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**The Impact of Peripheral Lighting Conditions on Pupillometric
Cognitive Load Assessment**

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Résumé

Évaluer avec précision la charge cognitive est essentiel pour concevoir des systèmes capables de s'adapter aux exigences attentionnelles des utilisateurs. La pupillométrie offre un moyen fiable et non invasif de mesurer la charge cognitive à travers les variations du diamètre pupillaire évoquées par la tâche. Cependant, la pupille est également très sensible à l'illumination environnementale. Bien que les recherches antérieures stabilisent généralement l'éclairage afin de préserver la validité interne, l'ampleur avec laquelle certaines caractéristiques lumineuses modulent la réactivité pupillaire demeure incertaine. Cette thèse examine comment l'intensité lumineuse et l'angle directionnel périphérique influencent la précision de la mesure de la charge cognitive pupillométrique lors d'une tâche de mémoire de travail. À l'aide d'un plan expérimental intra-sujets, quarante-neuf participants ont réalisé des tâches 1-back et 3-back sous quatre conditions d'éclairage manipulées à l'aide d'un Luminosity Dome novateur, construit sur mesure pour contrôler précisément l'intensité lumineuse périphérique (100 lx vs 1000 lx) et l'angle directionnel (11,10° vs 20,75°). La taille pupillaire et la variabilité de la fréquence cardiaque ont été enregistrées comme marqueurs physiologiques de la charge cognitive, en complément de mesures comportementales et subjectives. Les résultats montrent qu'une plus grande complexité de tâche suscitait une dilatation pupillaire augmentée et une diminution de la variabilité cardiaque. Toutefois, ni l'angle directionnel ni l'intensité lumineuse périphérique n'ont significativement modéré la relation entre la complexité de la tâche et les mesures pupillaires de charge cognitive. Ces résultats font progresser la compréhension théorique de l'interaction entre l'illumination environnementale et les mécanismes liés à l'effort cognitif.

Mots clés : Expérience utilisateur • Pupillométrie • Électrocardiographie • Charge cognitive

Méthodes de recherche : Expérience utilisateur • Expérience en laboratoire • Recherche quantitative • Pupillométrie

Abstract

Accurately assessing cognitive load is essential for designing systems that can adapt to users' attentional demands. Pupillometry offers a reliable and non-invasive means of measuring cognitive load through task-evoked changes in pupil diameter. However, because pupil size is also highly sensitive to environmental illumination, concerns remain regarding the robustness of pupillometric measures outside tightly controlled laboratory conditions. Although prior research typically stabilizes lighting to preserve internal validity, the extent to which specific lighting characteristics modulate pupillary reactivity remains unclear. This thesis investigates how peripheral light intensity and directional angle influence the precision of pupillometric-based cognitive load measurement during a working-memory task. Using a within-subjects experimental design, forty-nine participants completed 1-back and 3-back tasks under four lighting conditions manipulated through a custom-built Luminosity Dome that precisely controlled peripheral lighting intensity (100 lx vs. 1000 lx) and directional angle (11.10° vs. 20.75°). Pupil size and heart rate variability were recorded as physiological markers of cognitive load, alongside behavioral and self-reported measures. Results showed that higher task complexity elicited greater pupil dilation and reduced heart rate variability, suggesting that increased cognitive load engages sympathetic activation and impairs task performance accuracy. However, neither directional angle nor intensity of peripheral light significantly moderated the relationship between task complexity and pupil measures of cognitive load. These findings advance theoretical understanding of how environmental illumination interacts with autonomic mechanisms of cognitive effort. Methodologically, the Luminosity Dome offers a novel apparatus for systematically manipulating peripheral light under controlled conditions.

Keywords: User Experience • Pupillometry • Electrocardiography • Cognitive load

Research methods: User Experience • Laboratory experiment • Quantitative research • Pupillometry

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List of abbreviations and acronyms

HCI: Human-Computer interaction

UX: User Experience

CL: Cognitive Load

PLR: Pupillary Light Reflex

TEPR: Task Evoked Pupil Response

ICA: Index of Cognitive Activity

IPA: Index of Pupillary Activity

HRV: Heart Rate Variability

SDNN: Standard Deviation of Normal-to-Normal Intervals

RT: Reaction Time

LC-NE: Locus Coeruleus-Norepinephrine

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As I close this chapter, I’m excited to make space for new and meaningful opportunities. This journey has shaped me in lasting ways, and I look forward to seeing where these lessons lead me next.

Chapter 1

Introduction

1.1 Context and Background

In an increasingly digital and automated world, understanding how humans allocate attention and effort when interacting with complex systems has become a central challenge. Accurate assessment of cognitive load, the mental effort required to perform a task, is essential for advancing human-centered design and enabling technologies that can respond intelligently to users' cognitive states (Duchowski et al., 2018). Reliable measurement helps researchers and practitioners to identify when tasks become overly demanding or insufficiently stimulating, signaling moments where performance or engagement may decline. In the context of Human-Computer Interaction (HCI) and User Experience (UX), these insights support the development of adaptive interfaces capable of adjusting task difficulty, feedback, or visual complexity in real time (Duchowski et al., 2018; Montazer & Ahmadi, 2024). These capabilities align with the growing use of AI-based decision-support tools, which provide context-sensitive guidance that adapts to users' cognitive states and evolving task demands (Xiao et al., 2025). Such adaptivity is especially valuable in domains where situational awareness and mental effort management are critical.

Evidence from public safety and high-risk industries illustrates the scale of the problem. The United States National Highway Traffic Safety Administration reported that 94% of road collisions involved human error in 2018, an indication that many severe crashes can be traced to lapses in human performance (Read et al., 2021; Stewart, 2022). Safety-critical industries, such as in nuclear power (Xiao et al., 2024), aviation (Hämäläinen et al., 2024; Peißl et al., 2018), and healthcare (Mauriz et al., 2023), face similar challenges, where even minor disruptions in cognitive processes, such as distraction, mental overload, or fatigue, can rapidly escalate into catastrophic outcomes (Aricò et al., 2016). Historical industrial disasters, including Bhopal (1984), Piper Alpha (1988), Chernobyl (1986), and the Texaco Refinery explosion (1994), further demonstrate how operator errors within complex integrated human-machine systems have played

central roles in major accidents (Jahangiri et al., 2016). Together, these realities highlight the importance of developing reliable, objective measures of cognitive load. Such tools can inform training, enhance human-system integration, and support the development of adaptive technologies that assist operators as task demands intensify.

Importantly, the relevance of cognitive load assessment extends beyond safety-critical domains and into everyday contexts. Even in routine environments, such as online shopping, cognitive overload can impact decision-making and user experience. Understanding how mental effort shapes consumer choices is therefore essential for developing e-commerce platforms that are both efficient and user-friendly (Mateja et al., 2025), which in turn has direct implications for business outcomes.

Pupillometry has emerged as one of the most promising tools for real-time cognitive load assessment because it is non-invasive, minimally disruptive to task performance, low-cost, and increasingly portable (Liao et al., 2025; Meethal et al., 2024). However, while the pupil provides a sensitive optical index of mental effort, its main limitation is that it is also highly sensitive to environmental lighting, posing a major challenge to its robustness (Sirois & Brisson, 2014).

1.2 Research Gap

Despite decades of research on lighting and pupil dynamics (Sirois & Brisson, 2014), significant theoretical and methodological gaps remain in understanding how illumination affects the reliability of pupillometric cognitive load assessment (Meethal et al., 2024; Pan et al., 2022; Tsukahara & Engle, 2021). Only a limited number of studies have examined pupil responses under varying light conditions, and those that have often lacked methodological precision. Some manipulated ambient lighting without objective illuminance measurements, limiting interpretability (Ong et al., 2019), while others tested only narrow luminance ranges that restricted generalizability (Pan et al., 2022). Still others reported illumination effects but averaged pupil activity across long intervals without distinguishing baseline from task-evoked components (Steinhauer et al., 2004), reducing comparability with more recent component-specific analyses. These methodological inconsistencies may contribute to mixed findings. Some studies report heightened sensitivity to cognitive load in dim environments (Peysakhovich et al., 2015, 2017;

Pfleging et al., 2016), while others observe stronger modulation under bright conditions (Steinhauer et al., 2004). Although this body of work confirms that illumination influences both baseline pupil size and stimulus-evoked changes relative to that baseline, the direction and strength of these effects remain unclear.

