to L4) and four measures of sleepiness is summarised in Table 5.1.

Table 5.1. Interaction between lighting conditions (L1 to L4) with measures of sleepiness used in Experiment 1.

Sleepiness measure	Impact	Interpretation
Melatonin level	Not significant	Melatonin levels gradually increase as bedtime approaches, indicating a normal pattern of getting sleepy regardless of exposure to any of the lighting conditions.
Audio reaction time (PVT)	Not significant	Exposure to neither of the lighting conditions resulted in a faster reaction time.
Self-reported sleepiness	Not significant	Sleepiness scores gradually decreased as bedtime approached, indicating a normal pattern of getting sleepy regardless of exposure to any of the lighting conditions.
Skin temperature	Significant	Skin temperature was higher in lighting conditions L3 and L4 when compared with lighting condition L1, indicating higher levels of sleepiness.

As stated in hypothesis H1, this experiment aimed to mitigate sleepiness using lighting conditions with higher levels of melanopic EDIs. However, the findings regarding physiological arousal indicate that higher levels of melanopic EDI in lighting conditions L2 and L3 (≈ 10 lx) compared to L1 (3.4 lx) and

L4 (< 0.5 lx) were not sufficient to interfere with the expected gradual increase of melatonin hormone as habitual bedtime approached.

The other physiological measure of this study, skin temperature, exhibited significant changes which did not appear to be systematic. As noted in the literature review in Chapter 2, lower skin temperature levels are associated with lower levels of sleepiness [Wright et al., 2002; Kleitman and Jackson, 1950; Hull et al., 2003]. Therefore, as hypothesized, it was expected that exposure to higher levels of melanopic EDI would result in lower levels of skin temperature, while lower levels of melanopic EDI would result in higher levels of skin temperature.

However, while compared to lighting condition L1, exposure to higher levels of melanopic EDI in lighting condition L2 did not result in a significant effect, the same levels of melanopic EDI as lighting condition L2 with different spectrum and intensity, lighting condition L3 resulted in higher levels of skin temperature indicating higher levels of sleepiness despite the expectation of lower levels. Regarding lighting condition L4, however, as expected, higher skin temperature levels were observed only when compared to lighting condition L1, indicating higher levels of sleepiness under lower levels of melanopic EDIs. As a result of these inconsistencies in skin temperature, which might have occurred due to slight changes in room temperature in different sessions, the findings do not support hypothesis H1 and draw the same conclusion as the other physiological measure: melatonin levels.

The result of subjective assessment (KSS) and performance in the cognitive task (audio reaction time-PVT) support the findings of the physiological measures. Regarding subjective assessment, according to the hypothesis, it was expected that participants report lower levels of sleepiness when exposed to higher levels of melanopic EDI. However, participants reported higher levels of sleepiness as their habitual bedtime approached, regardless of the lighting conditions they were exposed to. Similarly, regarding performance in the cognitive task, it was anticipated that exposure to higher levels of melanopic EDI result in lower levels of sleepiness and, consequently, improved performance in the audio reaction time task. However, the result of this task also demonstrates comparable performance across all lighting conditions, indicating no significant impact of exposure to higher levels of melanopic EDI.

5.2. Comparison with previous research

Tables 5.2 and 5.3 summarise the current and similar previous studies design, and findings. These studies differed in terms of adaptation and test periods, lighting interventions, method of conduction (field vs. laboratory), and outcome metrics (sleepiness measurement techniques).

Table 5.2. Comparison of the current and previous studies' adaptation, timing, and lighting intervention.

Study	Method	Timing		Illuminance at the eye (lx)			
		Adaptation	Test	Adaptation period		Test period*	
		-	-	E_v**	Melanopic	Ev	Melanopic
Current experiment	Laboratory	21:00 – 22:00	22:00 – 00:00	25.0	10.7	8.0	10.7
Alshdaifat, and Fotios 2023	Laboratory	21:00 – 22:00	22:00 – 00:00	25	10.7	83	98.8
Bhagavathula et al., 2021	Field (closed road driving)	23:00 – 01:00	01:00 – 03:00	200.0	87.1	1.9	0.8
Rodríguez-Morilla et al., 2017	Laboratory (simulator driving)	21:00 – 21:45	21:45 – 23:00	< 1.0	< 1.0	469	224
Taillard et al., 2012	Field (motorway driving)	07:30 – 00:30	01:00 – 05:00	-	-	20	-
Phipps-Nelson et al., 2009	Laboratory (simulator driving)	18:00 – 21:00	21:00 – 09:00	< 1.0	-	1.15	-

* Only short wavelength lighting intervention with the highest intensity is reported here (refer to section 2.11.2).

** Vertical illuminance at the eye (photopic).

Table 5.3. Comparison of the outcome metrics used in the current and previous studies based on the presence of significant effect of short wavelength lighting intervention.

Study	Outcome metric (significant effect (✓), non-significant effect (✗))							
	Melatonin	Skin temperature	PVT	EEG	Ocular measure	Self-reports	Hazard detection	Driving performance
Current experiment	✗	✓	✗	-	-	✗	-	-
Alshdaifat, and Fotios 2023	✓	-	✓	-	-	-	-	-
Bhagavathula et al., 2021	✗	-	-	-	✗	✗	✗	✗
Rodríguez-Morilla et al., 2017	-	✓	✓	-	-	✗	-	✗
Taillard et al., 2012	-	-	-	-	-	-	-	✓
Phipps-Nelson et al., 2009	✗	-	✓	✓	✓	✗	-	✗

The current findings align with those of Bhagavathula et al., 2021, despite employing a higher melanopic EDI (10 lx) compared to their work (0.8 lx). However, the lack of a significant impact on sleepiness may not be surprising, considering that the highest melanopic EDI used in the current experiment approaches the recommended maximum threshold for the three hours before habitual bedtime to prevent melatonin suppression [Brown et al., 2022] and might not be sufficient to elicit the anticipated mitigation responses to sleepiness.

Conversely, Phipps-Nelson et al., 2009, demonstrated that short-wavelength blue light exposure of corneal illuminances as low as 1.15 lx has the potential to affect physiological measures of attention and mitigate sleepiness, as evidenced by suppressed EEG, reduced incidence of slow eye movement, and faster PVT reaction time. These findings are not replicated in the current experiment. However, these discrepancies in outcomes could be attributed to the timing of the study; participants in the current experiment were examined from 21:00 to midnight, whereas Phipps-Nelson et al., 2009, studied their participants at night from 01:00 to 05:00 (early morning), potentially resulting in greater sleep deprivation and higher sleep pressure.

Regardless of these differences, another study by Rodríguez-Morilla et al., 2017 revealed that even exposure to melanopic EDIs as high as 224 lx, which has been shown to have a high likelihood of affecting physiological measures of attention (e.g., melatonin level, body temperature, brain activity), was not sufficient to improve attention by mitigating sleepiness.

Another major distinction between these studies lies in the lighting levels during the adaptation period. Most of the fundamental studies that have proven an effect of light on sleepiness employed periods of dark adaptation [e.g., Rahman et al., 2014; Souman et al., 2018]. Among the driving-related studies discussed in this chapter, Phipps-Nelson et al., 2009, and Rodríguez-Morilla et al., 2017 utilized periods of dark adaptation prior to a bright test period. Conversely, the current experiment and the work of Bhagavathula et al., 2021 employed periods of bright adaptation. In terms of practical relevance, periods of dark adaptation are unlikely to occur before a real-life driving scenario.

The influence of light exposure on driving performance is a topic of ongoing research. Several factors affect the results driven by such studies:

I. Physiological Effects and Dark Adaptation:
Studies utilizing extended periods of dark adaptation followed by bright light exposure (often exceeding typical road illumination) have demonstrated significant psychophysiological effects on humans. These changes include alterations in melatonin suppression, pupillary response, and circadian rhythm regulation. While these findings offer valuable insights into the impact of light on human psychophysiological performance, the artificial nature of such dark adaptation

scenarios limits their generalizability to real-world driving situations where drivers are exposed to bright light within indoor environments before driving.

II. Limited Effects Under Realistic Lighting:

Conversely, research that replicates more realistic lighting conditions, such as transitioning from a brightly lit environment to road lighting levels, has yielded less conclusive results. These studies have not identified significant physiological changes that directly translate to compromised driving performance. This suggests that the human visual system adapts relatively quickly to standard bright light followed by lower illumination, potentially minimizing any negative effects on driving ability.

III. Adaptation as a Key Factor:

The contrasting findings from these research efforts underscore the importance of considering adaptation conditions when assessing the impact of light on driving performance. While extreme light exposure or prolonged darkness might trigger pronounced physiological responses, these scenarios are not representative of typical nighttime driving experiences. Future research should prioritize replicating realistic adaptation sequences to gain a more comprehensive understanding of how light influences drivers under actual road conditions.

To date, the studies that have successfully demonstrated a significant impact of light, at least at the physiological level, regardless of whether this effect translates to real-world tasks such as driving and improving its performance, are those that utilized dark adaptation periods or employed an extreme level of melanopic EDI (98.8 lx) combined with a bright period of adaptation [Alshdaifat, and Fotios 2023]. On the contrary, studies that employed bright adaptation periods combined with applicable levels of road lighting were unable to find significant effects of light, even at the physiological level. This suggests that adaptation conditions play a crucial role, and we may need to employ conditions (dark adaptation) that are atypical in natural settings to reveal an effect under lighting conditions relevant to outdoor lighting.

5.3. Limitations and future research

This study was limited to a young age group (18-30 years old) and therefore does not represent older drivers. There is evidence that ageing alters non-visual responses to light. With ageing, pupil size decreases, allowing less light to reach the retina. Additionally, ageing causes changes within the crystalline lens, such as increased lens density, which alters spectral absorption, particularly within the short wavelength light range. Furthermore, lens darkening due to ageing results in yellow pigmentation, reducing light transmission to the retina [Herljevic et al., 2005]. Exposure to short-wavelength blue light has been shown to modulate brain responses regardless of age. However, the impact of short-wavelength blue light diminishes with ageing [Daneault et al., 2018]. This implies that older adults require higher light levels to elicit similar non-visual responses as their younger counterparts. Therefore, for the null effect findings of this experiment, it is expected that including older age groups would yield similar conclusions. Nevertheless, it remains essential that future research considers a broader range of age groups, including the elderly, to further substantiate the findings of the current experiment.

The salivary sampling method employed in the current experiment for melatonin measurement was non-invasive and has been reported as a reliable tool specifically for application and field research where conducting blood sampling may interfere with the act of driving. However, blood sampling is reportedly more accurate. It has the potential to detect even small changes in melatonin levels, as plasma melatonin levels are approximately three times higher than salivary melatonin levels. Obtaining blood samples would require authorization from the UK National Health Service (NHS). Repeating this experiment with blood samples instead of salivary melatonin might reveal larger melatonin contrasts due to lighting interventions and potentially lead to a significant effect of the light interventions on melatonin levels. However, the result from the current experiment, using saliva sampling, revealed a significant increase in melatonin levels, and for a lighting intervention to be effective in mitigating sleepiness, a significant reduction or suppression would be required, implying a complete reversal of the melatonin secretion trends observed in the current experiment saliva sampling. Observing such a trend will be less likely even by blood sampling under lighting interventions of the current experiment. Blood sampling might be an option for future laboratory studies but is less likely to be feasible in field studies during driving, as it could interfere with the act of driving and pose safety concerns in the unsanitary environment of a car.

The current experiment was conducted in a controlled laboratory environment where any light spill from outside was excluded. The four lighting conditions were derived from the same LED array so that the only changes were of intensity and SPD – uniformity was maintained constant. In an outdoor environment, drivers would be exposed to changes in lighting due to vehicle headlights, light spills from buildings, moonlight, etc. While controlled laboratory exposure ensures measurement of the change caused by changes in lighting conditions, the exposure variability of field studies informs us about its relevance. Conducting this experiment in a laboratory environment allowed to investigate any effect of light intervention on sleepiness and performance in a safe environment [Davenne et al., 2012]. Real-world driving involves greater stimulation and cognitive load compared to a seated position in a laboratory setting [Philip et al., 2005]. To address this limitation, half the participants were asked to walk on a treadmill, as walking has been shown to increase cognitive workload [Perry et al., 2008; Hoang et al., 2020] which could potentially simulate the cognitive demands of driving. (Focuses on replicating cognitive workload).

Regarding melatonin levels, conducting this experiment in a naturalistic environment is likely to yield similar conclusions, as, to our knowledge, no interaction exists between cognitive load and melatonin levels. However, concerning the auditory reaction time (PVT) task, it is plausible that improved performance could be observed under exposure to a higher level of melanopic EDI (lx) when considering the combined effects of cognitive impairment induced by naturalistic driving and sleepiness. It is important to note that this could be the case if the effect of monotony on cognitive impairment is disregarded. Monotonous environments, such as seated positions in a laboratory setting, have also been shown to induce cognitive impairment [e.g., Körber et al., 2015]. Theoretically, this cognitive impairment, in combination with sleepiness, could have been mitigated by exposure to higher levels of melanopic EDI (lx) employed. However, this was not observed in the current experiment. Nevertheless, future work could benefit from replicating this experiment under more naturalistic conditions, such as in the field or test track, since cognitive load and sleepiness might not be the sole underlying mechanisms behind improved driving performance due to exposure to investigated lighting interventions.

Each experimental session involved two participants. The presence of multiple occupants in a vehicle is a common real-world driving scenario. Including two participants in a single experimental setup could enhance ecological validity by mirroring this aspect of real-world driving. However, from a psychological perspective, the simultaneous presence of two participants in the same room and experimental session could be considered a limitation of the findings due to potential effects of [Orne, 2017]:

I. Social Facilitation: The presence of others can sometimes enhance performance, particularly on simple tasks. Participants might feel motivated to work harder or more accurately when they know they are being observed.
II. Demand Characteristics: Participants might alter their behaviour to please the experimenter or avoid appearing incompetent. This can lead to biased results.
III. Distraction: The presence of another participant can be distracting, leading to reduced focus on the task at hand.
IV. Social Inhibition: In some cases, the presence of others can make participants feel anxious or self-conscious, leading to poorer performance.
V. Competition: If the task involves competition, participants might focus on outperforming each other rather than on the task itself, potentially distorting results.

To minimize the potential effects of these factors on the results, participants were given clear instructions and conducted practice trials to familiarize themselves with the experimental tasks. They were also explicitly instructed to avoid conversing with one another. Auditory stimuli for the PVT tests were presented to each participant at different (randomly assigned) time intervals to prevent one participant's response from influencing the others. Additionally, melatonin and skin temperature are physiological measures that are not influenced by the number of participants in a single experimental trial.

In the current experiment, participants were instructed to refrain from consuming caffeine-containing products after midday on the day of the experiment and to maintain a consistent sleep-wake schedule for one week prior to the experiment. This protocol was verified through sleep diaries and personal reports. To ensure that they follow this, participants received daily reminders. However, previous work has shown the tendency of the participants to misrepresent theoretically relevant information (e.g., demographics) to fulfil the explicitly defined criteria for participation in a study [Chandler and Paolacci, 2017]. Therefore, when participants provide responses for which verification is impossible (e.g. what time they went to bed, whether they had coffee that afternoon), it is not unlikely that they may provide inaccurate information. This is likely due to a lack of understanding of the implications of inaccurate responses and the desire to participate in order to earn money. Alternatively, there are other options (e.g., actigraphy) to monitor sleep-wake patterns objectively rather than relying solely on self-reported data. Actigraphy devices, worn on the wrist, provide objective measures of sleep patterns and parameters, allowing for the assessment of sleep habits in natural sleep environments. Previous research suggested actigraphy as an accurate measure to monitor circadian rhythms and sleep patterns prior to an experiment [Martin and Hakim, 2011]. However, it has also been suggested not to consider actigraphy as the only assessment method. To maximize the validity, future studies may consider using actigraphy in parallel with other evaluation methods such as interviews, sleep diaries, etc. [Martin and Hakim, 2011].

Further research is required to assess whether the no-effect findings in the current experiment are real. This could involve repeating the experiment with a broader range of lighting conditions, particularly lighting of higher melanopic EDI. Additionally, increasing participants' walking speed (thus enhancing their cognitive load) and recruiting older or sleep-deprived individuals might provide valuable insight. A recent study by Alshdaifat and Fotios in 2023 [Alshdaifat and Fotios, 2023], replicated the current experiment setup using a higher level of melanopic EDI (98.8 lx) and was able to prove an effect and, therefore, prove that the experiment setup works as expected. Nevertheless, it is crucial to investigate the impact of these lighting conditions on hazard detection while driving, as these changes may improve driving performance by mitigating sleepiness while simultaneously affecting object visibility and eye adaptation, potentially hindering hazard detection.

5.4. Summary

Chapter 5 discussed the findings of Experiment 1 undertaken to explore the potential of light in mitigating sleepiness, thereby aiding attention while driving. It further compared the results of the experiment to previous studies and established the reliability of the findings. Additionally, it highlighted the limitations of the current work and the implications of these limitations for the findings of the work and identified the potential for further research. The next chapter will discuss the method for Experiment 2.

Chapter 6. Method: Experiment 2

Chapter 6. Method: Experiment 2

6.1. Introduction

The literature review (Chapter 2) established that light can serve as an “aids to vision”, potentially influencing distraction by enhancing drivers’ cognitive and visual performance. This could lead to improved hazard detection and, consequently, a reduced crash risk. However, the literature lacks sufficient evidence to support using light as a distraction mitigator. Previous studies (section 2.9) which examined the effects of road lighting on driving performance:

I. Did not include parallel tasks of driving (e.g., navigating using GPS, conversing with other passengers, …).
II. Were conducted in highly controlled environments where distractive activities had a low chance of occurrence.
III. Tended to highly monitor and observe participants which makes it less likely that participants engage in common distractive tasks.
IV. Did not investigate the potential non-visual responses of light on drivers’ attention and reaction to hazards.

Consequently, there is a need to conduct further research into the potential of light, such as increased road surface luminance, in-vehicle short-wavelength blue light, and pedestrian-worn flashing LED devices, to mitigate driver distraction effectively.

Experiment 2 was conducted to test four hypotheses:

H2: Distraction (via acoustic or visual stimuli) leads to a deterioration in hazard detection, as indicated by an increase in reaction time from onset of the hazard stimulus to its detection or a decrease in detection rate.

H3: An increase in road surface luminance leads to an improvement in hazard detection, as indicated by an increase in reaction time from onset of the hazard stimulus to its detection or a decrease in detection rate while distracted.

H4: In-vehicle short-wavelength blue light (increment in melanopic EDI exposure) leads to an improvement in hazard detection, as indicated by an increase in reaction time from onset of the hazard stimulus to its detection or a decrease in detection rate while distracted.

H5: Pedestrian-worn “aids to vision” lead to an improvement in hazard detection, as indicated by an increase in reaction time from onset of the hazard stimulus to its detection or a decrease in detection rate while distracted.

This chapter details the methodology employed in Experiment 2, which aimed to investigate the extent to which light can serve as an “aids to vision” and enhance drivers’ attention during typical journeys under specific lighting conditions accessible in vehicles and on roads. This experiment was reviewed by the University of Sheffield ethics board and gained approval prior to conduction (reference number 049792, dated 19 August 2022).

6.2. Apparatus

Hazard detection was investigated using a 1:10 scale model simulating a driver’s view of a multi-lane road with an opposing carriageway (Figure 6.1).

Figure 6.1. The scene from just behind the observer’s position. The photo was taken under Lighting condition L2.

This apparatus was used in previous work [Fotios et al., 2018; Fotios et al., 2019] but extended with additional detection hazards. The scale model is in a cuboid chamber with dimensions approximately 5 m long, 2.5 m wide, and 1.5 m high (Figures 6.2 and 6.3), raised on stilts above the laboratory floor. A seated participant outside the chamber observed the interior via an acrylic window positioned at the base of one end wall. Two neutral density filters (each of transmittance = 0.5) were installed on the acrylic window to reduce the luminance from the participant’s perspective without a significant effect on the spectrum (spectral transmittance of the neutral density filters checked prior to the experiment using JETI spectroradiometer model no. 1511).

The chamber floor was constructed from MDF sheets painted predominantly in neutral grey (Munsell N5, reflectance = 0.2) to represent the diffuse reflectance of an asphalt road surface [CIE 144:2001]. The remaining chamber interior surfaces, including plywood sidewalls, ceiling accents, and the windowed end wall, were coated in matte black paint. A dark grey PVC rear projection screen formed the chamber's back wall. The road surface was marked with intermittent white lines to delineate lanes. Participants were positioned in chairs adjusted to achieve an eye level approximately 150 millimetres above the road surface, simulating a driver's perspective.

The view from the participants was in a middle lane, with additional lanes on the left and right-hand sides. Additionally, within the lanes, there was a strip on the nearside (left-hand) edge simulating a footpath or hard shoulder. There is an equal-width lane on either side of the centre lane and another reduced-width lane (hard shoulder/footpath) on each side (Figure 6.2).

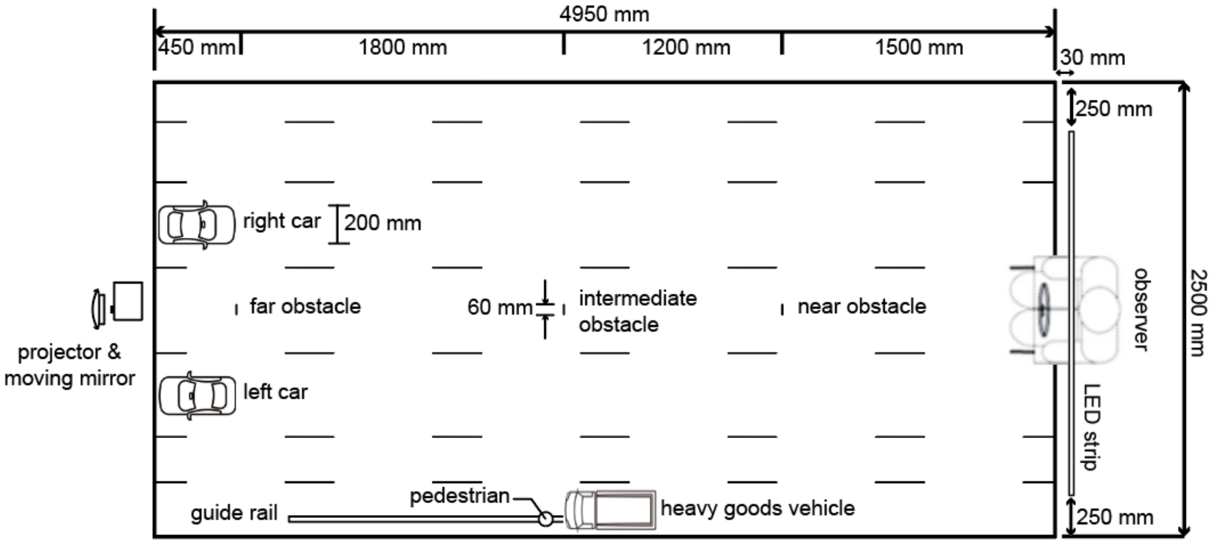


Figure 6.2. Plan view of the floor of the apparatus (not to scale).

The room's electric lighting was switched off during the experiment. The test environment was lit using a pair of LED arrays (THOUSLITE LED Cubes), the same model of LED array used in Experiment 1, to stimulate overhead road lighting (Figure 6.3). The LED strip (Figure 6.2), simulating the in-vehicle light, was a Philips light strip model plus V4 (2 metres) with tuneable SPD and intensity. It can provide a colour temperature range of 2000-6500 K and a lumen output of 1700 lm and 1140 lm at 4000 K and 2700 K, respectively.

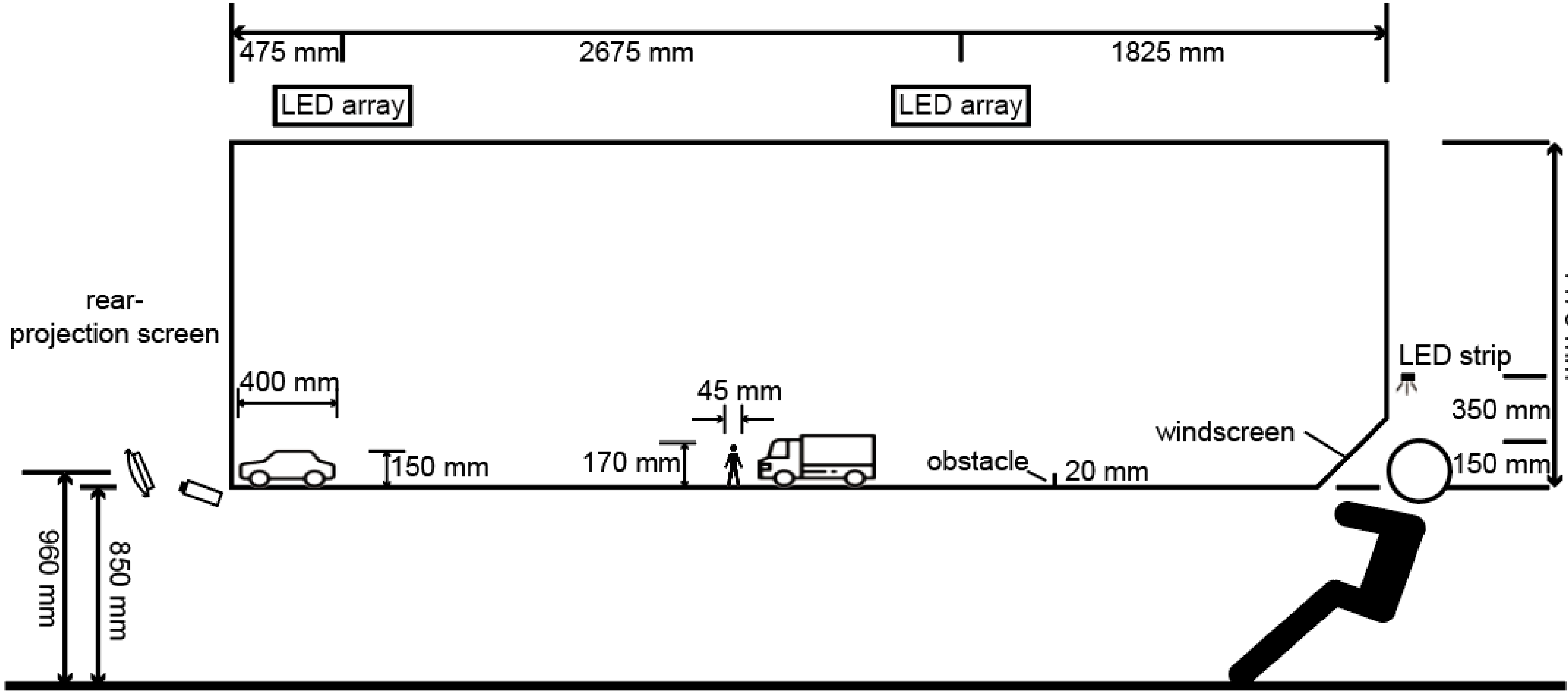


Figure 6.3. Side section of the apparatus (not to scale).

6.3. Independent variables

The independent variables used in this experiment were:

I. Lighting condition: there were four lighting conditions: two levels of road lighting (L1 and L2) and two levels of in-vehicle lighting mixed with road lighting (L3 and L4)
II. Distraction tasks: there were three levels, including a controlled setting (T1), a visual distraction (T2), and an acoustic distraction (T3)
III. Pedestrian model: there were three versions labelled as clothing levels: grey (C1), high visibility (C2), and Flashing LED (C3)

6.3.1. Lighting conditions

There were four lighting conditions (L1 to L4), as shown in Tables 6.1 and 6.2. lighting conditions L1 and L2 represented typical road lighting, each having the same SPD but different average road surface luminance. A grid of luminance was measured between the two LED arrays (simulating road lighting at a spacing of 27 m) to ensure uniformity and measure average luminance on the road surface. The details of these measurements are recorded in Appendix D.

The mean luminance of lighting condition L1 was 0.06 cd/m^2 with longitudinal uniformity (minimum/maximum) of 0.32. Similarly, the mean luminance of lighting condition L2 was 0.57 cd/m^2. Compared with the minimum maintained average luminance in dry conditions of M class in British Standard [BS EN 13201-2:2015], the mean luminance of L1 (0.06 cd/m^2) was lower than class M6 (0.3 cd/m^2). Similarly, the mean luminance in L2 (0.57 cd/m^2) was between class M4 (0.75 cd/m^2) and M5 (0.5 cd/m^2).

Lighting condition L3 was a combination of L1 with short-wavelength blue light delivered by an overhead LED strip (Figure 6.2), simulating an in-vehicle light source. The combination provided the same illuminance at the eye as did lighting condition L2. This was done to compare the contributions to detecting increased road surface luminance or enhanced short-wavelength blue light. The in-vehicle light was positioned directly above the participant observation point, at a height of 350 mm between the LED strip and the observation point (observer’s typical eye height) (Figures 6.2 and 6.3). Similar in-vehicle light installations were used in previous work, where a luminaire panel of dimensions 240 mm (L) × 160 mm (W) × 20 mm (H) was installed right above the driver's head and redirected light to the vehicle interior near the driver, illuminating the driver’s face and body [Canazei et al., 2021].

Lighting condition L4 was the same combination of road and in-vehicle light sources as L3 but increased the intensity of the in-vehicle short-wavelength blue light to investigate the potential of enhanced non-visual responses of this light content on visual and cognitive performance. Lighting condition L4 offered a 2-log unit increase of melanopic EDI over L3, a relatively extreme change chosen with the expectation of revealing an effect if one exists.

Table 6.1. Lighting conditions used in Experiment 2: general characteristics.

Light condition	Road lighting				In-vehicle light source		Combined effect	
	Ev* (lx)	L** (cd/m^2)	CCT	SP ratio	Ev (lx)	M*** EDI (lx)	Ev (lx)	M EDI (lx)
L1	0.03	0.1	2963	1.0	-	-	0.03	0.01
L2	0.13	0.9	2939	1.0	-	-	0.13	0.05
L3	0.03	0.1	2963	1.0	0.09	0.81	0.12	0.83
L4	0.03	0.1	2963	1.0	13.29	80.56	13.31	80.60

* Vertical illuminance measured at the eye of the observer.
** Nominal luminance – Measured by pointing the luminance meter from participant eye position to the location of furthest obstacle between the two cars.
** Melanopic content.

Table 6.2. Lighting conditions used in Experiment 2: SPD-derived metrics.

Lighting condition	Alpha-opic equivalent daylight (D65) illuminance (lx)*				
	S-cone	M-cone	L-cone	Rhodopic	Melanopic
L1	0.02	0.03	0.04	0.02	0.01
L2	0.04	0.10	0.13	0.06	0.05
L3	1.22	0.27	0.16	0.63	0.83
L4	118.15	27.68	16.80	61.80	80.60

* Alpha-opic equivalent daylight illuminance calculated using luox calculator (https://luox.app/) [Spitschan et al.]

6.3.2. Distraction tasks

Participants were required to perform one of the three distraction tasks: control (T1), visual distraction (T2), and acoustic distraction (T3). These tasks were designed to impose additional cognitive demands on the participants.

For the control task (T1), participants were instructed to focus their gaze on a cross projected onto the chamber's rear wall. Rather than being static, the cross moved, following a random path of movement within a 10-degree circle, with the lower fifth excluded to avoid it coming too close to the vehicle ahead. This movement represented the typical gaze behaviour of drivers [Winter et al., 2017].

This task was used to encourage participants to look ahead rather than toward any of the hazards, thus increasing the likelihood that hazards were detected with peripheral vision. However, the degree to which participants remained fixated on the cross was not measured. Measured using a Konica Minolta LS-150 luminance meter, the cross luminance (no other light sources present and at its central location), was1.3 cd/m^2 against the background luminance of 0.03 cd/m^2. From a viewing distance of roughly 5.1 metres, the cross occupied a visual angle ranging from 34 to 54 arcmin. This was consistent with previous works [Fotios et al., 2018; Fotios et al., 2019]. This task (following the dynamic fixation cross) was retained and extended in the other two distraction tasks (T2 and T3).

During the visual distraction task (T2) trials, the fixation cross was replaced by a random digit between 1 and 9, being presented for 500 ms every two seconds. Participants were asked to indicate the digit that had appeared on the rear screen by pressing the corresponding digit on a small dial pad (Storm Interface 720GFXi) located just above the steering wheel (Figure 6.4). The buttons from 1 to 9 on the dial pad were white to aid participants in seeing them during the experiment. The Python program measured the reaction time automatically and recorded it in a relative log file containing all inputs and outputs with accurate timestamps in milliseconds.

This task simulated that used in previous work [Fotios et al., 2019], but with the oral response replaced here by a manual response. This was done to simulate the common distraction to driving of using an in-vehicle device such as a mobile phone or infotainment system [Robbins and Fotios, 2021].

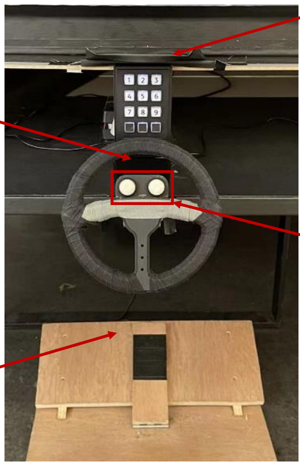


Figure 6.4. The steering wheel and response mechanisms.

The acoustic distraction task (T3) was achieved by asking participants to give an oral response to an acoustic stimulus in parallel to following the dynamic fixation cross. The stimulus was a synthetically voiced randomised series of letters (here, played over wired earbuds). Eight phonologically distinct letters (A, B, C, F, G, H, I, K), similar to what was used by Kane et al., 2007, were used to be easily distinctive for the researchers to record. These letters were randomised by the Python program, which was used to control the secondary tasks. The interval between each letter being read aloud was five seconds. They were played by in-ear headphones (Ludos SPECTA Wired Earbuds), and the voice was from Google text-to-speech, an assistive service that reads digital texts aloud.

The researchers recorded participants' verbal responses to the acoustic distraction task immediately after a response was given by entering the response directly into the Python program using a computer keyboard. To minimize the delay effect on recording a single response, researchers could see the order of random letter generation and were able to position their hands toward the correct key before the participant gave a response. The reaction time was measured automatically within the Python program immediately after a response entered by the researchers. A relative log file including all responses was created at the end of each trial, containing all inputs and outputs with accurate timestamps in milliseconds.

While performing the acoustic distraction task, rather than reporting the letter just heard, participants were required to repeat the letter heard two positions previously. This delayed letter recall task, known as an n-back task, involves participants repeating aloud the sequence presented to them but delayed by ‘n’ letters [Li et al., 2018, Mehler et al., 2011] (for more information, see section 2.7.1). In this case, we used n = 2, meaning participants repeated the letter two positions aloud before the current one. With n set to 2, this task presents a similar difficulty to that of a word generation task [Fotios et al., 2021] and mirrors the cognitive demands of a conversation with a passenger, a common driver distraction [Robbins and Fotios, 2022].

6.3.3. Pedestrian model versions

There were three versions of the pedestrian model (Figure 6.6), labelled in the analysis as clothing levels C1, C2 and C3. A description of the pedestrian model is given in section 6.4. The three levels of clothing were:

I. Grey (C1): The side facing the test participant was painted a uniform grey, of reflectance 20%, presenting luminances of 0.015 cd/m^2 and 0.142 cd/m^2 under lighting conditions L1 and L2, respectively. The colour Grey was chosen as a neutral colour that appears consistent under different lighting conditions [Bhagavathula et al., 2021a].

II. High-visibility material (C2): The model had a square piece (20 mm x 20 mm) of retroreflective and fluorescent material cut from an ANSI 107 class 2 high-visibility vest. This is the sort typically used by both pedestrians and cyclists at night, as well as for occupational safety [Sayer et al., 2004], presenting luminances of 0.022 cd/m^2 and 0.194 cd/m^2 under lighting conditions L1 and L2. Following previous work, this was positioned on the pedestrian's chest [Balk et al., 2008].

III. Flashing LED (C3): A flashing LED was placed at the centre of the grey pedestrian model. The LED flashed at a rate of 150 flashes per minute with a luminance of 0.15 cd/m^2 (measured in the L1 condition).

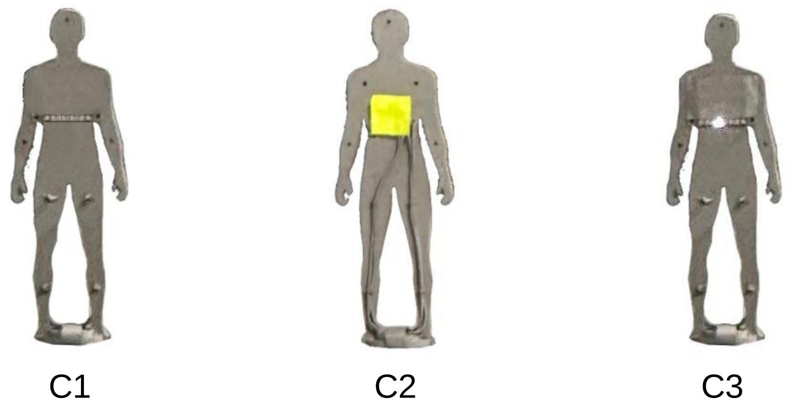


Figure 6.5. Types of pedestrian targets (from left to right: none, a flashing LED light, and a patch of high-visibility material).

6.4. Dependent variables

The two primary dependent variables in Experiment 2 were:

I. Hazards detection tasks: participants' ability to detect hazards was assessed using reaction time (ms) and detection rate (percentage).

II. Distraction task performance: participants' performance to the onset of distractive stimulus on visual and acoustic distraction tasks was measured using reaction time (ms) and detection rate (percentage).

Concerning hazard detection, participants were required to detect three hazards with different variations (Table 6.3). The following Sections (6.4.1 to 6.4.3) describe the hazard detection tasks.

Table 6.3. Experiment 2 hazards and their variations.

Hazard	Variation	Number of repeats
Road surface obstacle	Near distance	3
	Mid distance	3
	Far distance	3
Vehicle lane change	Left-hand side	3
	Right-hand side	3
Pedestrian detection	Grey clothing	3
	High-visibility clothing	3
	Flashing LED clothing	3

6.4.1 Road surface obstacle

Participants were required to detect an obstacle suddenly appearing on the surface of the road ahead. Detection of this obstacle was indicated by pressing a foot pedal, representing the action of using a brake pedal (Figure 6.4). There were three road surface obstacles, situated at near, intermediate and far locations in the driver's lane. The far obstacle was located 4.7 m ahead of the driver, a simulated distance ahead of 47 metres from the observer's eyes: this was the target used in previous work [Fotios et al., 2018]. The near and intermediate obstacles were installed for the current work, on the same axis along the road as the far obstacle, but at simulated distances ahead of 29 m and 17 m from the eyes.