Laboratory studies typically rely on constant, controlled lighting to preserve internal validity (Hayes & Petrov, 2016; Mahanama et al., 2022; Pan et al., 2022; Sirois & Brisson, 2014), but these static conditions limit the ecological relevance of current findings and their applicability to real-world settings. The few studies conducted on this topic have focused exclusively on light intensity, assuming uniform and centrally distributed illumination (Meethal et al., 2024). In contrast, real environments involve complex spatial variations in lighting. Despite this ecological importance, no study to date, to the best of our knowledge, systematically examined directional lighting as a source of variation in pupillometry measurement.

1.3 Research Purpose and Objectives

Therefore, this thesis investigates how variations in peripheral light intensity and direction influence the reliability of pupillometric cognitive load measurement during a working-memory task. The central research question guiding this work is:

To what extent can varying intensities and directional angles of peripheral light impact pupillometric measurements of cognitive load?

To answer this question, an experimental study was conducted using a novel apparatus, termed the Luminosity Dome, designed to manipulate peripheral illumination with high precision. Participants completed 1-back and 3-back working-memory tasks (Kirchner, 1958) under four lighting conditions that varied by peripheral intensity and directional angle. Pupil diameter and heart rate variability were recorded as physiological measures of cognitive load, alongside behavioral performance metrics and subjective workload ratings.

This thesis advances both the theoretical and methodological understanding of how lighting influences pupillometric measures of cognitive load. Theoretically, it addresses a key gap in existing literature by examining how peripheral light intensity, and particularly directional angle, influence the precision of task-evoked pupil response

measurement. Introducing directional angle as a new experimental variable, the study further explores how this spatial property of light interacts with task complexity. By manipulating both intensity and directional angle, the study provides new insight into how spatial characteristics of illumination shape the reliability of pupillometry, thereby extending current models of light-pupil interaction and contributing to a more ecologically grounded understanding of cognitive load assessment. Methodologically, this research introduces the Luminosity Dome, a novel experimental apparatus capable of delivering controlled peripheral illumination with adjustable intensity and angle. This innovation bridges the gap between the lighting in tightly controlled laboratory setups and the complex, variable lighting conditions typical of more naturalistic environments, enabling more robust and realistic assessments of cognitive load.

On a practical level, this research offers guidance for designing cognitive-load aware systems that must operate under variable lighting conditions. As pupillometry becomes increasingly integrated into adaptive interfaces, cockpit displays, training simulators, wearable technologies, and human-AI collaboration tools, understanding how peripheral illumination alters pupil-based metrics is essential for ensuring measurement reliability outside tightly controlled laboratory settings. By identifying the lighting conditions under which pupillometric signals remain stable and those under which they become distorted, this study provides actionable insight for researchers and practitioners who rely on pupil data to monitor mental effort in real time. These findings can inform decisions about sensor placement, environmental lighting design, interface calibration, and data-cleaning strategies, ultimately supporting the development of more robust cognitive load assessment pipelines. Beyond safety-critical contexts, the results also have relevance for UX research, commercial eye-tracking applications, and emerging consumer-facing technologies that use the pupil as an input signal. In this sense, the work not only advances scientific understanding but also offers practical recommendations that can improve the accuracy, applicability, and ecological validity of pupillometry-based systems across diverse real-world environments.

1.4 Personal Contribution

This thesis was conducted within the Tech3lab, where several collaborators contributed at various stages of the project. Table 1 outlines the student's individual contributions across each phase of the research process and thesis development. The percentages reflect the estimated proportion of responsibility the student carried for each step.

Table 1. *Contribution and responsibilities in the completion of this thesis*

Research Questions	Defining the research problem - 50% - The broad research question was established prior - Implementing additional variables based on the literature
Literature Review	Development of literature review - 90% - Identifying existing literature on the topic - Assistance from supervisors on identifying foundational papers
Experimental Design	Planning and structuring of experiment - 50% - Establishing experimental protocols and procedures - Incorporating feedback from supervisors
Stimuli	Development of the stimuli - 40% - Members of the Tech3lab developed necessary equipment for the experimental setup
Pre-tests	Testing procedures prior to experimentation - 95% - Pilot testing and refining protocols according to feedback - Validating tools and measures - Ensuring equipment functionality
Ethics	Requesting ethical approval from CER - 40%
Participants Recruitment	Recruitment and management of participants - 80%

	- Conducting participant recruitment, with partial support from HEC's research panel.
Data Collection	Systematic collection of research data - 95% - Research assistants from Tech3lab collected some participant sessions as needed.
Analysis	Pre-processing the data - 50% - The data was pre-processed in part by the tech3lab team. Statistical Analyses - 70% - Support from Tech3lab's statistician in the analysis process
Writing	Writing of the thesis - 100% - All thesis chapters were written independently, with supervisors providing guidance and feedback throughout the revision process.

1.5 Thesis Structure

This thesis is structured into four chapters, followed by a bibliography and appendix. Chapter 1, the introduction, outlines the research context, objectives, and significance of the study. Chapter 2 presents the literature review. Chapter 3 contains the article, offering a detailed account of the study's methodology, data analysis, and findings related to pupillary cognitive load assessment across varying peripheral light conditions. Chapter 4, the conclusion, synthesizes the major findings, highlights the study's contributions to the existing body of knowledge, identifies its limitations, and outlines directions for future research. The bibliography includes all referenced works, and the appendix provides supplementary materials relevant to the study.

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Chapter 2

Literature review

Ambient lighting refers to the general background illumination within an environment (Bogucki et al., 2024). In laboratory research, ambient lighting is typically quantified through illuminance, a measure expressed in lux that captures how much light from any direction falls onto a given surface, such as the pupil (Bao et al., 2021; Mathôt & Vilotijević, 2022). Ong et al. (2019, p. 317) describe “bright ambient lighting conditions” as “overhead LED lighting in a room with ample natural light,” and “dark ambient conditions” as “a windowless or drawn blinded room with no overhead light source.” In the present study, however, we use the term peripheral light to describe illumination occurring within the peripheral field of vision, meaning the outer area of the visual field where movement and shapes can still be detected (Merriam-Webster, 2025). This distinction stems from the configuration of our novel experimental apparatus, the Luminosity Dome, which was positioned in front of the participants but behind the monitor on which they completed the tasks. As such, it did not provide full environmental or overhead illumination, nor direct frontal lighting. Given that this is the first study to employ such an apparatus, creating a new definition for peripheral light was necessary to capture its unique lighting configuration. Consequently, peripheral light or peripheral illumination serves as an intermediate definition between ambient and direct lighting. For the literature review, we nevertheless included the term ambient in our database searches to ensure comprehensiveness, as it represents the most closely related and frequently used construct in existing research.

2.1 Theoretical Framing of Cognitive Load

The construct of *cognitive load* originates from Cognitive Load Theory (CLT), developed by John Sweller (1988), defined as the mental effort that a task requires (Wigert & Sutton, 2023). Since its introduction, CLT has become a widely used and empirically supported framework for understanding learning and performance (Bannert, 2002). CLT proposes that working memory has a limited capacity, and that learning and performance outcomes depend on how task demands interact with this capacity. Cognitive load induced

by the complexity of instructional material is referred to as *intrinsic cognitive load*. For learning to occur, a certain level of intrinsic cognitive load is necessary, as learners must engage with the instructional stimuli. Thus, CLT's central objective is to optimize learning by managing intrinsic cognitive load so that it remains within the available limits of working-memory (Greenberg & Zheng, 2022). When cognitive demands exceed this capacity, cognitive overload can occur, hindering both learning and performance (Paas & Van Merriënboer, 2020). Although developed in educational psychology, CLT has since been extended to domains such as HCI, where tasks and interface design are manipulated to examine cognitive load under varying performance contexts (Hollender et al., 2010).