The obstacles were formed from a balsawood vane, 60 mm wide and painted matt grey (Munsell N5) visually resembling a car tyre lying on its side at a distance. These obstacles, normally hidden below the road surface, randomly appeared by a servo motor arm via a designated slot, rising 20 mm above the road level. The far, middle and near obstacles subtended angles at the observer's eyes of 14.6 arcmin, 23.7 arcmin and 40.4 arcmin in height, and 121.3 arcmin, 71.1 arcmin, and 43.8 arcmin in width. The obstacles rose to a height of 20 mm in one second, maintained that height for two seconds, and then descended back to the road surface over one second. This rate of growth in visual height is comparable with the increase in the apparent size of a static obstacle approached when driving. Only one obstacle appeared per trial.

6.4.2 Vehicle lane change

The scene included two vehicles ahead, one in each of the lanes adjacent to the test participant's, located 4.7 m ahead of the driver, simulating a distance ahead of 47 m. The second detection task was to note when one or other of these vehicles moved from their home lane into the driver's lane, a lateral movement with the distance ahead remaining unchanged. Participants indicated detection by pressing a button on the steering wheel (Figure 6.4), an action similar to sounding the vehicle horn.

The two target vehicles were 1/10th scale body shells of a car (Ford Focus shape), painted the same neutral grey (Munsell N5) as the road surface and the lower section of the back wall. The rear of a car subtended an angle of 109.7 arcmin in height and 146.3 arcmin in width at the observer's eyes. Headlight and taillight operation was disabled during trials to ensure detection performance was solely dependent on changes in road lighting. Lane-changing manoeuvres were enabled by connecting the cars, through designated slots in the road surface, to carriages situated beneath, travelling on a shared linear guide rail perpendicular to the road and encompassing the three active lanes.

Two movement protocols were implemented for the vehicles: purposeful lane change and simulated in-lane drift. During lane changes, the motor drives followed a pre-programmed acceleration profile (60 mm/s^2) to reach a steady lateral speed of 75 mm/s, completing a move from lane-centre to lane-centre in 6 seconds. This mimics the typical speed of a lane change [Olsen et al., 2002]. Upon reaching the target lane centre (participant's lane), the car mirrored the exact same manoeuvre to return to its original lane.

In-lane drift, a common consequence of imperfect human steering, was replicated in the vehicles by implementing a continuous series of randomized lateral manoeuvres with speeds ranging from 5 mm/s to 15 mm/s (and acceleration of 4 mm/s^2) keeping the vehicles within a 40mm margin from the lane centre.

6.4.3 Pedestrian detection

A pedestrian model was located on the hard shoulder on the left-hand side. The pedestrian was initially hidden from view behind a model heavy goods vehicle (HGV) parked on the hard shoulder. Upon initiating the detection event, the pedestrian model would move along the hard shoulder, parallel to the direction of travel, mimicking a similar scenario used in previous research [Ābele et al. 2019]. Upon its first appearance, the initial distance between the participant's eyes and the pedestrians was 3835 mm (3690 mm forward and 1050 mm to the left). The pedestrian was measured 45 mm wide at the shoulder and 170 mm tall, subtending a height of 152.3 arcmin when first visible to the observer after emerging from behind the HGV. Detection of the pedestrian was indicated by the participant operating a paddle shifter behind the steering wheel (Figure 6.4), an action similar to flashing the vehicle's headlights. The HGV was positioned facing the driving direction and remained stationary throughout the experiment. It was a 1/10th scale body shell (classic Mercedes Unimog), also painted the same neutral grey (Munsell N5) as the other vehicles. Taillights were switched off, as were the other vehicles, during trials.

The pedestrian model was a simple, non-articulated model with no moving parts other than its traverse along the side of the road. This model was connected through a slot in the road surface to a carriage underneath on a one-metre guide rail, parallel to the run of the road along the hard shoulder lane. The pedestrian target travelled along the guide rail at 120 mm/s, mimicking a walking speed of 1.2 m/s. A complete trip along the rail took approximately nine seconds, with around 7.7 seconds visible for the participants. The reverse side of the pedestrian model featured a square piece (20 mm x 20 mm) of retro-reflective material positioned on the pedestrian's chest in accordance with previous work [Balk et al., 2008]. When the high-visibility pedestrian was the next target, the figure rotated behind the HGV; afterwards, it rotated back to display either dark clothing or a flashing LED.

Upon detecting a hazard using one of the three response mechanisms, test participants received auditory feedback: "obstacle" for pressing the pedal, "lane change" for pressing the button on the steering wheel, and "pedestrian" for operating the paddle shifter behind the steering wheel. This feedback served as confirmation of their response registration and indicated whether the correct response mechanism had been used.

The following section will describe the other dependent variable, distraction task performance, which was the participants' performance to the onset of distractive stimulus on visual and acoustic distraction tasks.

6.4.4. Distraction tasks performance

Distraction task performance was measured by analysing reaction time (ms) and detection rate (percentage) for both the acoustic and visual distraction tasks, primarily to assess the impact of the additional in-vehicle short-wavelength blue light employed in conditions L3 and L4. The distraction tasks employed in this experiment fell under the category of secondary tasks used to measure cognitive workload (section 2.7.1), with an n = 2 back task employed for acoustic distraction and an n = 0 back task for visual distraction. These tasks effectively assessed cognitive performance and held the potential to investigate the influence of mitigation strategies on cognitive performance (e.g., the effects of short-wavelength blue light rich in melanopic content).

6.5. Procedure

The experiment was conducted between the 3rd of November 2022, and the 6th of December, 2022. Three sessions were scheduled on a single day (11:00 – 13:30, 15:00 – 17:30, and 19:00 – 21:30) to explore the impact of time-of-day (the results from this analysis are not included in the current thesis), with one participant attending each session. Upon the start of each session, before the adaptation and practice period, participants completed several tasks:

I. Was invited to sign the consent form in accordance with ethical approval.
II. Visual acuity was checked using a Landolt C chart to ensure an acuity of at least 6/12 (minimum standard for driving in the UK [Government Digital Service, 2012]) with participants wearing their normal corrective lenses.
III. Colour blindness was evaluated using Ishihara colour plates.
IV. Was seated in the chair for the adaptation period. An adjustable seat was used to keep the eye height of participants similar.
V. Wore the noise reduction earmuff (ProCase model PC-08362515) and kept it worn during the entire experiment to eliminate the effect of background noise produced by the mechanical movement of different parts in the apparatus and, therefore, not providing an auditory clue to the visual hazard detection tasks, which otherwise could occur and affect the reaction.

Figure 6.6 summarises the experimental procedure. The experiment consisted of four blocks of trials corresponding to four lighting conditions, presented in a randomised order. Each lighting block comprised three sub-blocks corresponding to three types of distraction also presented in a randomised order. Each sub-block included 24 presentations of the detection targets: two vehicle lane changes, three pedestrians, and three obstacles, each repeated three times in a randomised order (Table 6.3). A participant attended a single 2.5-hour test session. Starting with 20 minutes to allow for adaptation to the low light level under lighting condition L2, as it was also used for a practice session to enhance participants' familiarity with the experiment. In each trial, the participant was required to perform the primary visual task (hazard detection) simultaneously with the distraction task (one per trial). There was a random interval of five to ten seconds between each hazard detection task. No two hazards overlapped. The number of lane changes was balanced between the two cars.

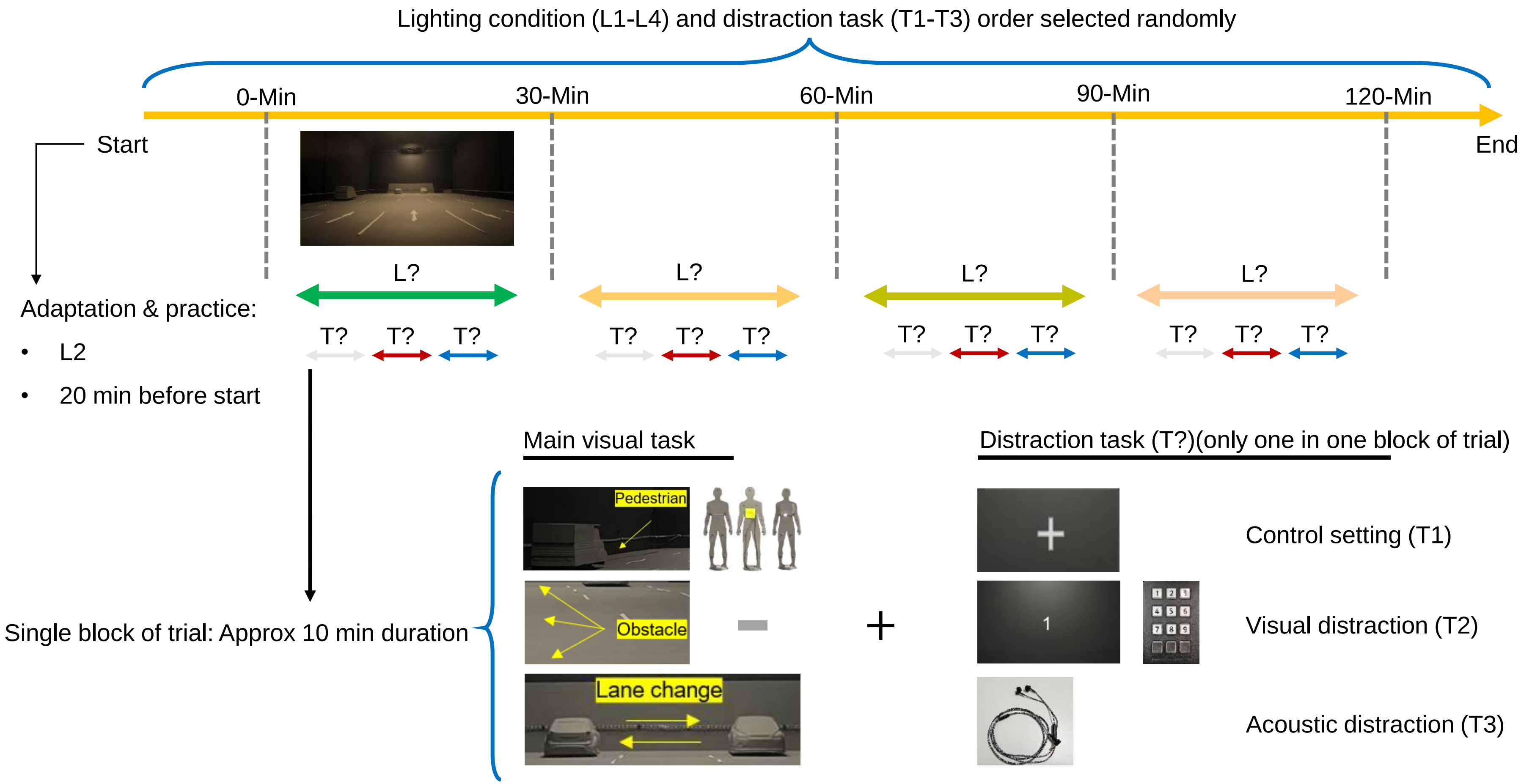


Figure 6.6. The procedure of Experiment 2.

6.6 Sample

Participants were recruited through emails posted on volunteer recruitment lists to staff and students at the university. Participants were selected from those meeting the following criteria: aged between 18 and 30 years.

Sixty participants were recruited for this experiment. Table 6.5 summarizes the age and gender diversity of the participants in each test session. All participants reported normal or corrected-to-normal vision, as confirmed by an acuity test and Ishihara colour vision plates. Participants selected their preferred time slots from the available options, and researchers ensured proper diversity of participant numbers and gender in each test session throughout the day (11:00 – 13:30, 15:00 – 17:30, and 19:00 – 21:30) (Table 6.4).

Table 6.4. Age and gender of the participants in each test session.

Test session	**No. of participants**	**Age (years)**			**Gender (No.)**	
		Median	**Min.**	**Max.**	**Male**	**Female**
11:00 – 13:30	21	23	18	30	9	12
15:00 – 17:30	21	23	18	30	10	11
19:00 – 21:30	18	24.5	19	30	9	9

6.7. Summary

Chapter 6 detailed the design of Experiment 2. It described the selection and implementation of independent variables: lighting condition, distraction task, and pedestrian model variation. Furthermore, the chapter comprehensively described the measurement techniques including hazard detection tasks (road surface obstacle, vehicle lane change, pedestrian model) and distraction task performance which were used to investigate how changes in independent variables affected the hypothesized aim: distraction mitigation. A step-by-step protocol outlining the tasks performed by experimenters and participants before and during the experiment was presented. This chapter concluded with a description of the study sample's demographics and their distribution across different experimental groups. The next chapter focuses on the statistical analysis of Experiment 2 findings.

Chapter 7. Results: Experiment 2

Chapter 7. Results: Experiment 2

7.1. Introduction

This chapter presents the results of Experiment 2, the methodology for which was described in Chapter 6. Experiment 2 investigated the effect of changes in three independent variables (lighting conditions, distraction tasks, and pedestrian model versions) on hazard detection tasks (vehicle lane change, road surface obstacle and pedestrian appearance) and distraction task performance (acoustic and visual n-back tasks). Analyses were performed using IBM SPSS Statistics version 28.0.0.0. The statistical significance level (alpha) was set at 0.05. When necessary, p-values were adjusted using Bonferroni correction to account for multiple comparisons [Chen et al., 2017].

7.2. Data preparation

Initial data cleaning procedures focused on identifying and addressing instances of missing or erroneous values. These instances typically arose from participants' early, delayed, or absent responses to stimuli or hazard detection tasks.

7.2.1. Error cleaning

Each participant completed 12 sub-blocks of tests (four lighting conditions (L1 to L4) at each of three distraction tasks (control (T1), visual (T2) and acoustic (T3)).

For hazard detection in a single test sub-block, each test participant responded to 24 visual stimuli (Table 5.3). Two types of error were anticipated – early or late responses.

Early responses are those where the participant’s response was given in a shorter time than likely possible, indicating a response at random rather than a response to the stimulus. Responses given before 500 ms were assumed to be early responses for all response tasks, consistent with the time required for perception and making the required movement, as characterized for drivers in previous work [Droździel et al., 2020].

Late responses were defined by the time taken for each hazard to reach the extent of its travel and were set at 6000 ms for the vehicle lane change, 3000 ms for road surface obstacles, and 7700 ms for the pedestrian model. Incorrect responses, such as pressing the paddle shifter instead of the response button in response to the vehicle lane change, were also considered as errors.

Considering the distraction tasks, each test participant responded to approximately 170 visual distraction stimuli and 90 acoustic distraction stimuli under each of the four lighting conditions (L1 to L4). Recorded results were first checked to exclude any errors. The Python programs developed for these tasks were designed only to record responses within 2.5-second intervals for visual distraction and five-second intervals for acoustic distraction, covering the entire period of a single stimulus. If a participant did not respond within these intervals, an automated "no response" was recorded for that stimulus. Therefore, the responses in these tasks are divided into two groups: "no responses" and "number of valid responses".

7.2.2. Missing data

Cases of missing data occur when a participant misses all the iterations in which each hazard appeared in a sub-block of the test (e.g., missed all three times that the pedestrian grey model was presented). Dong and Peng (2013) stated, *"Missing data are a rule rather than an exception in quantitative research"*. The existence of missing data is inevitable as variables need to be designed to be difficult enough to be sensitive to changes as they occur. However, missing values are problematic due to:

I. Introduction of potential bias in estimations and generalisability of the result [Rubin, 1996; Schafer, 1997].
II. Loss of information in the extent of losing power and increased standard errors [Peng et al., 2006].
III. The design of the statistical procedure is based on the availability of a complete dataset without missing values [Schafer and Graham., 2002].

Therefore, before analysis, these missing values must be dealt with carefully. Appendix E presents the different methods for dealing with missing data. For each case of missing data, different approaches were considered, and the results of these methods were compared (Appendix E).

The cases of missing data were present for hazards road surface obstacle, and pedestrian model but not for the hazard vehicle lane change. To minimize the risk of data manipulation, listwise deletion and conservative imputation using mean and maximum were implemented in cases of missing values of reaction time to different hazards in this study. Each approach's outcomes were compared with others, and any noticeable differences were highlighted. Finally, the most appropriate approach was selected for further analysis to provide reliable conclusions while maintaining good statistical power.

Concerning road surface obstacle participants responded to 36 blocks of tests (four lighting conditions, three levels of distraction, and three distances of obstacle). Instances of missing data occurred when data was unavailable for one or more of these 36 test blocks. There were 149 cases of missing data among the total 2160 average responses to road surface obstacles provided by the 60 participants. In total, 40 participants must be dealt with in at least one case of missing data. As stated in Appendix E, the three implemented fixes provide the same result for lighting conditions, distraction and obstacle distance. Replacing with mean and maximum resulted in similar differences for all variables and their interactions. The only difference noticed was when comparing the listwise deletion method with replacing with mean and maximum for interactions between lighting*distraction and lighting* distraction*distance, where listwise deletion highlighted no significant effect of these interactions. This could be expected due to deleting a large proportion of the sample (60 to 20), which could make identifying smaller differences more difficult (see Appendix E for further details).

Concerning pedestrian model participants responded to 36 blocks of tests (four lighting conditions, three levels of distraction, and three pedestrian models). Cases of missing data occurred when no data was available for one or more of these 36 test blocks. There were 28 cases of missing data among the total 2160 average responses to pedestrian models provided by the 60 participants. In total, 18 participants must be dealt with in at least one case of missing data. As stated in Appendix E, the three implemented fixes provide the same result for lighting conditions, distraction and obstacle distance. Listwise deletion and replacement with maximum resulted in similar differences for all variables and their interactions. The only difference noticed was when comparing the replacing mean method with listwise deletion and replacing with the maximum for interactions between lighting*distraction, where replacing with mean highlights a significant effect of lighting on reaction to pedestrian model when distracted. At the same time, the other two treatments suggest no significant difference. For this interaction, looking into pairwise comparison listwise deletion fix shows similar trends (significant effect of visual distraction while compared to control and acoustic distraction) when compared to listwise deletion and replacing with maximum fixes under lighting condition L1 to L3 but under lighting condition L4 replacing with mean does not suggest a significant effect of any distraction while the other two methods to fix missing data still highlights the significant effect of visual distraction on reaction time under this lighting condition. Therefore, the three methods provide almost the same result with some negligible changes (see Appendix E for further details). In Experiment 2, missing data were addressed through conservative imputation using the maximum value within each series.

7.2.3. Representative values

In a given test block, each hazard was presented multiple times (Table 5.3) to better estimate the detection rate and response time. Subsequent analysis requires that a single value is used to represent the response.

There were three repeated trials per clothing level to detect the pedestrian model. The arithmetic mean was used to provide a single value from those three trials.

The same process was followed for road surface obstacles, and arithmetic mean was used to provide a single value as the representative of reaction time to obstacles at each distance for a single participant.

For lane changes, there were three repeated trials for the left-hand and right-hand vehicles. The current work does not consider differences between left-hand and right-hand sides; hence, this gives a set of six responses per condition. The best representative of these data might be the mean or the median. For the 60 participants, with four light conditions and three distraction tasks, there are 720 data sets. Reaction times are continuous data and are expected to be normally distributed. Forty-six of these data sets were assessed (see section 4.3 for normality test method, Appendix F, Table F.1 for results), of which 37 (80%) were considered to be normally distributed. Given the difficulty of demonstrating normality for small samples, it was assumed that the lane change RT data were drawn from a normally distributed population. Therefore, arithmetic mean was used to provide a single value as the representative of reaction time to vehicle lane change for a single participant.

Regarding distraction tasks, participants approximately responded to visual distraction (170 times) and acoustic distraction (90 times). For the 60 participants, with four lighting conditions, there are 240 data sets for visual distraction and 240 data sets for acoustic distraction. For each distraction task, 24 of these data sets were assessed (Appendix F, Table F.2, and F.3), of which 21 (88%) and 23 (96%) were considered to be non-normally distributed for visual and acoustic distractions, respectively. Therefore, the median was used to provide a single value as the representative of reaction time to both visual and acoustic distractions for a single participant.

7.3. Testing the distribution

The distributions of the dependent variables were examined to determine whether or not they were drawn from normally distributed populations and to select the appropriate statistical method for analysis.

Data normality was checked for the hazard detection and distraction tasks, encompassing both reaction time and performance rates.

7.3.1. Hazard detection

For each participant (60 total): under each combination of lighting conditions and distraction task, each participant's performance is represented by a single value (section 7.2.3) for both reaction time and performance rate. The distributions of these values from the 60 participants were analysed using the methods described in section 4.2. These analyses are reported in Appendix F. Table 7.1 summarises the decisions reached.

Consider first the reaction time data. Among the 36 combinations of lighting condition, distraction task, and obstacle distance or pedestrian model, 29 (80%) road surface obstacle cases and 28 (78%) pedestrian model cases were suggested to be normally distributed (Appendix F, Tables F.4 and F.5). For vehicle lane change, with 12 combinations of lighting conditions and distraction tasks, eight (67%) were suggested to be normally distributed (Appendix F, Table F.6).

Regarding performance rate, data for the majority of combinations across all three hazards were not suggested to be normally distributed (Appendix F, Tables F.7, F.8, and F.9).

To conclude, reaction times to hazards were analysed using parametric tests as they followed a normal distribution and relative performance rates were analysed using nonparametric tests as they followed a non-normal distribution.

Table 7.1. Data distribution for detection representatives of road surface obstacles, vehicle lane change, and pedestrian models.

Hazard type	Levels	Reaction time	Performance rate
Road surface obstacle	Near	Normal	Non-normal
	Middle	Normal	Non-normal
	Far	Normal	Non-normal
Vehicle lane change	Left and right combined	Normal	Non-normal
Pedestrian model	Grey	Normal	Non-normal
	High-visibility	Normal	Non-normal
	Flashing LED	Normal	Non-normal

7.3.2. Distraction tasks

For each participant (60 total), there is now a single value representing reaction time and performance rate for each distraction task ((visual (T2), and acoustic (T3)) under each lighting condition (L1 to L4)

To determine the appropriate statistical method for analysis, the distribution of these representative reaction times and performance rates among the 60 participants for each distraction task needs to be examined. Table 7.2 summarizes the normality checks conducted.

Table 7.2. Data distribution for detection representatives of visual- and acoustic-distraction.

Hazard type	Reaction time	Performance rate
Visual distraction	Normal	Non-normal
Acoustic distraction	Normal*	Non-normal

* Normality gained while checking residuals.

Regarding reaction time, four (100%) and three (75%) of all files (four lighting conditions) suggested a normal to near-normal distribution for visual (T2) and acoustic distraction (T3), respectively (Appendix F, Tables F.10 and F.11). Regarding performance rate, under all lighting conditions (L1 to L4), the distribution was non-normal (Appendix F, Tables F.12 and F.13).

To conclude, reaction times to hazards were analysed using parametric tests as they followed a normal distribution and relative performance rates were analysed using nonparametric tests as they followed a non-normal distribution.

The following section will present the statistical analysis conducted and their respective results. As discussed in section 4.4, reaction time data, which followed a normal distribution, were analysed using repeated-measure ANOVA. Conversely, performance data, which followed a non-normal distribution, were analysed using the Friedman test.

7.4. Analysis of hazard detection results

This section will present the analysis of the result for reaction time and performance rate to road surface obstacles, vehicle lane change, and pedestrian detection.

7.4.1. Road surface obstacle: reaction time

Figure 7.1 shows the mean reaction time to road surface obstacles according to lighting conditions, distraction tasks, and obstacle distance. Table 7.3 summarises the statistical tests. The results suggest significant main effects of lighting conditions, distraction tasks, obstacle distance, and significant interactions between lighting*distraction and lighting*distance, except for the interactions between distraction*distance and lighting*distraction*distance where no significant difference was found.

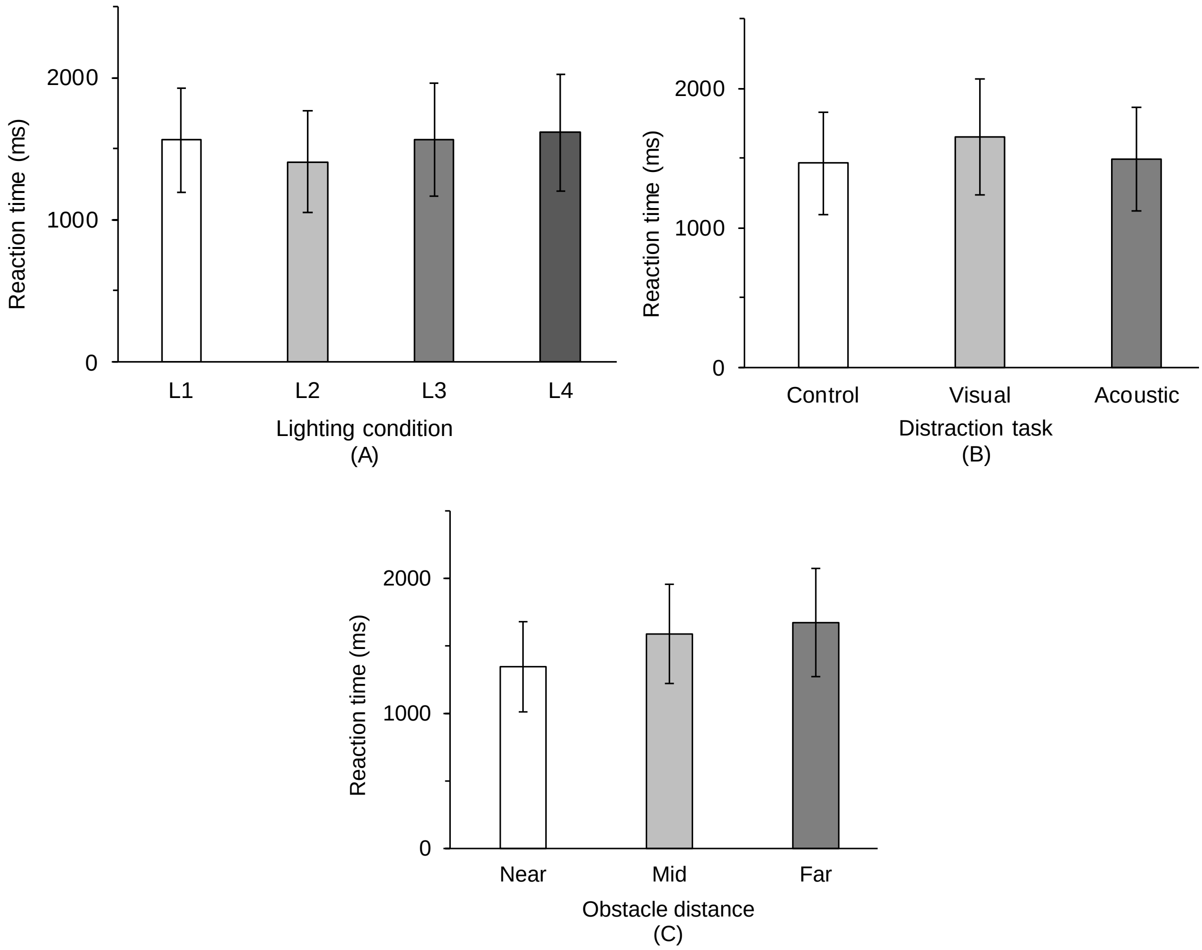


Figure 7.1. The effect of lighting condition (A), distraction task (B), and obstacle distance (C) on mean reaction time to detection of the road surface obstacle. Error bars show one standard deviation above and below the mean.

Table 7.3. Reaction time to road surface obstacle, interaction with lighting conditions, distraction task, and obstacle distance.

Variables	**F** (df main, df error)	**p-value**	**Effect size**
Lighting condition	(3, 177) = 27.968	<0.001*	0.322
Distraction task	(2, 118) = 72.435	<0.001*	0.551
Obstacle distance	(2, 118) = 119.883	<0.001*	0.670
Lighting condition*distraction task	(6, 354) = 2.145	0.048*	0.035
Lighting condition*obstacle distance	(6, 354) = 2.869	0.01*	0.046
Distraction task*obstacle distance	(4, 236) = 0.720	0.579*	0.012
Lighting condition*distraction task*obstacle distance	(10.83, 638.93) = 1.693	0.072**	0.028

* Sphericity assumed.
** Hyynh-Feldt correction.

Pairwise comparison for changes in lighting condition (Table 7.4) revealed a significant difference between lighting condition L2 and any other lighting conditions but did not indicate significant differences between any other pairs of lighting conditions. Participants reacted to the road surface obstacle significantly faster, as identified by mean reaction time, under lighting condition L2 (1407 ms) than under lighting conditions L1 (1560 ms), L3 (1564 ms), and L4 (1612 ms).

Table 7.4. p-values for pairwise comparison of reaction time to detection of the road surface obstacle according to lighting condition.

Lighting condition	L2	L3	L4
L1	<0.001	1.000	0.076
L2	-	<0.001	<0.001
L3	-	-	0.301

* Bonferroni adjusted (significant level < 0.05).

Pairwise comparison for changes in distraction task (Table 7.5) revealed a significant difference between distraction tasks T1 (control) vs. T2 (visual distraction), as well as between T2 vs. T3 (acoustic distraction). However, no significant differences were found between the distraction tasks T1 vs. T3. Participants responded to the road surface obstacle significantly slower, as identified by mean reaction time, under visual distraction (1652 ms) compared to both control (1462 ms) and acoustic distraction (1493 ms).

Table 7.5. p-values for pairwise comparison of reaction time to detection of the road surface obstacle according to distraction task.

Distraction task	T2	T3
T1	<0.001	0.171
T2	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

Pairwise comparison for changes in obstacle distance (Table 7.6) revealed a significant difference in reaction time among all three distances: near, mid, and far. As the obstacle distance increased, reaction time also increased. This pattern is evident in the mean reaction times for each distance (near: 1346 ms, mid: 1589 ms, and far: 1673 ms).

Table 7.6. p-values for pairwise comparison of reaction time to detection of the road surface obstacle according to obstacle distance.

Obstacle distance	Mid	Far
Near	<0.001	<0.001
Mid	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

The results indicated an interaction between lighting*distraction (Table 7.3), suggesting that changes in lighting conditions may mitigate some of the reported impairments caused by distraction. However, pairwise comparisons (Table 7.7) revealed a consistent trend across all lighting conditions (L1 to L4), where visual distraction (T2) significantly impaired reaction time to the road surface obstacle compared to control condition (T1) and acoustic distraction (T3) (Figure 7.2).

Table 7.7. p-values for pairwise comparison of reaction time to detection of the road surface obstacle according to the interaction of lighting*distraction.

Lighting condition	Distraction task	T2	T3
L1	T1	<0.001	1.000
	T2	-	<0.001
L2	T1	<0.001	1.000
	T2	-	<0.001
L3	T1	<0.001	1.000
	T2	-	<0.001
L4	T1	<0.001	0.041
	T2	-	0.014

* Bonferroni adjusted (significant level < 0.05).

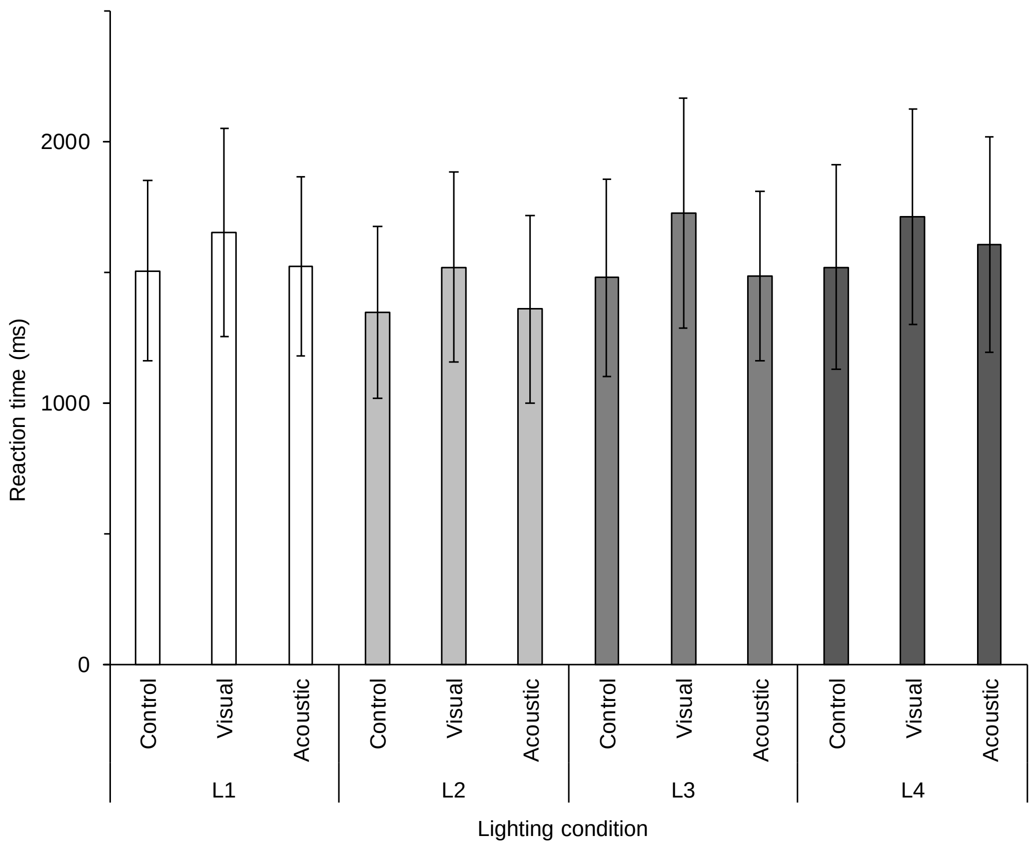


Figure 7.2. Lighting*distraction interaction, impact on reaction time to detection of road surface obstacle. Error bars show one standard deviation above and below the mean.

The result indicated an interaction between lighting*distance (Table 7.3), suggesting that changes in lighting conditions significantly affected the reaction time to obstacles at different distances. Pairwise comparisons (Table 7.8) revealed similar trends under lighting conditions L1, L2, and L4, where significant differences were observed between near vs. mid and near vs. far distances, with longer reaction times for further distances. However, no significant difference was found between the reaction times for mid vs. far distances under these lighting conditions. Under lighting condition L3, the same significant differences were observed between near vs. mid and near vs. far distances. Additionally, a significant difference was found between mid and far distances, with longer reaction times for further distances (Figure 7.3).

Table 7.8. p-values for pairwise comparison of reaction time to detection of the road surface obstacle according to the interaction of lighting*distance.

Lighting condition	Obstacle distance	Mid	Far
L1	Near	<0.001	<0.001
	Mid	-	0.054
L2	Near	<0.001	<0.001
	Mid	-	0.139
L3	Near	<0.001	<0.001
	Mid	-	<0.001
L4	Near	<0.001	<0.001
	Mid	-	0.848

* Bonferroni adjusted (significant level < 0.05).

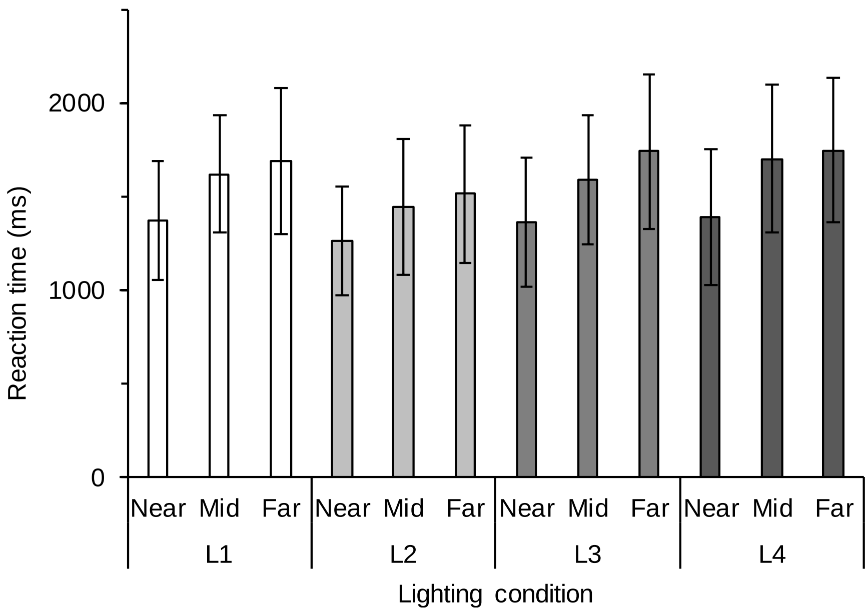


Figure 7.3. Lighting*distance interaction, impact on reaction time to detection of road surface obstacle. Error bars show one standard deviation above and below the mean.

7.4.2. Road surface obstacle: performance rate

Figure 7.4 illustrates the median performance rate in response to road surface obstacles across different lighting conditions, distraction tasks, and obstacle distances. Table 7.9 summarises the statistical tests performed on the data. The results indicate significant main effects of lighting conditions and obstacle distance on reaction time but no significant effect of distraction tasks.