Complementary to CLT, Kahneman's (1973) theory of attention and effort conceptualized attention as a capacity-limited system in which effort reflects the dynamic allocation of cognitive resources. Within this framework, cognitive effort is interpreted as an increase in metabolic activity in the brain associated with sympathetic dominance of the autonomic nervous system, observable through physiological markers such as pupil dilation (Bruya & Tang, 2018).

A pioneering demonstration of this link was provided by Kahneman and Beatty (1966), who demonstrated that pupil diameter increases systematically with working-memory load. Participants retaining more digits in working memory exhibited greater dilation, which returned to baseline once the task ended. This finding laid the groundwork for the use of pupillometry as an objective measure of cognitive load. Subsequent research has repeatedly confirmed that changes in pupil diameter reliably reflect the intensity of working-memory processing (Fietz et al., 2022).

2.2 Neurophysiological Foundations of Pupillometry

The pupil is controlled by two opposing branches of the autonomic nervous system (ANS): The *parasympathetic constriction pathway* and the *sympathetic dilation pathway*. The iris sphincter muscle, triggered by the parasympathetic branch, encircles the pupil and constricts it in response to light, an essential component of the pupillary light reflex (PLR). Conversely, the iris dilator muscle, controlled by the sympathetic branch, pulls the iris outward when contracting, causing pupil dilation associated with arousal, wakefulness, and the fight-or-flight response. This dilation pathway originates subcortically in the hypothalamus and the locus coeruleus (LC) before connecting to the

iris dilator muscle. The balance between these pathways determines instantaneous pupil size (Ferencová et al., 2021; Mathôt, 2018).

The relationship between pupil size and activity in the locus coeruleus-norepinephrine (LC-NE) system was first demonstrated in primates (Rajkowski et al., 1994), and later in humans (Murphy et al., 2014). The LC is a small brainstem nucleus that provides most norepinephrine to the brain, playing a central role in regulating arousal, attention, and adaptive behavior (Peysakhovich et al., 2017). Cognitive effort triggers the sympathetic branch of the ANS, often via the LC-NE system, producing task-evoked pupillary responses (TEPRs). TEPRs are brief pupil dilations relative to a tonic baseline, reflecting phasic fluctuations in moment-to-moment changes in cognitive demand (Strauch et al., 2022). The LC itself also operates in these two principal activation modes: the phasic mode, characterized by rapid neuronal firing that enhances task-specific performance and attentional focus, and the tonic mode, marked by elevated baseline activity that supports sustained processing but is also associated with reduced task engagement and exploratory behavior (Sirois & Brisson, 2014).

Beatty (1982) formalized the TEPR as a central construct in cognitive load pupillometry, stating that transient increases in pupil diameter correspond to the intensity of cognitive processing. Since then, numerous studies have replicated the pattern across diverse paradigms, including n-back working-memory tasks (Belayachi et al., 2015; Brouwer et al., 2014; Hopstaken et al., 2015; Niezgoda et al., 2015; Pehlivanoglu et al., 2014), mental arithmetic (Jainta & Baccino, 2010; Klingner et al., 2011), and dual-task coordination (Katidioti et al., 2014). Moreover, a meta-analytic review has consistently shown that pupil dilation increases with task difficulty and the number of items held in working memory (Van Der Wel & Van Steenbergen, 2018).

Because the PLR strongly constrains baseline diameter, distinguishing light-induced constriction from cognitive-induced dilation is critical. The PLR is primarily a parasympathetic reflex to retinal illumination changes, while the TEPR originates from sympathetic excitation. However, both act on the same Iris muscles, leading to overlapping temporal dynamics. This interaction renders ambient light one of the most consequential confounds in cognitive load pupillometry (Mathôt, 2018; Sirois & Brisson, 2014; Strauch et al., 2022).

2.3 Light-Pupil Interaction as Confound of Cognitive Load Assessment

The PLR constrains the dynamic range within which cognitive dilation can occur. Under bright illumination, the baseline pupil diameter is small, leaving little room for additional dilation; under dim conditions, the baseline is larger, and dilations are more pronounced. Furthermore, many cognitive load studies neglect to specify illuminance levels or control for display contrast, thereby conflating PLR effects with task-evoked changes (Sirois & Brisson, 2014). Similarly, Strauch et al. (2022) demonstrated that even subtle fluctuations in monitor brightness can introduce systematic noise into TEPR amplitude, emphasizing the necessity of calibrated, constant lighting conditions.

A growing body of research has examined how lighting conditions interact with cognitive load manipulations. Peysakhovich et al. (2015, 2017) systematically varied ambient illuminance during dual-task paradigms and found that bright light reduced both baseline pupil size and task-evoked dilation amplitude. This decrease implies that excessive illuminance compresses the physiological range available for cognitive responses. Ong et al. (2019) extended these findings, demonstrating that illuminance not only alters baseline diameter but also shifts the timing of peak dilation, indicating slower recovery under dim light. Although Beatty (1982) initially proposed that TEPR amplitude remains a consistent indicator of cognitive activity across lighting conditions, subsequent results have been mixed. For instance, Bradshaw (1969) observed no significant difference in dilation peaks between bright and dim conditions during a simple reaction task, while Pomplun and Sunkara (2003) and Xu et al. (2011) similarly found no interaction between cognitive load and illuminance in visual and arithmetic tasks (as reviewed in Peysakhovich, 2015). Shelton et al. (2022) and Bao et al. (2021) demonstrated that ambient light levels and color temperature influence both perceived workload and physiological responses, including changes in heart rate and pupil size. Similarly, Shahidi et al. (2025) observed that higher illuminance in simulated driving environments improved subjective alertness but reduced pupil dilation amplitude. Holmskär et al. (2025) found that quantitative pupillometry metrics vary systematically with ambient illuminance, even when cognitive demands remain constant. Collectively, these inconsistencies highlight that the interaction between light level and cognitive dilation remains unresolved.

More recent studies have replicated and refined these effects. Pfleging et al. (2016) examined driving-simulator tasks under dynamic daylight conditions and reported that varying illumination confounded the interpretation of TEPRs as indicators of situational awareness. Mahanama et al. (2022) further demonstrated that local contrast and spectral composition of light, rather than intensity alone, modulate both baseline pupil size (tonic) and stimulus-evoked (phasic) pupil changes relative to that baseline. Meethal et al. (2024) explored pupillometry in field environments and emphasized that ambient light must be treated as a continuous covariate rather than a fixed control variable. However, despite increasing attention to lighting effects, the literature explicitly examining the directional angle of ambient illumination remains scarce. Williamson et al. (2023) and Shahidi et al. (2025) reported that side-angled lighting produces greater eye discomfort and localized glare, which can induce tonic constriction and alter baseline pupil size. Shelton et al. (2022) further suggested that off-axis light affects attention distribution and visual salience, indirectly influencing cognitive load responses. Despite these observations, systematic investigations of directional light effects on pupillometry remain rare. Collectively, these studies converge on the conclusion that light intensity and directionality may significantly distort the relationship between cognitive demand and pupil dynamics.