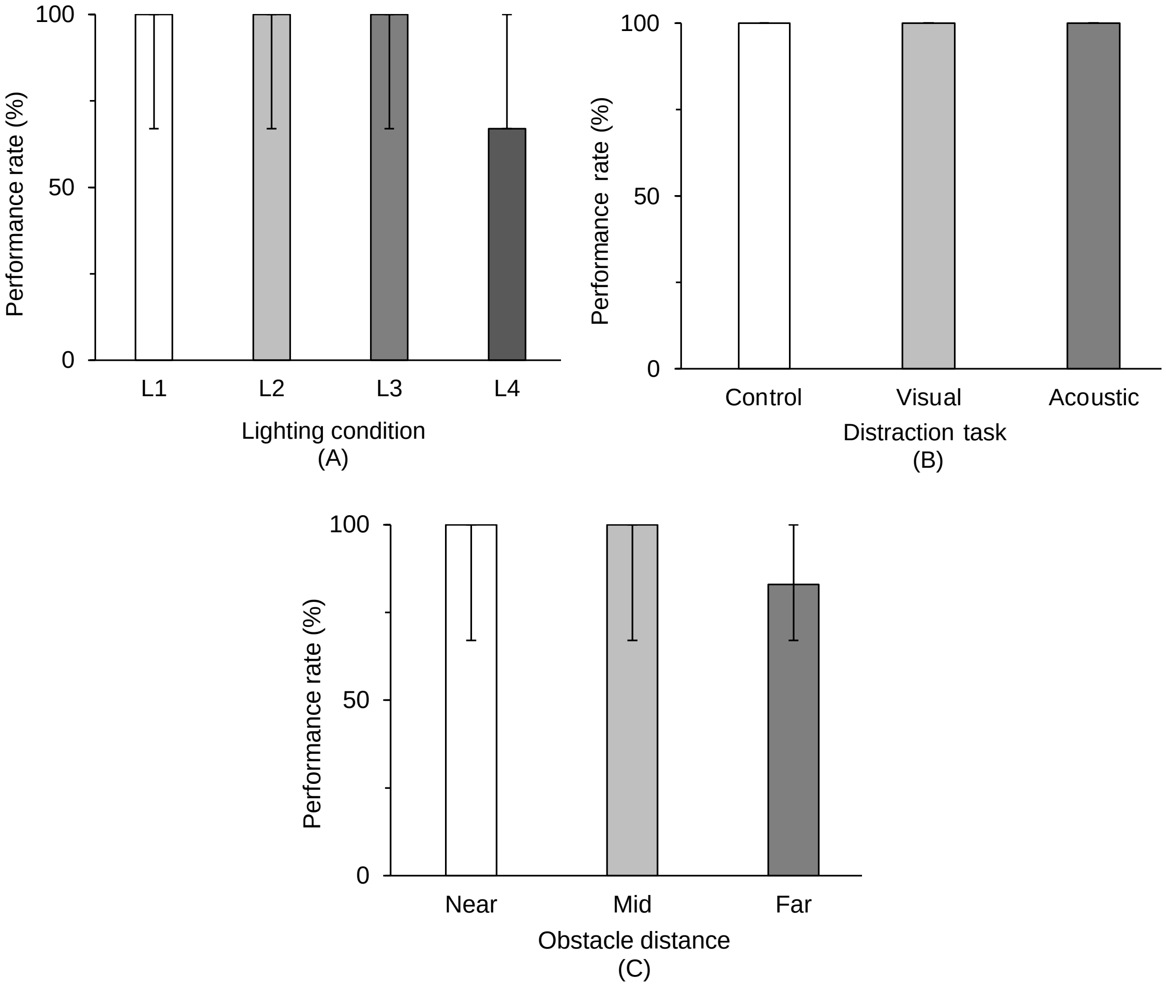


Figure 7.4. The effect of lighting condition (A), distraction task (B), and obstacle distance (C) on median performance rate to detection of the road surface obstacle. Error bars show the IQR.

Table 7.9. Performance rate to detection of road surface obstacles according to lighting condition, distraction task, and obstacle distance.

Variable	p-value	Chi-square
Lighting	0.012	10.910
Distraction	0.368	2.000
Distance	0.004	11.264

Pairwise comparison for changes in lighting condition (Table 7.10) revealed significant differences between lighting conditions L2 vs. L3 and L2 vs. L4. However, no significant differences were found between any other pairs of lighting conditions (L1, L3, and L4). Participant performance rates were significantly higher under lighting condition L2 (median: 100%; mean: 88%) compared to L3 (median: 100%; mean: 81%) and L4 (median: 67%; mean: 78%).

Table 7.10. p-values for pairwise comparison of performance rate to detection of the road surface obstacle according to lighting condition.

Lighting condition	L2	L3	L4
L1	0.234	1.000	0.69
L2	-	0.036	<0.001
L3	-	-	1.000

* Bonferroni adjusted (significant level < 0.05).

Pairwise comparison for changes in obstacle distance (Table 7.11) revealed significant differences between obstacle distances near vs. far and mid vs. far. However, no significant difference was found between obstacle distances near vs. mid. Participant performance rate was significantly higher when the obstacle was closer: near (median: 100%; mean: 88%), mid (median: 100%; mean: 84%), and far (median: 100%; mean: 76%).

Table 7.11. p-values for pairwise comparison of performance rate to detection of the road surface obstacle according to obstacle distance.

Obstacle distance	Mid	Far
Near	1.000	0.012
Mid	-	0.02

* Bonferroni adjusted (significant level < 0.05).

The interactions for different obstacle distances were examined under the same lighting condition and the same distraction task across the lighting condition and distraction task categories. Significant differences in performance rate to different obstacle distances were noticed under all lighting conditions for visual distraction (T2) (Table 7.12).

Table 7.12. Performance rate to detection of road surface obstacles across categories of lighting conditions and distraction tasks according to different obstacle distances.

Lighting condition	p-value – Chi-square		
	T1	T2	T3
L1	0.494 – 1.411	0.01 – 9.185	0.004 – 10.818
L2	0.07 – 5.309	0.008 – 9.597	0.246 – 2.804
L3	0.857 – 0.309	0.035 – 6.710	0.639 – 0.897
L4	0.575 – 1.106	0.022 – 7.641	0.972 – 0.056

Pairwise compassion reveals significant differences in performance between distances near (median: 67%; mean: 73%) vs. far (median: 67%; mean: 69%) and mid vs. far (median: 67%; mean: 56%) under lighting condition L1. Additionally, under lighting condition L4, a significant difference is observed between distances near (median: 67%; mean: 68%) vs. far (median: 67%; mean: 52%) (Table 7.13).

Table 7.13. p-values for pairwise comparison of the performance rate to detection of road surface obstacles across categories of lighting conditions for visual distraction according to different obstacle distances.

Lighting condition	Obstacle distance	Mid	Far
L1	Near	0.867	0.015
	Mid		0.036
L2	Near	1.000	0.216
	Mid		0.903
L3	Near	1.000	0.234
	Mid		0.114
L4	Near	0.600	0.039
	Mid		0.561

* Bonferroni adjusted (significant level < 0.05).

The interactions for different distraction tasks were examined under the same lighting condition and the same obstacle distance across the categories of lighting conditions and obstacle distances (Table 7.14). For the far obstacle, significant to near-significant effects of distraction were noticed under all lighting conditions. Significant to near-significant differences were observed for the near-obstacle under lighting conditions L1 and L2.

Table 7.14. Distribution of the performance rate to detection of road surface obstacles across categories of lighting condition and obstacle distance according to different distraction tasks.

Lighting condition	p-value – Chi-square		
	Near	Mid	Far
L1	0.024 – 9.726	<0.001 – 14.824	<0.001 – 14.134
L2	0.009 – 11.943	0.366 – 4.210	<0.001 – 21.795
L3	0.063 – 7.740	0.075 – 7.371	<0.001 – 22.025
L4	1.000 – 1.422	<0.001 – 19.006	<0.001 – 28.387

Pairwise comparison (Table 7.15) and the summary of the median and mean (Table 7.16) indicate that distraction tasks had minimal impact on the near obstacle detection under any lighting condition (L1 to L4). However, under lighting conditions, L1, L4, and L3 (near significance; see Table 7.13), visual distraction (T2) significantly impaired the detection performance of mid-obstacle compared to control (T1) and acoustic distraction (T3). No significant impact of distraction was observed for mid-obstacle under lighting condition L2. For the far obstacles under all lighting conditions, visual distraction (T2) significantly impaired detection performance when compared to control (T1) and Acoustic distraction (T3). No significant difference was observed between control and acoustic distraction under any of the lighting conditions and obstacle distances.

Table 7.15. p-values for pairwise comparison of the performance rate to detection of road surface obstacles across categories of lighting conditions and obstacle distances according to different distraction tasks.

Lighting condition	Obstacle distance	Distraction task	T2	T3
L1	Near	T1	0.171	1.000
		T2		0.081
	Mid	T1	<0.001	0.501
		T2		0.009
	Far	T1	<0.001	0.054
		T2		0.051
L2	Near	T1	0.051	1.000
		T2		0.016
	Far	T1	<0.001	1.000
		T2		<0.001
L3	Far	T1	<0.001	0.534
		T2		0.006
L4	Mid	T1	<0.001	1.000
		T2		<0.001
	Far	T1	<0.001	1.000
		T2		<0.001

* Bonferroni adjusted (significant level < 0.05).

Table 7.16. Median and mean for pairwise comparison of the performance rate to detection of road surface obstacle across categories of lighting condition and obstacle distances according to different distraction tasks.

Lighting condition	Obstacle distance	Distraction task	Performance rate (%)	
			Median	Mean
L1	Mid	T1	100	87
		T2	67	69
		T3	100	81
	Far	T1	100	79
		T2	67	56
		T3	67	70
L2	Near	T1	100	88
		T2	100	77
		T3	100	88
	Far	T1	100	84
		T2	67	66
		T3	100	85
L3	Far	T1	100	82
		T2	67	58
		T3	83	76
L4	Mid	T1	100	81
		T2	67	60
		T3	100	79
	Far	T1	100	77
		T2	67	52
		T3	100	76

The interactions for different lighting conditions were examined under the same distraction task and the same obstacle distance across the categories of distraction tasks and obstacle distances (Table 7.17). For near-obstacle, a significant effect of lighting conditions was observed for control (T1) and acoustic distraction (T3) but not for visual distraction (T2). For mid-obstacle, a contrasting trend was observed, where a significant impact of lighting condition was found for visual distraction (T2), but no significant impact was noticed for control (T1) and acoustic distraction (T3). For the far-obstacle, no significant impact of changes in lighting condition was noticed for the control condition (T1), while a significant impact was found for visual (T2) and acoustic distractions (T3).

Table 7.17. Distribution of the performance rate to detection of road surface obstacles across categories of distraction task and obstacle distance according to different lighting conditions.

Distraction task	p-value – Chi-square		
	Near	Mid	Far
T1	0.004 – 13.466	0.771 – 1.126	0.519 – 2.266
T2	0.569 – 2.015	0.024 – 9.483	0.045 – 8.069
T3	0.061 – 7.365	0.613 – 1.808	0.014 – 10.660

Pairwise comparison (Table 7.18) and summary of the median and mean (Table 7.19) highlights that for the control condition (T1), the detection performance of only near-obstacle was under impact of lighting condition when comparing lighting condition L2 and L4 with better performance under lighting condition L2. For visual distraction (T2), the same trend was noticed but only for far obstacles, where the detection performance of this obstacle was better under lighting condition L2 when compared to L4. No significant impact of change in lighting was noticed under visual distraction for the near obstacle. For the acoustic distraction (T3), a significant difference was noticed only for the far obstacle while comparing lighting conditions L1 vs. L2 and L2 vs. L4, where higher performance was noticed under lighting condition L2 compared to L1 and L4.

Table 7.18. p-values for pairwise comparison of the performance rate to detection of road surface obstacles across categories of distraction tasks and obstacle distances according to different lighting conditions.

Distraction task	Obstacle distance	Lighting condition	L2	L3	L4
T1	Near	L1	0.978	1.000	0.372
		L2		0.774	0.024
		L3			0.786
T2	Mid	L1	1.000	1.000	0.618
		L2		1.000	0.054
		L3			0.324
	Far	L1	0.216	1.000	1.000
		L2		0.468	0.024
		L3			0.972
T3	Far	L1	0.018	1.000	1.000
		L2		0.282	0.120
		L3			1.000

* Bonferroni adjusted (significant level < 0.05).

Table 7.19. Median and mean for pairwise comparison of the performance rate to detection of road surface obstacles across categories of distraction tasks and obstacle distances according to different lighting conditions.

Distraction task	Obstacle distance	Lighting condition	Performance rate (%)	
			Median	Mean
T1	Near	L2	100	88
		L4	100	75
T2	Mid	L2	100	84
		L4	67	60
	Far	L2	67	66
		L4	67	52
T3	Far	L1	67	70
		L2	100	85
		L4	100	76

7.4.3. Vehicle lane change: reaction time

Figure 7.5 illustrates the mean reaction time to vehicle lane change according to lighting conditions and distraction tasks. Table 7.20 summarises the statistical tests performed on the data. The results indicate significant main effects of lighting condition and distraction task but did not suggest significant difference for their interaction, lighting*distraction.

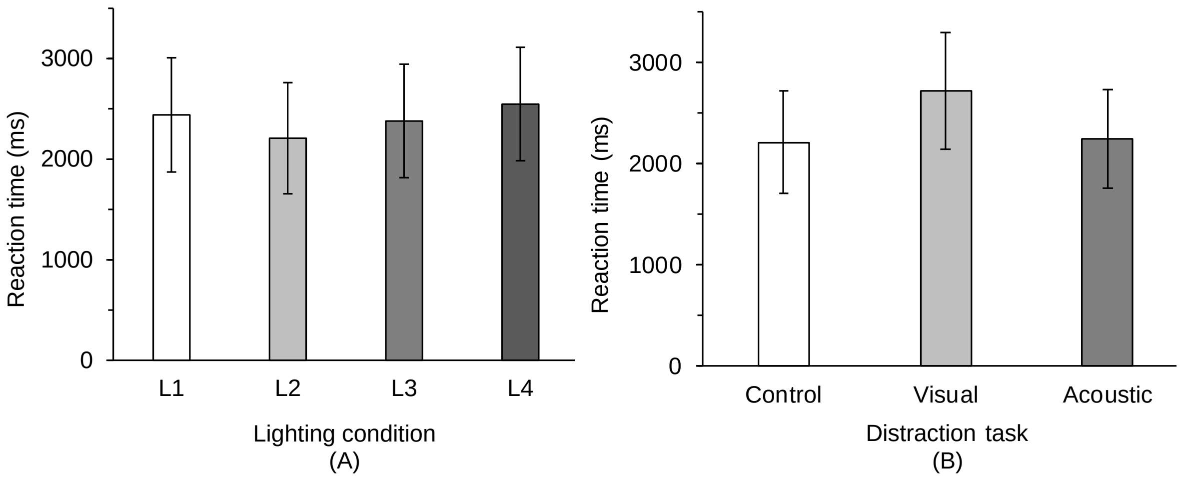


Figure 7.5. The effect of lighting condition (A) and distraction task (B) on mean reaction time to detection of the vehicle lane change. Error bars show one standard deviation above and below the mean.

Table 7.20. Reaction time to detection of vehicle lane change interaction with lighting condition and distraction task.

Variables	**F** (df main, df error)	**p-value***	**Effect size**
Lighting condition	(3, 177) = 26.449	<0.001	0.310
Distraction task	(2, 118) = 84.065	<0.001	0.588
Lighting condition*distraction task	(6, 354) = 1.745	0.110	0.029

* Sphericity Assumed.

Pairwise comparison for changes in lighting condition (Table 7.21) revealed significant differences between all pairs of lighting conditions except lighting condition L1 vs. L3. Participants responded to vehicle lane change significantly faster, as identified by mean reaction time, under lighting condition L2 (2208 ms) compared to lighting condition L1 (2440 ms), L3 (2380 ms), and L4 (2548 ms).

Table 7.21. p-values for pairwise comparison of reaction time to detection of vehicle lane change according to lighting condition.

Lighting condition	L2	L3	L4
L1	<0.001	0.774	0.034
L2	-	<0.001	<0.001
L3	-	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

Pairwise comparison for changes in distraction task (Table 7.22) revealed a significant difference between distraction tasks T1 (control) vs. T2 (visual distraction), as well as between T2 vs. T3 (acoustic distraction). However, no significant difference was found between the control (T1) and acoustic distraction (T3). Participants responded to vehicle lane change significantly slower, as identified by mean reaction time, when visually distracted (2723 ms) compared to control (2213 ms) and acoustic distraction (2245 ms).

Table 7.22. p-values for pairwise comparison of reaction time to detection of vehicle lane change according to distraction task.

Distraction task	T2	T3
T1	<0.001	1.000
T2	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

7.4.4. Vehicle lane change: performance rate

Figure 7.6 illustrates the median performance rate for vehicle lane change according to lighting conditions and distraction tasks.

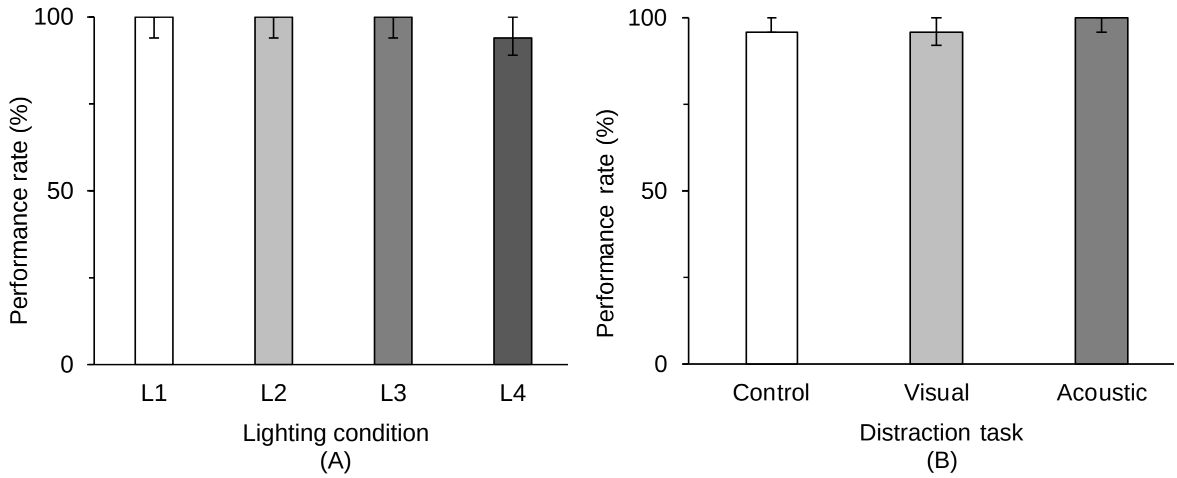


Figure 7.6. The effect of lighting condition (A) and distraction task (B) on median performance rate to vehicle lane change. Error bars show the IQR.

The impact of lighting conditions was investigated for each of the three distraction tasks separately. The distraction tasks T1 (control) and T3 (acoustic) did not significantly affect the performance rate under any of the lighting conditions. However, a significant impact was observed for distraction task T2 (visual) (Table 7.23).

Table 7.23. Performance rate to detection of vehicle lane changes across categories of lighting conditions based on the distraction task.

Distraction task	p-value	Chi-square
T1	0.302	3.645
T2	0.006	12.440
T3	0.119	5.851

Pairwise comparison (Table 7.24) revealed a significant difference in the performance during distraction task T2 (visual) under lighting conditions L2 vs. L4. The performance rate for vehicle lane change was significantly higher under lighting condition L2 (median: 100%; mean: 98%) compared to lighting condition L4 (median: 100%; mean: 92%).

Table 7.24. p-values for pairwise comparison of performance rate to detection of vehicle lane change across categories of lighting condition for visual distraction (T2).

Lighting condition	L2	L3	L4
L1	0.054	1.000	1.000
L2	-	0.156	<0.001
L3	-	-	1.000

* Bonferroni adjusted (significant level < 0.05).

The impact of distraction tasks on performance rate was investigated separately for each of the four lighting conditions. Participants' performance to vehicle lane change did not differ significantly under lighting conditions L2, L3, and L4. However, a significant difference was observed under lighting condition L1 (Table 7.25).

Table 7.25. Performance rate to detection of vehicle lane changes across categories of distraction task based on the lighting condition.

Lighting condition	p-value	Chi-square
L1	0.01	9.185
L2	0.195	3.265
L3	0.079	5.072
L4	0.089	4.843

Pairwise comparison (Table 7.26) revealed a significant difference in the performance of visual distraction (T2) compared to control (T1) and acoustic distraction (T2) under lighting condition L1. Visually distracted participants exhibited a lower performance rate (median: 100%; mean: 93%) when compared to both control (median: 100%; mean: 97%) and acoustic distraction (median: 100%; mean: 98%).

Table 7.26. p-values for pairwise comparison of the performance rate to detection of vehicle lane change across categories of distraction task under lighting condition L1.

Distraction task	T2	T3
T1	0.036	1.000
T2	-	0.021

* Bonferroni adjusted (significant level < 0.05).

7.4.5. Pedestrian model: reaction time

Figure 7.7 shows the mean reaction time to the pedestrian model according to lighting conditions, distraction task, and obstacle distance. Table 7.27 summarises the statistical tests on the dataset. The results suggest significant main effects of lighting condition, distraction task, clothing level, and significant interaction between lighting*clothing and distraction*clothing. However, no significant differences were found for the interactions between lighting*distraction and lighting*distraction* clothing.

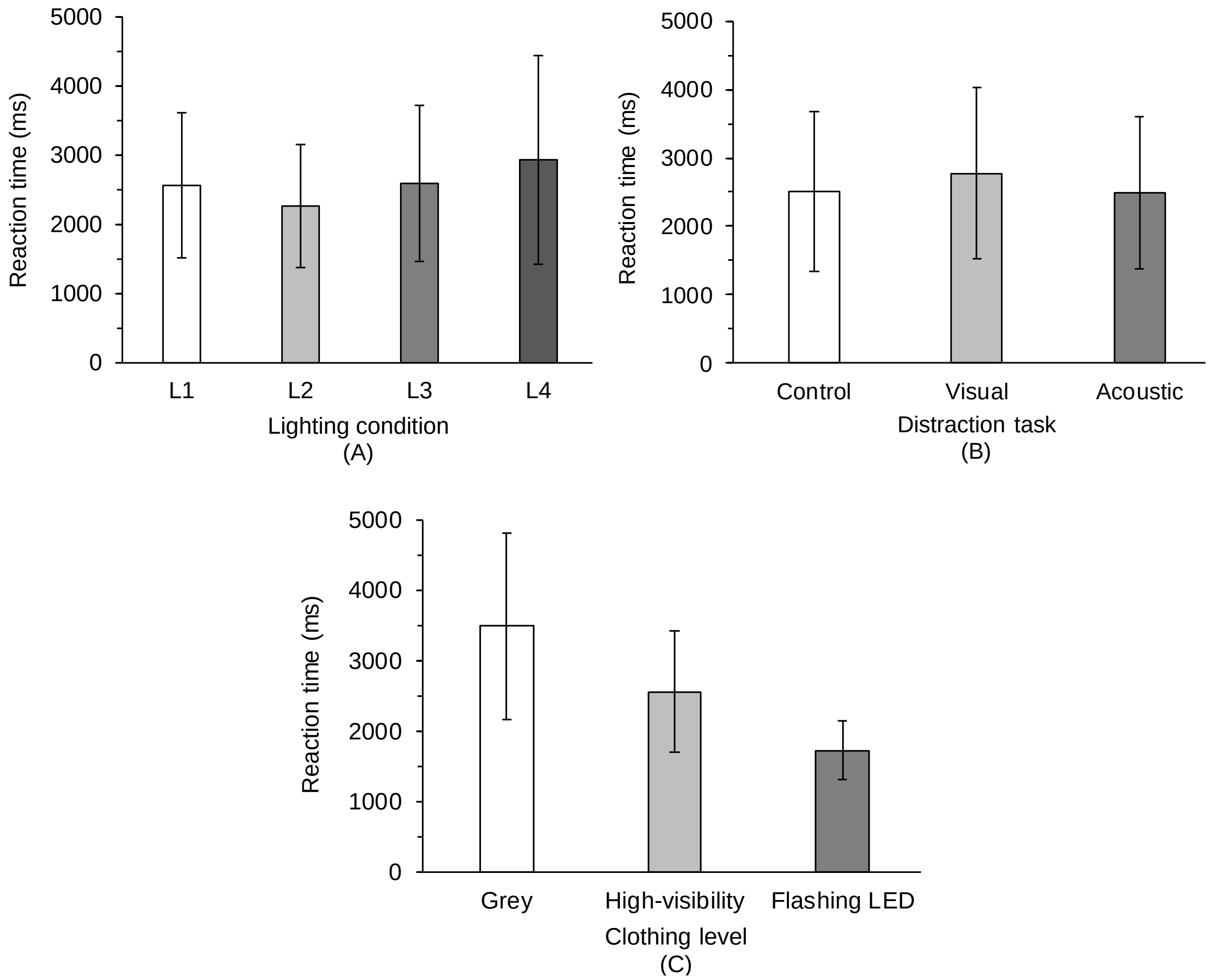


Figure 7.7. The effect of lighting condition (A), distraction task (B), and obstacle distance (C) on mean reaction time to detection of the pedestrian model. Error bars show one standard deviation above and below the mean.

Table 7.27. Reaction time to pedestrian model interaction with lighting condition, distraction task, and clothing level.

Variables	**F** (df main, df error)	**p-value**	**Effect size**
Lighting condition	(2.701, 159.357) = 48.592	<0.001*	0.452
Distraction task	(2, 118) = 20.933	<0.001**	0.262
Clothing level	(1.364, 80.456) = 381.992	<0.001***	0.866
Lighting condition*distraction task	(5.505, 324.805) = 1.526	0.175*	0.025
Lighting condition*clothing level	(4.156, 245.185) = 29.385	<0.001**	0.332
Distraction task*clothing level	(2.732, 161.171) = 9.341	<0.001***	0.137
Lighting condition*distraction task*clothing level	(6.098, 359.806) = 0.758	0.605***	0.013

* Huynh-Feldt correction.
** Sphericity assumed.
*** Greenhouse-Geisser.

Pairwise comparison for changes in lighting condition (Table 7.28) revealed a significant difference between all pairs of lighting conditions except lighting condition L1 vs. L3. The rest of the comparisons highlight a significant impact of lighting conditions with changes in mean reaction time (Table 7.29).

Table 7.28. p-values for pairwise comparison of reaction time to detection of the pedestrian model according to lighting condition.

Lighting condition	L2	L3	L4
L1	<0.001	1.000	<0.001
L2	-	<0.001	<0.001
L3	-	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

Table 7.29. Mean values for pairwise comparison of reaction time to detection of the pedestrian model according to lighting condition.

Lighting condition	**Mean reaction time (ms)**
L1	2566
L2	2266
L3	2594
L4	2934

Pairwise comparison for changes in distraction task (Table 7.30) revealed a significant difference between distraction tasks T1 (control) vs. T2 (visual distraction), as well as between T2 vs. T3 (acoustic distraction). However, no significant difference was found between the control (T1) and acoustic distraction (T3). Participants responded to the pedestrian model significantly slower, as identified by mean reaction time, when visually distracted (2772 ms) compared to control (2507 ms) and acoustic distraction (2491 ms).

Table 7.30. p-values for pairwise comparison of reaction time to detection of the pedestrian model according to distraction task.

Distraction task	T2	T3
T1	<0.001	1.000
T2	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

Pairwise comparisons of changes in clothing level (Table 7.31) revealed a significant difference between all three clothing levels. Flashing LED clothing exhibited the fastest reaction time (1721 ms), followed by high-visibility clothing (2560 ms), and finally, the grey model had the slowest reaction time (3489 ms).

Table 7.31. p-values for pairwise comparison of reaction time to detection of the pedestrian model according to different levels of clothing.

Clothing level	High-visibility	Flashing LED
Grey	<0.001	<0.001
High-visibility	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

The results did not suggest an interaction between lighting*distraction (Table 7.27); in other words, changes in lighting condition did not offset the reported impairment from distraction.

In contrast, a significant difference was observed in the interaction between lighting*clothing (Table 7.27). In other words, changes in lighting conditions significantly affected the reaction time to pedestrian models of different clothing levels. Pairwise comparison (Table 7.32) revealed similar trends for grey and high-visibility clothing, with significant differences observed when comparing reaction times under different lighting conditions. However, no significant differences were found between the lighting conditions when responding to the pedestrian model wearing flashing LED clothing. In other words, the use of flashing LED clothing is dominant to the changes in lighting conditions (Figure 7.8).

Table 7.32. p-values for pairwise comparison of reaction time to detection of the pedestrian model according to the interaction of lighting * clothing.

Clothing level	Lighting condition	L2	L3	L4
Grey	L1	<0.001	1.000	<0.001
	L2	-	<0.001	<0.001
	L3	-	-	<0.001
High-visibility	L1	<0.001	1.000	<0.001
	L2	-	0.005	<0.001
	L3	-	-	<0.001
Flashing LED	L1	1.000	1.000	1.000
	L2	-	1.000	1.000
	L3	-	-	1.000

* Bonferroni adjusted (significant level < 0.05).

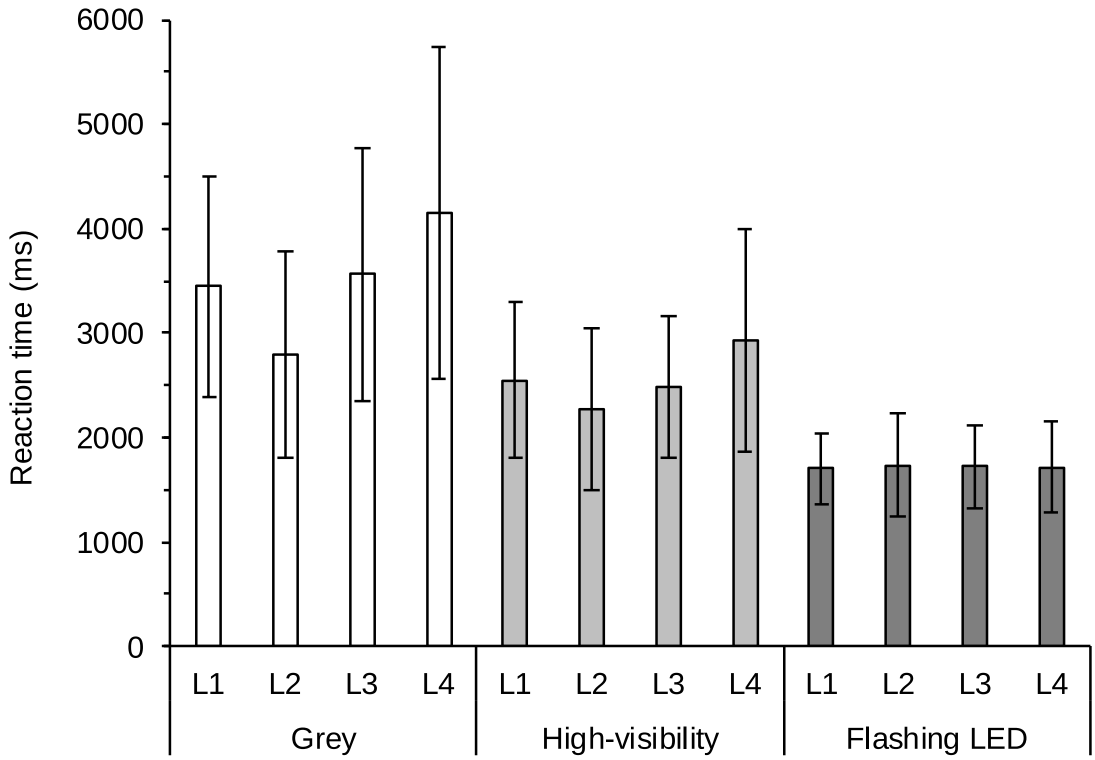


Figure 7.8. Lighting*clothing interaction, impact on reaction time to detection of pedestrian models. Error bars show one standard deviation above and below the mean.

For the interaction of distraction*clothing, the results indicated a significant difference (Table 7.27), meaning that changes in clothing significantly affected the reaction time to the pedestrian model of different clothing levels. Pairwise comparisons (Table 7.33) revealed similar trends for grey clothing and high-visibility clothing where visual distraction (T2) significantly impaired reaction time compared to control (T1) and acoustic distraction (T3). However, no significant differences were noticed between any of the distraction tasks when responding to the pedestrian model wearing flashing LED clothing. In other words, the use of flashing LED clothing mitigated the negative impact of visual distraction (Figure 7.9).

Table 7.33. p-values for pairwise comparison of reaction time to detection of the pedestrian model according to the interaction of distraction*clothing.

Clothing level	**Distraction task**	T2	T3
Grey	T1	<0.001	1.000
	T2	-	<0.001
High-visibility	T1	<0.001	1.000
	T2	-	<0.001
Flashing LED	T1	0.103	0.139
	T2	-	1.000

*Bonferroni adjusted (significant level < 0.05).

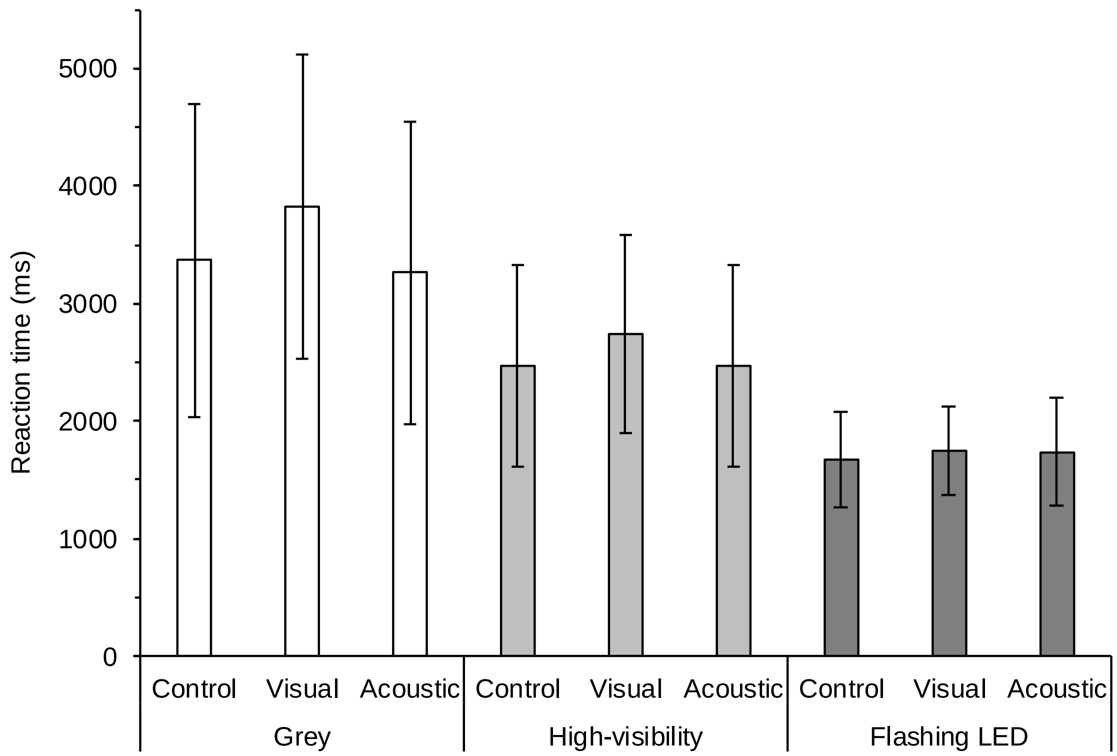


Figure 7.9. distraction*clothing interaction, impact on reaction time to detection of pedestrian models. Error bars show one standard deviation above and below the mean.

7.4.6. Pedestrian model: performance rate

Figure 7.10 illustrates the median performance rate of the pedestrian models across the lighting conditions (L1 to L4), distraction tasks, and clothing levels. Table 7.34 summarises the statistical tests, emphasizing the significant differences in performance changes due to lighting conditions, distraction tasks, and clothing levels.

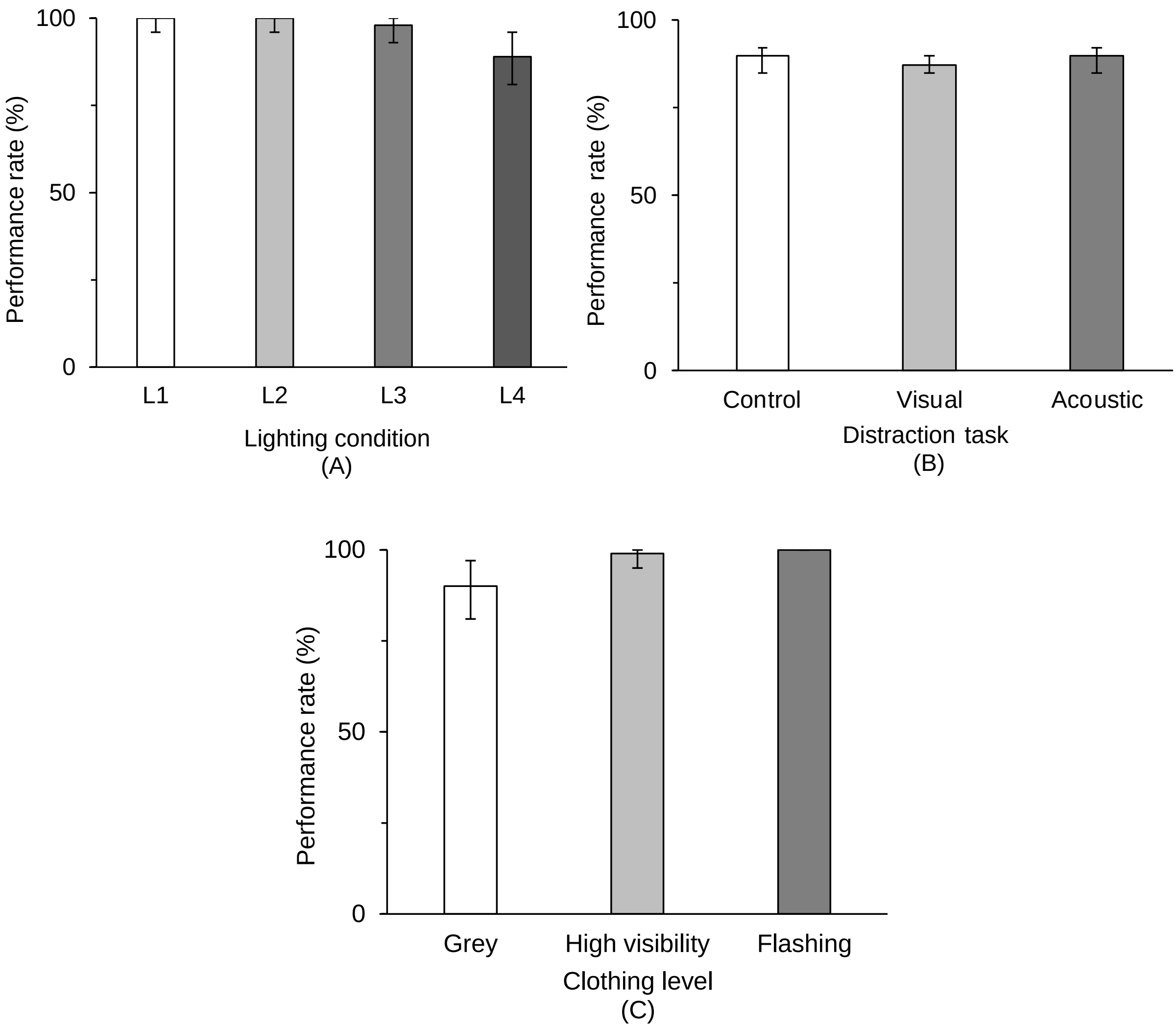


Figure 7.10. The effect of lighting condition (A), distraction task (B), and clothing level (C) on median performance rate to detection of the pedestrian model. Error bars show the IQR.

Table 7.34. Performance rate to detection of pedestrian models according to lighting condition, distraction task, and clothing level.

Variable	p-value	Chi-square
Lighting	<0.001	70.309
Distraction	<0.001	16.698
Distance	<0.001	98.596

Pairwise comparison for changes in lighting condition (Table 7.35) revealed a significant difference between all pairs of lighting conditions, except L1 vs. L2. Participant performance rate was higher in lighting conditions L1 (median: 100%; mean: 97%) and L2 (median: 100%; mean: 98%) compared to L3 (median: 98%; mean: 95%) and L4 (median: 89%; mean: 87%).

Table 7.35. p-values for pairwise comparison of performance rate to detection of the pedestrian model according to lighting condition.

Lighting condition	L2	L3	L4
L1	1.000	0.042	<0.001
L2	-	<0.001	<0.001
L3	-	-	<0.001

*Bonferroni adjusted (significant level < 0.05).

Pairwise comparison for changes in distraction tasks (Table 7.36) revealed a significant effect of visual distraction (T2) compared to both control (T1) and acoustic distraction (T3) but did not suggest a significant difference between control and acoustic distraction. Performance rate was significantly lower while visually distracted (median: 87%; mean: 86%), compared to control (median: 90%; mean: 88%) and acoustic distraction (median: 90%; mean: 88%).

Table 7.36. p-values for pairwise comparison of performance rate to detection of the pedestrian model according to distraction task.

Distraction task	T2	T3
T1	<0.001	1.000
T2	-	<0.006

* Bonferroni adjusted (significant level < 0.05).

Pairwise comparisons for changes in clothing level (Table 7.37) revealed significant differences between all three clothing levels. Participant performance rate was highest for flashing LED clothing (median:100%; mean: 100%), followed by high-visibility clothing (median: 99%; mean: 97%). Grey clothing (median: 90%; mean: 86%) resulted in the lowest performance rate compared to the other two types of clothing levels.

Table 7.37. p-values for pairwise comparison of performance rate to detection of pedestrian models according to clothing level.

Clothing level	High-visibility	Flashing LED
Grey	<0.001	<0.001
High-visibility	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

The interactions for different clothing levels were investigated under the same lighting condition and same distraction task across the categories of light condition and distraction task. Significant differences were noticed under all lighting conditions and distraction task levels except lighting condition L2 under distraction tasks T1 (control) and T3 (acoustic) when comparing different clothing levels (Table 7.38).

Table 7.38. Distribution of the performance rate to pedestrian model across categories of lighting condition and distraction task.

Lighting condition	**p-value – Chi-square**		
	T1	T2	T3
L1	<0.001 – 18.000	<0.001 – 24.043	0.008 – 9.750
L2	0.368 – 2.000	<0.001 – 14.000	1.000 – 0.000
L3	<0.001 – 27.395	<0.001 – 34.900	0.024 – 7.429
L4	<0.001 – 49.563	<0.001 – 66.682	<0.001 – 44.133

Pairwise comparison (Table 7.39) and the summary of median and mean (Table 7.40) highlight significant differences in the performance between clothing grey vs. high-visibility and grey vs. flashing LED in almost all lighting conditions and distraction tasks, but no significant difference was found between clothing high-visibility vs. flashing LED. Under lighting condition L4, significant differences were noticed between all clothing.

Table 7.39. p-values for pairwise comparison of the performance rate to detection of the pedestrian model across categories of lighting and distraction tasks according to different clothing levels.

Lighting condition	**Distraction task**	**Clothing level**	High-visibility	Flashing LED
L1	T1	Grey	0.015	0.015
		High-visibility		1.000
	T2	Grey	0.003	<0.001
		High-visibility		0.471
	T3	Grey	0.141	0.048
		High-visibility		0.471
L2	T2	Grey	0.024	0.015
		High-visibility		1.000
L3	T1	Grey	<0.001	<0.001
		High-visibility		0.951
	T2	Grey	<0.001	<0.001
		High-visibility		0.249
	T3	Grey	0.144	0.051
		High-visibility		0.951
L4	T1	Grey	<0.001	<0.001
		High-visibility		0.021
	T2	Grey	<0.001	<0.001
		High-visibility		0.006
	T3	Grey	<0.001	<0.001
		High-visibility		0.003

* Bonferroni adjusted (significant level < 0.05).

Table 7.40. Median and mean for pairwise comparison of the performance rate to detection of the pedestrian model across categories of lighting and distraction tasks according to different clothing levels.

Lighting condition	Distraction task	Clothing level	Performance rate (%)	
			Median	Mean
L1	T1	Grey	100	94
		High-visibility	100	100
		Flashing LED	100	100
	T2	Grey	100	89
		High-visibility	100	99
		Flashing LED	100	100
	T3	Grey	100	94
		High-visibility	100	98
		Flashing LED	100	99
L2	T2	Grey	100	93
		High-visibility	100	99
		Flashing LED	100	99
L3	T1	Grey	100	88
		High-visibility	100	99
		Flashing LED	100	100
	T2	Grey	100	83
		High-visibility	100	98
		Flashing LED	100	100
	T3	Grey	100	93
		High-visibility	100	98
		Flashing LED	100	99
L4	T1	Grey	83	71
		High-visibility	100	95
		Flashing LED	100	100
	T2	Grey	67	61
		High-visibility	100	93
		Flashing LED	100	100
	T3	Grey	67	73
		High-visibility	100	92
		Flashing LED	100	99

The interaction for different distraction tasks was investigated under the same lighting condition and same clothing level across the categories of lighting condition and clothing level. Significant differences were noticed only under lighting conditions L2 and L3 for grey clothing when comparing different distraction tasks (Table 7.41).

Table 7.41. Distribution of the performance rate to the pedestrian model of different clothing levels across categories of lighting conditions based on distraction tasks.

Lighting condition	**p-value – Chi-square**		
	Grey	High-visibility	Flashing LED
L1	0.113 – 4.361	0.174 – 3.500	0.368 – 2.000
L2	0.011 – 8.933	0.846 – 0.333	0.779 – 0.500
L3	0.008 – 9.692	0.483 – 1.455	0.135 – 4.000
L4	0.014 – 8.510	0.672 – 0.794	0.368 – 2.000

Pairwise comparison (Table 7.42) and the summary of median and mean (Table 7.43) highlight a significant difference in the performance only when comparing distraction tasks T2 (visual) vs. T3 (acoustic), where visual distraction significantly impaired performance rate compared to acoustic distraction.

Table 7.42. p-values for pairwise comparison of the performance rate to detection of the pedestrian model across categories of lighting condition and clothing level according to different distraction tasks.

Lighting condition	**Clothing level**	**Distraction task**	T2	T3
L2	Grey	T1	0.087	1.000
		T2	-	0.036
L3	Grey	T1	0.372	0.312
		T2	-	0.015

* Bonferroni adjusted (significant level < 0.05).

Table 7.43. Median and mean for pairwise comparison of the performance rate to detection of the pedestrian model across categories of lighting condition and clothing level according to different distraction tasks.

Lighting condition	**Clothing level**	**Distraction task**	**Performance rate (%)**	
			Median	**Mean**
L2	Grey	T1	100	98
		T2	100	93
		T3	100	99
L3	Grey	T2	100	83
		T3	100	93

The interactions for different lighting conditions were investigated under the same distraction task and same clothing level across the categories of distraction task and clothing level. Significant differences were noticed under all tasks and clothing levels except C3 (flashing LED) when comparing different light conditions (Table 7.44).

Table 7.44. Distribution of the performance rate to the pedestrian model of different clothing levels across categories of distraction tasks based on lighting conditions.

Lighting condition	**p-value – Chi-square**		
	Grey	High-visibility	Flashing LED
T1	0.004 – 13.466	0.005 – 12.913	0.392 – 3.000
T2	<0.001 – 42.591	0.002 – 14.870	0.392 – 3.000
T3	<0.001 – 56.690	0.005 – 12.763	0.861 – 0.750

Pairwise comparison (Table 7.45) and summary of the median and mean (Table 7.46) highlight a significant difference in performance only when comparing lighting conditions L1 vs. L4 for all distraction tasks and clothing levels, L2 vs. L4 for all the distraction tasks and clothing levels except distraction tasks T1, clothing level C2, and L3 vs. L4 for all the distraction tasks and clothing levels except for all the tasks on clothing level C2.

Table 7.45. p-values for pairwise comparison of the performance rate to detection of the pedestrian model across categories of distraction tasks and clothing levels according to different lighting conditions.

Distraction task	**Clothing level**	**Lighting condition**	L2	L3	L4
T1	Grey	L1	0.528	0.606	<0.001
		L2	-	0.024	<0.001
		L3	-	-	0.012
	High-visibility	L1	0.498	1.000	0.042
		L2	-	1.000	0.654
		L3	-	-	0.480
T2	Grey	L1	1.000	0.804	<0.001
		L2	-	0.09	<0.001
		L3	-	-	<0.001
	High-visibility	L1	1.000	1.000	0.048
		L2	-	1.000	0.048
		L3	-	-	0.078
T3	Grey	L1	0.342	1.000	<0.001
		L2	-	0.102	<0.001
		L3	-	-	<0.001
	High-visibility	L1	1.000	1.000	0.072
		L2	-	1.000	0.042
		L3	-	-	0.150

* Bonferroni adjusted (significant level < 0.05).

Table 7.46. Median and mean for pairwise comparison of the performance rate to detection of the pedestrian model across categories of distraction tasks and clothing levels according to different lighting conditions.

Distraction task	Clothing type	Lighting condition	Performance rate (%)	
			Median	Mean
T1	Grey	L1	100	94
		L2	100	98
		L3	100	88
		L4	83	71
	High-visibility	L1	100	100
		L4	100	95
T2	Grey	L1	100	89
		L2	100	93
		L3	100	83
		L4	67	61
	High-visibility	L1	100	99
		L2	100	99
		L3	100	98
		L4	100	93
T3	Grey	L1	100	94
		L2	100	99
		L3	100	93
		L4	67	73
	High-visibility	L1	100	98
		L2	100	99
		L4	100	92

7.5. Statistical analysis: hazard detection alternative analysis

Section 7.4 investigated the likelihood of significant differences by considering variations in road surface obstacles at different distances and different clothing levels of the pedestrian model. To focus on distraction, an alternative analysis could be performed by ignoring the variations in road surface obstacle distances and different clothing levels of the pedestrian model. This approach would yield nine responses for road surface obstacles or pedestrian models instead of three responses at each distance or clothing level. Additionally, this method would mitigate the issues arising from missing data. This is because, between the nine responses to the road surface obstacle or pedestrian model in one block of test for a single participant, it is less probable that all iterations were missed, and representative values are less likely to be missing values.

Similar to the approach described in section 7.2.3, participants' multiple reaction times to road surface obstacle and pedestrian model were replaced with a single representative value per block of test using the mean as they followed a normal distribution (Appendix F, Tables F.14, and F.15). For road surface obstacles, missing data were present for only two participants, who were excluded from the analysis. The results were analysed for the remaining 58 participants. No missing data were found for pedestrian models. As discussed in section 7.3.1, the distribution of those representative values among the 60 participants was checked (Appendix F, Tables F.16 to F.19), where reaction times were found to follow a normal distribution and performance rates followed a non-normal distribution.

7.5.1 Road surface obstacle: reaction time (alternative analysis)

Figure 7.11 illustrates the mean reaction time to road surface obstacles according to lighting conditions and distraction tasks. Table 7.47 summarises the statistical tests performed. The result indicates significant main effects of lighting conditions and distraction tasks, but no significant interaction effect was found between lighting*distraction.

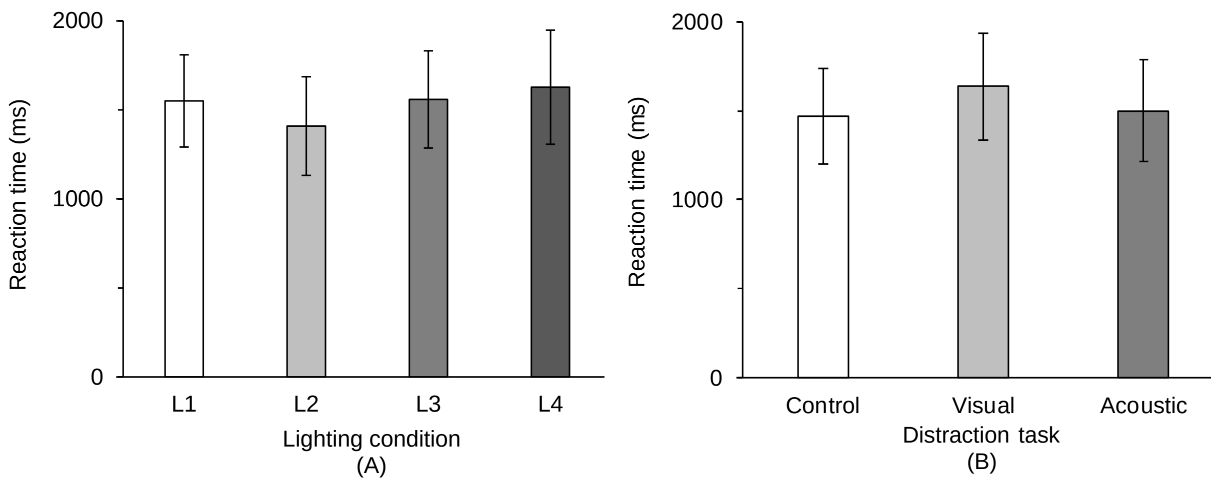


Figure 7.11. The effect of lighting condition (A) and distraction task (B) on mean reaction time to detection of the road surface obstacle. Error bars show one standard deviation above and below the mean.

Table 7.47. Reaction time to detection of road surface obstacle interaction with lighting condition and distraction task.

Variables	**F** (df main, df error)	**p-value***	**Effect size**
Lighting condition	(3, 171) = 24.392	<0.001	0.300
Distraction task	(2, 114) = 49.126	<0.001	0.463
Lighting condition*distraction task	(6, 342) = 1.616	0.142	0.028

* Sphericity Assumed.

Pairwise comparison for changes in lighting conditions (Table 7.48) revealed significant differences between all pairs of lighting conditions except lighting conditions L1 vs. L3 and L3 vs. L4. Participants responded to road surface obstacles significantly faster, as identified by the mean reaction time, under lighting condition L2 (1409 ms) compared to lighting condition L1 (1550 ms), L3 (1559 ms), and L4 (1627 ms).

Table 7.48. p-values for pairwise comparison of reaction time to detection of road surface obstacle according to lighting condition.

Lighting condition	L2	L3	L4
L1	<0.001	1.000	0.041
L2	-	<0.001	<0.001
L3	-	-	0.181

* Bonferroni adjusted (significant level < 0.05).

Pairwise comparison for changes in distraction task (Table 7.49) revealed significant differences between distraction tasks T1 (control) vs. T2 (visual distraction) and T2 vs. T3 (acoustic distraction), but no significant difference between the control (T1) and acoustic distraction (T3). Participants responded to road surface obstacles significantly slower, as identified by mean reaction time, when visually distracted (1638 ms) compared to control (1470 ms) and acoustic distraction (1501 ms).

Table 7.49. p-values for pairwise comparison of reaction time to detection of road surface obstacle according to distraction task.

Distraction task	T2	T3
T1	<0.001	0.323
T2	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

7.5.2. Road surface obstacle: performance rate (alternative analysis)

Figure 7.12 illustrates the median performance rate for road surface obstacles according to lighting conditions and distraction tasks. The effects of lighting conditions were examined individually for each of the three distraction tasks. The distraction tasks T1 and T3 did not significantly influence performance rate under any of the lighting conditions, while a significant impact was observed for distraction task T2 (Table 7.50).

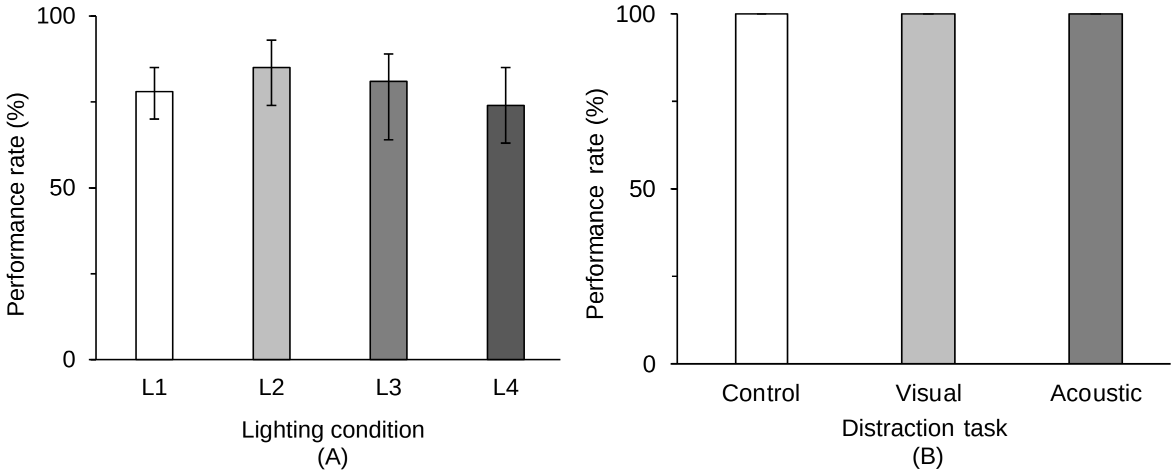


Figure 7.12. The effect of lighting condition (A), and distraction task (B) on median performance rate to road surface obstacle. Error bars show the IQR.

Table 7.50. Performance rate to detection of road surface obstacles across categories of lighting conditions based on the distraction task.

Distraction task	**p-value**	**Chi-square**
T1	0.027	9.171
T2	0.004	13.500
T3	0.081	6.759

Pairwise comparison (Table 7.51) reveals a significant difference in performance during distraction tasks T1 (control) and T2 (visual) in lighting conditions L2 vs. L4. Performance rate to road surface obstacle was significantly higher for control (T1) under lighting condition L2 (median: 89%; mean: 85%) compared to L4 (median: 78%; mean: 78%). Similarly, for visual distraction (T2), the performance rate to road surface obstacles was significantly higher under lighting condition L2 (median: 78%; mean: 72%) compared to L4 (median: 67%; mean: 60%).

Table 7.51. p-values for pairwise comparison of performance rate to detection of road surface obstacle across categories of lighting condition for control (T1) and visual distraction (T2)

Distraction task	**Lighting condition**	L2	L3	L4
T1	L1	1.000	1.000	0.330
	L2	-	0.858	0.018
	L3	-	-	1.000
T2	L1	0.486	1.000	0.666
	L2	-	0.450	<0.001
	L3	-	-	0.558

* Bonferroni adjusted (significant level < 0.05).

The impacts of distraction tasks on performance rate were investigated in each of the four lighting conditions separately. Participants' performances in responding to road surface obstacles were significantly different under all lighting conditions (L1 to L4) (Table 7.52).

Table 7.52. Performance rate to detection of road surface obstacles across categories of distraction tasks based on the lighting condition.

Lighting condition	p-value	Chi-square
L1	<0.001	20.643
L2	<0.001	31.875
L3	<0.001	26.435
L4	<0.001	32.657

Pairwise comparison (Tables 7.53) and summary of the median and mean (Table 7.54) reveal significant differences in the performance of visual distraction (T2) compared to control (T1) and acoustic distraction (T2) under all lighting conditions (L1 to L4), but no significant difference was observed between control (T1) and acoustic distraction under none of the lighting conditions.

Table 7.53. p-values for pairwise comparison of the performance rate to detection of road surface obstacles across categories of distraction task under lighting conditions L1 to L4.

Lighting condition	Distraction task	T2	T3
L1	T1	<0.001	0.417
	T2	-	<0.001
L2	T1	<0.001	1.000
	T2	-	<0.001
L3	T1	<0.001	1.000
	T2	-	<0.001
L4	T1	<0.001	1.000
	T2	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

Table 7.54. Median and mean for pairwise comparison of the performance rate to detection of road surface obstacle across categories of distraction task under lighting conditions L1 to L4.

Lighting condition	Distraction task	Performance rate (%)	
		Median	Mean
L1	T1	89	83
	T2	67	66
	T3	89	79
L2	T1	89	85
	T2	78	72
	T3	89	86
L3	T1	89	82
	T2	67	66
	T3	89	79
L4	T1	78	78
	T2	67	60
	T3	78	77

7.5.3. Pedestrian model: reaction time (alternative analysis)

Figure 7.13 illustrates the mean reaction time to pedestrian models according to lighting conditions and distraction tasks. Table 7.55 summarises the statistical tests performed. The findings reveal significant main effects of lighting condition and distraction task along with a significant interaction between lighting*distraction.

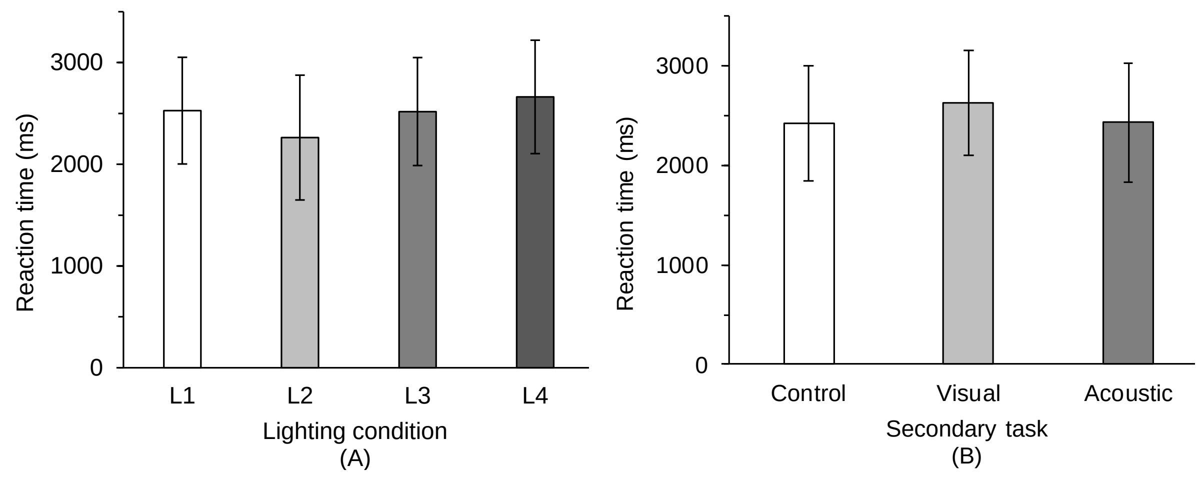


Figure 7.13. The effect of lighting condition (A) and distraction task (B) impact on reaction time to detection of the pedestrian model. Error bars show one standard deviation above and below the mean.

Table 7.55. Reaction time to detection of pedestrian model interaction with lighting condition and distraction task.

Variables	**F** (df main, df error)	**p-value***	**Effect size**
Lighting condition	(3, 177) = 23.906	<0.001	0.288
Distraction task	(2, 118) = 14.941	<0.001	0.202
Lighting condition*distraction task	(6, 354) = 3.538	0.002	0.057

* Sphericity Assumed.

Pairwise comparison for changes in lighting condition (Table 7.56) revealed significant differences between all pairs of lighting conditions except L1 vs. L3. Participants responded to pedestrian models significantly faster, as identified by mean reaction time, under lighting condition L2 (2262 ms) compared to lighting condition L1 (2528 ms), L3 (2518 ms), and L4 (2662 ms).

Table 7.56. p-values for pairwise comparison of reaction time to detection of pedestrian models according to the lighting condition.

Lighting condition	L2	L3	L4
L1	<0.001	1.000	0.029
L2	-	<0.001	<0.001
L3	-	-	0.043

* Bonferroni adjusted (significant level < 0.05).

Pairwise comparison for changes in distraction tasks (Table 7.57) revealed significant effects between distraction tasks T1 (control) vs. T2 (visual distraction) and T2 vs. T3 (acoustic distraction). However, no significant difference was found between the control (T1) and acoustic distraction (T3). Participants responded to pedestrian models significantly slower, as identified by mean reaction time, when visually distracted (2723 ms) compared to control (2213 ms) and acoustic distraction (2245 ms).

Table 7.57. p-values for pairwise comparison of reaction time to detection of the pedestrian model according to distraction task.

Distraction task	T2	T3
T1	<0.001	1.000
T2	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

Pairwise comparison (Table 7.58) and summary of means (Table 7.59) highlight significant effects of lighting conditions on reaction time for both control (T1) and acoustic distraction (T3) under lighting conditions L1 vs. L2, L2 vs. L3, L2 vs. L4, with faster reaction times under lighting condition L2. For visual distraction, there were no significant differences in reaction times under different lighting conditions. In other words, changes in lighting levels did not significantly mitigate the negative impact of visual distraction on reaction time to pedestrian models.

Table 7.58. p-values for pairwise comparison of reaction time to pedestrian model according to lighting condition*secondary task interaction for control (T1), visual (T2), and acoustic distraction (T3).

Distraction task	Lighting condition	L2	L3	L4
T1	L1	<0.001	1.000	0.072
	L2	-	<0.001	<0.001
	L3	-	-	0.446
T2	L1	0.193	1.000	1.000
	L2	-	0.199	0.106
	L3	-	-	1.000
T3	L1	<0.001	1.000	0.026
	L2	-	<0.001	<0.001
	L3	-	-	0.019

* Bonferroni adjusted (significant level < 0.05).

Table 7.59. Median and mean for pairwise comparison of reaction time to pedestrian model according to lighting condition*secondary task interaction for control (T1), visual (T2), and acoustic distraction (T3).

Distraction task	Lighting condition	Mean reaction time (ms)
T1	L1	2443
	L2	2121
	L3	2483
	L4	2624
T3	L1	2469
	L2	2158
	L3	2415
	L4	2673

7.5.4. Pedestrian model: Performance rate

Figure 7.14 shows the median performance rate of the pedestrian models according to lighting conditions and distraction tasks.

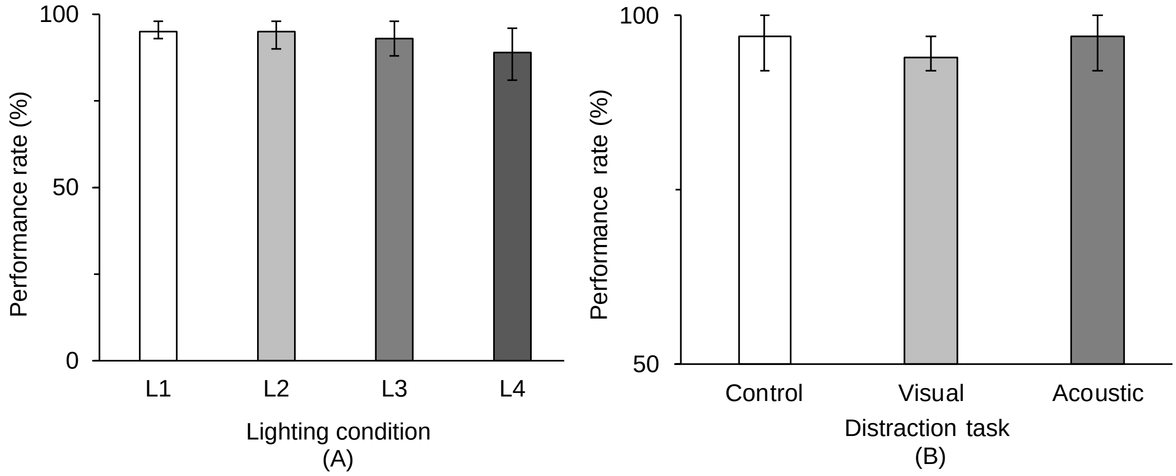


Figure 7.14. The effect of lighting condition (A) and distraction task (B) on mean reaction time to detection of the pedestrian model. Error bars show one standard deviation above and below the mean.

The impacts of lighting conditions were investigated for each of the three secondary tasks separately. Under all four lighting conditions, the performance rate was significantly different across categories of secondary tasks (Table 7.60).

Table 7.60. Performance rate to detection of pedestrian models across categories of lighting conditions based on the distraction task.

Distraction task	p-value	Chi-square
T1	<0.001	38.100
T2	<0.001	49.036
T3	<0.001	50.651

Pairwise comparison (Table 7.61) and the summary of median and mean (Table 7.62) reveal significant differences in performance during secondary tasks T1, T2, and T3 between L1 vs. L4, L2 vs. L4, and L3 vs. L4. The highest performance rate was observed under lighting condition L2, followed by L3, and the lowest performance under lighting condition L4.

Table 7.61. p-values for pairwise comparison of performance rate to detection of pedestrian models across categories of lighting condition for control (T1) and visual distraction (T3).

Distraction task	**Lighting condition**	L2	L3	L4
T1	L1	1.000	1.000	<0.001
	L2	-	0.072	<0.001
	L3	-	-	<0.001
T2	L1	1.000	0.504	<0.001
	L2	-	0.066	<0.001
	L3	-	-	<0.001
T3	L1	1.000	1.000	<0.001
	L2	-	0.126	<0.001
	L3	-	-	<0.001

* Bonferroni adjusted (significant level < 0.05).

Table 7.62. Median and mean for pairwise comparison of performance rate to detection of pedestrian models across categories of lighting condition for control (T1) and visual distraction (T3).

Distraction task	**Lighting condition**	**Performance rate (%)**	
		Median	**Mean**
T1	L1	100	98
	L2	100	99
	L3	100	96
	L4	89	89
T2	L1	100	96
	L2	100	97
	L3	100	94
	L4	89	84
T3	L1	100	97
	L2	100	99
	L3	100	96
	L4	89	88

The impacts of distraction tasks on performance rate were investigated separately in each of the four lighting conditions. Participants' reaction performances to pedestrian models differed significantly under lighting conditions L3 and L4 (Table 7.63).

Table 7.63. Performance rate to detection of pedestrian models across categories of distraction tasks based on the lighting conditions.

Lighting condition	p-value	Chi-square
L1	0.262	2.676
L2	0.117	4.290
L3	0.048	6.062
L4	0.03	6.994

However, pairwise comparison revealed no significant differences in performance rate across categories of lighting conditions (Tables 7.64).

Table 7.64. p-values for pairwise comparison of the performance rate to detection of pedestrian models across categories of distraction tasks under lighting conditions L1 to L4.

Lighting condition	Distraction task	T2	T3
L3	T1	0.219	1
	T2	-	0.102
L4	T1	0.147	1
	T2	-	0.135

* Bonferroni adjusted (significant level < 0.05).

7.6. Statistical analysis: distraction tasks

To investigate how exposure to different lighting conditions affects cognitive performance and whether participants divert their attention to distraction tasks when the primary visual tasks become more challenging due to changes in cognitive load or lighting condition, participant reaction time and performance rate to distraction tasks T2 (visual distraction) and T3 (acoustic distraction) were recorded and analysed. Due to a system failure, data for one participant while performing the visual distraction task was not correctly recorded. This participant was excluded from the analysis, and the responses of the remaining 59 participants were used. Concerning acoustic distraction, data analysed for the total of 60 participants.

7.6.1. Visual distraction (T2): reaction time

Figure 7.15 illustrates the mean reaction time to the visual distraction (T2) task as influenced by lighting conditions. Table 7.65 summarises the statistical tests performed. The findings reveal significant effects of lighting conditions on reaction time to visual distraction tasks.

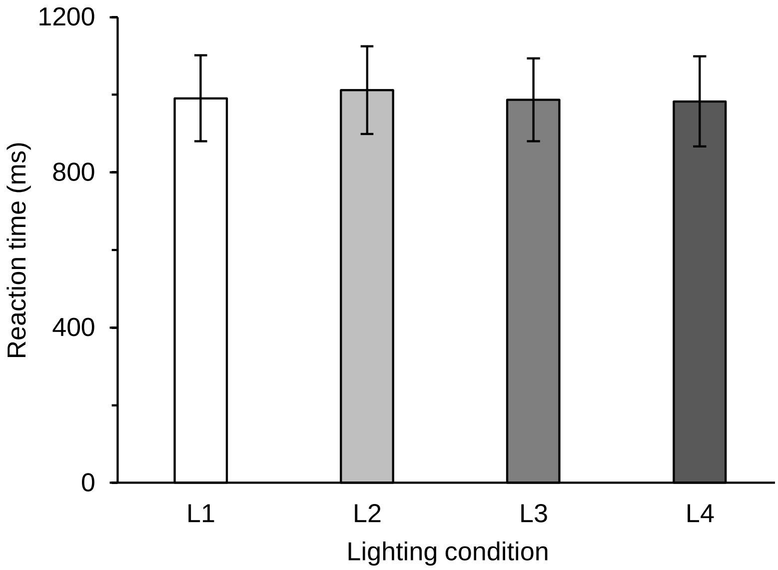


Figure 7.15. Lighting conditions impact on reaction time to visual distraction (T2) task. Error bars show one standard deviation above and below the mean.

Table 7.65. Reaction time to visual distraction (T2) task interaction with lighting condition.

Variables	**F** (df main, df error)	**p-value***	**Effect size**
Lighting condition	(3, 174) = 4.401	0.005	0.071

* Sphericity Assumed.

Pairwise comparison for changes in lighting condition (Table 7.66) revealed significant differences between lighting conditions L2 vs. L3 and L2 vs. L4. Participants responded to visual distraction tasks significantly faster, as identified by mean reaction time, under lighting conditions L4 (983 ms) and L3 (987 ms) compared to lighting condition L2 (1012 ms).

Table 7.66. p-values for pairwise comparison of reaction time to visual distraction (T2) task according to the lighting condition.

Lighting condition	L2	L3	L4
L1	0.140	1.000	1.000
L2	-	0.018	0.014
L3	-	-	1.000

* Bonferroni adjusted (significant level < 0.05).

7.6.2. Visual distraction (T2): performance rate

Figure 7.16 illustrates the median performance rate for the visual distraction task (T2) as influenced by lighting conditions. Significant differences were noticed in performance due to changes in lighting conditions (Table 7.67).

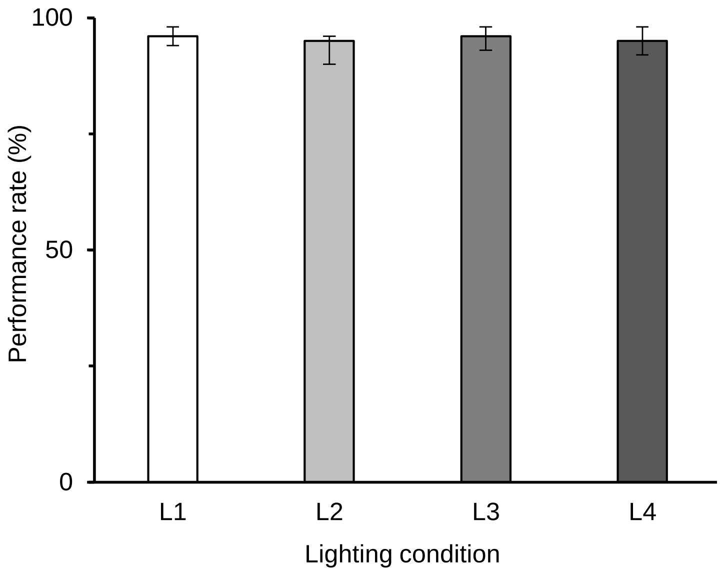


Figure 7.16. Distribution of the performance rate to visual distraction (T2) task across categories of lighting condition. Error bars show the IQR.

Table 7.67. Distribution of the performance rate to visual distraction (T2) task across categories of lighting condition

Variable	**p-value**	**Chi-square**
Lighting condition	<0.001	22.580

Pairwise comparison (Table 7.68) highlighted a significant difference in the performance rate between lighting condition L1 (median: 96%; mean: 95%) vs. L2 (median: 95%; mean: 93%), L1 vs. L4 (median: 95%; mean: 93%), and L2 vs. L3 (median: 96%; mean: 93%).

Table 7.68. p-values for pairwise comparison of performance rate to visual distraction (T2) task according to lighting condition.

Lighting condition	L2	L3	L4
L1	<0.001	1.000	0.012
L2	-	<0.001	0.714
L3	-	-	0.096

* Bonferroni adjusted (significant level < 0.05).

7.6.3. Acoustic distraction (T3): reaction time

Figure 7.17 illustrates the mean reaction time to the acoustic distraction (T3) task as influenced by lighting conditions. Table 7.69 summarises the statistical tests performed. The findings reveal significant effects of lighting conditions on reaction time to acoustic distraction tasks.

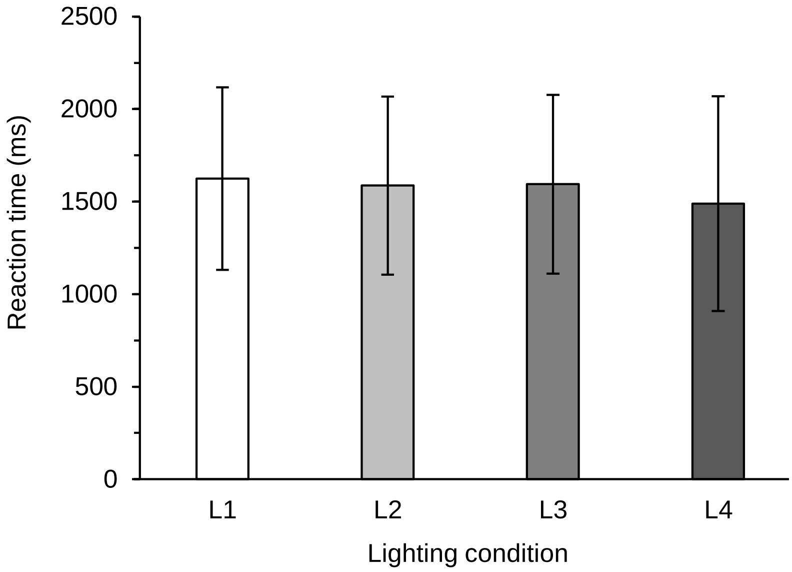


Figure 7.17. Lighting condition impact on reaction time to acoustic distraction (T3) task. Error bars show one standard deviation above and below the mean.