2.4 Integrating Multimodal Physiological Indices of Cognitive Load

While the pupil provides a direct optical window into cognitive effort, it represents only one facet of autonomic regulation. Heart rate variability (HRV), particularly the standard deviation of NN intervals (SDNN) offers complementary information about parasympathetic withdrawal and sympathetic activation. SDNN is a time-domain index of HRV reflecting the overall variability in heart rate (Kim et al., 2018). Because both sympathetic and parasympathetic systems co-modulate during effortful cognition, integrating HRV with pupillometry enables a richer characterization of lived cognitive load (Alshanskaia et al., 2024).

HRV indices quantify fluctuations between successive heartbeats and thus index the flexibility of autonomic control. Cao et al. (2019) found that SDNN decreased as working-memory load increases, signifying reduced parasympathetic influence and

heightened sympathetic arousal during cognitively demanding tasks. Kim et al. (2018) similarly demonstrated that low-frequency HRV components diminish as attentional effort intensifies, while high frequency components related to respiration remain stable. These findings align with the notion that cognitive effort is accompanied by autonomic shifts toward sympathetic activation. Table 2 summarizes the constructs investigated in the present study and their definitions.

Table 2. *Constructs of Interest*

Construct	Definition
Task Complexity	Resource requirements imposed by a task (Liu & Li, 2012).
Peripheral Light	Illumination occurring within the peripheral field of vision • Illumination: the amount of light that falls from any direction onto a surface (such as the pupil) (Mathôt & Vilotijević, 2022).
Cognitive Load	The mental effort that a task requires (Sweller, 1988; Wigert & Sutton, 2023).
Task Performance	• Accuracy: proportion of correct responses to targets in an n-back block (Meule, 2017). • Reaction Time: time interval between the display of the letter and a response to a detected target in an n-back block (Haucke et al., 2025)

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Chapter 3

The Impact of Peripheral Illuminance Intensity and Direction on Pupillometric Cognitive Load Assessment

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Abstract: Pupillometry provides a reliable, non-invasive measure of cognitive load through pupil diameter changes associated with mental effort. However, its reliability can be compromised by lighting conditions. Most existing research controls for lighting by maintaining constant illumination throughout the study, but the extent to which lighting conditions modulate pupillary reactivity remains unclear. This study examined how peripheral light intensity and directional angle influenced the precision of pupillometric measurements of cognitive load during working-memory tasks. Using a within-subjects experimental design, forty-nine participants completed 1-back and 3-back tasks under four lighting conditions that varied in peripheral intensity (100 lx vs. 1000 lx) and directional angle (11.10° vs. 20.75°) within a custom-built luminosity apparatus. Pupil size and heart rate variability were recorded as physiological markers of cognitive load, alongside behavioral and self-reported measures. Results showed that higher task complexity elicited greater pupil dilation and reduced heart rate variation, confirming that increased cognitive load engages sympathetic activation and impairs task performance accuracy. Neither the directional angle or intensity of peripheral light significantly moderated the relationship between task complexity and pupil measures of cognitive load. These findings advance theoretical understanding of how environmental illumination interacts with autonomic mechanisms of cognitive effort. Methodologically, the Luminosity Dome offers a novel apparatus for systematically manipulating peripheral light under controlled conditions.

Keywords: User Experience • Pupillometry • Electrocardiography • Eye tracking

3.1 Introduction

Pupillometry, the measurement of pupil diameter changes as an indicator of cognitive activity, has long been a widely used method of assessing cognitive load (Hess & Polt, 1964; Kahneman & Beatty, 1966; Peysakhovich et al., 2015). However, its robustness as a methodological tool is limited by a major challenge: pupil responses are highly sensitive to lighting. The pupillary light reflex (PLR) causes constriction in bright conditions and dilation in darkness, making it difficult to distinguish between light-induced reflexes and cognitively driven responses (Sirois & Brisson, 2014).

Accurate estimation of cognitive load is essential for advancing Human-Computer Interaction (HCI) and User Experience (UX) design, as it enables adaptive systems to recognize and respond to users' cognitive states. In turn, this can greatly enhance the experience and performance of users interacting with computers or machinery such as in education, aviation and medicine (Duchowski et al., 2018; Hollender et al., 2010; Mauriz et al., 2023; Palinko et al., 2010; Peißl et al., 2018). These systems could detect when a task is becoming too demanding or is insufficiently challenging and adapt the task difficulty. Their effectiveness, however, depends on the ability to accurately estimate cognitive load with minimal interference with task execution (Duchowski et al., 2018).

This capability is particularly valuable in high-stakes environments such as aviation, where simulators have long been used to train pilots. Eye tracking systems have been increasingly integrated into these simulators to monitor pilot workload and provide adaptive feedback that improves training effectiveness and operational safety (Hämäläinen et al., 2024; Peißl et al., 2018). While aviation exemplifies a critical use case, accurate cognitive load estimation is equally relevant to broader HCI contexts, where dynamic adaptation to users' cognitive states, whether in complex control systems or everyday computing, can enhance both usability and performance (Hollender et al., 2010).

To address the sensitivity of pupillometry to environmental lighting, researchers have typically relied on tightly controlled laboratory environments with stable lighting conditions (Hayes & Petrov, 2016; Mahanama et al., 2022; Pan et al., 2022; Sirois & Brisson, 2014). While such methods enhance internal validity, they constrain ecological validity, limiting the applicability of pupillometric findings to real-world contexts.

Moreover, addressing the influence of peripheral light is essential if pupillometry is to evolve into a robust and ecologically valid tool for workload assessment outside the laboratory, as this methodology becomes more portable and affordable (Liao et al., 2025; Meethal et al., 2024).

Only a small body of research has examined pupillometric cognitive load assessment under changing illumination, and the resulting evidence remains inconsistent. While this work generally acknowledges that illuminance modulates both baseline pupil size (tonic) and stimulus-evoked pupil changes (phasic) relative to that baseline, methodological inconsistencies limit interpretability. Some studies manipulated lighting without objective illuminance measurements (Ong et al., 2019) or examined only narrow luminance ranges (Pan et al., 2022), restricting precision and generalizability. Others reported illumination effects but averaged pupil activity across long intervals without distinguishing baseline from task-evoked components (Steinhauer et al., 2004), reducing comparability with more recent component-specific analyses. Some evidence suggests that dimmer environments heighten sensitivity to cognitive load by increasing tonic diameter and amplifying task-evoked dilation (Peysakhovich et al., 2015, 2017; Pflieger et al., 2016), whereas other work demonstrates greater load-related modulation under brighter conditions (Steinhauer et al., 2004). Thus, the literature offers conflicting evidence of whether low or high illuminance best preserves the dynamic range of pupillary responses to cognitive demand.

Beyond raw pupillometry, algorithmic approaches have been widely adopted. The Index of Cognitive Activity (ICA) has been tested and found to be relatively insensitive to illuminance conditions (Marshall, 2002). However, because ICA algorithms are proprietary and not fully disclosed, methodological transparency is limited (Mahanama et al., 2022). By contrast, the Index of Pupillary Activity (IPA), a metric inspired by the ICA, has made its computation processes accessible, providing a potential alternative for future validation (Duchowski et al., 2018).

While prior studies have explored pupillometry under general changes in illumination, few have systematically manipulated peripheral light variables such as intensity, and none have investigated directional angle (Meethal et al., 2024). Consequently, it remains unclear how resilient pupillometric measures are to illuminance

variation and whether methodological adjustments could improve their robustness in field applications.

Accordingly, future research should extend current findings by testing a broader and more extreme range of luminance conditions, as the luminance levels tested in a study by Pan et al. (2022) only ranged from 0.92 to 233.37 cd/m². Moreover, Peysakhovich (2015) emphasized the importance of validating pupillometric measures by simultaneously recording cardiac, respiratory, and pupillary activity across different illuminance environments and over longer observational windows. The present study sought to answer the following research question:

To what extent can varying intensities and directional angles of peripheral light impact pupillometric measurements of cognitive load?

This research helps to address the limited understanding of how peripheral light intensity and direction influence the reliability of pupillometric measures of cognitive load by experimentally manipulating task complexity under several peripheral light conditions. Task complexity was varied using an N-back working-memory paradigm, while peripheral illumination was systematically manipulated in both intensity and directional angle. Peripheral light was delivered via an experimental apparatus developed at our research laboratory specifically for this study.

This study appears to be one of very few to assess impacts of peripheral light intensity on pupillometry, and the first to investigate directional angle. Its novelty lies in the use of an experimental apparatus termed the Luminosity Dome, which allows precise, reproducible control over peripheral light intensity and direction.

Our findings make three key contributions. First, our results suggest that increasing task complexity reliably elevates cognitive load, reflected in larger pupil diameter and reduced heart rate variability, which were in turn associated with lower task performance. This extends prior work linking physiological indicators to cognitive efficiency. Second, the analyses show that neither the directional angle nor the intensity of peripheral light significantly moderated the effect of task complexity on pupillometric measures of cognitive load. This contributes to emerging research on how environmental illumination shapes pupillary reactivity, highlighting that lighting factors may shift

baseline pupil size without altering the underlying cognitive response. Third, by introducing the Luminosity Dome as a controlled method for manipulating peripheral illumination, this study offers both methodological and theoretical contributions. These findings may help clarify the threshold under which pupillometry can serve as a valid index of cognitive load in environments with dynamic lighting and offer methodological advances for cognitive workload assessment in field applications. It provides new empirical evidence delineating how specific light parameters affect pupillometric measurement and helps clarify the conditions under which pupillometry can serve as a valid index of cognitive load in dynamic lighting environments, with implications for field-based workload assessment.

This article outlines the experimental design and data collection procedures, followed by the main analyses and findings. We then discuss their theoretical, methodological and practical implications, and conclude by addressing the study's limitations and directions for future research.

3.2 Hypothesis Development

Prior research has consistently demonstrated that task complexity modulates cognitive load and performance in ways consistent with the Yerkes-Dodson law (1908). This framework posits that performance improves with increasing task demands only up to an optimal point, after which excessive difficulty leads to performance decline (Cohen, 2018). Cognitive Load Theory (CLT) provides a complementary explanation for this pattern by emphasizing that task complexity directly influences intrinsic cognitive load by imposing greater demands on the limited capacity of working memory (Sweller, 1988; Wigert & Sutton, 2023). As task difficulty increases, these demands consume a larger proportion of available cognitive resources, leaving fewer resources for efficient task execution and thereby elevating the risk of performance breakdown once capacity limits are exceeded (Paas & Van Merriënboer, 2020).

Empirical findings align with these theoretical predictions. Across multiple studies, increases in N-back level reliably produce greater cognitive load, reflected in both subjective ratings and physiological indicators (Belayachi et al., 2015; Brouwer et al., 2014; Hopstaken et al., 2015; Niezgoda et al., 2015; Pehlivanoglu et al., 2014). Notably,

this heightened load is frequently accompanied by measurable reductions in performance accuracy. Van der Meer et al. (2010), for instance, observed that participants showed larger task-evoked pupil dilation and reduced accuracy in high-load conditions, indicating that rising cognitive demands both increased load and impaired task success. Such findings support the notion that performance deteriorates once task complexity exceeds an individual's processing bandwidth, consistent with CLT and the Yerkes-Dodson framework.

Physiological evidence further reinforces these relationships. Classic pupillometry research established that pupil diameter systematically increases with working memory load (Beatty, 1982; Kahneman & Beatty, 1966), and more recent work confirms that dilation remains a robust indicator of cognitive effort across varying N-back difficulty levels (Fietz et al., 2022). Together, these theoretical and empirical insights converge on the expectation that more complex tasks elicit greater cognitive load and that, beyond a certain threshold, elevated load impairs performance. Based on this reasoning, we hypothesize that:

H1. Task complexity is positively associated with cognitive load

H2. Cognitive load is negatively associated with performance

Task-evoked pupillary responses (TEPRs) are widely regarded as reliable physiological indices of cognitive load, with studies showing that pupil dilation scales with working-memory demands (Beatty, 1982; Kahneman & Beatty, 1966; Van Der Wel & Van Steenbergen, 2018). This dilation reflects Locus Coeruleus-Norepinephrine (LC-NE) system mobilization of cognitive resources and is expressed as a phasic increase in pupil diameter relative to baseline. However, the magnitude of these cognitive dilations is constrained by the PLR, which determines the tonic operating range of the pupil. When environmental illumination increases, the PLR induces constriction that reduces baseline pupil size and thereby limits the amplitude with which cognitive dilations can be expressed (Sirois & Brisson, 2014).

Although findings across studies are not fully consistent, a substantial portion of the literature indicates that illumination can decrease the physiological range available for

cognitive responses. Several studies report that brighter illumination reduces both baseline pupil size and TEPR amplitude, suggesting that excessive illuminance may compress the dynamic range within which cognitive load can be detected (Mathôt, 2018; Peysakhovich et al., 2015, 2017; Sirois & Brisson, 2014). More recent research extends these findings by demonstrating that properties such as brightness and color temperature shape both subjective workload and physiological measures, including heart rate and pupil diameter (Bao et al., 2021; Shahidi et al., 2025; Shelton et al., 2022).

At the same time, some earlier studies reported little to no interaction between illuminance and task-evoked pupil dilation, indicating that illumination effects on TEPRs are not universally observed (Bradshaw, 1969; Pomplun & Sunkara, 2003; Xu et al., 2011). These mixed findings highlight that the mechanisms through which environmental light shapes cognitive dilations remain incompletely understood. Nonetheless, the broader pattern in the literature, particularly in more recent work, suggests that higher illumination often reduces the measurable magnitude of pupillary responses. Based on this reasoning, we hypothesize that:

H3a. Intensity of peripheral light negatively moderates the relationship between task complexity and cognitive load, such that higher peripheral light intensity reduces changes in pupil size associated with increases in task complexity

Beyond illumination intensity, the direction from which light enters the visual field may also alter pupillary reactivity. Evidence from lighting ergonomics suggests that side-angled or off-axis illumination can produce localized glare, elevate visual discomfort, and induce tonic constriction of the pupil, even when overall illuminance remains constant (Williamson et al., 2023). Such glare effects reduce contrast sensitivity and increase visual load, leading the oculomotor system to adopt a more constricted baseline as a protective response. Research in applied cognitive settings similarly shows that asymmetric or oblique light sources can alter alertness, visual comfort, subjective workload, and pupillary dynamics across different task conditions (Shahidi et al., 2025). Although these studies do not isolate TEPRs under controlled manipulations of directional

angle, together they suggest that off-axis illumination may shift the tonic pupil state in ways that influence the measurable range of cognitive dilations.

Directional angle of peripheral lighting may also affect attentional allocation, particularly when peripheral light competes subtly with task-related stimuli. Studies examining peripheral visual events have shown that even unobtrusive cues can alter attentional focus and working-memory performance (Shelton et al., 2022). Accordingly, directional light entering from the periphery may act as a mild distractor, redirecting visual resources under high-load conditions. Because TEPRs are sensitive to both cognitive effort and attentional shifts, such off-axis lighting could disrupt baseline pupil stability or alter the amplitude of task-evoked dilations.

Taken together, these findings suggest that directional angle may reduce the precision of pupillometric cognitive load estimation not only through physiological mechanisms (e.g., glare-induced constriction) but also through perceptual and attentional pathways. Given that empirical work on directional lighting and pupillometry remains limited, this relationship is examined through an exploratory lens. We hypothesize that:

H3b. Directional angle of peripheral light moderates the relationship between task complexity and cognitive load, such that changes in directional angle alter the magnitude of pupil-size changes associated with increases in task complexity

The relationships between constructs hypothesized above are reflected in the proposed research model shown in Figure 1.