Table 7.69. Reaction time to visual distraction (T2) task interaction with lighting condition.

Variables	**F** (df main, df error)	**p-value***
Lighting condition	(3, 177) = 4.139	0.007

* Sphericity Assumed.

Pairwise comparison for changes in lighting condition (Table 7.70) revealed significant differences between lighting condition L1 vs. L4. Participant reaction time was faster, as identified by mean reaction time, under lighting condition L4 (1489 ms) compared to L1 (1624 ms), L2 (1587 ms), and L3 (1594 ms).

Table 7.70. p-values for pairwise comparison of reaction time to acoustic distraction (T3) task according to lighting condition.

Lighting condition	L2	L3	L4
L1	1.000	1.000	0.026
L2	-	1.000	0.140
L3	-	-	0.088

* Bonferroni adjusted (significant level < 0.05).

7.6.4. Acoustic distraction (T3): performance rate

Figure 7.18 illustrates the median performance rate for the acoustic distraction (T3) task as influenced by lighting conditions. Table 7.71 summarises the test performed. The result revealed significant differences in performance rate to acoustic distraction due to changes in lighting conditions.

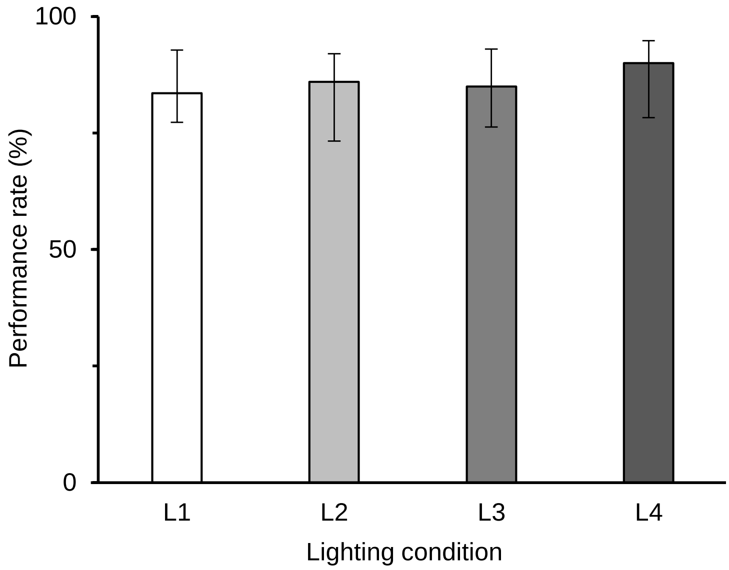


Figure 7.18. Distribution of the performance rate to acoustic distraction (T3) task across categories of lighting condition. Error bars show the IQR.

Table 7.71. Distribution of the performance rate to acoustic distraction (T3) task across categories of lighting condition.

Variable	**p-value**	**Chi-square**
Lighting condition	<0.001	22.580

Pairwise comparison (Table 7.72) revealed significant differences between performance rate under lighting condition L1 (median: 83%; mean: 82%) vs. L4 (median: 90%; mean: 86%) and L2 (median: 86%; mean: 82%) vs. L4.

Table 7.72. p-values for pairwise comparison of performance rate to acoustic distraction (T3) task according to lighting condition.

Lighting condition	L2	L3	L4
L1	1.000	1.000	0.030
L2	-	1.000	0.024
L3	-	-	0.090

* Bonferroni adjusted (significant level < 0.05).

7.7. Summary

Experiment 2 aimed to investigate the impact of distraction tasks (visual and acoustic) on reaction time and performance rate for primary visual tasks (road surface obstacles, vehicle lane change, pedestrian models). Furthermore, the experiment aimed to determine whether different "aids to vision" (increment in road surface illuminance, in-vehicle short-wavelength blue light, and pedestrian-worn high-visibility or flashing LED clothing) could mitigate the negative effects of the distraction tasks by improving visual and/or cognitive performance.

The findings revealed significant effects on reaction time and performance of primary visual tasks while visually distracted, with no such effect observed for acoustic distraction. An increase in road surface luminance (L1 to L2) resulted in significant improvements in reaction time and performance for primary visual tasks. However, this improvement was not further enhanced by the addition of in-vehicle short-wavelength blue light (L3 and L4). Pedestrian-worn "aids to vision" (high-visibility clothing and flashing LED) significantly improved reaction time and performance for pedestrian models, with flashing LED clothing specifically mitigating the negative impact of visual distraction.

Finally, analysing the reaction time and performance rate on secondary tasks (visual and acoustic distraction) highlights that the extreme levels of in-vehicle short-wavelength blue light (L4) can potentially improve cognitive performance as recorded by faster reaction time and better performance rates. However, this trend was inconsistent across all lighting conditions compared to lighting condition L4.

The subsequent section will discuss the findings of Experiment 2 and compare them with similar previous work. This chapter will further highlight current limitations to the experimental setup and suggest potential areas for further research.

Chapter 8. Discussion: Experiment 2

Chapter 8. Discussion: Experiment 2

8.1. Introduction

The current chapter initially evaluates whether the experimental findings support the hypotheses. It then proceeds to critically examine the validity of the current findings by comparison with previous research, identifies the limitations of the study, and makes suggestions for further research.

Experiment 2 investigated hypotheses H2 to H5:

> H2: Distraction (via acoustic or visual stimuli) leads to a deterioration in hazard detection, as indicated by an increase in reaction time from onset of the hazard stimulus to its detection or a decrease in detection rate.
>
> H3: An increase in road surface luminance leads to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.
>
> H4: In-vehicle short-wavelength blue light (increment in melanopic EDI exposure) leads to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.
>
> H5: Pedestrian-worn "aids to vision" lead to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.

This experiment was a scale model of a real driving scene in which participants' reaction time to and probability of detecting three potential hazards (road surface obstacle, vehicle lane change, pedestrian detection) was investigated. The assumption in Experiment 2 was that enhanced road surface luminance, added in-vehicle short-wavelength blue light, and pedestrian-worn "aids to vision" could each mitigate the increase in reaction time and decrease in hazard detection rate caused by distraction by improving visual and cognitive performance. Table 8.4 summarises whether this experiment's result supported each hypothesis:

Table 8.1. Experiment 2 hypothesis evaluation based on the result.

Hypothesis	Approved (✓), Rejected (✗)	Notes
H2	✓	Visual distraction impaired hazard detection, while acoustic distraction did not.
H3	✓	Improved hazard detection was noticed but did not overcome the negative impact of visual distraction.
H4	✗	Improved hazard detection was not noticed; even deterioration was noticed under extreme levels (L4).
H5	✓	Improved hazard detection was noticed, which was sufficient to overcome the negative impact of visual distraction.

The following section will evaluate each hypothesis based on the experiment result and compare the findings with previous work.

8.2. Comparison with previous research

This section presents a discussion of each hypothesis and how the experimental outcomes are assessed within the context of the proposed relationships. Further comparisons evaluate the alignment of the findings with the previous literature on the subject. For each hypothesis, this analysis will identify whether the findings are in line with previous research and further highlight the extent to which the findings develop the current knowledge.

8.2.1. Hypothesis 2:

H2: Distraction (via acoustic or visual stimuli) leads to a deterioration in hazard detection, as indicated by an increase in reaction time from onset of the hazard stimulus to its detection or a decrease in detection rate.

As expected, supporting this hypothesis, visual distraction significantly impaired reaction time and detection rate to all three hazards (road surface obstacle, vehicle lane change, pedestrian detection). However, our results indicate that acoustic distraction did not cause any significant impairment in reaction time and detection performance to these hazards.

Table 8.5. summarises previous research on the effect of distraction while driving. These studies differed in their conducted environment (field vs. laboratory), nature of distraction tasks, demographic

of the participants (e.g., different age groups), and measurement techniques for assessment of driving performance. They employed various measurement techniques to assess the impact of distraction on driving performance, including vehicle longitudinal and lateral control, visual performance, cognitive performance and hazard detection. The findings from these methods for visual and acoustic distractions are discussed next.

Regarding visual distraction, the current experiment's findings align with those of previous studies, including Engström et al., 2005, Liang and Lee, 2010, Kaber et al., 2012, Young et al., 2013, Chan and Singhal, 2013, and Peng et al., 2014, which reported impaired vehicle lateral control due to visual distraction. Similar impairment in driving performance, as identified by impaired vehicle longitudinal control, have been observed in the works of Engström et al., 2005, Horberry et al., 2006, Kaber et al., 2012, Young et al., 2013, Chan and Singhal, 2013, Peng et al., 2014, and Strayer et al., 2015. Additionally, visual distraction has been shown to impair driving performance by deteriorating visual performance, as observed in the studies of Engström et al., 2005, and Kaber et al., 2012, where an increment in cognitive load due to distraction resulted in increased gaze concentration and impaired peripheral visual scanning. Finally, visual distraction has been observed to impair driving performance by reducing the ability to detect hazards [Horberry et al., 2006; Liang and Lee, 2010; Chan and Singhal, 2013].

While the findings of previous studies generally support the detrimental impact of visual distraction on driving performance, the evidence surrounding acoustic or auditory distraction is more inconclusive, with a tendency for visual distraction to exert a stronger negative impact.

Regarding vehicle lateral control, studies by Liang and Lee, 2010, Garrison and Williams, 2013, and Tarabay and Abou-Zeid, 2018, have observed impairments in driving performance due to acoustic distraction, while studies by Rakauskas et al., 2004, Engström et al., 2005a, Törnros, and Bolling 2005, and Kaber et al., 2012, have not found such impairments. Similarly, concerning vehicle longitudinal control, studies by Rakauskas et al., 2004, Patten et al., 2004, Horberry et al., 2006, Garrison and Williams, 2013, and Strayer et al., 2015, have detected impairments in driving performance due to acoustic distraction, while studies by Engström et al., 2005a, Kaber et al., 2012, and Tarabay and Abou-Zeid, 2018, have not observed such effects. Comparably, in terms of visual performance, the study by Engström et al., 2005a demonstrated impaired driving performance due to acoustic distraction, while Kaber et al., 2012 did not find such a detrimental effect. Lastly, regarding hazard detection, studies by Horberry et al., 2006, Caird et al., 2008, Liang and Lee, 2010, and Strayer et al., 2015, have identified impaired driving performance due to acoustic distraction.

These studies have demonstrated consistent findings regarding driving performance measures while visually distracted, where visual distraction has been shown to impair driving performance significantly. The current experiment corroborates this conclusion, finding that visual distraction significantly impaired reaction time and hazard detection rate for all three hazard types (road surface obstacle, vehicle lane change, pedestrian model).

In contrast, the effect of acoustic distraction on driving performance has been less consistent, with some studies reporting significant impairments and others demonstrating minimal or no significant influence. The current experiment found no significant difference between the presence of acoustic distraction and control condition in terms of reaction time and detection rate to hazards. These discrepancies may be attributable to demographical and methodological differences between different studies (Table 8.5):

I. **Task complexity:** The impact of distraction depends heavily on the complexity of the driving task at hand. Simple tasks like highway driving with minimal traffic might be less affected by distraction compared to complex tasks like navigating busy city streets or merging into heavy traffic. Drivers can sometimes compensate for distraction on simpler tasks.

II. **Individual differences:** People have varying susceptibility to distraction. Some individuals are naturally better at multitasking or filtering out irrelevant information, allowing them to perform relatively well while distracted. Conversely, others might be easily overwhelmed by distractions, leading to significant performance drops.

III. **Difficulty level of the distraction task:** The severity of the distraction also plays a role - a complex conversation is more distracting than listening to calming music.

IV. **Experience and skill:** More experienced drivers can sometimes compensate for distraction to a greater degree than novice drivers. They might rely on muscle memory and anticipation to handle basic driving tasks while their attention is diverted.

V. **Measurement challenges:** Measuring the impact of cognitive distraction on driving performance can be complex. Methods like collision data analysis might not accurately capture near misses or close calls caused by distraction. Simulator studies offer more controlled environments but may not fully replicate real-world driving situations.

VI. **Adaptation and habituation:** Over time, some drivers might adapt to a certain level of distraction, becoming accustomed to multitasking while driving.

Notably, a common limitation of previous research is the lack of proper documentation regarding the timing of the study. Circadian rhythm and sleep pressure, in addition to distraction, are crucial factors influencing participants' cognitive workload. Consequently, the lack of precise information regarding the time of day in which experiments were conducted (e.g., morning, evening) hinders the comparability of findings across these studies.

Table 8.2. Previous research on distraction and driving performance. Studies are presented in chronological order (measurement techniques codded as M1: ocular measures; M2: vehicle longitudinal control; M3: vehicle lateral control; M4: hazard detection; M5: subjective; M6: Peripheral detection task; M7: skin conductance; M8: cognitive task performance; M9: EEG; M10: cardiac).

Reference	**Method**	**Distraction tasks**	**Measurement techniques**									
			M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
Recarte and Nunes, 2000	Field	Acoustic	✓									
Rakauskas et al., 2004	Laboratory	Acoustic		✓	✓	✓	✓					
Patten et al., 2004	Field	Acoustic & Manual		✓			✓	✓				
Engström et al., 2005a	Field Laboratory	Acoustic & Visual		✓	✓		✓		✓			✓
Törnros, and Bolling 2005	Laboratory	Acoustic		✓	✓		✓	✓				
Horberry et al., 2006	Laboratory	Acoustic & Visual		✓		✓	✓					
Caird et al., 2008	Meta-analysis	Acoustic		✓	✓	✓		✓				
Liang and Lee, 2010	Laboratory	Acoustic & Visual	✓		✓	✓						
Kaber et al., 2012	Laboratory	Acoustic & Visual	✓	✓	✓					✓		
Young et al., 2013	Field	Visual		✓	✓							
Chan and Singhal, 2013	Laboratory	Visual		✓	✓	✓						
Garrison and Williams, 2013	Laboratory	Acoustic	✓	✓	✓					✓		
Sonnleitner et al., 2014	Field	Acoustic		✓							✓	
Peng et al., 2014	Laboratory	Acoustic & Visual		✓	✓							
Wang et al., 2015	Laboratory	Visual			✓						✓	
Strayer et al., 2015	Field Laboratory	Acoustic & Visual	✓	✓			✓	✓		✓	✓	
Karthaus et al., 2018	Laboratory	Acoustic & Visual				✓					✓	
Tarabay and Abou-Zeid, 2018	Laboratory	Acoustic		✓	✓	✓						
Öztürk et al., 2023	Laboratory	Acoustic		✓	✓			✓		✓		

8.2.2. Hypothesis 3:

H3: An increase in road surface luminance leads to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.

Table 8.6 summarizes the overall effect of increasing road surface luminance from lighting condition L1 (0.1 cd/m2) to L2 (0.9 cd/m2) on reaction time and hazard detection rate.

Table 8.3. Effect of increment in road surface luminance from L1 to L2 on reaction time and detection rate to road surface obstacle, vehicle lane change, and pedestrian detection.

Reaction time			Detection rate		
Obstacle	Lane change	Pedestrian	Obstacle	Lane change	Pedestrian
Significant	Significant	Significant	Not significant	Significant	Not significant

The findings of the current experiment demonstrate a substantial improvement in reaction time for all three hazards. However, regarding hazard detection rate, the improvement observed due to increased road surface luminance was only evident for vehicle lane change. On the other hand, as discussed in hypothesis H2, reaction time and detection rate to hazards were impaired when visual distraction was present compared to the control condition. To determine if the improvement noted in reaction time and detection rate to hazards owing to increased luminance can counteract the adverse impact of visual distraction, it is crucial to investigate the interaction between these two variables. Table 8.7 summarizes the result of this interaction.

Table 8.4. Effect of interaction between increment in road surface luminance from L1 to L2 on decrement of reaction time and detection rate to road surface obstacle, vehicle lane change, and pedestrian detection while visually distracted.

Reaction time			Detection rate		
Obstacle	Lane change	Pedestrian	Obstacle	Lane change	Pedestrian
Not significant	Not significant	Not significant	Not significant	Significant	Not significant

The findings reveal that while the impairment in lane change detection rate caused by visual distraction is partially alleviated by increasing road surface luminance, this improvement does not extend to the other hazard detection rates nor to their relative reaction times. Therefore, an increment in road surface luminance from 0.1 cd/m^2 to 0.9 cd/m^2, while improving the reaction time and detection rate, falls short of fully mitigating the adverse impacts of visual distraction on hazard detection.

8.2.3. Hypothesis 4:

H4: In-vehicle short-wavelength blue light (increment in melanopic EDI exposure) leads to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.

The result indicates that lighting condition L3 with a dimmer amount of melanopic EDI (0.83 lx) and lighting condition L4 with extreme levels of melanopic EDI (80.60 lx) did not significantly improve reaction time and detection rate to hazards. However, looking only at the distraction tasks (visual and acoustic) performance, a trend of improvement in reaction times and performance rate to visual and acoustic stimuli can be observed under lighting conditions L3 and L4, which indicate a significant effect of added in-vehicle short-wavelength blue light. This finding is in line with the findings of Alkozei et al., 2016, who showed similar improvement in performance during an n-back task due to exposure to 214 lx of blue-enriched light with peak sensitivity at 469 nm. However, the observed trend in the current experiment was not consistent across all lighting conditions, and the results of reaction time and detection rate to hazards on the road show that the potential noticed improvement in the distraction tasks performance may not lead to an improved driving performance as identified by hazard detection. There are several reasons why this might have occurred, which require further investigation.

Firstly, an in-vehicle short-wavelength blue light source may affect the eye's adaptation and, as a result, deteriorate the visual performance, leading to poorer or similar reaction times and detection rates than lighting conditions without in-vehicle light. Secondly, the observed decline in hazard detection in the current experiment may result from participants diverting their attention from the hazard detection task to their distraction task performance as the visual task became more challenging due to the presence of in-vehicle short-wavelength blue light. This is evident in the consistent performance rates on distraction tasks across all lighting conditions, while hazard detection performance deteriorated. Finally, regarding acoustic distraction, the experimenters manually entered the participants' responses, which introduces the possibility of error due to missed or delayed entry. However, the noticeable improvement in the reaction time and performance rate to the visual distraction task remains valid as it was recorded directly by the participants (dial pad entry recording, see section 6.3.2).

It has been suggested that modulating cortical activity using short-wavelength blue light could influence behaviour, but the potential may be constrained by the requirement for a certain threshold of neuronal activation to trigger conscious experience [Sergent et al., 2004]. Additionally, the potential for short-wavelength blue light to efficiently affect higher-level cognitive processing, particularly in tasks like driving, has not been extensively explored [Killgore et al., 2020]. To our knowledge, the current experiment represents the first attempt to investigate whether the observed acute benefits of short-wavelength blue light on cognitive performance extend to improved hazard detection while driving. The findings of the current experiment did not reveal a significant improvement in reaction time and detection rate to hazards in response to exposure to an in-vehicle short-wavelength blue light source.

8.2.4. Hypothesis 5:

H5: Pedestrian-worn "aids to vision" lead to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.

The findings regarding the overall effect of changes in clothing level from grey to high-visibility, and, subsequently, flashing LED, demonstrate a notable improvement in reaction time and performance rate to pedestrians for both high-visibility clothing and flashing LED compared to grey clothing. This aligns with the findings of Sayer and Mefford 2004, who observed that incorporating retroreflective material into a dark-clad pedestrian increased the detection distance, although the amount of retroreflective material did not have an effect. Additionally, Fekety et al., 2016 established that integrating self-luminous material (electroluminescent in their study) into retroreflective clothing enabled pedestrian detection at a greater distance than retroreflective clothing alone. To our knowledge, the use of flashing LEDs to improve pedestrian detection has not been previously explored.

In the presence of visual distraction, consistent with hypothesis H2, reaction time and detection rate were impaired compared to the control condition. To examine whether the observed improvement in reaction time and performance rate resulting from the alteration of pedestrian clothing from grey to high-visibility and flashing LED mitigates the detrimental impact of distraction, it is essential to investigate the interaction between these two variables.

The findings of the current experiment indicate that while high-visibility clothing improved reaction time and detection rate compared to grey clothing, visual distraction still resulted in an impairment compared to the control condition. However, when utilizing flashing LED clothing, the detrimental impact of visual distraction was mitigated, and no difference was observed between the reaction time and performance rate while visually distracted compared to the control condition. This suggests that employing flashing LED clothing is crucial in mitigating the negative influence of visual distraction on pedestrian detection.

8.3. Limitations and future research

The participants in the current experiment were limited to a younger age group (18-30 years old). With ageing, alterations in the eye and visual system occur, resulting in a decline in the intensity of short-wavelength blue light reaching the retina. This implies that higher levels of short-wavelength blue light would be required to elicit comparable cognitive benefits in older age groups. While providing more light may help deliver enough retinal illumination to induce anticipated non-visual responses like enhancing cognitive performance in the elderly, it will be ineffective in addressing the challenges associated with increased light scatter as we age. Scattered light diminishes the quality and colour of the retinal image [Boyce, 2014]. For drivers, deteriorating visual acuity, contrast sensitivity, colour discrimination, visual field size, …, that are associated with ageing, could lead to reduced driving performance and safety, particularly when performing manoeuvres in which visibility is restricted, such as detecting and avoiding low contrast road hazards [Boyce, 2014].

For the current experiment, this implies that a further improvement in hazard detection might have been observed by increasing the road surface illuminance if older individuals had been included in the study. Additionally, while driving, the speed of processing visual information is critical for safe and efficient driving performance, highlighting the importance of the cognitive component. Ageing can result in slower visual and information processing speeds, particularly when attention is divided [Boyce, 2014]. Therefore, with the inclusion of older participants, it is also likely that greater non-visual benefits would have been observed in cognitive task performance. However, further investigations are required to confirm the existence of these effects, and future studies must consider the investigation of elderly individuals.

The findings of the current experiment suggest that using in-vehicle short-wavelength blue light at the intensities employed in this study is insufficient to trigger cognitive benefits that translate to enhanced performance in tasks such as hazard detection. However, the present experiment exclusively examined the non-visual benefits of short-wavelength blue light. Future research could explore other wavelengths, like red light, which has also been shown to induce non-visual potentials [Plitnick et al., 2010]. Future investigations might also delve into ocular alterations, both for measuring cognitive performance and uncovering any pupillary changes induced by installing an in-vehicle light system, which is likely to influence visual performance.

Pedestrian-worn flashing LED clothing was more effective in mitigating visual distraction than increasing road surface luminance. As a result, equipping pedestrians with flashing LED clothing would offer a greater advantage for pedestrian safety than simply increasing road surface luminance. However, these findings are limited to the simple non-articulated pedestrian model used in the experiment. It has been demonstrated that biomotion, wearing the retroreflective material on moving limbs, further enhances pedestrian conspicuity [Wood, 2023]. Consequently, future research could consider implementing this technique in combination with flashing LEDs and investigating its potential benefits on distraction mitigation. Moreover, it would be of considerable value to investigate the modulation of illuminance and flashing rate of the LED device to demonstrate the optimum thresholds.

The researchers recorded participant responses to acoustic distraction. To ensure accurate differentiation while recording, phonologically distinct letters were picked for this task (section 5.3.2). Additionally, the computer program for recording this task was designed to display the sequence of letter generation to researchers in advance, enabling them to prepare to enter participant responses correctly and without delay. However, this method of recording may introduce errors due to researcher mistakes, such as entering the wrong letter or responding slowly. This potential limitation to the recording method could be addressed in future studies by exploring alternative approaches that ensure reliable recording, such as automated scoring using speech recognition techniques [e.g., Monk et al., 2011] or recording participant responses using a voice recorder [e.g., Öztürk et al., 2023].

Conducting this experiment in the laboratory provided good control of variables, as discussed in Experiment 1 (section 5.2.2). To enhance the similarity of the hazard detection task to actual road driving and improve generalisability, participants were asked to follow a dynamic moving cross alongside the hazard detection task. This ensured the use of peripheral vision for hazard detection. However, the participants in the current experiment did not engage in the actual task of driving, which might induce higher levels of cognitive load. Furthermore, drivers' visual scenery and lighting exposure on real roads are dynamic, unlike in the current experiment. Future field studies are needed to substantiate the findings.

8.4. Summary

Chapter 8 discussed the findings of the two experiments undertaken to explore the potential of light in mitigating distraction and sleepiness, thereby enhancing attention while driving. It further compared the results of each experiment to previous studies and established the reliability of the findings. Additionally, it highlighted the limitations of the current work and the implications of these limitations for the findings of the work and identified the potential for further research. The next chapter will summarize the key takeaways from both experiments and underscore the potential implications for lighting practice.

Chapter 9. Conclusion

Chapter 9. Conclusion

9.1. Thesis aim:

In 2018, there were 1.35 million road traffic deaths globally [World Health Organization, 2018]. In Great Britain, in 2022, there were 153,158 road traffic collisions (RTC) casualties of all severities, including 25,945 severe injuries and 1,752 reported deaths [Department for Transport, 2023]. The total value of prevention of these collisions is estimated over 43 billion British Pound Sterling [Department for Transport, 2024].

Historically, research into the human-light interaction has focused primarily on the image-forming visual system, investigating the mechanisms underlying light perception and image formation. A recent paradigm shift in research occurred following the discovery of non-visual photoreceptors. These findings laid the groundwork for exploring the broader influence of light on human psychophysiology beyond visual perception – the non-image-forming (NIF) response. Light can modulate various physiological processes, including circadian rhythms, sleep, attention, fatigue, body temperature, neuroendocrine function, and mood. In recent years, there has been a growing interest in understanding methods utilizing light to counter sleepiness and cognitive impairment. For example, a meta-analysis by Figueiro et al. [Figueiro et al., 2017] underscored light's potential to induce a rapid acute attentional response, similar to caffeine consumption (for a comprehensive overview of visual and non-visual light impacts, refer to Chapter 2. Literature Review). These light-modulated responses to human performance offer the potential to develop research in traffic collision prevention and mitigation by targeting the mechanisms through which light influences driver attention.

In line with the United Nations resolution [United Nations General Assembly, 2021] to improve global road safety and reduce road traffic casualties by at least 50% by 2030, this thesis explored the potential of light to support drivers’ attention, specifically addressing impairments caused by sleepiness and distraction.

9.2. Research hypothesis and methodological frameworks:

In this thesis, triangulation techniques [Thurmond, 2001] were employed for both the methodological development of the experiments and the overall research design. The primary objective of utilizing these techniques was to enhance the robustness and credibility of research findings by offsetting the inherent limitations of individual research methods [Thurmond, 2001].

Regarding the methodological framework, multiple subjective and objective measurement techniques were concurrently employed within each experiment to comprehensively assess dependent variables. Concerning the overall thesis design, aligned with the study's objective of identifying the potential of light to mitigate driver inattention due to sleepiness and distraction, distinct experimental designs were adopted for each inattention factor. Sleepiness was investigated in Experiment 1, as outlined in Hypothesis H1, while distraction was the focus of Experiment 2, as specified in Hypotheses H2 to H5. This approach was necessary due to the divergent nature of sleepiness and distraction, requiring distinct measurement strategies and experimental conditions.

> H1: An increase in melanopic EDI (lx) leads to a decrease in sleepiness when driving in the evening after dark.
>
> H2: Distraction (via acoustic or visual stimuli) leads to a deterioration in hazard detection, as indicated by an increase in reaction time from onset of the hazard stimulus to its detection or a decrease in detection rate.
>
> H3: An increase in road surface luminance leads to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.
>
> H4: In-vehicle short-wavelength blue light (increment in melanopic EDI exposure) leads to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.
>
> H5: Pedestrian-worn “aids to vision” lead to an improvement in hazard detection, as indicated by a decrease in reaction time from onset of the hazard stimulus to its detection or an increase in detection rate while distracted.

Experiment 1 investigated four different measures of sleepiness (melatonin level, audio reaction time, self-reported sleepiness, and skin temperature) in a laboratory setting. The experiment commenced after dark and three hours before the participants’ habitual bedtime. Previous research suggests that as the time approaches an individual habitual bedtime, he/she would experience increased levels of sleepiness as indicated by higher melatonin levels, slower audio reaction time and higher error rates, increased self-reported sleepiness, and higher skin temperature. This experiment aimed to determine whether exposure to a light intervention with higher melanopic EDI (lx) than typically used in road lighting (up to 10 melnopic lx) could mitigate sleepiness.

Experiment 2 used a scale model of a real driving scene in which participants' reaction time to and probability of detecting three potential hazards (road surface obstacle, vehicle lane change, pedestrian detection) was investigated. This experiment explored the impact of distraction tasks (visual and acoustic) on hazard detection. Additionally, the experiment sought to ascertain whether various visual aids (increased road surface illuminance, in-vehicle short-wavelength blue light, and high-visibility or flashing LED clothing worn by pedestrians) could counteract the adverse effects of distraction tasks by enhancing visual and/or cognitive performance. The assumption in Experiment 2 was that enhanced road surface luminance, added in-vehicle short-wavelength blue light, and pedestrian-worn "aids to vision" could each mitigate the increase in reaction time and decrease in hazard detection rate caused by distraction by improving visual and cognitive performance.

Experiments 1 and 2 were collaboratively designed to enhance our understanding of how light can potentially mitigate driver inattention induced by sleepiness and distraction. Subsequent section will summarize the findings of these experiments.

9.3. Conclusions for this work

The two laboratory experiments conducted in this thesis provided insight into the potential benefits of light (if any) in enhancing or aiding driver attention and ultimately mitigating RTCs and, hence the associated casualties.

Concerning Experiment 1, the four lighting conditions that presented melanopic EDIs of approximately less than half lux to 10 lx, failed to reveal notable differences in reaction time to an acoustic stimulus, melatonin levels derived from saliva samples, self-reported sleepiness, nor skin temperature. The findings of this experiment do not suggest that road lighting at current levels has any effect on driver sleepiness after dark.

Concerning Experiment 2, the findings revealed a negative effect of visual distraction on hazard detection (for all three types of hazards), while no such effects were observed under acoustic distraction. An elevation in road surface luminance from 0.06 cd/m2 to 0.57 cd/m2 (L1 to L2) was associated with improved hazard detection (all three used hazards). However, this improvement was insufficient to mitigate the impairment observed due to visual distraction. The use of in-vehicle short-wavelength blue light (L3 and L4) did not improve hazard detection and even adversely affected visual performance as identified by hazard detection under extreme levels of in-vehicle lighting condition L4 (13.3 lx at the eye). Regarding various pedestrian clothing in Experiment 2, both high-visibility clothing and flashing LEDs improved reaction time and performance rate, with flashing LED clothing specifically mitigating the negative impact of visual distraction. Analysing the reaction time and performance rate on secondary tasks (visual and acoustic distraction) reveals that the extreme levels of in-vehicle short-wavelength blue light of lighting condition L4 can potentially enhance cognitive performance, as demonstrated by faster reaction times and improved performance rates. However, it is crucial to acknowledge that this trend was not consistently observed across all lighting conditions compared to lighting condition L4, and further investigation is necessary to establish the benefits of such exposure.

The findings from Experiments 1 and 2 represent a novel contribution to the field, as to our knowledge, they constitute the first known attempts to mitigate driver inattention through light manipulation, specifically targeting non-visual responses. These results advance current knowledge and provide a foundation for future research, which will be discussed in subsequent sections.

9.4. Contribution to knowledge, limitations, and future research:

The empirical findings from Experiment 1 do not support that road lighting alteration can be used to effectively mitigate sleepiness of drivers after dark and current standard road lighting levels do not appear to suppress nocturnal melatonin levels. These findings are important on two fronts:

I. Previous research indicates that light sources rich in blue wavelengths can enhance human attention and cognitive functions. Consequently, it has been hypothesized that blue-enriched roadway lighting compared to traditional lighting, could potentially augment driver alertness, thereby contributing to enhanced nighttime traffic safety. However, the findings of this research indicate that, given current technology and applicable road lighting levels, such modifications would not effectively enhance driver attention and consequently improve nighttime road safety. This study focused on young adults (18-30 years old), limiting its applicability to a broader age range of drivers, particularly older individuals. Age-related changes in ocular physiology and light perception may influence results. Future research should broaden the scope by including diverse age groups. Additionally, the study was conducted in a controlled laboratory environment to isolate the effects of light on sleepiness and performance. While this enabled precise measurements, it lacked real-world driving complexities. Further research is necessary to verify the null findings of the current experiment. This could involve replicating the study with a wider range of lighting conditions, particularly those with higher melanopic EDI.

II. Past studies have shown that optimal circadian and neuroendocrine function necessitates sufficient exposure to bright daylight and subsequent darkness. However, concerns have been raised that the prevalence of artificial lighting such as road lighting may disrupt normal sleep, circadian rhythms, and neuroendocrine physiology. Such disruptions can cause adverse health outcomes, including increased risk of certain cancers, heart disease, and metabolic disorders [Bedrosian et al., 2016]. Notably, the circadian system is particularly sensitive to short-wavelength (459-484 nm) blue-enriched light, which is prevalent in LED road lighting. Evening exposure to LED light has been associated with sleep loss and circadian disruption [Cajochen et al., 2011; Chang et al., 2015]. The findings of this thesis demonstrate that alterations in the spectral distribution and intensity of roadway lighting exerted no significant influence on salivary melatonin suppression among participants. As a result, the spectral power distribution of road lighting is unlikely to affect the sleep health of road users, particularly drivers, given the subthreshold light dosage encountered in roadway environments. However, this study was limited to only one aspect of sleep health (salivary melatonin suppression). Future research should extend salivary melatonin measurement into plasma melatonin measurement across longer nighttime periods. Additionally, a comprehensive assessment of sleep health, including sleep onset, awakenings, duration, efficiency, and quality, is necessary in more naturalistic settings to fully understand the impact of roadway lighting on sleep health.

The empirical findings from Experiment 2, highlight that in-vehicle short-wavelength blue light not only fails to mitigate the negative impact of distraction but may also exacerbate visual performance and hazard detection challenges. These findings do not support the notion of using such in-vehicle light sources to enhance drivers' attention and cognitive performance while distracted. Furthermore, they argue against the increasing number of installed displays within vehicles. Such displays not only may deter visual performance and hazard detection tasks while driving but could also introduce an additional source of visual distraction, which this study found to significantly impair drivers' hazard detection capabilities. However, the current study did not investigate ocular changes due to the presence of an in-vehicle light and is limited to in-vehicle short-wavelength blue-enriched light. Future research could explore other wavelengths, like red light, which has also been shown to induce non-visual potentials. Future investigations might also delve into ocular alterations to uncover any pupillary changes induced by installing an in-vehicle light system, which is likely to influence visual performance.

Additionally, the results indicated that the use of flashing LEDs could potentially mitigate the negative impact on hazard detection for visually distracted drivers, unlike high-visibility clothing. Given the increasing prevalence of in-vehicle visual displays and the continued use of mobile phones by drivers, despite warnings, high-visibility clothing alone is insufficient to maximize pedestrian safety. This thesis posits the implementation of wearable, flashing LED devices for pedestrians as a potential countermeasure to mitigate the heightened risk of pedestrian-vehicle collisions associated with increasing driver distraction. By enhancing pedestrian detectability, these devices aim to provide a critical margin of safety in an environment characterized by divided driver attention. These findings are limited to the simple non-articulated pedestrian model used in the experiment. It has been demonstrated that biomotion, wearing the retroreflective material on moving limbs, further enhances pedestrian conspicuity [Wood, 2023]. Consequently, future research could consider implementing this technique in combination with flashing LEDs and investigating its potential benefits on distraction mitigation. Moreover, it would be of considerable value to investigate the modulation of illuminance and flashing rate of the LED device to demonstrate the optimum thresholds.

Finally, the result from the second experiment indicates that an increment in road surface luminance improved driver hazard detection. Therefore, for road lighting practice and design, the increased road surface luminance, in general, should be of benefit when improved hazard detection of all types is a priority. Yet, the threshold of increment and its potential benefits is beyond the scope of this research and needs further investigation.

Appendices

Appendix A.

Spectral power distribution, illuminance and luminance: measurement grid and relative values, Experiment 1.

The illuminance, luminance and SPD were measured at angles of sight of -30°, -15°, 0°, 15° and 30° and on the tabletop, using the illuminance meter (Konica Minolta illuminance meter T-10), luminance meter (Konica Minolta luminance meter LS-150), and spectroradiometer (JETI spectroradiometer model no 1511) respectively. Figure A.1 shows the measurement grid on the end wall of the laboratory (front wall to the participants), with vertical and horizontal alignments of the measurement grid shown in sections (A) and (B), respectively. Red and black dots represent the measurement points of participants 1(left) and participant 2 (right).

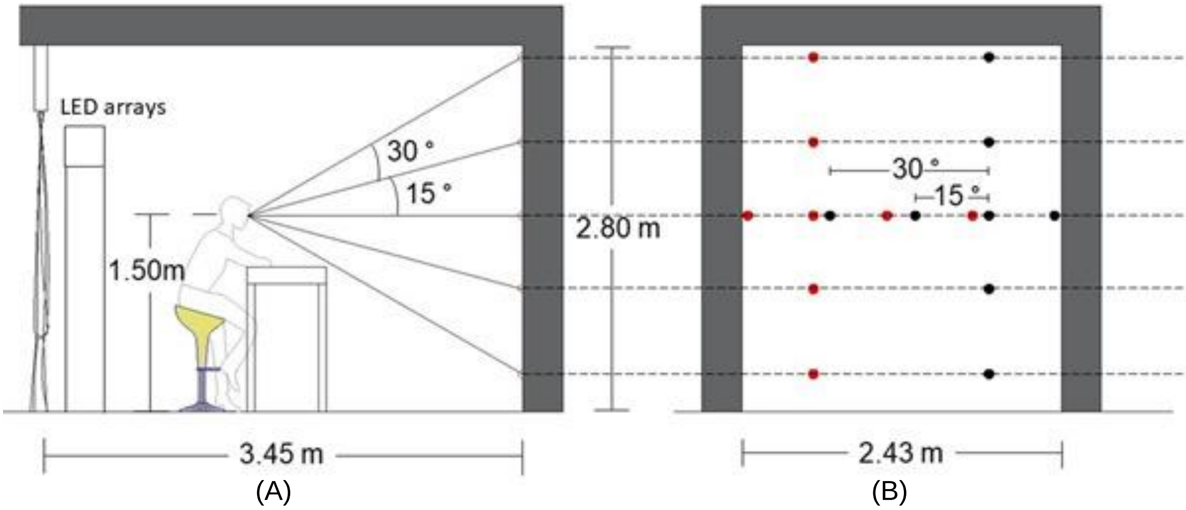


Figure A.1. The grid of measurement on the end wall of the laboratory (sections (A) and (B) represent vertical and horizontal alignments, respectively).