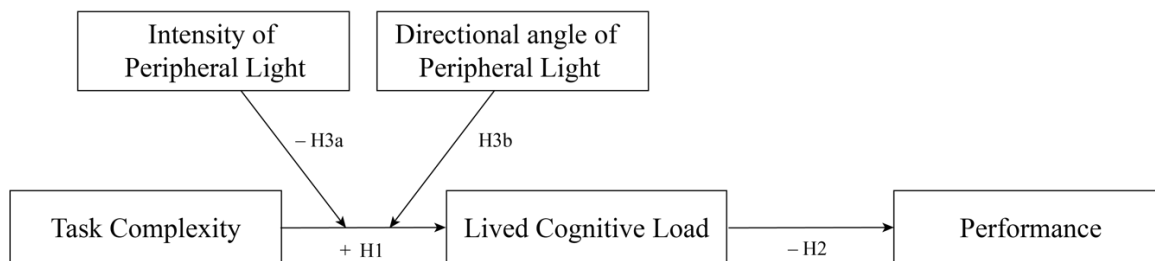


Figure 1. Proposed Research Model

3.3 Methods

3.3.1 Subjects

The subjects were 49 healthy individuals (18 males, all right-handed, age 27 ± 6.93 years), recruited through convenience sampling and consisting primarily of university students, along with some professionals. All participants reported normal or corrected to normal vision and did not suffer from any skin allergies or epilepsy. Written informed consent was obtained from all participants in accordance with the requirements of our institution's ethical board (2025-6354). Participants received \$30 compensation for their participation in the study.

3.3.2 Experimental Setup

The study employed a within-subjects $2 \times 2 \times 2$ factorial design, with factors being peripheral lighting angle (close vs. far), lighting intensity (low vs. high), and task complexity (1-back vs. 3-back). This experimental design allows us to assess the independent contributions of peripheral light angle, peripheral lighting intensity, and task complexity, while also examining how these factors may combine to influence cognitive load. Incorporating all three variables within a single factorial structure enables efficient comparison of their main effects and supports the examination of interaction terms, which are essential for testing moderation hypotheses (Haerling (Adamson) & Prion, 2020). Because each participant completes all experimental conditions, within-subjects designs minimize the influence of individual differences on outcome measures. Therefore, enhancing statistical power, making it easier to detect effects attributable to the manipulated variables (Elmes, 2024). Additionally, a within-subjects design requires fewer participants to achieve adequate statistical power. This was particularly relevant in the present study, which relied on a sample of 49 participants (Elmes, 2024).

The experiment was conducted in a dark room, with artificial lights turned off, and the windows were covered to prevent external light from entering. Participants were seated at a viewing distance of approximately 65cm from a 23.8-inch LCD screen-based eye tracker (1920x1080 pixels screen resolution; 60Hz refresh rate), without the use of a head immobilization device, consistent with prior cognitive pupillometry research investigating environmental lighting influences (Peysakhovich et al., 2015, 2017).

To manipulate peripheral light, we developed a custom Luminosity Dome positioned behind the monitor, shown in Figure 2. Four regions of the dome were used to vary peripheral lighting intensity and directional angle. The dome was divided into two hemispheres: the upper hemisphere, defined as *far* from the focal point of the monitor, and the lower hemisphere, defined as *close* to the screen-based eye tracker. Within each hemisphere, two symmetrical areas were paired such that they were always illuminated simultaneously. Peripheral light intensity was varied at two levels: low (approximately 100 lx at the site of the participant's eyes) and high (approximately 1000 lx). These illuminance levels were measured with a handheld light meter by positioning the sensor at the approximate location of the participant's eyes and orienting it toward the screen, following recommended procedures in cognitive pupillometry (Mathôt & Vilotijević, 2022).

Illuminance values correspond to the International Commission of Illumination (CIE) Sky Brightness Distribution Model, which defines typical states of sky brightness distribution used in research (Lin et al., 2022; Zhu et al., 2024). Because the screen on which participants completed the task also emitted light, the measured values of 100 lx and 1000 lx values inherently included both the illuminance contribution of the dome and the screen at the site of the participant's eyes. During the baseline block, in which no peripheral light was present, and the screen displayed a uniform grey background with lighter grey letters, illuminance at the site of the participant's eyes was approximately 12.95 lx. The low intensity condition therefore needed to exceed this baseline level to constitute a meaningful manipulation. Therefore, illumination levels below 10 lx, the CIE-defined dawn/dusk category, were excluded. The next appropriate CIE-defined level "overcast 1," corresponding to approximately 100 lx, was selected as the low intensity condition. The high intensity condition of 1000 lx corresponded to "overcast 2," matched the maximum output of the Luminosity dome at the time of testing and remained comfortable for participants during pre-testing. Together, these levels provided an ecologically grounded and appropriate range of peripheral lighting intensities for evaluating their influence on pupillometric measurement. Intensity levels of environmental lighting according to the CIE Sky Brightness Distribution Model are shown in Table 3.

Table 3. *Intensity Levels according to CIE Sky Brightness Distribution Model*

Environmental light	Environmental illumination (lx)
Full Moon Night 1	0.1
Full Moon Night 2	1
Dawn/dusk	10
Overcast1	100
Overcast 2	1000
Sunny day 1	10000
Sunny day 2	50000
Direct light on sunny days	110000

The task monitor served as a central reference point, and directional angles were selected to maximize peripheral contrast relative to it. The upper hemisphere represented the region farthest from the monitor and was selected first. To create the widest geometric contrast, the lower hemisphere was chosen as the opposing condition, as it represented the most distinct available peripheral position without being fully obstructed by the screen.

Accordingly, the upper hemisphere (*far*) was positioned at 20.75 degrees, and the lower hemisphere (*close*) at 11.10 degrees from the site of the participant's eye. These angles corresponded to the maximum and minimum peripheral positions permitted by the geometry of the Luminosity Dome and its alignment with the task monitor, allowing us to capture the widest angular range available within the apparatus. Angles were measured with a digital inclinometer positioned at the approximate location of the participant's eyes and directed toward the illuminated dome regions. Selecting the two most distinct angles provided a strong contrast in peripheral illumination geometry. This design choice aligns with recommendations to examine broader and more diverse lighting configurations when evaluating how illumination parameters influence pupil-based measures (Pan et al., 2022).

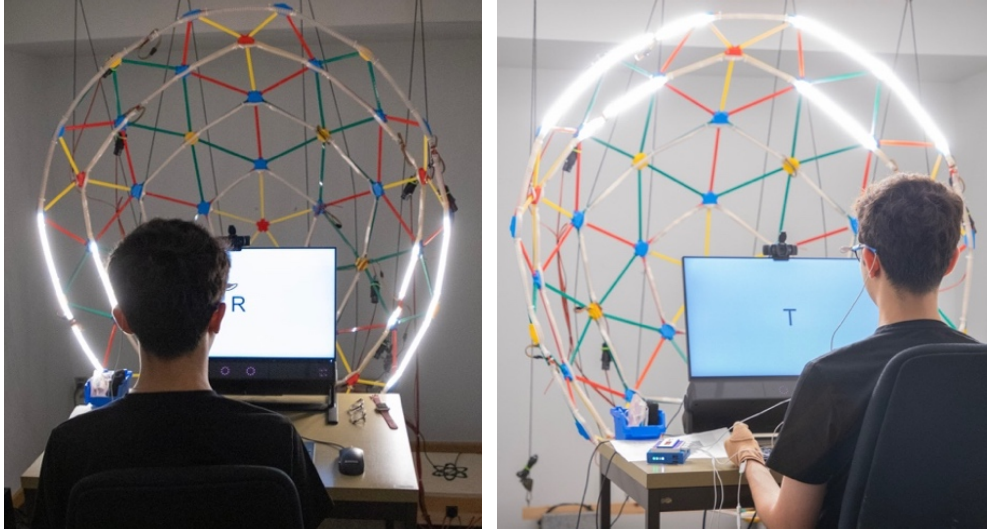


Figure 2. Luminosity dome in close-low (left) and far-high conditions (right).