The measurements were repeated three times, and the average values were recorded (Table A.1). The differences between the participants' lighting exposure were lower than 5%.

Table A.1. Illuminance and luminance measurements on the grid.

Light condition*	Measured value**	Participant no	Measurement points								
-	-	-	Horizontal				Vertical				Table top
-	-	-	-15°	0°	15°	30°	-30°	-15°	15°	30°	-
L1	Illuminance***	1	8.05	7.84	7.90	8.21	6.77	7.20	8.99	10.59	6.21
		2	8.06	7.91	7.91	8.18	6.70	7.19	9.03	1.67	6.02
	Luminance****	1	2.33	2.40	2.43	2.32	1.43	1.84	2.95	2.96	1.94
		2	2.11	2.30	2.41	2.39	1.18	1.78	2.85	2.93	2.09
L2	Illuminance***	1	8.21	8.03	8.06	8.37	6.90	7.33	9.17	10.81	6.4
		2	8.24	8.07	8.07	8.34	6.82	7.32	9.23	10.90	6.38
	Luminance****	1	2.40	2.48	2.52	2.40	1.48	1.90	3.06	3.07	2.16
		2	2.14	2.37	2.48	2.47	1.27	1.86	2.96	3.04	2.21
L3	Illuminance***	1	25.50	24.87	25.03	26.00	21.41	22.80	28.47	34.07	19.76
		2	25.52	25.04	25.08	25.93	21.22	22.75	28.63	33.77	19.07
	Luminance****	1	7.39	7.62	7.72	7.37	4.51	5.83	9.41	9.43	6.20
		2	6.60	7.34	7.66	7.59	3.90	5.71	9.12	9.29	6.61

* The naming is as reported in Chapter.
** Average value of the three measurements.
*** Vertical illuminance at the eye aiming at each measurement grid point.
**** Luminance of each point at the measurement grid (luminance meter set at the eye position).

Appendix B.

The survey of vertical illuminance measurement on minor and major roads in Sheffield, United Kingdom / Comparison graphs between first and second block of PVT test.

Two major roads (one in a residential neighbourhood with no shops nearby and one in a shopping neighbourhood) and one minor road (in a residential neighbourhood) in Sheffield, United Kingdom, were selected for measurement. Illuminance was measured using an illuminance meter KONICA MINOLTA model no T-10M, as follows:

I. An observer held the illuminance meter at forehead level (approximate height: 170 cm) between his eyes and walked from one lamp pole to another.
II. Illuminance was recorded every metre. A total of 10 measurements were made for each location.
III. Illuminance was measured three times at each point and averaged to obtain the value for that specific location.

Road 1: Granville, Sheffield, is a major road in a residential neighbourhood with no shops around (Figure B.1). Table B.1 presents the illuminance at each measurement point between the two lamp posts.

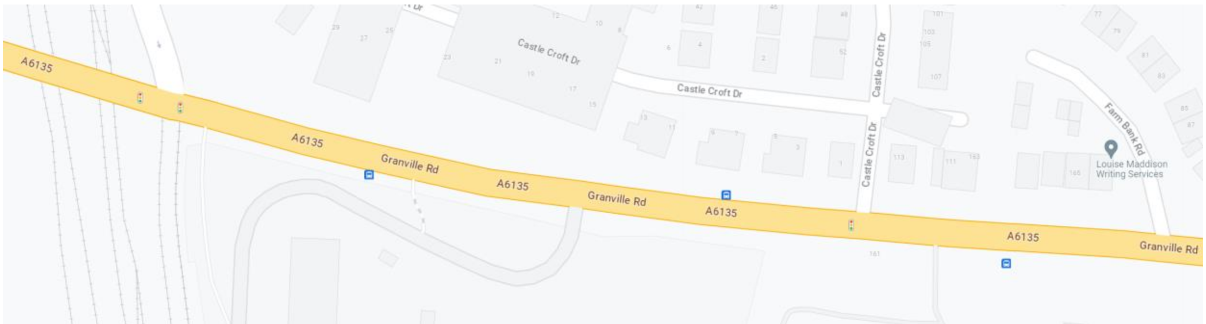


Figure B.1. Granville Road, Sheffield, United Kingdom.

Table B.1. Measured illuminances between the two lamp posts at each point.

Measurement point (no)	Illuminance (lx)*
1	4.2
2	3.5
3	3.2
4	3.0
5	2.6
6	1.3
7	2.2
8	2.7
9	3.2
10	3.5

* Vertical illuminance at eye (approx. height 170 cm).

Road 2: West Street, Sheffield, a major shopping neighbourhood road (Figure B.2). Table B.2 presents the illuminance at each measurement point between the two lamp posts.

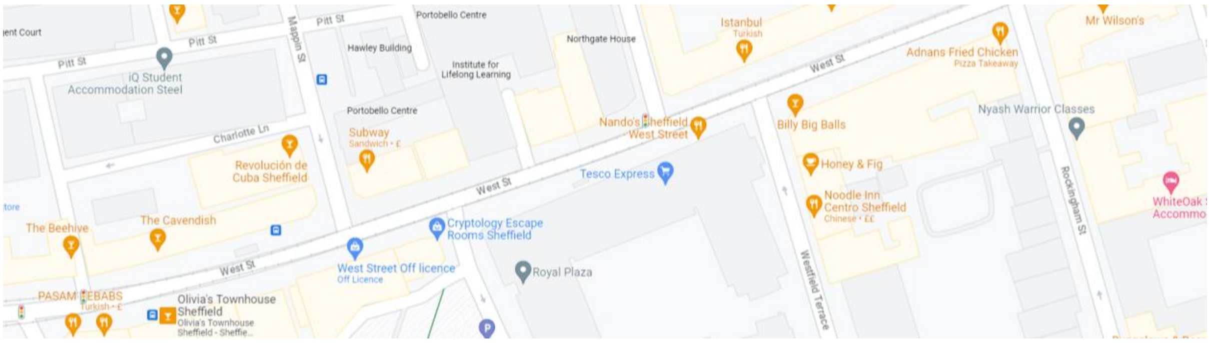


Figure B.1. West Street, Sheffield, United Kingdom.

Table B.2. Measured illuminances between the two lamp posts at each point.

Measurement point (no)	Illuminance (lx)*
1	20
2	17
3	16
4	16
5	15
6	15
7	17
8	18
9	18
10	19

* Vertical illuminance at eye (approx. height 170 cm).

Road 3: Trafalgar, Sheffield, a minor road in a residential neighbourhood (Figure B.3). Table B.3 presents the illuminance at each measurement point between the two lamp posts.

Figure B.3. Trafalgar Street, Sheffield, United Kingdom.

Table B.3. Measured illuminances between the two lamp posts at each point.

Measurement point (no)	Illuminance (lx)*
1	9.1
2	8.3
3	7.2
4	4.2
5	1.5
6	1.6
7	1.8
8	2.2
9	4.5
10	7.8

* Vertical illuminance at eye (approx. height 170 cm).

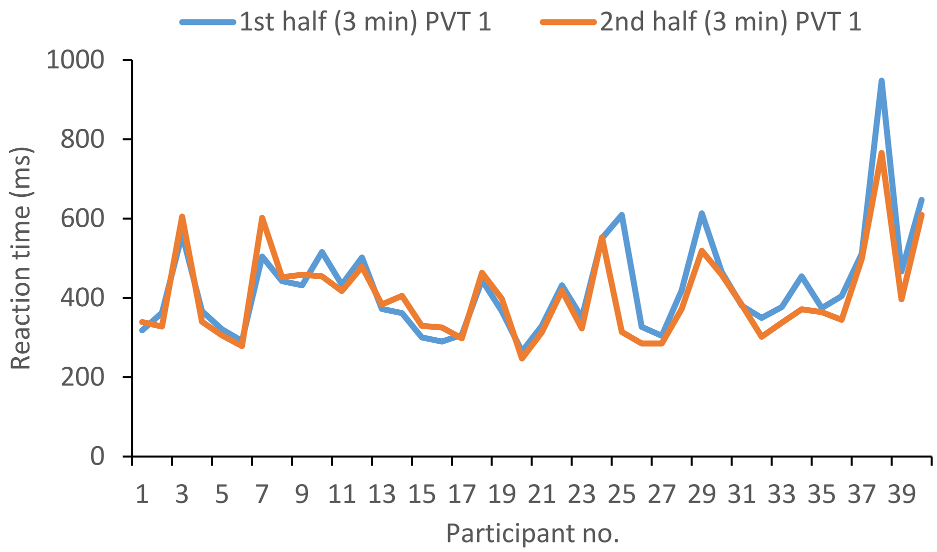


Figure B.4. Median reaction times to the first and second block of the PVT test for the first round of the PVT test.

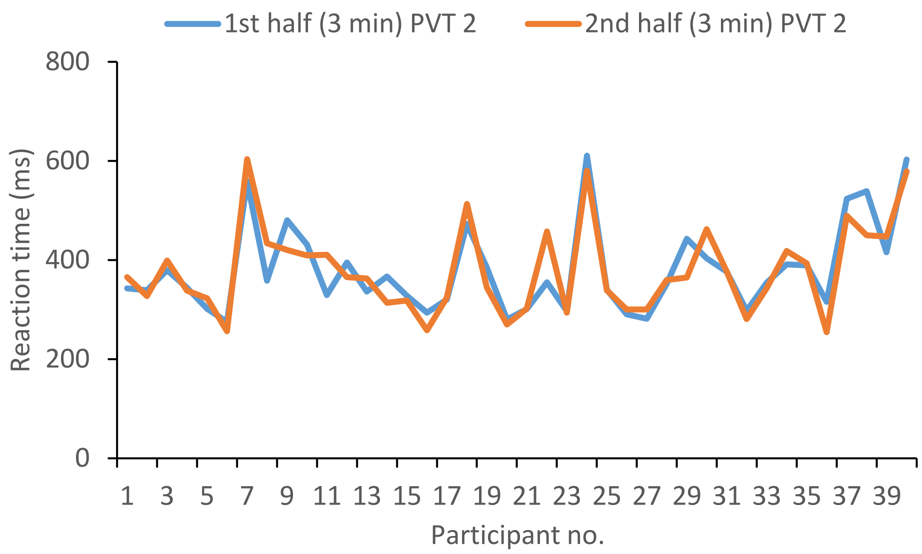


Figure B.5. Median reaction times to the first and second block block of the PVT test for the second round of the PVT test.

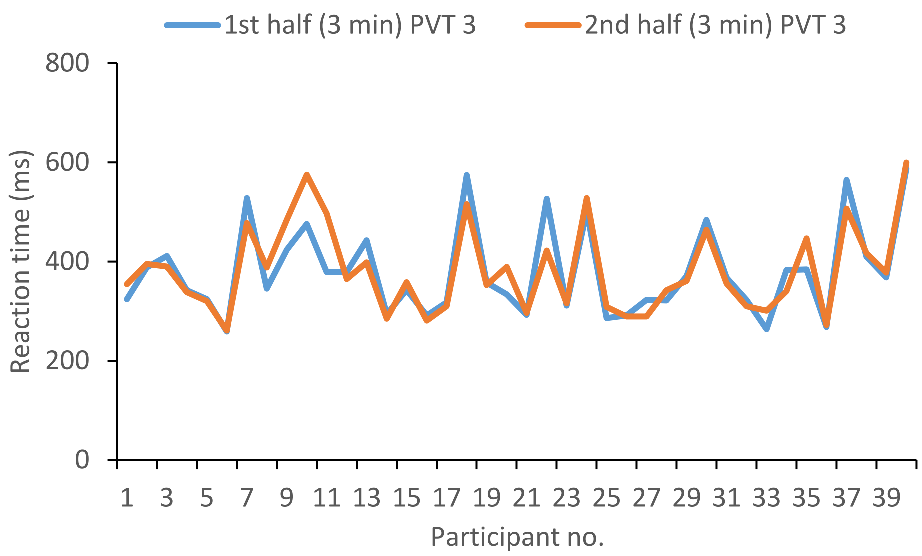


Figure B.6. Median reaction times to the first and second block block of the PVT test for the third round of the PVT test.

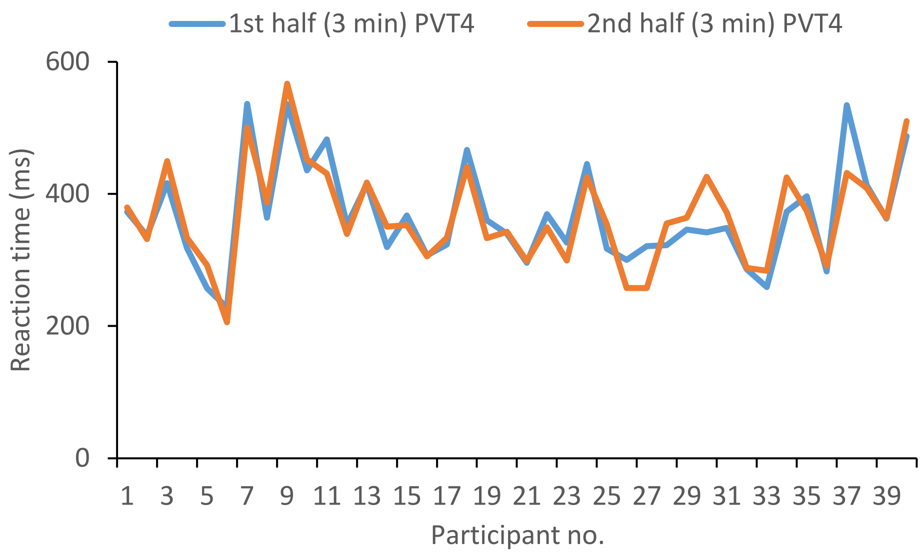


Figure B.7. Median reaction times to the first and second block block of the PVT test for the fourth round of the PVT test.

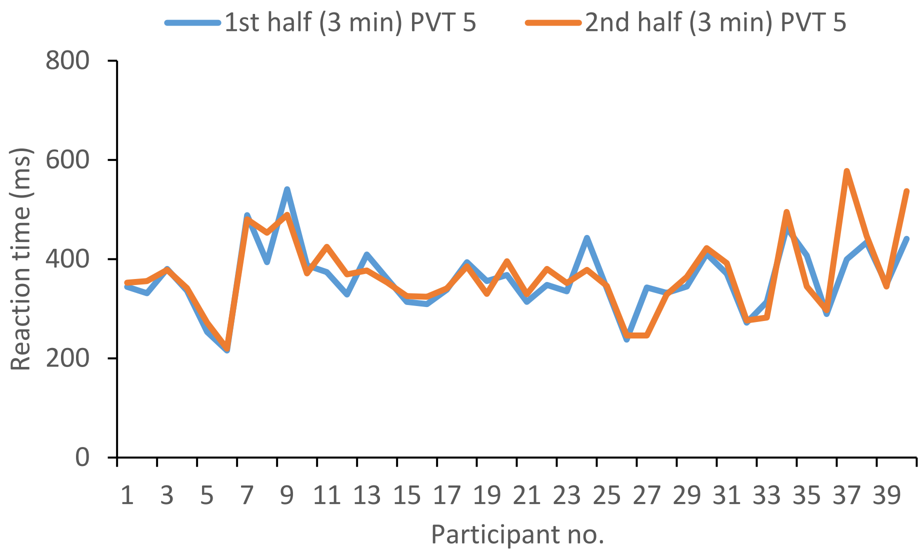


Figure B.8. Median reaction times to the first and second block block of the PVT test for the fifth round of the PVT test.

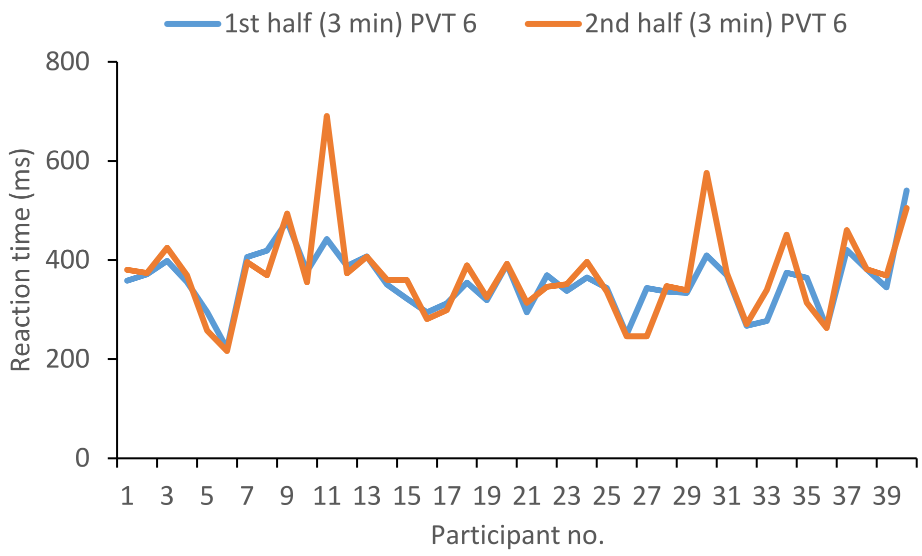


Figure B.9. Median reaction times to the first and second block block of the PVT test for the sixth round of the PVT test.

Appendix C.

Normality checks, Experiment 1.

Table C.1. Audio reaction time normality checks for 20 randomly selected out of 240 trials.

PVT valid reaction times (participant no_test no)		1_5	2_6	6_5	7_4	8_2	9_3	10_1	11_4	13_3	17_1	19_6	21_3	25_1	27_6	28_4	30_3	31_2	35_2	37_1	39_4
Central Tendency	Mean	359	383.83	216	533	406.15	475	498.42	500.5	450	320	327	302	478	329	341.37	488.46	378	395.44	516	373
	95% CI of Mean	345	365.45	203.56	505	383.68	445	469.2	450.68	414	300	315	289	433	314	330.29	450.63	364	375.99	490	355
		372	402.21	228.44	561	428.62	505	527.64	549.42	485	340	339	314	522	344	352.45	526.29	392	414.89	541	391
	Median	350	372	214	516	397.5	452	509	459.5	411	302	320	296	478	318	329	467.5	376	391	501	363
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	No	Near	Yes	No	No	No	No	No	No	No	No	No	No	No	Near	Near	Yes	Near	Yes	No
	Box Plot	No	Near	Yes	No	Yes	No	No	No	No	No	No	No	No	No	No	Near	Yes	Near	Yes	No
Normality?	automated check	No	Near	Yes	No	Near	No	No	No	No	No	No	No	No	No	Near	Near	Yes	Near	Yes	No
Measures of dispersion	Skewness (within ± 0.5)	0.311	1.125	0.025	0.581	0.498	1.09	0.994	1.313	0.997	1.635	0.939	2.471	0.444	0.703	0.499	0.878	0.309	0.95	0.683	1.508
		yes	no	yes	no	yes	no	no	no	no	no	no	no	yes	no	yes	no	yes	no	no	no
	Kurtosis (within ±1.0)	0.613	1.634	10.11	-0.143	0.174	2.1	2.702	1.331	0.036	3.323	1.85	11.31	-0.756	0.3	-0.342	0.544	0.608	1.973	0.597	3.318
		yes	no	no	yes	yes	no	no	no	yes	no	no	no	yes	yes	yes	yes	yes	no	yes	no
Normality?	automated check	Yes	No	Near	Near	Yes	No	No	No	Near	No	No	No	Yes	Near	Yes	Near	Yes	No	Near	No
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	0.001	0.014	0.128	0.005	0.001	0.001	0.001	0.001	0.012	0.001	0.005	0.047	0.093	0.005	0.392	0.017	0.174	0.001
		no	no	no	no	yes	no	no	no	no	no	no	no	no	no	yes	no	yes	no	yes	no
	Kolmogorov-Smirnov (level of significance)	0.004	0.006	0.001	0.001	0.008	0.013	0.031	0.001	0.001	0.001	0.2	0.024	0.03	0.072	0.024	0.067	0.2	0.2	0.2	0.002
		no	no	no	no	no	no	no	no	no	no	yes	no	no	yes	no	yes	yes	yes	yes	no
Noramlity?	automated check	No	No	No	No	Near	No	No	No	No	No	Near	No	No	Near	Near	Near	Yes	Near	Yes	No
Overal Assessment of Normality	select mannually	Near	No	Near	No	Yes	No	No	No	No	No	No	No	Near	Near	Near	Yes	Yes	Near	Yes	No

Table C.2. Normality checks for melatonin levels among the 40 participants.

Trial		AD1	AD2	AD3	AD4	AD5	T1	T2	T3
Central Tendency	Mean	0.92	2.278	4.303	7.415	8.768	10.655	13.945	15.86
	95% CI of Mean	0.419	1.217	2.63	4.939	6.462	8.306	10.814	13.207
		1.421	3.338	5.975	9.891	11.073	13.004	17.076	18.513
	Median	0.25	0.65	1.7	4.8	7.85	9.25	12.5	15
Normality? (Yes if median is in 95% CI of mean)	automated check	No	No	No	No	Yes	Yes	Yes	Yes
Graphical	Histogram	No	No	No	No	No	No	No	No
	Box Plot	No	No	No	No	No	Near	Near	Near
Normality?	automated check	No	No	No	No	No	Near	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	2.238	1.85	1.195	1.04	0.589	0.333	0.936	0.009
		no	no	no	no	no	yes	no	yes
	Kurtosis (within ±1.0)	4.405	3.126	0.509	0.203	-0.617	-0.949	0.76	-0.952
		no	no	yes	yes	yes	yes	yes	yes
Normality?	automated check	No	No	Near	Near	Near	Yes	Near	Yes
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	0.001	0.001	0.016	0.032	0.017	0.212
		no	no	no	no	no	no	no	yes
	Kolmogorov-Smirnov (level of significance)	0.001	0.001	0.001	0.006	0.2	0.105	0.038	0.099
		no	no	no	no	yes	yes	no	yes
Noramlity?	automated check	No	No	No	No	Near	Near	No	Yes
Overal Assessment of Normality	select mannually	No	No	No	No	Near	Yes	Near	Yes

Table C.3. Normality checks for median audio reaction time among the 40 participants.

Trial (orginal)		AD1	AD2	AD3	T1	T2	T3
Central Tendency	Mean	415	378	380	366	364	362
	95% CI of Mean	377 452	350 407	351 409	343 389	342 385	339 385
	Median	382	357	359	356	353	359
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	No	No	No	Yes	Yes	Yes
	Box Plot	No	No	No	Yes	Yes	Yes
Normality?	automated check	No	No	No	Yes	Yes	Yes
Measures of dispersion	Skewness (within ± 0.5)	1.782	1.063	1.01	0.416	0.241	0.666
		no	no	no	yes	yes	no
	Kurtosis (within ±1.0)	5.236	0.658	0.426	-0.091	0.087	1.075
		no	yes	yes	yes	yes	no
Normality?	automated check	No	Near	Near	Yes	Yes	No
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.002	0.005	0.391	0.409	0.296
		no	no	no	yes	yes	yes
	Kolmogorov-Smirnov (level of significance)	0.075	0.016	0.022	0.2	0.2	0.2
		yes	no	no	yes	yes	yes
Noramlity?	automated check	Near	No	No	Yes	Yes	Yes
Overal Assessment of Normality	select manually	No	No	No	Yes	Yes	Yes

Trial (residual)		AD1	AD2	AD3	T1	T2	T3
Central Tendency	Mean	0.001	0.001	0.001	0.001	0.001	0.001
	95% CI of Mean	-0.289 0.289	-0.289 0.289	-0.289 0.289	-0.289 0.289	-0.289 0.289	-0.289 0.289
	Median	-0.1691	-0.1525	-0.1208	-0.1479	0.0194	-0.1426
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	Yes	Near	Near	Yes	Yes	Yes
	Box Plot	Yes	Near	Near	Yes	Yes	Yes
Normality?	automated check	Yes	Near	Near	Yes	Yes	Yes
Measures of dispersion	Skewness (within ± 0.5)	1.773	0.665	0.663	0.271	0.097	0.435
		no	no	no	yes	yes	yes
	Kurtosis (within ±1.0)	5.636	0.496	0.545	-0.2	-0.376	0.424
		no	yes	yes	yes	yes	yes
Normality?	automated check	No	Near	Near	Yes	Yes	Yes
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.124	0.335	0.741	0.86	0.366
		no	yes	yes	yes	yes	yes
	Kolmogorov-Smirnov (level of significance)	0.07	0.2	0.2	0.2	0.2	0.2
		yes	yes	yes	yes	yes	yes
Noramlity?	automated check	Near	Yes	Yes	Yes	Yes	Yes
Overal Assessment of Normality	select manually	Yes	Yes	Yes	Yes	Yes	Yes

Table C.4. Normality checks for self-reported sleepiness scores.

Trial		AD1	AD2	AD3	AD4	AD5	T1	T2	T3
Central Tendency	Mean	32.63	32.63	32.51	32.42	32.46	32.22	32.33	32.52
	95% CI of Mean	32.38	32.36	32.22	32.17	32.21	31.92	32.05	32.25
		32.89	32.89	32.79	32.67	32.71	32.53	32.61	32.78
	Median	32.59	32.76	32.72	32.56	32.41	32.37	32.29	32.58
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	No	No	No	Yes	Near	Near	No	Yes
	Box Plot	Near	No	No	Yes	Yes	Near	Yes	No
Normality?	automated check	Near	No	No	Yes	Near	Near	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	-1.319	-0.474	-0.565	-0.198	-0.337	-0.609	0.254	-0.179
		no	yes	no	yes	yes	no	yes	yes
	Kurtosis (within ±1.0)	4.813	-0.191	-0.16	0.332	0.291	0.789	-0.766	-0.098
		no	yes	yes	yes	yes	yes	yes	yes
Normality?	automated check	No	Yes	Near	Yes	Yes	Near	Yes	Yes
Statistical tests	Shapiro-Wilks (level of significance)	0.003	0.488	0.18	0.902	0.942	0.253	0.229	0.898
		no	yes	yes	yes	yes	yes	yes	yes
	Kolmogorov-Smirnov (level of significance)	0.189	0.2	0.014	0.2	0.2	0.2	0.2	0.2
		yes	yes	no	yes	yes	yes	yes	yes
Noramlity?	automated check	Near	Yes	Near	Yes	Yes	Yes	Yes	Yes
Overal Assessment of Normality	select mannually	Near	Yes	Near	Yes	Yes	Yes	Yes	Yes

Table C.5. Normality checks for mean skin temperature among the 40 participants.

Trial		AD1	AD2	AD3	AD4	AD5	T1	T2	T3
Central Tendency	Mean	32.63	32.63	32.51	32.42	32.46	32.22	32.33	32.52
	95% CI of Mean	32.38	32.36	32.22	32.17	32.21	31.92	32.05	32.25
		32.89	32.89	32.79	32.67	32.71	32.53	32.61	32.78
	Median	32.59	32.76	32.72	32.56	32.41	32.37	32.29	32.58
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	No	No	No	Yes	Near	Near	No	Yes
	Box Plot	Near	No	No	Yes	Yes	Near	Yes	No
Normality?	automated check	Near	No	No	Yes	Near	Near	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	-1.319	-0.474	-0.565	-0.198	-0.337	-0.609	0.254	-0.179
		no	yes	no	yes	yes	no	yes	yes
	Kurtosis (within ±1.0)	4.813	-0.191	-0.16	0.332	0.291	0.789	-0.766	-0.098
		no	yes	yes	yes	yes	yes	yes	yes
Normality?	automated check	No	Yes	Near	Yes	Yes	Near	Yes	Yes
Statistical tests	Shapiro-Wilks (level of significance)	0.003	0.488	0.18	0.902	0.942	0.253	0.229	0.898
		no	yes	yes	yes	yes	yes	yes	yes
	Kolmogorov-Smirnov (level of significance)	0.189	0.2	0.014	0.2	0.2	0.2	0.2	0.2
		yes	yes	no	yes	yes	yes	yes	yes
Noramlity?	automated check	Near	Yes	Near	Yes	Yes	Yes	Yes	Yes
Overal Assessment of Normality	select mannually	Near	Yes	Near	Yes	Yes	Yes	Yes	Yes

Appendix D.

Road surface luminance: measurement grid and relative values, Experiment 2.

Luminance was measured in a grid on the floor of the apparatus. The measurements were made by placing the luminance meter (Konica Minolta luminance meter LS-150) at the approximate position of the participant's eye and directing it toward the measurement points (Figure D.1). The measurements were repeated three times. The average values were recorded in Table D.1 and D.2 for lighting conditions L1 and L2, respectively.

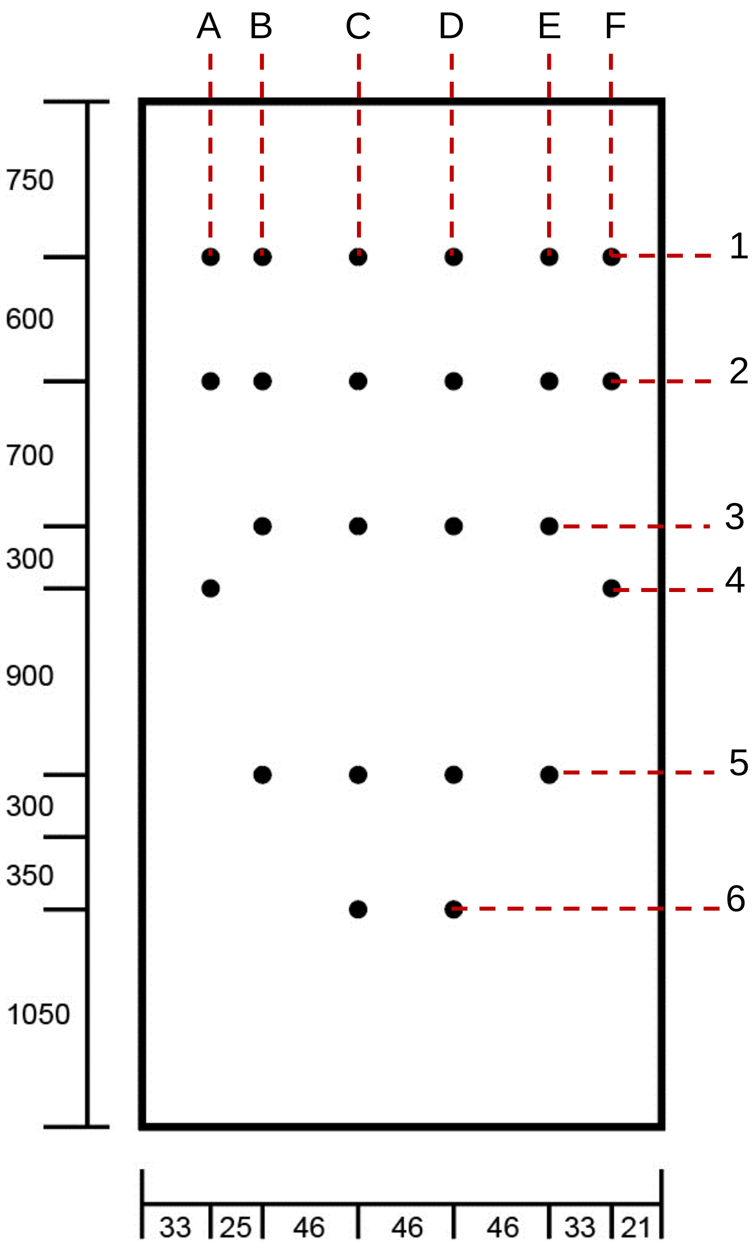


Figure D.1. Grid for luminance measurement (distances are approximate in centimetres).

Table D.1. luminance measurement on the grid under light condition L1.

Row			**Column – Luminance***			
-	A	B	C	D	E	F
1	0.02	0.06	0.09	0.08	0.06	0.02
2	0.04	0.07	0.09	0.08	0.06	0.04
3	-	0.07	0.08	0.08	0.06	-
4	0.04	-	-	-	-	0.03
5	-	0.05	0.1	0.09	0.05	-
6	-	-	0.07	0.07	-	-

* Luminance of each point at the measurement grid (luminance meter set at the eye position).

Table D.2. luminance measurement on the grid under light condition L2.

Row			**Column – Luminance***			
-	A	B	C	D	E	F
1	0.47	0.65	0.79	0.75	0.54	0.45
2	0.44	0.61	0.78	0.76	0.56	0.43
3	-	0.49	0.65	0.65	0.47	-
4	0.37	-	-	-	-	0.35
5	-	0.56	0.82	0.81	0.47	-
6	-	-	0.57	0.56	-	-

* Luminance of each point at the measurement grid (luminance meter set at the eye position).

Appendix E.
Dealing with missing data.

Instances of missing data were noticed during the analysis of Experiment 2 results. This section explores various methods to deal with missing data, along with an illustrative example. The rationale behind the chosen approach for addressing missing data in Experiment 2 will be discussed at the end of this section.

There are various methods for handling missing data in statistics. These techniques include complete-case analysis (listwise deletion), pairwise deletion, last observation carried backwards, conservative imputation, multiple imputation using logistic regression, and multiple imputation using predictive mean matching [Peeters et al., 2015; Graham, 2009]. The following paragraphs will provide a detailed description of each method and an illustrative example to highlight their advantages and disadvantages. Consider the following example dataset (Table E.1) showcasing the reaction time of 14 participants under six different test conditions. Cases of missing data are represented as cells with "none" values. There are nine missing values out of 84 responses provided by the 14 participants.

Table E.1. Example of a data set with missing data.

Participant (no)	Test round (reaction times in ms)					
	1	2	3	4	5	6
1	1412	1130	1146	1265	2351	none
2	1579	1308	1830	1363	1252	1766
3	1086	1067	1191	984	974	1583
4	1095	1502	1433	1438	1570	none
5	1077	1140	1282	1310	1485	2912
6	923	1530	1482	none	1478	1309
7	1482	2060	none	1412	1472	none
8	1151	1789	1540	1171	1533	none
9	1813	1857	none	1577	1989	1629
10	1306	1362	1567	1187	1800	1860
11	1411	1411	1683	none	2005	1315
12	2185	1922	2106	1647	2333	2494
13	1700	1436	1105	1560	2117	2202
14	1577	1257	none	1678	1326	1269

Listwise deletion, also known as complete-case analysis, involves excluding participants with any missing value from the analysis. It is the simplest method for dealing with missing data, which allows the closest analysis of a data set to its original values without generating any artificial data. However, listwise deletion can significantly reduce sample size, decreasing the relative statistical analysis's power. Moreover, it can introduce bias into the results due to the systematic differences between the values that are dropped and those that are retained. For instance, if observations with missing data tend to belong to a particular subgroup, then listwise deletion will bias the results towards that subgroup.

In the example dataset (Table E.1), listwise deletion would entail removing eight out of the 14 participants, eliminating 40 valid responses out of the 84 total responses due to the presence of only nine missing values. In this case, listwise deletion reduces the sample size from 14 to six participants, significantly diminishing the analysis's power and altering the dataset's mean, median, and standard deviation (Table E.2).

Pairwise deletion only drops observation from the analysis if they have missing data for the analysed variables. This can help reduce sample size loss but can introduce bias if the missing data are not missing completely at random. In this method, pairwise comparisons only exclude variables when a missing value exists specifically between the two comparisons being made. For instance, in our example dataset, while comparing test rounds one and two, the comparison is made between all 14 participants. However, when comparing test rounds one and three, the comparison is made between only 11 participants due to missing values for three of the participants in test round three. The changes in sample size can affect the effect size and power when comparing different trials with each other.

Last observation carried backward imputes missing values with the last observed value for the same variable. This method is straightforward to implement and can handle various types of missing data. However, if the missing data pattern is not random, this method can introduce bias to the analysis. It is also sensitive to outliers, as replacing a missing value with a subsequent value, which could be an outlier, can significantly impact the sample’s mean, median, and standard deviation. Moreover, this method can also be problematic if the missing value is the first observation or if two consecutive values are missing. In our example dataset, the changes can be seen in Table E.2.

Conservative imputation is designed to be as unbiased as possible, considering that missing data may not be missing at random. This means that the probability of a missing value is related to the observed values in the dataset. This method replaces the missing values with the most conservative estimates possible. This means that the imputed values are likely to be lower or higher than actual values. For example, in cases dealing with missing data of a participant's reaction time, a missing value means a complete miss of a stimulus. The most conservative value to replace a reaction time needs to be a very long reaction time to highlight the effect of missing in the analysis. Therefore, the maximum reaction time among a specific participant and several reaction times can be selected as the replacement value while running conservative imputation. This method is designed to be unbiased, but selecting the most suitable and conservative approach to replace missing values is under the effect of the researcher's judgment. Moreover, there is a chance of underestimating the true values, which can reduce the power of the analysis. In our example dataset, the changes can be seen in Table E.2.

Multiple imputations using logistic regression are based on creating multiple complete datasets from the original dataset. This is done by imputing the missing values for each variable in the dataset multiple times, using a logistic regression model to predict the missing values. There are several steps when using multiple imputations:

I. Fit a logistic regression model to the observed data using the variables that do not have missing values.
II. Use the logistic regression model to predict the missing values for each variable.
III. Impute the missing values for each variable multiple times using the predicted values.
IV. Create multiple complete datasets from the original dataset by combining the imputed values with the observed values.
V. Analyse the multiple imputed datasets separately.
VI. Combine the results of the analyses to produce a final estimate.

Multiple imputation using logistic regression is a relatively complex method. It is particularly useful when the missing data are not missing at random or when the variables with missing data are highly important for the analysis. However, increasing complexity in a method might be considered data manipulation or raise concerns around type I (false positive) or type II (false negative) errors while evaluating the results as exact changes made to the original dataset might not be clearly traceable.

Multiple imputations using predictive mean matching replace the missing values multiple times using the predicted values from the matching observations of multiple complete datasets created from the original dataset. There are several steps when using multiple imputation using predictive mean:

I. Fit a predictive model to the observed data using the variables that do not have missing values.
II. Use the predictive model to predict the missing values for each variable.
III. Match observations with missing data to observations with complete data that are similar in terms of their predicted values.
IV. Impute the missing values for each variable multiple times, using the predicted values from the matching observations.
V. Create multiple complete datasets from the original dataset by combining the imputed values with the observed values.
VI. Analyse the multiple imputed datasets separately.
VII. Combine the results of the analyses to produce a final estimate.

Table E.2. Effects of different methods of dealing with missing data on the example dataset's mean, median, and standard deviation.