3.3.3 Procedure

Before each participant arrived, the researcher launched the necessary software and configured all data recording and synchronization tools. Individual profiles were created using a standardized naming convention. Upon arrival, participants were instructed to store personal items in secure lockers, silence their phones, discard of chewing gum, and to remove jewelry to prevent interference with ECG signals. They were offered a restroom break before reading and signing the Qualtrics consent form on an iPad, after which the moderator recorded demographic information and addressed any questions.

Physiological setup began with placing ECG sensors under each clavicle and a third on the participant's lower left rib. The wires were connected to the Cobalt BlueBox system (Courtemanche et al., 2022; Léger et al., 2022), and signal quality was verified by having the participant take a deep breath to ensure clear visibility of the cardiac electrical waveform. Once confirmed, the BlueBox was temporarily turned off. Once this was ensured the blue box was turned off. The moderator then informed the participant that all room lighting would be turned off for eye-tracker calibration. After calibration, both the eye-tracker and BlueBox recordings were initiated, and participants proceeded to the Qualtrics pre-task questionnaire.

Each participant was assigned a randomized order of n-back task conditions, and instructions for each n level were provided to the participant in verbal and written formats.

Once participants confirmed they did not have any further questions regarding the task, the 1-back or 3-back task was launched in PsychoPy under each lighting condition. After completing all lighting conditions for a given task complexity, participants completed a post-task questionnaire. At the end of the session, all recordings were saved using the appropriate naming convention. The researcher then removed the physiological sensors, cleaned the attachment sites, and facilitated the compensation process. Participants were thanked for their participation and escorted out of the laboratory.

3.3.4 Task

Task complexity was operationalized using the N-back paradigm, in which participants indicate whether the currently presented letter matches the letter presented n trials earlier. Thus, task difficulty increases with increasing n (Kirchner, 1958). In the present study two levels of task complexity were produced with the N-back task, the 1-back and the 3-back. The task was administered using PsychoPy software.

Participants first completed a baseline block, consisting of either a 1-back or 3-back (randomized), under a uniform gray background with letters in light gray. No peripheral light was present during this block. This produced minimal visual contrast, allowing comparisons with the experimental conditions. In pupillometry research, baseline measures are assumed to reflect the tonic component of pupil activity, while stimulus-evoked changes relative to this baseline are interpreted as the phasic component (Williamson et al., 2023).

Following the baseline, blocks combined lighting and task manipulations, with four repetitions per N-back level in a randomized order. In these blocks, the background remained gray, but letters were displayed in black. As illustrated in Figure 3, each block began with a centrally displayed cue and instructions for either the 1-back or 3-back and remained until the participants pressed the space bar to initiate the task. Stimuli were presented for 500 ms, followed by a 2000 ms inter-trial interval, consistent with previous pupillometry studies using the n-back task (Herff et al., 2014; Yeung et al., 2021). Each block contained 20 trials, including four targets, and participants responded to targets by pressing the space bar. The experiment lasted approximately 45 minutes in total.

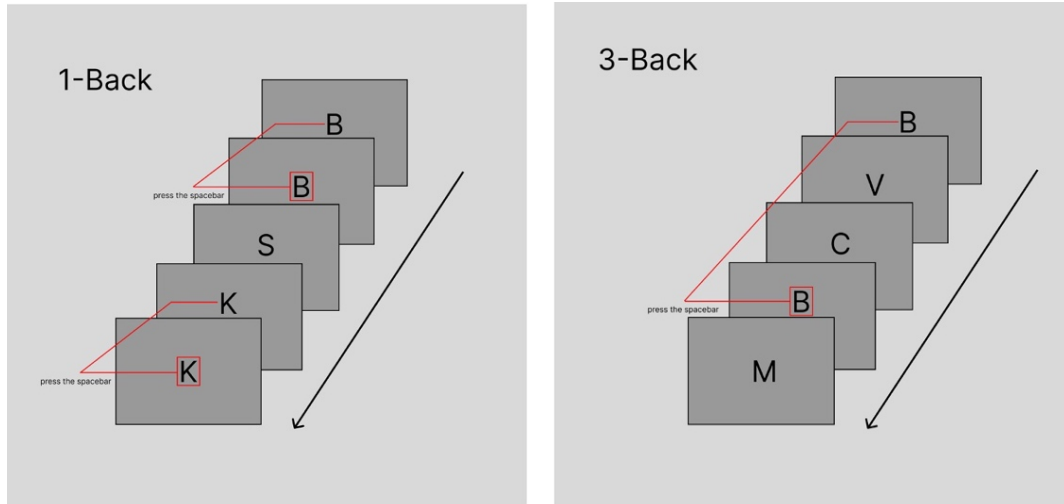


Figure 3. Illustrations of the N-back Task paradigm.

3.3.5 Questionnaires

Questionnaires were administered via Qualtrics (Provo, United States, 2025) on the same monitor used for the experimental task. Pre-task measures included the Stanford Sleepiness Scale (Hoddes et al., 1972), the Leiden Visual Sensitivity Scale (Perenboom et al., 2018), and the Visual Fatigue Scale (Heuer et al., 1989), which were used to assess potential confounding factors. After each N-back block, participants completed the NASA Task Load Index (NASA-TLX) (Hart & Staveland, 1988). Upon completing all task segments, participants again completed the Visual Fatigue Scale.

3.3.6 Pupillometry

Participants' gaze position and pupil size were recorded at 600Hz using a Tobii Pro Spectrum eye tracker (Tobii Technology AB, Danderyd, Sweden) in conjunction with Tobii Pro Lab software. The device uses video-based pupil and corneal reflection eye tracking with both dark and bright pupil illumination modes. Stereo images of both eyes were captured using dual cameras, allowing for robust three-dimensional pupil size estimation. At the beginning of the experiment, a 5-point calibration was validated with four additional fixation points, until the precision of gaze position was inferior to 1.5°.

3.2.7 Heart Rate Variability

HRV was included as a secondary physiological measure of cognitive load. Electrocardiogram (ECG) signals were acquired using a Cobalt Bluebox system

(Courtemanche et al., 2022; Léger et al., 2022), at a sampling rate of 100Hz. ECG was recorded using three electrodes placed below the left and right clavicles, and lower left ribs, in line with previous studies using ECG (Wagner et al., 2021). HRV features were extracted from the raw ECG signal of the Cobalt Bluebox over a window of 10 normal-to-normal (NN) inter-beat intervals. Within each window, the time domain feature of standard deviation of NN intervals (SDNN) was calculated to serve as the primary HRV metric for subsequent analysis.

3.3.8 Statistical Analyses

All statistical analyses were conducted in SAS Studio (SAS Institute Inc., Cary, NC, USA). Descriptive statistics were reported as means $\pm$ standard errors. The significance level was set at $p < .05$. Two linear regression models with random intercepts were applied to examine the effect of task complexity (1-back vs. 3-back) on pupil size and SDNN. Four additional regression models with random intercepts were applied to test the effects of task complexity and cognitive load (pupil size, SDNN) on n-back accuracy rate and reaction time. To assess moderation, two repeated measures ANOVAs were performed to evaluate whether peripheral light intensity and directional angle moderated the relationship between task complexity and cognitive load. Two pairwise comparisons from linear regression models were used to assess the main effect of directional angle and intensity of peripheral light on cognitive load. Finally, correlational analyses were conducted to assess the relationship between lived and perceived cognitive load.

To control for inflation of Type I error due to multiple comparisons, we applied the Bonferroni-Holm correction to post-hoc pairwise tests. Adjusted p-values (p_{adj}) and effect sizes (d) are reported. Multiple regression tests were corrected for multiple comparisons also using the Holm-Bonferroni method, and adjusted p-values are also reported.