Method	Test round																	
	1			2			3			4			5			6		
	Mean	Median	STD	Mean	Median	STD	Mean	Median	STD	Mean	Median	STD	Mean	Median	STD	Mean	Median	STD
Original	1414	1412	332	1484	1424	302	1488	1482	293	1383	1388	202	1692	1552	400	1834	1698	520
M1	1489	1443	388	1373	1335	276	1514	1425	360	1342	1337	221	1660	1643	474	2136	2031	457
M2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
M3	1414	1412	332	1484	1424	302	1464	1482	278	1364	1337	195	1692	1552	400	1736	1606	478
M4	1414	1412	332	1484	1424	302	1576	1514	338	1425	1425	214	1692	1552	400	2082	2031	600
M5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
M6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

M1: Listwise deletion; M2: pairwise deletion; M3: last observation carried backwards; M4: conservative imputation (replacing with maximum reaction time); M5: multiple imputation using logistic regression; M6: multiple imputation using predictive mean matching.

To minimize the risk of data manipulation, listwise deletion and conservative imputation using mean and maximum were implemented in cases of missing values of reaction time to different hazards in this study. Each approach's outcomes were compared with others, and any noticeable differences were highlighted. Finally, the most appropriate approach was selected for further analysis to provide reliable conclusions while maintaining good statistical power.

Road surface obstacle

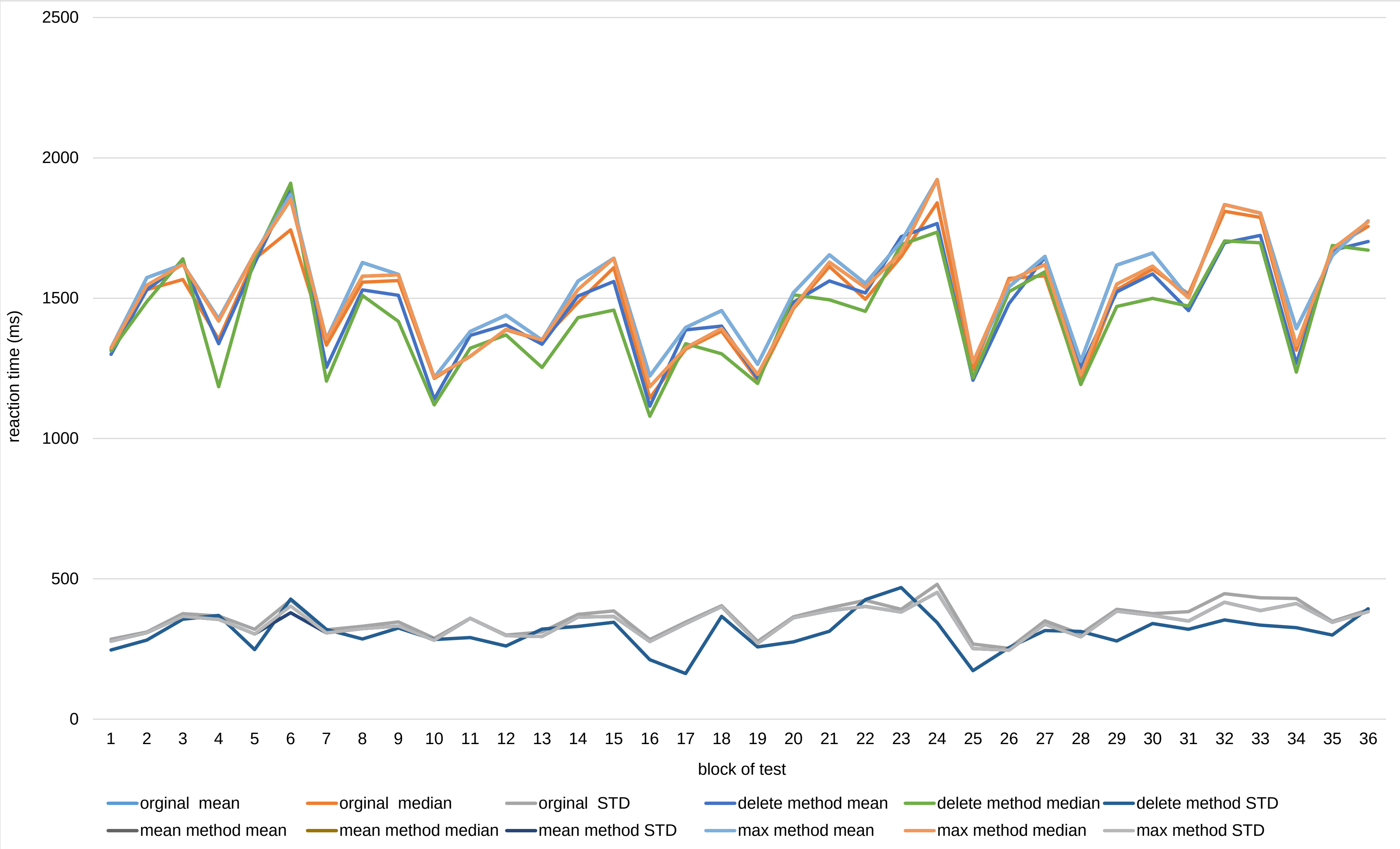
Participants responded to 36 blocks of tests (four lighting conditions, three levels of distraction, three distances of obstacle). Instances of missing data occurred when data was unavailable for one or more of these 36 test blocks. There were 149 cases of missing data among the total 2160 average responses to road surface obstacles provided by the 60 participants. In total, 40 participants must be dealt with in at least one case of missing data. Table E.3 highlights the differences that occurred if any existed, while implementing each treatment. Figure E.1 highlights the variations in the mean, median and standard deviation of the 36 blocks of the test when implementing each missing data treatment.

Table E.3. Comparison of the effects of different approaches to deal with missing values while reacting to road surface obstacles.

Variables	Methods to deal with missing data		
	Listwise deletion	**Replacing with mean**	**Replacing with maximum**
Lighting condition	Significant	Significant	Significant
Distraction	Significant	Significant	Significant
Obstacle distance	Significant	Significant	Significant
Lighting*distraction	Not significant	Significant	Significant
Lighting*distance	Significant	Significant	Significant
Distraction*distance	Significant	Significant	Significant
Lighting*distraction*distance	Not significant	Significant	Significant

As stated in Table E.3, the three implemented fixes provide the same result for lighting conditions, distraction and obstacle distance. Replacing with mean and maximum resulted in similar differences for all variables and their interactions. The only difference noticed was when comparing the listwise deletion method with replacing with mean and maximum for interactions between lighting*distraction and lighting* distraction*distance, where listwise deletion highlighted no significant effect of these interactions with respective p values of 0.067, 0.06. However, these p values are near the threshold of 0.05, and this result is expected due to a significant reduction in sample size (60 to 20) by deleting a large proportion of the sample, which could make identifying smaller differences more difficult.

Figure E.1. Variations in mean, median and standard deviation of the 36 test blocks when implementing each missing data treatment for road surface obstacle.



Pedestrian model

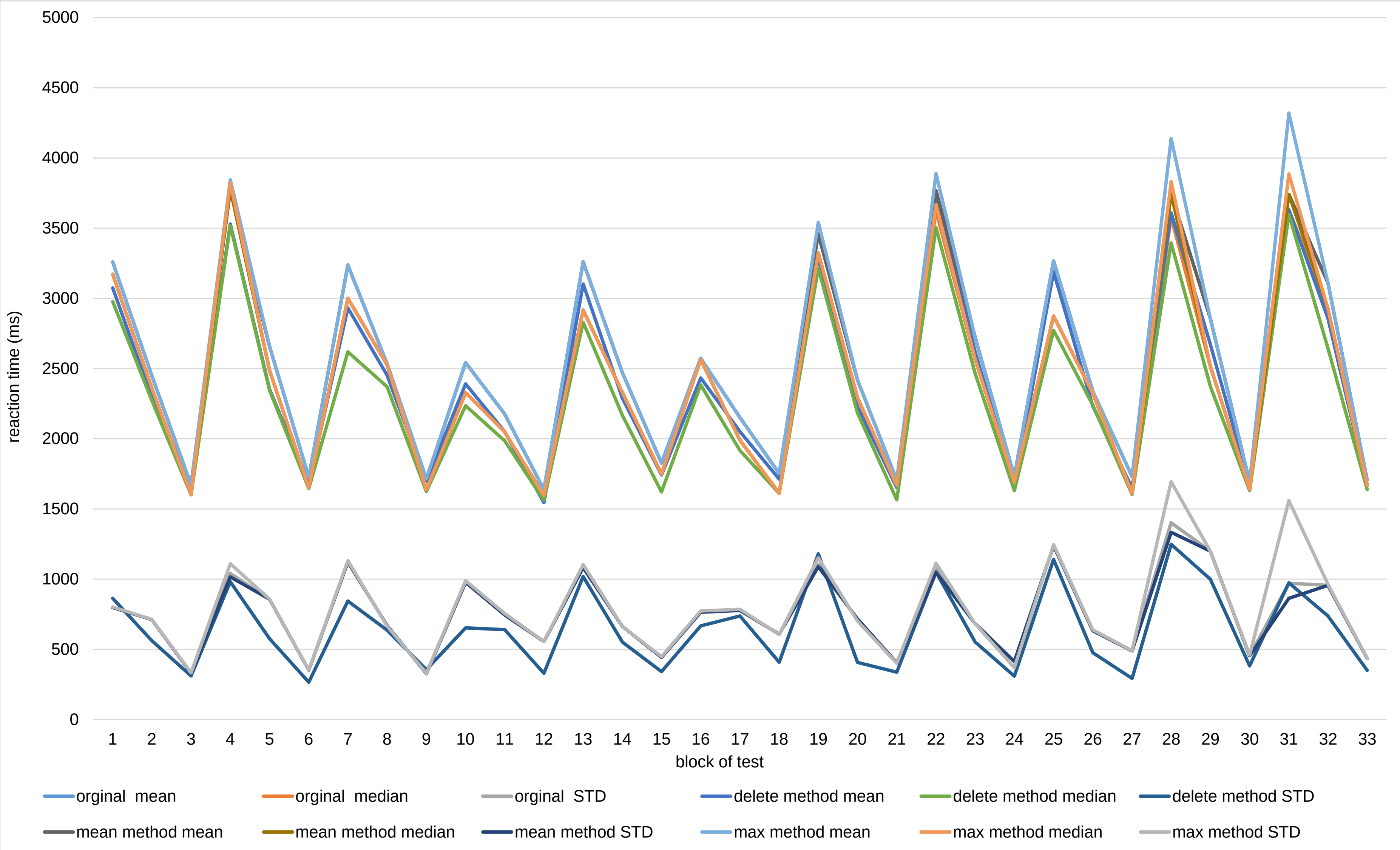
Participants responded to 36 blocks of tests (four lighting conditions, three levels of distraction, and three pedestrian models). Cases of missing data occurred when no data was available for one or more of these 36 test blocks. There were 28 cases of missing data among the total 2160 average responses to pedestrian models provided by the 60 participants. In total, 18 participants must be dealt with in at least one case of missing data. Table E.4 highlights the differences that occurred if any existed while implementing each treatment for the missing values. Figure E.2 highlights the variations in the mean, median and standard deviation of the 36 blocks of the test when implementing each missing data treatment.

Table E.4. Comparison of the effects of different approaches to deal with missing values while reacting to pedestrian models.

Variables	Methods to deal with missing data		
	Listwise deletion	**Replacing with mean**	**Replacing with maximum**
Lighting condition	Significant	Significant	Significant
Distraction	Significant	Significant	Significant
Pedestrian model	Significant	Significant	Significant
Lighting*distraction	Not significant	Significant	Not significant
Lighting*model	Significant	Significant	Significant
Distraction*model	Significant	Significant	Significant
Lighting*distraction*model	Significant	Significant	Significant

As stated in Table E.4, the three implemented fixes provide the same result for lighting conditions, distraction and obstacle distance. Listwise deletion and replacement with maximum resulted in similar differences for all variables and their interactions. The only difference noticed was when comparing the replacing mean method with listwise deletion and replacing with the maximum for interactions between lighting*distraction, where replacing with mean highlights a significant effect of lighting on reaction to pedestrian model when distracted. At the same time, the other two treatments suggest no significant difference. For this interaction, looking into pairwise comparison listwise deletion fix shows similar trends (significant effect of visual distraction (T2) while compared to control (T1) and acoustic distraction (T3)) when compared to listwise deletion and replacing with maximum fixes under lighting condition L1 to L3 but under lighting condition L4 replacing with mean does not suggest a significant effect of any distraction while the other two methods to fix missing data still highlights the significant effect of visual distraction on reaction time under this lighting condition. Therefore, the three methods provide almost the same result with some negligible changes.

Figure E.2. Variations in the mean, median and standard deviation of the 36 blocks of the test when implementing each missing data treatment for pedestrian models.



Appendix F.

Normality checks, Experiment 2.

Table F.1. Vehicle lane change: 46 randomly selected out of 720 data files (continued on next page).

(participant no_light condition no)		2_1	5_4	7_3	10_1	14_4	16_1	22_4	23_1	23_3	25_4	31_4	36_1	37_4	38_3	41_1	45_2	47_2	49_2	52_4	54_2	55_4	58_1	59_2
Central Tendency	Mean	1577	2423.83	2024.5	2695.67	1878.17	1930.4	2555	2021.83	2364	2840.33	2390	2467.17	1913.83	1894.33	2897	1826.5	2153.67	1865.8	2345.33	3139.33	2720.83	2082.5	2367.33
	95% CI of Mean	1227	1455.64	1798.62	1057.67	1404.18	1533.97	1903.75	1737.12	1662.61	1578.36	1820.47	1762.8	1431.31	1672.14	2154.84	1180.19	1723.58	1289.72	1515.15	1797	2097.03	1707.03	1610.03
		1926	3392.02	2250.38	4333.66	2352.15	2326.83	3206.25	2306.55	3065.39	4102.3	2959.53	3171.53	2396.35	2116.53	3639.16	2472.81	2583.75	2441.88	3175.51	4481.67	3344.64	2457.97	3124.64
	Median	1586	2321	1995.5	2233	1719.5	1889	2449	1881	2449	2586.5	2537	2377.5	1843	1867	3006	1739	2230	1728	2098.5	2660.5	2723.5	1946.5	2186
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	Yes	Near	No	No	Near	Yes	No	No	No	No	Near	No	Near	No	No	No	No	No	Near	No	Yes	Near	No
	Box Plot	Near	Near	Near	No	Near	Near	No	Near	Near	No	Near	Near	No	Near	Near	Near	Near	No	No	No	Yes	No	Near
Normality?	automated check	Near	Near	Near	No	Near	Near	No	Near	Near	No	Near	Near	Near	Near	Near	Near	Near	No	Near	No	Yes	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	0.421	0.551	-0.061	2.041	0.62	-0.156	0.745	0.909	-0.248	2.045	-0.454	0.418	0.847	0.921	-0.2	0.548	-0.131	1.836	2.152	1.01	-0.103	0.816	0.477
		yes	no	yes	no	no	yes	no	no	yes	no	yes	yes	no	no	yes	no	yes	no	no	no	yes	no	yes
	Kurtosis (within ±1.0)	0.387	-0.339	0.038	4.588	-1.929	-1.034	-0.801	-1.812	-1.754	4.63	0.085	-1.81	1.775	0.617	-2.636	-1.232	-1.274	3.868	5.039	-0.462	-0.751	-1.323	-1.554
		yes	yes	yes	no	no	no	yes	no	no	no	yes	no	no	yes	no	no	no	no	no	yes	yes	no	no
Normality?	automated check	Yes	Near	Yes	No	No	Near	Near	No	Near	No	Yes	Near	No	Near	Near	No	Near	No	No	Near	Yes	No	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.928	0.841	0.939	0.022	0.181	0.905	0.468	0.024	0.329	0.018	0.849	0.241	0.69	0.626	0.154	0.447	0.645	0.058	0.007	0.202	0.933	0.22	0.38
		yes	yes	yes	no	yes	yes	yes	no	yes	no	yes	yes	yes	yes	yes	yes	yes	yes	no	yes	yes	yes	yes
	Kolmogorov-Smirnov (level of significance)	0.2	0.2	0.2	0.017	0.2	0.2	0.2	0.048	0.2	0.005	0.2	0.158	0.2	0.2	0.2	0.2	0.2	0.02	0.003	0.2	0.2	0.2	0.2
		yes	yes	yes	no	yes	yes	yes	no	yes	no	yes	yes	yes	yes	yes	yes	yes	no	no	yes	yes	yes	yes
Noramlity?	automated check	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Near	No	Yes	Yes	Yes	Yes
Overal Assessment of Normality	select manually	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Near	Yes	Near	Yes	Yes	No	No	Yes	Yes	Near	Yes

Table F.1. Vehicle lane change: 46 randomly selected out of 720 data files (rest).

(participant no_light condition no)		1_3	2_3	5_2	6_1	12_3	13_4	15_2	16_2	19_3	26_4	27_4	30_2	34_4	36_2	38_2	39_3	40_2	44_3	44_4	49_1	54_1	57_2	60_3
Central Tendency	Mean	2542	2589.2	2487.8	1998.4	2573.6	1723.8	2518.6	2302	1942.4	2084.2	2938.4	1948.4	2153.6	2478.8	1874.2	1903.6	2115	3461.8	2438.2	3063.2	2026	1723	3514.4
	95% CI of Mean	1503.72	1403.83	1143.53	1628.42	1332	1323.89	2081.85	1760.6	1634.39	1905.6	2254.78	1797.3	1812.43	1466.1	1502.8	1415.21	1698.69	1451.73	1603.56	2484.53	1552.8	1410.82	2121.99
		3580.28	3774.57	3832.07	2368.38	3815.2	2123.71	2955.35	2843.4	2250.41	2262.8	3622.02	2099.5	2494.77	3491.5	2245.6	2391.99	2534.31	5471.87	3272.84	3641.87	2499.2	2035.18	4906.81
	Median	2614	2291	2062	1885	2369	1661	2633	2251	1837	2103	2697	1882	2102	2151	1731	1801	2096	2662	2368	2912	1929	1745	4102
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	No	No	No	No	No	No	No	No	Near	No	No	No	No	No	No	No	No	No	No	No	No	No	No
	Box Plot	Near	No	Near	Near	No	Near	No	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near
Normality?	automated check	Near	No	Near	Near	No	Near	No	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	-0.023	0.807	2.084	0.394	1.91	1.509	-0.904	0.699	1.875	-1.099	0.634	0.526	0.331	0.329	1.731	0.285	0.334	1.031	-0.243	1.508	1.91	-0.521	-0.414
		yes	no	no	yes	no	no	no	no	no	no	no	no	yes	yes	no	yes	yes	no	yes	no	no	no	yes
	Kurtosis (within ±1.0)	-1.617	-1.008	4.427	-2.966	3.891	2.367	-0.571	1.981	3.704	1.321	-1.126	-3.205	-0.834	-2.606	3.028	-2.102	-1.334	0.157	-0.237	2.411	3.835	-1.29	-2.909
		no	no	no	no	no	no	yes	no	no	no	no	no	yes	no	no	no	no	yes	yes	no	no	no	no
Normality?	automated check	Near	No	No	Near	No	No	Near	No	No	No	No	No	Yes	Near	No	Near	Near	Near	Yes	No	No	No	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.888	0.322	0.008	0.206	0.04	0.161	0.394	0.618	0.057	0.605	0.598	0.057	0.947	0.351	0.092	0.665	0.855	0.411	0.964	0.275	0.032	0.469	0.157
		yes	yes	no	yes	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	no	yes	yes
	Kolmogorov-Smirnov (level of significance)	0.2	0.2	0.021	0.2	0.02	0.2	0.2	0.2	0.104	0.2	0.2	0.138	0.2	0.2	0.2	0.2	0.2	0.199	0.2	0.2	0.042	0.2	0.161
		yes	yes	no	yes	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	no	yes	yes
Noramlity?	automated check	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Overal Assessment of Normality	select mannually	Yes	Near	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes

Table F.2. Distraction task T2 (visual distraction): 24 randomly selected out of 240.

participant no_lighting condition		6_3	12_1	17_1	18_1	19_1	19_4	20_3	22_3	23_3	25_2	25_3	28_2	29_3	33_4	35_1	45_4	46_1	46_4	47_4	48_2	48_4	58_1	59_3	60_1
Central Tendency	Mean	867.8	1048.22	946.9	874.52	1140.49	1079.82	1047.73	982.54	1004.3	1066.6	1101.29	1008.46	981.57	969.37	1029.48	963.38	973.91	861.02	920.47	875.91	859.43	970.81	1210.66	1128.02
	95% CI of Mean	844.78	1025.64	919.74	849.47	1101.25	1047.16	1023.11	945.72	980.71	1034.21	1043.3	982.37	947.71	945.56	993.74	943.59	942.14	834.91	893.73	853.12	837.71	936.5	1177.02	1095.38
		890.81	1070.79	974.06	899.56	1179.74	1112.47	1072.36	1019.35	1027.9	1098.99	1159.28	1034.56	1015.43	993.18	1065.23	983.17	1005.48	887.12	947.22	898.71	881.15	1005.13	1244.31	1160.65
	Median	843.52	1031	942.58	844	1113.54	1031	1015	906	969	1047	1000	976.5	937	953	984	937	937	828	875	844	828	922	1156	1078
Normality? (Yes if median is in 95% CI of mean)	automated check	No	Yes	Yes	No	Yes	No	No	No	No	Yes	No	No	No	Yes	No	No	No	No	No	No	No	No	No	No
Graphical	Histogram	Near	Near	Near	No	No	No	No	No	Near	Yes	No	No	No	Near	No	Near	Near	No	No	No	No	No	No	No
	Box Plot	Near	Near	Yes	Near	No	Near	Near	No	Near	Yes	No	Near	Near	Yes	No	Near	Near	Near	Near	Near	Near	No	No	No
Normality?	automated check	Near	Near	Near	Near	No	Near	Near	No	Near	Yes	No	Near	Near	Near	No	Near	Near	Near	Near	Near	Near	No	No	No
Measures of dispersion	Skewness (within ± 0.5)	1.492	0.932	0.355	1.878	1.574	1.386	0.754	2.432	1.231	0.815	1.511	1.756	1.743	0.954	1.489	1.611	1.458	2.19	1.299	1.436	2.129	1.766	1.443	1.128
		no	no	yes	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no
	Kurtosis (within ±1.0)	3.521	1.786	-0.219	5.841	2.747	2.225	0.806	10.103	1.871	0.939	3.038	6.306	5.463	1.846	4.343	4.976	3.638	8.657	2.547	2.346	9.255	3.888	3.053	1.039
		no	no	yes	no	no	no	yes	no	no	yes	no	no	no	no	no	no	no	no	no	no	no	no	no	no
Normality?	automated check	No	No	Yes	No	No	No	Near	No	No	Near	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	0.046	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0..001
		no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	yes
	Kolmogorov-Smirnov (level of significance)	0.001	0	0.2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.007	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
		no	no	yes	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no
Noramlity?	automated check	No	No	Near	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	Near
Overal Assessment of Normality	select mannually	No	No	Yes	No	No	No	No	No	No	Yes	No	No	No	Near	No	No	No	No	No	No	No	No	No	No

Table F.3. Distraction task T3 (Acoustic distraction): 24 randomly selected out of 240.

participant no_lighting condition		2_3	4_4	6_2	11_2	12_2	12_3	16_2	17_4	18_2	29_3	30_1	35_1	35_4	38_2	40_4	43_2	43_3	43_4	45_3	47_4	52_1	53_2	58_1	59_1
Central Tendency	Mean	1484.84	1683.67	1272.3	1448.79	1456.29	1534.35	1581.47	934.07	2201.53	1351.25	1355.5	1413.09	1122.26	1787.16	1251.59	1398.26	1298.4	1627.26	1010.91	1370.93	2529.08	2250.66	1171.92	1710.01
	95% CI of Mean	1379.48	1503.6	1146.12	1306.04	1369.26	1455.74	1488.6	879.28	2075.88	1276.03	1231.03	1275.11	1000.49	1662.87	1184.38	1335.14	1228.33	1510.76	962	1255.52	2295.77	2190.41	1123.76	1563.01
		1590.2	1863.74	1398.5	1591.53	1543.31	1612.96	1674.36	988.87	2327.18	1426.47	1479.97	1551.06	1244.03	1911.44	1318.81	1461.37	1368.46	1743.76	1059.81	1486.35	2762.39	2310.9	1220.09	1857.02
	Median	1468	1484	1109	1265	1406	1453	1484	922	2078	1312	1203	1257.5	1015	1656	1140	1351	1234	1547	976.5	1187	2241.5	2218	1140	1562
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	No	No	No	Yes	No	No	Yes	Yes	Yes	No	No	Yes	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	No
Graphical	Histogram	No	No	No	No	Near	Near	Near	No	Near	Near	Near	No	Near	No	No	No	No	Yes	No	No	No	No	No	No
	Box Plot	Near	No	No	Near	Near	Near	No	Near	No	Near	Near	Near	Near	No	No	Near	Near	Near	Near	No	No	Near	Near	No
Normality?	automated check	Near	No	No	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	No	No	Near	Near	Near	Near	No	No	Near	Near	No
Measures of dispersion	Skewness (within ± 0.5)	1.063	2.523	1.832	1.975	2.289	2.078	1.26	0.811	0.863	1.567	1.618	3.628	1.93	0.838	2.441	1.119	1.77	1.147	1.5	1.535	0.945	1.844	1.232	1.941
		no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no
	Kurtosis (within ±1.0)	3.57	7.644	3.192	4.522	9.795	5.847	1.887	1.552	0.222	3.524	3.515	16.4	5.587	-0.128	8.266	2.114	3.687	2.865	6.431	3.243	0.102	6.468	1.913	6.337
		no	no	no	no	no	no	no	no	yes	no	no	no	no	yes	no	no	no	no	no	no	yes	no	no	no
Normality?	automated check	No	No	No	No	No	No	No	No	Near	No	No	No	No	Near	No	No	No	No	No	No	Near	No	No	No
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.004	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
		no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.2	0.047	0.002	0.001	0.001	0.02	0.006	0.001	0.066	0.001	0.007	0.001	0.001	0.002	0.001	0.001	0.002
		no	no	no	no	no	no	no	yes	no	no	no	no	no	no	no	yes	no	no	no	no	no	no	no	no
Noramlity?	automated check	No	No	No	No	No	No	No	Near	No	No	No	No	No	No	No	Near	No	No	No	No	No	No	No	No
Overal Assessment of Normality	select mannually	No	No	No	No	Near	No	No	Near	Near	Near	No	No	Near	No	No	Yes	No	Near	No	No	No	No	Near	No

Table F.4. Obstacle detection: Mean reaction among the 60 participants (continued on next page).

Lightcondition-task		L1T1N	L1T1M	L1T1F	L1T2N	L1T2M	L1T2F	L1T3N	L1T3M	L1T3F	L2T1N	L2T1M	L2T1F	L2T2N	L2T2M	L2T2F	L2T3N	L2T3M	L2T3F
Central Tendency	Mean	1322.83	1573.3	1620.48	1426.43	1658.8	1852.27	1353.65	1627.03	1584.68	1217.28	1381.61	1439.48	1350.93	1560.88	1642.88	1223.1	1395.7	1455.7
	95% CI of Mean	1250.49	1493	1524.98	1333.9	1579.67	1753.45	1273.5	1542.91	1498.18	1144.13	1287.98	1361.96	1274.14	1466.09	1547.58	1151.04	1307.13	1351.19
		1395.18	1653.59	1715.99	1518.96	1737.93	1951.08	1433.79	1711.15	1671.19	1290.44	1475.25	1517	1427.72	1655.67	1738.19	1295.16	1484.27	1560.2
	Median	1323	1546	1620	1419	1659	1852	1354	1578.5	1583.5	1217	1293	1389	1351	1531	1643	1184.5	1323.5	1392.5
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	Yes	Near	Yes	No	No	Yes	No	Near	Near	Near	No	Yes	Near	No	Yes	Near	Yes	No
	Box Plot	Near	Near	Yes	Near	Yes	Near	No	Near	Near	Yes	No	Near	Near	Near	Near	Yes	Yes	No
Normality?	automated check	Near	Near	Yes	Near	Near	Near	No	Near	Near	Near	No	Near	Near	Near	Near	Near	Yes	No
Measures of dispersion	Skewness (within ± 0.5)	0.431	0.755	0.791	1.072	0.035	0.707	0.677	0.704	0.464	0.159	1.308	0.859	0.011	1.009	0.392	1.008	1.887	0.77
		yes	no	no	no	yes	no	no	no	yes	yes	no	no	yes	no	yes	no	no	no
	Kurtosis (within ±1.0)	0.51	0.479	0.847	1.785	-0.38	0.568	0.164	0.019	0.095	-0.679	2.12	0.464	-0.788	1.06	0.063	1.645	6.387	0.004
		yes	yes	yes	no	yes	yes	yes	yes	yes	yes	no	yes	yes	no	yes	no	no	yes
Normality?	automated check	Yes	Near	Near	No	Yes	Near	Near	Near	Yes	Yes	No	Near	Yes	No	Yes	No	No	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.456	0.034	0.046	0.003	0.801	0.014	0.021	0.016	0.324	0.236	0.001	0.003	0.343	0.001	0.406	0.007	0.001	0.007
		yes	no	no	no	yes	no	no	no	yes	yes	no	no	yes	no	yes	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.2	0.2	0.2	0.172	0.2	0.001	0.091	0.2	0.2	0.2	0.007	0.027	0.2	0.2	0.2	0.074	0.012	0.042
		yes	yes	yes	yes	yes	no	yes	yes	yes	yes	no	no	yes	yes	yes	yes	no	no
Noramlity?	automated check	Yes	Near	Near	Near	Yes	No	Near	Near	Yes	Yes	No	No	Yes	Near	Yes	Near	No	No
Overal Assessment of Normality	select mannually	Yes	Yes	Yes	Near	Yes	Near	Near	Yes	Yes	Yes	No	Near	Yes	Near	Yes	Near	Near	No

Table F.4. Obstacle detection: Mean reaction among the 60 participants (rest).

Lightcondition-task		L3T1C1	L3T1C2	L3T1C3	L3T2C1	L3T2C2	L3T2C3	L3T3C1	L3T3C2	L3T3C3	L4T1C1	L4T1C2	L4T1C3	L4T2C1	L4T2C2	L4T2C3	L4T3C1	L4T3C2	L4T3C3
Central Tendency	Mean	4589.83	3526.48	2952.55	5020.62	3922.09	2963.5	4489.98	3531.64	2948.88	4909.64	3971.76	2971.24	4932.45	4157.59	2971.67	4990.05	3784.48	3065.36
	95% CI of Mean	4217.47	3398.08	2845.79	4689.35	3747.6	2865.78	4130.17	3381.37	2856.45	4515.88	3656.38	2850.35	4625.32	3924.73	2860.88	4589.94	3583.89	2898.4
		4962.19	3654.87	3059.3	5351.89	4096.59	3061.22	4849.78	3681.91	3041.31	5303.4	4287.14	3092.13	5239.58	4390.46	3082.45	5390.36	3985.05	3232.31
	Median	4514.5	3483.5	2865.5	4804	3766.5	2930.5	4071.5	3540	2904	4965	3673	2930	4898.5	3945	2938	4966.5	3822.5	2935
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	Near	Yes	No	Near	Yes	No	No	Near	Yes	Near	Yes	Yes	Yes	Near	Yes	Yes	Yes	Near
	Box Plot	Yes	Yes	Near	No	Near	Yes	No	Near	Yes	Near	Near	Yes	Yes	No	Yes	Near	Yes	Yes
Normality?	automated check	Near	Yes	Near	Near	Near	Near	No	Near	Yes	Near	Near	Yes	Yes	Near	Yes	Near	Yes	Near
Measures of dispersion	Skewness (within ± 0.5)	0.611	0.227	1.13	0.648	0.956	1.929	1.415	0.566	0.801	0.709	1.948	1.667	0.65	0.291	3.228	0.59	0.608	2.303
		no	yes	no	no	no	no	no	no	no	no	no	no	no	yes	no	no	no	no
	Kurtosis (within ±1.0)	-0.451	-0.621	1.941	-0.202	0.903	6.979	1.995	0.503	0.612	0.308	6.211	4.272	1.451	-0.884	16.361	0.599	1.172	6.49
		yes	yes	no	yes	yes	no	no	yes	yes	yes	no	no	no	yes	no	yes	no	no
Normality?	automated check	Near	Yes	No	Near	Near	No	No	Near	Near	Near	No	No	No	Yes	No	Near	No	No
Statistical tests	Shapiro-Wilks (level of significance)	0.041	0.65	0.006	0.079	0.026	0.001	0.001	0.279	0.06	0.164	0.001	0.001	0.372	0.168	0.001	0.109	0.309	0.001
		no	yes	no	yes	no	no	no	yes	yes	yes	no	no	yes	yes	no	yes	yes	no
	Kolmogorov-Smirnov (level of significance)	0.4	0.2	0.055	0.2	0.084	0.2	0.003	0.2	0.069	0.2	0.002	0.003	0.2	0.074	0.002	0.172	0.2	0.001
		yes	yes	yes	yes	yes	yes	no	yes	yes	yes	no	no	yes	yes	no	yes	yes	no
Noramlity?	automated check	Near	Yes	Near	Yes	Near	Near	No	Yes	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	No
Overal Assessment of Normality	select mannually	Yes	Yes	Near	Yes	Yes	Near	No	Yes	Yes	Yes	No	Near	Yes	Yes	Near	Yes	Yes	No

Table F.5. Pedestrian model: Mean reaction among the 60 participants (continued on next page).

Lightcondition-task		L1T1C1	L1T1C2	L1T1C3	L1T2C1	L1T2C2	L1T2C3	L1T3C1	L1T3C2	L1T3C3	L2T1C1	L2T1C2	L2T1C3	L2T2C1	L2T2C2	L2T2C3	L2T3C1	L2T3C2	L2T3C3
Central Tendency	Mean	4374.14	3591.98	2957.12	4829.14	3653.21	2976.38	4231.59	3752.43	2997.24	3691.4	3351.57	2844.43	4402.89	3588.33	3041.67	3732.9	351.09	3013.19
	95% CI of Mean	4101.72 4646.57	3414.63 3769.32	2858.92 3055.32	4519.71 5138.58	3471.45 3834.97	2892.57 3060.19	3965.11 4498.08	3551.49 3953.37	2885.01 3109.47	3485.2 3897.61	3149.57 3553.58	2740.33 2948.53	4081.68 4724.08	3414.32 3762.34	2934.02 3149.31	3522.57 3943.23	3118.15 3584.04	2884.25 3142.13
	Median	4276.5	3573.5	2900.5	4818.5	3644.5	2946	3919.5	3670	2925	3536.5	3285.5	2861.5	4129.5	3466	2921.5	3683	3216.5	2912
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Graphical	Histogram	Near	Yes	No	No	No	Yes	No	Near	Yes	No	Yes	Near	Near	Yes	No	No	No	No
	Box Plot	Near	Yes	Near	No	No	Near	No	Near	Yes	Near	Yes	Near	Near	Near	No	No	No	Near
Normality?	automated check	Near	Yes	Near	No	No	Near	No	Near	Yes	Near	Yes	Near	Near	Near	No	No	No	Near
Measures of dispersion	Skewness (within ± 0.5)	0.66	0.252	0.633	0.405	0.524	0.419	0.685	0.385	1.312	1.082	0.791	1.269	0.83	0.383	2.044	0.549	1.824	1.701
		no	yes	no	yes	no	yes	no	yes	no	no	no	no	no	yes	no	no	no	no
	Kurtosis (within ±1.0)	0.021	-0.563	-0.313	-0.332	-0.269	-0.458	0.093	-0.44	2.411	1.243	1.745	4.246	0.698	-0.553	6.481	-0.27	4.477	3.958
		yes	yes	yes	yes	yes	yes	yes	yes	no	no	no	no	yes	yes	no	yes	no	no
Normality?	automated check	Near	Yes	Near	Yes	Near	Yes	Near	Yes	No	No	No	No	Near	Yes	No	Near	No	No
Statistical tests	Shapiro-Wilks (level of significance)	0.066	0.351	0.018	0.427	0.172	0.352	0.113	0.462	0.003	0.007	0.117	0.004	0.049	0.384	0.001	0.116	0.001	0.001
		yes	yes	no	yes	yes	yes	yes	yes	no	no	yes	no	no	yes	no	yes	no	no
	Kolmogorov-Smirnov (level of significance)	0.082	0.2	0.009	0.2	0.2	0.2	0.006	0.2	0.026	0.03	0.2	0.2	0.54	0.2	0.005	0.2	0.007	0.036
		yes	yes	no	yes	yes	yes	no	yes	no	no	yes	yes	yes	yes	no	yes	no	no
Noramlity?	automated check	Yes	Yes	No	Yes	Yes	Yes	Near	Yes	No	No	Yes	Near	Near	Yes	No	Yes	No	No
Overal Assessment of Normality	select mannually	Yes	Yes	Near	Yes	Yes	Yes	No	Yes	Near	No	Yes	Near	Yes	Yes	No	Yes	No	No

Table F.5. Pedestrian model: Mean reaction time among the 60 participants (rest).

Lightcondition-task		L3T1C1	L3T1C2	L3T1C3	L3T2C1	L3T2C2	L3T2C3	L3T3C1	L3T3C2	L3T3C3	L4T1C1	L4T1C2	L4T1C3	L4T2C1	L4T2C2	L4T2C3	L4T3C1	L4T3C2	L4T3C3
Central Tendency	Mean	4589.83	3526.48	2952.55	5020.62	3922.09	2963.5	4489.98	3531.64	2948.88	4909.64	3971.76	2971.24	4932.45	4157.59	2971.67	4990.05	3784.48	3065.36
	95% CI of Mean	4217.47 4962.19	3398.08 3654.87	2845.79 3059.3	4689.35 5351.89	3747.6 4096.59	2865.78 3061.22	4130.17 4849.78	3381.37 3681.91	2856.45 3041.31	4515.88 5303.4	3656.38 4287.14	2850.35 3092.13	4625.32 5239.58	3924.73 4390.46	2860.88 3082.45	4589.94 5390.36	3583.89 3985.05	2898.4 3232.31
	Median	4514.5	3483.5	2865.5	4804	3766.5	2930.5	4071.5	3540	2904	4965	3673	2930	4898.5	3945	2938	4966.5	3822.5	2935
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	Near	Yes	No	Near	Yes	No	No	Near	Yes	Near	Yes	Yes	Yes	Near	Yes	Yes	Yes	Near
	Box Plot	Yes	Yes	Near	No	Near	Yes	No	Near	Yes	Near	Near	Yes	Yes	No	Yes	Near	Yes	Yes
Normality?	automated check	Near	Yes	Near	Near	Near	Near	No	Near	Yes	Near	Near	Yes	Yes	Near	Yes	Near	Yes	Near
Measures of dispersion	Skewness (within ± 0.5)	0.611	0.227	1.13	0.648	0.956	1.929	1.415	0.566	0.801	0.709	1.948	1.667	0.65	0.291	3.228	0.59	0.608	2.303
		no	yes	no	no	no	no	no	no	no	no	no	no	no	yes	no	no	no	no
	Kurtosis (within ±1.0)	-0.451	-0.621	1.941	-0.202	0.903	6.979	1.995	0.503	0.612	0.308	6.211	4.272	1.451	-0.884	16.361	0.599	1.172	6.49
		yes	yes	no	yes	yes	no	no	yes	yes	yes	no	no	no	yes	no	yes	no	no
Normality?	automated check	Near	Yes	No	Near	Near	No	No	Near	Near	Near	No	No	No	Yes	No	Near	No	No
Statistical tests	Shapiro-Wilks (level of significance)	0.041	0.65	0.006	0.079	0.026	0.001	0.001	0.279	0.06	0.164	0.001	0.001	0.372	0.168	0.001	0.109	0.309	0.001
		no	yes	no	yes	no	no	no	yes	yes	yes	no	no	yes	yes	no	yes	yes	no
	Kolmogorov-Smirnov (level of significance)	0.4	0.2	0.055	0.2	0.084	0.2	0.003	0.2	0.069	0.2	0.002	0.003	0.2	0.074	0.002	0.172	0.2	0.001
		yes	yes	yes	yes	yes	yes	no	yes	yes	yes	no	no	yes	yes	no	yes	yes	no
Noramlity?	automated check	Near	Yes	Near	Yes	Near	Near	No	Yes	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	No
Overal Assessment of Normality	select mannually	Yes	Yes	Near	Yes	Yes	Near	No	Yes	Yes	Yes	No	Near	Yes	Yes	Near	Yes	Yes	No

Table F.6. Vehicle lane change: Mean reaction time among the 60 participants.

Lightcondition-task		C1-Cross	C1-Visaul	C1-Auditory	C2-Cross	C2-Visaul	C2-Auditory	C3-Cross	C3-Visaul	C3-Auditory	C4-Cross	C4-Visaul	C4-Auditory
Central Tendency	Mean	2242.05	2794.52	2282.33	2081.36	2447.27	2095.43	2198.78	2727	2212.82	2330.87	2923.18	2389.72
	95% CI of Mean	2122.28 2361.82	2636.98 2952.05	2166.29 2398.37	1933.44 2229.19	2316.73 2577.8	1964.19 2226.08	2078.7 2318.87	2575.55 2878.45	2090.56 2335.08	2204.11 2457.62	2787.14 3059.23	2264.85 2514.58
	Median	2091	2801.5	2210	1946.5	2363	1976.5	2190.5	2626	2153	2321	2870	2275.5
Normality? (Yes if median is in 95% CI of mean)	automated check	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	Near	No	Near	No	No	No	No	Yes	No	No	Near	No
	Box Plot	Near	Near	Near	Near	No	No	Near	Yes	Near	Yes	Yes	No
Normality?	automated check	Near	Near	Near	Near	No	No	Near	Yes	Near	Near	Near	No
Measures of dispersion	Skewness (within ± 0.5)	0.408	1.36	0.526	1.731	0.662	1.208	0.893	0.496	0.718	1.076	0.446	0.635
		yes	no	no	no	no	no	no	yes	no	no	yes	no
	Kurtosis (within ±1.0)	-0.558	4.834	0.242	5.149	0.061	1.341	1.603	0.346	0.758	2.842	-0.461	-0.449
		yes	no	yes	no	yes	no	no	yes	yes	no	yes	yes
Normality?	automated check	Yes	No	Near	No	Near	No	No	Yes	Near	No	Yes	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.036	0.001	0.274	0.001	0.032	0.001	0.014	0.157	0.051	0.006	0.062	0.008
		no	no	yes	no	no	no	no	yes	yes	no	yes	no
	Kolmogorov-Smirnov (level of significance)	0.001	0.2	0.175	0.001	0.2	0.001	0.2	0.971	0.2	0.073	0.2	0.009
		no	yes	yes	no	yes	no	yes	yes	yes	yes	yes	no
Noramlity?	automated check	No	Near	Yes	No	Near	No	Near	Yes	Yes	Near	Yes	No
Overal Assessment of Normality	select mannually	No	Yes	Yes	No	Near	No	Near	Yes	Yes	Yes	Yes	No

Table F.7. Road surface obstacle: Performance rate among the 60 participants (continued on next page).

Lightcondition-task		L1T1N	L1T1M	L1T1F	L1T2N	L1T2M	L1T2F	L1T3N	L1T3M	L1T3F	L2T1N	L2T1M	L2T1F	L2T2N	L2T2M	L2T2F	L2T3N	L2T3M	L2T3F
Central Tendency	Mean	82.85	86.75	79.53	73.42	68.95	56.13	85.03	81.17	70.05	88.37	83.42	84.5	76.73	73.37	66.2	88.38	84.5	85.08
	95% CI of Mean	75.86 89.84	81.23 92.27	72.43 86.64	65.68 81.16	60.42 77.48	46.54 65.73	77.53 92.54	73.84 88.5	61.69 78.41	81.68 95.06	77.82 89.02	78.27 90.73	68.3 85.17	65.46 81.28	58.03 74.37	81.89 94.88	77.88 91.12	79.29 90.88
	Median	100	100	100	67	67	67	100	100	67	100	100	100	100	67	67	100	100	100
Normality? (Yes if median is in 95% CI of mean)	automated check	No	No	No	Yes	Yes	No	No	No	Yes	No	No	No	No	Yes	Yes	No	No	No
Graphical	Histogram	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
	Box Plot	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Normality?	automated check	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Measures of dispersion	Skewness (within ± 0.5)	-1.823	-1.798	-1.408	-1.006	-0.797	-0.254	-1.991	-1.503	-0.792	-2.436	-0.98	-1.524	-1.326	-0.833	-0.718	-2.502	-1.747	-1.582
		no	no	no	no	no	yes	no	no	no	no	no	no	no	no	no	no	no	no
	Kurtosis (within ±1.0)	2.576	3.775	1.604	0.295	-0.415	-1.289	3.005	1.542	-0.416	5.362	-0.065	1.809	0.684	-0.369	-0.309	6.024	2.647	2.631
		no	no	no	yes	yes	no	no	no	yes	no	yes	no	yes	yes	yes	no	no	no
Normality?	automated check	No	No	No	Near	Near	Near	No	No	Near	No	Near	No	Near	Near	Near	No	No	No
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
		no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
		no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no
Noramlity?	automated check	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Overal Assessment of Normality	select mannually	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Table F.7. Road surface obstacle: Performance rate among the 60 participants (rest).

Lightcondition-task		L3T1N	L3T1M	L3T1F	L3T2N	L3T2M	L3T2F	L3T3N	L3T3M	L3T3F	L4T1N	L4T1M	L4T1F	L4T2N	L4T2M	L4T2F	L4T3N	L4T3M	L4T3F
Central Tendency	Mean	81.17	83.38	81.73	69.48	70.58	53.37	80.07	81.18	75.63	75.03	81.13	77.27	67.82	60.03	51.7	76.7	78.95	75.58
	95% CI of Mean	73.84	76.94	74.57	60.74	62.62	50.01	71.51	74.03	67.88	66.84	73.79	69.91	58.04	51.21	42.79	68.26	72.22	67.99
		88.5	89.83	88.9	78.22	78.54	66.73	88.63	88.34	83.38	83.23	88.47	84.63	77.59	68.85	60.61	85.14	85.58	83.18
	Median	100	100	100	67	67	67	100	100	83.5	100	100	100	67	67	67	100	100	100
Normality? (Yes if median is in 95% CI of mean)	automated check	No	No	No	Yes	Yes	No	No	No	No	No	No	No	Yes	Yes	No	No	No	No
Graphical	Histogram	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
	Box Plot	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Normality?	automated check	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Measures of dispersion	Skewness (within ± 0.5)	-1.503	-1.4	-1.585	-0.784	-0.649	-0.288	-1.646	-1.538	-1.153	-1.027	-1.33	-1.02	-0.791	-0.375	-0.14	-1.211	-0.995	-0.877
		no	no	no	no	no	yes	no	no	no	no	no	no	no	yes	yes	no	no	no
	Kurtosis (within ±1.0)	1.542	1.253	1.962	-0.566	-0.666	-0.882	1.493	1.857	0.582	-0.054	0.726	0.102	-0.846	-0.986	-1.119	4.045	0.153	-0.336
		no	no	no	yes	yes	yes	no	no	yes	yes	yes	yes	yes	yes	no	0.28	yes	yes
Normality?	automated check	No	No	No	Near	Near	Yes	No	No	Near	Near	Near	Near	Near	Yes	Near	Near	Near	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
		no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
		no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no	no
Noramlity?	automated check	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Overal Assessment of Normality	select manually	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No

Table F.8. Pedestrian model: Performance rate among the 60 participants (continued on next page).

Lightcondition-task		L1T1C1	L1T1C2	L1T1C3	L1T2C1	L1T2C2	L1T2C3	L1T3C1	L1T3C2	L1T3C3	L2T1C1	L2T1C2	L2T1C3	L2T2C1	L2T2C2	L2T2C3	L2T3C1	L2T3C2	L2T3C3
Central Tendency	Mean	0.94	1	1	0.89	0.99	1	0.94	0.98	0.99	0.98	0.98	0.99	0.93	0.99	0.99	0.99	0.99	0.99
	95% CI of Mean	0.9 0.98	1 1	1 1	0.83 0.95	0.97 1.0044	1 1	0.9 0.99	0.96 1.0022	0.98 1.0055	0.96 0.99	0.96 1.0022	0.98 1.0055	0.89 0.97	0.97 1.0044	0.98 1.0055	0.97 1.0044	0.97 1.0044	0.97 1.0044
	Median	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Normality? (Yes if median is in 95% CI of mean)	automated check	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram																		
	Box Plot																		
Normality?	automated check	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	-2.659	0	0	-2.439	-5.334	0	-3.03	-4.236	-7.746	-3.564	-4.236	-7.746	-2.285	-5.334	-7.746	-5.334	-5.334	-5.334
		no	yes	yes	no	no	yes	no	no	no	no	no	no	no	no	no	no	no	no
	Kurtosis (within ±1.0)	6.722	0	0	5.963	27.36	0	8.384	16.494	60	11.071	16.494	60	4.737	27.36	60	27.36	27.36	27.36
		no	yes	yes	no	no	yes	no	no	no	no	no	no	no	no	no	no	no	no
Normality?	automated check	No	Yes	Yes	No	No	Yes	No	No	No	No	No	No	No	No	No	No	No	No
Statistical tests	Shapiro-Wilks (level of significance)	0.001	1	1	0.001	0.001	1	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.0041	0.001	0.001	0.001
		no	yes	yes	no	no	yes	no	no	no	no	no	no	no	no	no	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.001	1	1	0.001	0.001	1	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.0041	0.001	0.001	0.001
		no	yes	yes	no	no	yes	no	no	no	no	no	no	no	no	no	no	no	no
Noramlity?	automated check	No	Yes	Yes	No	No	Yes	No	No	No	No	No	No	No	No	No	No	No	No
Overal Assessment of Normality	select mannually	No	Yes	Yes	No	No	Yes	No	No	No	No	No	No	No	No	No	No	No	No

Table F.8. Pedestrian model: Performance rate among the 60 participants (rest).

Lightcondition-task		L3T1C1	L3T1C2	L3T1C3	L3T2C1	L3T2C2	L3T2C3	L3T3C1	L3T3C2	L3T3C3	L4T1C1	L4T1C2	L4T1C3	L4T2C1	L4T2C2	L4T2C3	L4T3C1	L4T3C2	L4T3C3
Central Tendency	Mean	0.88	0.99	1	0.83	0.98	1	0.93	0.98	0.99	0.71	0.95	1	0.61	0.93	1	0.73	0.92	0.99
	95% CI of Mean	0.82	0.97	1	0.75	0.96	1	0.88	0.96	0.97	0.62	0.92	1	0.51	0.89	1	0.65	0.88	0.98
		0.95	1.0112	1	0.9	1.0022	1	0.97	0.99	1.0044	0.8	0.99	1	0.7	0.97	1	0.81	0.97	1.0055
	Median	1	1	1	1	1	1	1	1	1	0.84	1	1	0.67	1	1	0.67	1	1
Normality? (Yes if median is in 95% CI of mean)	automated check	No	Yes	Yes	No	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No	Yes	Yes	No	Yes
Graphical	Histogram																		
	Box Plot																		
Normality?	automated check	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	-2.297	-7.746	0	-1.648	-4.236	0	-2.449	-3.564	-5.334	-0.918	-2.802	0	-0.504	-2.285	0	-0.833	-2.125	-7.746
		no	no	yes	no	no	yes	no	no	no	no	no	yes	no	no	yes	no	no	no
	Kurtosis (within ±1.0)	4.923	60	0	1.878	16.494	0	5.247	11.07	27.396	-0.446	7.914	0	-1.052	4.737	0	-0.369	3.969	60
		no	no	yes	no	no	yes	no	no	no	yes	no	yes	no	no	yes	yes	no	no
Normality?	automated check	No	No	Yes	No	No	Yes	No	No	No	Near	No	Yes	No	No	Yes	Near	No	No
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	1	0.001	0.001	1	0.001	0.001	0.001	0.001	0.001	1	0.001	0.001	1	0.001	0.001	0.001
		no	no	yes	no	no	yes	no	no	no	no	no	yes	no	no	yes	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.001	0.001	1	0.001	0.001	1	0.001	0.001	0.001	0.001	0.001	1	0.001	0.001	1	0.001	0.001	0.001
		no	no	yes	no	no	yes	no	no	no	no	no	yes	no	no	yes	no	no	no
Noramlity?	automated check	No	No	Yes	No	No	Yes	No	No	No	No	No	Yes	No	No	Yes	No	No	No
Overal Assessment of Normality	select mannually	No	No	Yes	No	No	Yes	No	No	No	No	No	Yes	No	No	Yes	No	No	No

Table F.9. Vehicle lane change: Performance rate among the 60 participants.

Lightcondition-task		C1-Cross	C1-Visaul	C1-Auditory	C2-Cross	C2-Visaul	C2-Auditory	C3-Cross	C3-Visaul	C3-Auditory	C4-Cross	C4-Visaul	C4-Auditory
Central Tendency	Mean	0.97	0.93	0.98	0.96	0.98	0.97	0.97	0.94	0.98	0.95	0.92	0.96
	95% CI of Mean	0.96	0.89	0.96	0.93	0.97	0.95	0.95	0.91	0.96	0.93	0.88	0.93
		0.99	0.96	0.99	0.98	0.99	0.99	0.99	0.97	0.99	0.98	0.95	0.98
	Median	1	1	1	1	1	1	1	1	1	1	1	1
Normality? (Yes if median is in 95% CI of mean)	automated check	No	No	No	No	No	No	No	No	No	No	No	No
Graphical	Histogram	No	No	No	No	No	No	No	No	No	No	No	No
	Box Plot	No	No	No	No	No	No	No	No	No	No	No	No
Normality?	automated check	No	No	No	No	No	No	No	No	No	No	No	No
Measures of dispersion	Skewness (within ± 0.5)	-2.713	-3.076	-3.343	-2.723	-3.768	-2.471	-3.549	-2.995	-1.501	1.076	-1.545	-1.776
		no	no	no	no	no	no	no	no	no	no	no	no
	Kurtosis (within ±1.0)	7.121	13.112	11.432	9.723	14.779	5.674	15.563	11.81	1.184	2.842	1.589	2.268
		no	no	no	no	no	no	no	no	no	no	no	no
Normality?	automated check	No	No	No	No	No	No	No	No	No	No	No	No
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
		no	no	no	no	no	no	no	no	no	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
		no	no	no	no	no	no	no	no	no	no	no	no
Noramlity?	automated check	No	No	No	No	No	No	No	No	No	No	No	No
Overal Assessment of Normality	select mannually	No	No	No	No	No	No	No	No	No	No	No	No

Table F.10. Distraction task T2 (visual distraction): Median reaction time among the 60 participants.

lighting condition		L1	L2	L3	L4
Central Tendency	Mean	991.24	1011.71	986.88	982.92
	95% CI of Mean	962.97 1019.5	982.8 1040.63	958.66 1015.1	953.22 1012.61
	Median	987	1000	984	953
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	No
Graphical	Histogram	Near	Yes	Near	Near
	Box Plot	Yes	Yes	Yes	No
Normality?	automated check	Near	Yes	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	0.299	0.242	0.11	0.588
		yes	yes	yes	no
	Kurtosis (within ±1.0)	0.839	-0.181	-0.244	-0.265
		yes	yes	yes	yes
Normality?	automated check	Yes	Yes	Yes	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.305	0.724	0.887	0.027
		yes	yes	yes	no
	Kolmogorov-Smirnov (level of significance)	0.2	0.2	0.2	0.016
		yes	yes	yes	no
Noramlity?	automated check	Yes	Yes	Yes	No
Overal Assessment of Normality	select mannually	Yes	Yes	Yes	Near

Table F.11. Distraction task T3 (Acoustic distraction): Median reaction time among the 60 participants. (Left original and right residuals).

lighting condition		L1	L2	L3	L4
Central Tendency	Mean	1623.63	1587.18	1593.98	1489.05
	95% CI of Mean	1496.26	1463.03	1469.22	1339.27
		1751.01	1711.33	1718.75	1638.83
	Median	1422	1453	1499.5	1254
Normality? (Yes if median is in 95% CI of mean)	automated check	No	No	Yes	No
Graphical	Histogram	No	No	No	No
	Box Plot	No	No	No	No
Normality?	automated check	No	No	No	No
Measures of dispersion	Skewness (within ± 0.5)	0.566	0.615	0.496	0.571
		no	no	yes	no
	Kurtosis (within ±1.0)	0.839	-0.499	-0.403	-0.647
		-0.622	yes	yes	yes
Normality?	automated check	Near	Near	Yes	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.004	0.003	0.02	0.001
		no	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.001	0.002	0.095	0.001
		no	no	yes	no
Noramlity?	automated check	No	No	Near	No
Overal Assessment of Normality	select manually	No	No	Yes	No

lighting condition		L1	L2	L3	L4
Central Tendency	Mean	-42.174	71.7	51.9	86.67
	95% CI of Mean	-206.56	-85.57	-108.56	-103.74
		122.21	228.99	212.38	277.1
	Median	-217	-29.18	-0.98	57.95
Normality? (Yes if median is in 95% CI of mean)	automated check	No	Yes	Yes	Yes
Graphical	Histogram	No	Near	Near	No
	Box Plot	No	Near	Near	Yes
Normality?	automated check	No	Near	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	0.644	0.475	0.429	0.254
		no	yes	yes	yes
	Kurtosis (within ±1.0)	-0.735	-0.328	-0.097	-0.946
		yes	yes	yes	yes
Normality?	automated check	Near	Yes	Yes	Yes
Statistical tests	Shapiro-Wilks (level of significance)	0.006	0.176	0.427	0.055
		no	yes	yes	yes
	Kolmogorov-Smirnov (level of significance)	0.001	0.2	0.2	0.003
		no	yes	yes	no
Noramlity?	automated check	No	Yes	Yes	Near
Overal Assessment of Normality	select manually	No	Yes	Yes	Yes

Table F.12. Distraction task T2 (visual distraction): Performance rate among the 60 participants.

lighting condition		L1	L2	L3	L4
Central Tendency	Mean	95.29	92.73	94.47	92.9
	95% CI of Mean	94.43 96.14	91.18 94.27	92.74 96.21	91 94.8
	Median	96	95	96	95
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	No	Yes	No
Graphical	Histogram	No	No	No	No
	Box Plot	No	No	Near	Near
Normality?	automated check	No	No	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	-0.675	-2.054	-3.397	-3.332
		no	no	no	no
	Kurtosis (within ±1.0)	-0.449	6.167	13.889	16.327
		yes	no	no	no
Normality?	automated check	Near	No	No	No
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	0.001	0.001
		no	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.002	0.001	0.001	0.001
		no	no	no	no
Noramlity?	automated check	No	No	No	No
Overal Assessment of Normality	select mannually	No	No	No	No

Table F.13. Distraction task T3 (Acoustic distraction): Performance rate among the 60 participants.

lighting condition		L1	L2	L3	L4
Central Tendency	Mean	82	81.9	82.6	86.3
	95% CI of Mean	78.5 85.5	78.5 85.3	79.2 85.9	83.5 89.05
	Median	83.5	86	85	90
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	No	Yes	No
Graphical	Histogram	No	No	No	No
	Box Plot	No	No	No	No
Normality?	automated check	No	No	No	No
Measures of dispersion	Skewness (within ± 0.5)	-1.053	-1.047	-1.208	-0.806
		no	no	no	no
	Kurtosis (within ±1.0)	0.558	0.951	1.589	-0.44
		-0.622	yes	no	yes
Normality?	automated check	Near	Near	No	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	0.001	0.001
		no	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.003	0.001	0.086	0.001
		no	no	yes	no
Noramlity?	automated check	No	No	Near	No
Overal Assessment of Normality	select mannually	No	No	No	No

Table F.14. Road surface obstacle: 23 randomly selected out of 720 data files (alternative analysis combining all three distances).

(participant no_light condition no)		2_1	5_4	7_3	10_1	14_4	16_1	22_4	23_1	23_3	25_4	31_4	36_1	37_4	38_3	41_1	45_2	47_2	49_2	52_4	54_2	55_4	58_1	59_2
Central Tendency	Mean	1598.67	1587.33	1880.17	1365.67	1591.83	1614.8	1894.4	1409.67	1476.17	1307.33	1479	2009	1338.83	1224.33	1816	1295.5	1078	1267.4	1262.5	1299.83	1510	1729.33	1480.67
	95% CI of Mean	1174.94 2022.4	657.27 2517.39	1308.8 2451.53	1189.99 1541.35	979.57 2204.1	958.81 2270.79	1244.52 2544.28	941.96 1877.37	1034.61 1917.73	810.16 1804.49	1320.79 1637.21	1501.48 2516.85	905.39 1772.28	924.27 1524.39	1206.66 2425.34	994 1596.78	700.71 1455.29	1069.88 1464.92	863.5 1661.5	929.99 1669.68	1226.23 1793.77	1509.91 1948.75	1077.68 1883.65
	Median	1435	1128.5	1734.5	1312.5	1502.5	1300	1742	1304	1332.5	1233	1468	1935.5	1351.5	1179	1559	1219.5	978	1317	1312.5	1265	1475.5	1827.5	1387.5
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	No	No	Near	No	No	No	Near	Near	No	No	Near	Near	No	Near	No	No	No	No	Near	Yes	No	No	No
	Box Plot	Near	Near	No	Near	No	Near	No	Near	Near	No	No	No	Near	No	Near	No	No	No	Yes	Yes	No	No	No
Normality?	automated check	Near	Near	Near	Near	No	Near	Near	Near	Near	No	Near	Near	Near	Near	Near	No	No	No	Near	Yes	No	No	No
Measures of dispersion	Skewness (within ± 0.5)	0.82	0.896	1.455	0.446	1.578	0.617	1.399	0.403	0.563	1.441	-0.575	0.548	0.083	1.647	0.888	1.729	0.846	-1.61	-0.208	0.17	0.658	-0.888	1.14
		no	no	no	yes	no	no	no	yes	no	no	no	no	yes	no	no	no	no	no	yes	yes	no	no	no
	Kurtosis (within ±1.0)	-1.64	-1.862	2.324	-1.177	3.002	-2.791	2.719	-0.282	-1.948	-	-0.322	2.249	-1.156	3.175	-1.529	3.316	-0.464	2.588	-1.987	-0.163	-0.683	-1.715	0.863
		no	no	no	no	no	no	no	yes	no	no	yes	no	no	no	no	no	yes	no	no	yes	yes	no	yes
Normality?	automated check	No	No	No	Near	No	No	No	Yes	No	No	Near	No	Near	No	No	No	Near	No	Near	Yes	Near	No	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.114	0.022	0.27	0.485	0.139	0.128	0.306	0.853	0.218	0.375	0.699	0.365	0.942	0.122	0.088	0.099	0.172	0.137	0.572	0.966	0.456	0.046	0.245
		yes	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	no	yes
	Kolmogorov-Smirnov (level of significance)	0.088	0.039	0.2	0.2	0.154	0.093	0.2	0.2	0.2	-	0.2	0.2	0.2	0.07	0.049	0.2	0.138	0.2	0.2	0.2	0.2	0.023	0.2
		yes	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	no	yes	yes	yes	yes	yes	yes	no	yes
Noramlity?	automated check	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Near	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Overal Assessment of Normality	select mannually	Yes	No	Yes	Yes	Near	Yes	Yes	Yes	Yes	Near	Yes	Near	Yes	Near	Near	Near	Yes	Near	Yes	Yes	Yes	No	Yes

Table F.15. Pedestrian model: 23 randomly selected out of 720 (alternative analysis combining all three clothing levels).

(participant no_light condition no)		2_1	5_4	7_3	10_1	14_4	16_1	22_4	23_1	23_3	25_4	31_4	36_1	37_4	38_3	41_1	45_2	47_2	49_2	52_4	54_2	55_4	58_1	59_2
Central Tendency	Mean	2661.83	4086.83	4935.67	3193.17	3154.83	4120	3888	3626	4145.5	4991.71	4204.4	4439.5	4264.83	3878.17	3356.17	3464.33	3089.83	3051.4	3202.67	2969.2	4633.33	3290	3987.5
	95% CI of Mean	2186.1 3137.57	2473.27 5700.39	3028.37 6842.96	2272.37 3613.97	2338.68 3970.99	1658.32 6598.68	2698.55 5077.35	2770.93 4481.07	2468.92 5822.08	2997.34 6989.08	1840.41 6568.39	2785.94 6093.06	2141.97 6387.7	3024.25 4732.08	2957.38 3754.96	2431.45 4497.22	2657.9 3521.77	2996.62 3106.18	2665 3740	2720.39 3218.61	2248.13 7018.54	2915 3664.5	3048.26 4926.74
	Median	2576	3763.5	4220	3184.5	2772.5	3295	4407	3297	3765	4546	3271	4444	3446.5	3871	3346.5	3030	3284	3070	3144	2999.5	3711.5	3262.5	4157.5
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	Near	No	No	No	No	No	No	No	No	No	No	No	No	Near	No	No	No	No	No	Near	No	No	No
	Box Plot	Near	Near	Near	No	Near	No	Near	No	No	Near	No	No	No	Yes	No	No	Near	No	Near	Near	No	Yes	Yes
Normality?	automated check	Near	Near	Near	No	Near	No	Near	No	No	Near	No	No	No	Near	No	No	Near	No	Near	Near	No	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	0.216	0.738	0.769	1.256	0.915	1.166	-0.529	1.507	1.47	0.402	1.613	1.029	1.124	0.291	-0.108	2.256	-0.898	-1.9	0.157	-0.624	1.137	0.086	-0.476
		yes	no	no	no	no	no	no	no	no	yes	no	no	no	yes	yes	no	no	no	yes	no	no	yes	yes
	Kurtosis (within ±1.0)	1	-0.582	-1.857	2.194	-1.713	0.357	-3.14	1.853	2.244	-1.753	2.458	1.545	0.196	-0.068	-2.03	5.185	-1.446	3.774	-2.408	-0.267	0.146	-2.598	-1.67
		yes	yes	no	no	no	yes	no	no	no	no	no	no	yes	yes	no	no	no	no	no	yes	yes	no	no
Normality?	automated check	Yes	Near	No	No	No	Near	No	No	No	Near	No	No	Near	Yes	Near	No	No	No	Near	Near	Near	Near	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.904	0.623	0.057	0.192	0.036	0.237	0.091	0.081	0.175	0.328	0.128	0.354	0.123	0.939	0.406	0.002	0.102	0.05	0.356	0.701	0.154	0.261	0.466
		yes	yes	yes	yes	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	no	yes	no	yes	yes	yes	yes	yes
	Kolmogorov-Smirnov (level of significance)	0.2	0.2	0.057	0.123	0.035	0.2	0.142	0.2	0.2	0.2	0.2	0.2	0.198	0.2	0.2	0.024	0.093	0.095	0.2	0.2	0.2	0.2	0.2
		yes	yes	yes	yes	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	no	yes	yes	yes	yes	yes	yes	yes
Noramlity?	automated check	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Near	Yes	Yes	Yes	Yes	Yes
Overal Assessment of Normality	select mannually	Yes	Yes	Yes	Near	No	Yes	Yes	Near	Near	Yes	Near	Near	Yes	Yes	Yes	No	Near	No	Yes	Yes	Yes	Yes	Yes

Table F.16. Mean reaction time to road surface obstacle among the 60 participants (alternative analysis combining all three distances).

Lighting condition - task		C1-Cross	C1-Visaul	C1-Auditory	C2-Cross	C2-Visaul	C2-Auditory	C3-Cross	C3-Visaul	C3-Auditory	C4-Cross	C4-Visaul	C4-Auditory
Central Tendency	Mean	1503.29	1616.43	1503.78	1348.38	1505.1	1348.5	1483.48	1683.97	1485.66	1513.05	1711.72	1614.21
	95% CI of Mean	1437.63 1568.95	1550.59 1682.27	1439.75 1567.8	1283.07 1413.69	1436.15 1574.06	1276.77 1420.23	1415.29 1551.67	1609.32 1758.61	1431.41 1539.9	1447.58 1578.53	1619.34 1804.11	1539.22 1689.19
	Median	1461	1598	1448.5	1322.5	1504.5	1301.5	1473.5	1720.5	1482	1483	1652.5	1555.5
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	No	Yes	No	Yes	Near	No	No	No	Near	No	No	Near
	Box Plot	No	Yes	No	Near	Near	Near	Near	No	Near	Near	Near	No
Normality?	automated check	No	Yes	No	Near	Near	Near	Near	No	Near	Near	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	0.614	0.322	0.654	0.53	0.178	0.933	0.469	0.243	0.131	0.591	0.808	1.362
		no	yes	no	no	yes	no	yes	yes	yes	no	no	no
	Kurtosis (within ±1.0)	0.052	0.397	-0.499	0.235	-0.128	0.686	-0.165	-0.546	-0.53	-0.576	0.724	3.613
		yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	no
Normality?	automated check	Near	Yes	Near	Near	Yes	Near	Yes	Yes	Yes	Near	Near	No
Statistical tests	Shapiro-Wilks (level of significance)	0.062	0.746	0.005	0.156	0.706	0.004	0.177	0.16	0.551	0.009	0.032	0.001
		yes	yes	no	yes	yes	no	yes	yes	yes	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.035	0.2	0.01	0.2	0.2	0.004	0.2	0.2	0.2	0.057	0.2	0.2
		no	yes	no	yes	yes	no	yes	yes	yes	yes	yes	yes
Noramlity?	automated check	Near	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Near	Near	Near
Overal Assessment of Normality	select mannually	Yes	Yes	No	Yes	Yes	Near	Yes	Yes	Yes	Near	Near	Near

Table F.17. Mean reaction time to pedestrians among the 60 participants (alternative analysis combining all three clothing levels).

Lightcondition-task		C1-Cross	C1-Visaul	C1-Auditory	C2-Cross	C2-Visaul	C2-Auditory	C3-Cross	C3-Visaul	C3-Auditory	C4-Cross	C4-Visaul	C4-Auditory
Central Tendency	Mean	3742.5	3972.17	3768.62	3421.37	3805.3	3458.27	3783.25	3955.17	3715.03	3924.27	3988.83	3972.85
	95% CI of Mean	3616.69 3868.31	3832.26 4112.07	3632.9 3904.34	3268.53 3574.21	3646.62 3961.98	3308.04 3608.49	3648.8 3914.7	3830.1 4080.23	3568.83 3861	3768.85 4079.69	3870.39 4107.27	3815.28 4130.42
	Median	3772	3957.5	3662.5	3345	3764.5	3347	3749.5	3890.5	3583	3903	4032.5	3965.5
Normality? (Yes if median is in 95% CI of mean)	automated check	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graphical	Histogram	Yes	Yes	Near	Yes	No	No	Near	Near	No	Near	Near	No
	Box Plot	Near	Near	Near	Yes	No	Near	Yes	Near	No	Near	Near	Near
Normality?	automated check	Near	Near	Near	Yes	No	Near	Near	Near	No	Near	Near	Near
Measures of dispersion	Skewness (within ± 0.5)	0.415	0.301	0.342	1.465	0.785	1.775	0.513	0.744	1.224	0.555	-0.126	0.478
		yes	yes	yes	no	no	no	no	no	no	no	yes	yes
	Kurtosis (within ±1.0)	0.017	-0.212	-0.211	2.978	0.297	5.822	0.485	0.599	2.171	1.544	-0.438	0.316
		yes	yes	yes	no	yes	no	yes	yes	no	no	yes	yes
Normality?	automated check	Yes	Yes	Yes	No	Near	No	Near	Near	No	No	Yes	Yes
Statistical tests	Shapiro-Wilks (level of significance)	0.477	0.514	0.504	0.001	0.013	0.001	0.298	0.078	0.001	0.106	0.565	0.131
		yes	yes	yes	no	no	no	yes	yes	no	yes	yes	yes
	Kolmogorov-Smirnov (level of significance)	0.089	0.2	0.2	0.006	0.2	0.052	0.2	0.2	0.017	0.2	0.2	0.2
		yes	yes	yes	no	yes	yes	yes	yes	no	yes	yes	yes
Noramlity?	automated check	Yes	Yes	Yes	No	Near	Near	Yes	Yes	No	Yes	Yes	Yes
Overal Assessment of Normality	select mannually	Yes	Yes	Yes	Near	Near	Near	Yes	Yes	No	Yes	Yes	Yes

Table F.18. Performance rate to road surface obstacle among the 60 participants (alternative analysis combining all three distances).

Lighting condition - task		C1-Cross	C1-Visaul	C1-Auditory	C2-Cross	C2-Visaul	C2-Auditory	C3-Cross	C3-Visaul	C3-Auditory	C4-Cross	C4-Visaul	C4-Auditory
Central Tendency	Mean	0.83	0.66	0.79	0.85	0.75	0.86	0.82	0.66	0.79	0.78	0.6	0.77
	95% CI of Mean	0.79 0.87	0.6 0.73	0.73 0.84	0.81 0.9	0.67 0.78	0.81 0.91	0.77 0.87	0.61 0.72	0.73 0.85	0.73 0.83	0.54 0.66	0.72 0.83
	Median	0.89	0.67	0.89	0.89	0.78	0.89	0.89	0.67	0.89	0.78	0.67	0.78
Normality? (Yes if median is in 95% CI of mean)	automated check	No	Yes	No	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes
Graphical	Histogram	No	No	No	No	No	No	No	Near	No	No	No	No
	Box Plot	No	No	No	No	No	No	No	Yes	No	No	Near	No
Normality?	automated check	No	No	No	No	No	No	No	Near	No	No	Near	No
Measures of dispersion	Skewness (within ± 0.5)	-1.13	-0.741	-1.178	-1.368	-0.706	-1.971	-1.709	-0.36	-1.327	-1258	-0.454	-1.041
		no	no	no	no	no	no	no	yes	no	no	yes	no
	Kurtosis (within ±1.0)	1.51	0.144	0.89	1.461	-0.124	4.72	4.386	-0.548	1.031	1.608	-0.788	0.599
		no	yes	yes	no	yes	no	no	yes	no	no	yes	yes
Normality?	automated check	No	Near	Near	No	Near	No	No	Yes	No	No	Yes	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.011	0.001	0.001	0.003	0.001
		no	no	no	no	no	no	no	no	no	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.003	0.001	0.001	0.001	0.001
		no	no	no	no	no	no	no	no	no	no	no	no
Noramlity?	automated check	No	No	No	No	No	No	No	No	No	No	No	No
Overal Assessment of Normality	select mannually	No	Near	No	No	Near	No	No	Yes	No	No	Near	Near

Table F.19. Performance rate to pedestrian among the 60 participants (alternative analysis combining all three clothing levels).

Lightcondition-task		C1-Cross	C1-Visaul	C1-Auditory	C2-Cross	C2-Visaul	C2-Auditory	C3-Cross	C3-Visaul	C3-Auditory	C4-Cross	C4-Visaul	C4-Auditory
Central Tendency	Mean	0.98	0.96	0.97	0.99	0.97	0.99	0.96	0.94	0.97	0.89	0.85	0.88
	95% CI of Mean	0.96	0.94	0.95	0.97	0.95	0.98	0.93	0.91	0.95	0.85	0.8	0.85
		0.99	0.98	0.99	0.99	0.99	0.99	0.98	0.96	0.98	0.92	0.88	0.92
	Median	1	1	1	1	1	1	1	1	1	0.89	0.89	0.89
Normality? (Yes if median is in 95% CI of mean)	automated check	No	No	No	No	No	No	No	No	No	Yes	No	Yes
Graphical	Histogram	No	No	No	No	No	No	No	No	No	No	No	No
	Box Plot	No	No	No	No	No	No	No	No	No	No	No	No
Normality?	automated check	No	No	No	No	No	No	No	No	No	No	No	No
Measures of dispersion	Skewness (within ± 0.5)	-2.434	-2.786	-3.669	-3.061	-1.987	-2.736	-3.307	-1.407	-1.822	-1.127	-0.943	-0.849
		no	no	no	no	no	no	no	no	no	no	no	no
	Kurtosis (within ±1.0)	5.441	8.94	15.2	9.563	3.116	5.671	13.337	0.785	2.105	0.802	0.351	-0.365
		no	no	no	no	no	no	no	yes	no	yes	yes	yes
Normality?	automated check	No	No	No	No	No	No	No	Near	No	Near	Near	Near
Statistical tests	Shapiro-Wilks (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
		no	no	no	no	no	no	no	no	no	no	no	no
	Kolmogorov-Smirnov (level of significance)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
		no	no	no	no	no	no	no	no	no	no	no	no
Noramlity?	automated check	No	No	No	No	No	No	No	No	No	No	No	No
Overal Assessment of Normality	select mannually	No	No	No	No	No	No	No	No	No	No	No	No

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