3.4 Results

3.4.1 Descriptive Statistics

Table 4 and Table 5 contain the descriptive statistics for all measured variables in each of the four lighting conditions during the 1-back and 3-back tasks, respectively. They

include means and standard deviations for variables: average adjusted pupil size, heart rate variability, task accuracy, and task reaction time.

Table 4. *Summary of Descriptive Statistics for 1-back task*

Variable	Baseline (N=49)	Far-Low (N=49)	Far-High (N=49)	Close-Low (N=49)	Close-High (N=49)
	$M \pm SD$	$M \pm SD$	$M \pm SD$	$M \pm SD$	$M \pm SD$
Pupil size	0.11 ± 0.25	0.17 ± 0.33	0.01 ± 0.26	0.05 ± 0.23	-0.00 ± 0.40
HRV	3.57 ± 0.82	3.48 ± 0.77	3.59 ± 0.76	3.57 ± 0.78	3.51 ± 0.69
Accuracy	0.61 ± 0.25	0.45 ± 0.36	0.39 ± 0.33	0.39 ± 0.32	0.41 ± 0.30
RT	0.41 ± 0.04	0.42 ± 0.02	0.41 ± 0.03	0.40 ± 0.03	0.41 ± 0.04

Table 5. *Summary of Descriptive Statistics for 3-back task*

Variable	Baseline (N=49)	Far-Low (N=49)	Far-High (N=49)	Close-Low (N=49)	Close-High (N=49)
	$M \pm SD$	$M \pm SD$	$M \pm SD$	$M \pm SD$	$M \pm SD$
Pupil size	0.17 ± 0.31	0.32 ± 0.31	0.16 ± 0.30	0.26 ± 0.30	0.08 ± 0.25
HRV	3.49 ± 0.75	3.60 ± 0.91	3.41 ± 0.78	3.41 ± 0.77	3.55 ± 0.87
Accuracy	0.10 ± 0.16	0.14 ± 0.20	0.18 ± 0.22	0.18 ± 0.23	0.16 ± 0.18
RT	0.41 ± 0.04	0.40 ± 0.05	0.39 ± 0.05	0.39 ± 0.08	0.39 ± 0.04

3.4.2 Cognitive Load

The lived cognitive load measures, including pupil size and SDNN, are displayed in Figure 4. A one-tailed linear mixed-effects regression with random intercepts for participants showed there was a significant main effect of n-back level on pupil size, $F(1, 426.3) = 41.60$, $p_{adj} < .001$, with pupil size being larger in the 3-back compared with the 1-back task.

A one-tailed linear mixed-effects regression with random intercepts for participants showed there was a marginally significant main effect of n-back level on SDNN, $F(1, 409.6) = 3.18$, $p_{adj} = .038$, with SDNN being slightly lower in the 3-back compared with the 1-back task.

Two-tailed correlations between pupil size and NASA TLX scores, showed they were positively correlated $r(462) = .18$, $p < .001$. Specifically for our NASA TLX dimensions, pupil size and self-reported scores of mental demand were positively correlated $r(465) = .22$, $p < .001$. Pupil size and self-reported scores of performance were negatively correlated $r(453) = -.22$, $p < .001$. Pupil size and self-reported scores of effort

were positively correlated $r(459) = .09, p = .046$. Pupil size and self-reported scores of frustration level were not correlated $r(444) = .08, p = .074$.

Collectively, these results suggest that higher task complexity elicited greater cognitive load, as reflected by both physiological markers, pupil size and SDNN, and the subjective NASA-TLX measures. Therefore, H1: Task complexity is positively associated with cognitive load is supported.

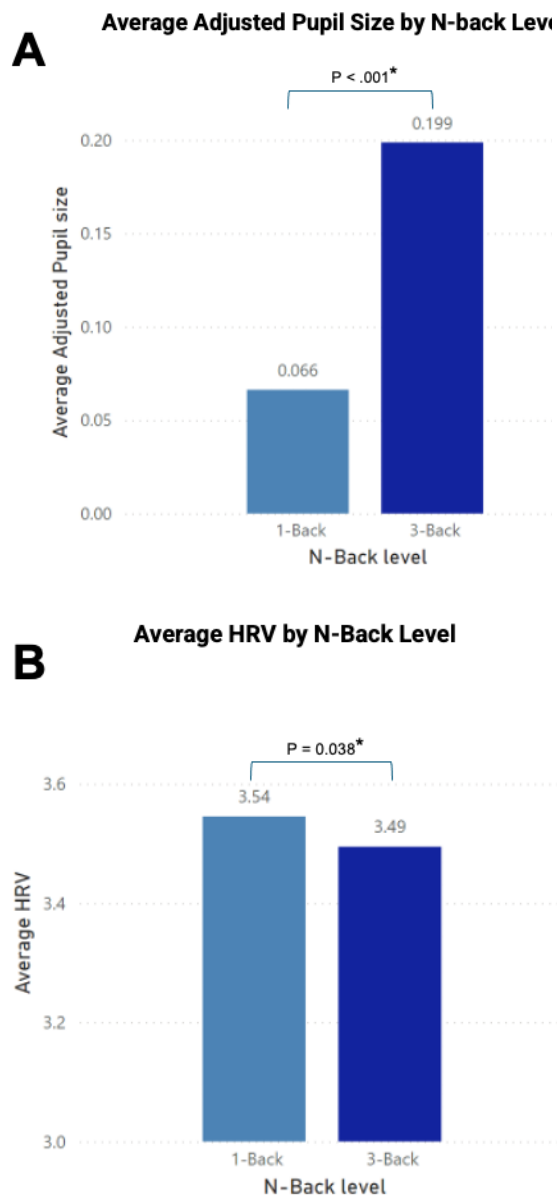


Figure 4. Mean pupil size (A) and HRV (B) for 1-back and 3-back tasks

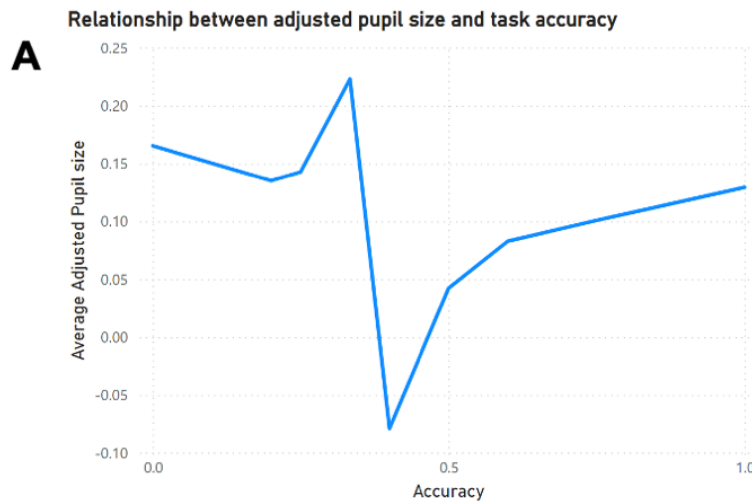
3.4.3 Potential Confounds in pupillary Cognitive Load Assessment

A two-tailed linear mixed-effects regression with random intercepts for participants showed the interaction of sleepiness ($F(1, 46.96) = 0.01, p = .925.$), visual sensitivity ($F(1, 46.01) = 0.15, p = .700.$), and visual fatigue ($F(1, 46.09) = 0.00, p = .986.$) on n-back level predicting pupil size was non-significant.

Collectively, these findings suggest that participants' self-reported sleepiness, visual sensitivity, and visual fatigue were unlikely to have introduced meaningful confounds into our pupillometric assessments of cognitive load.

3.4.4 Behavioral Performance

The behavioral performance measures are presented in Figure 5. The one-tailed quadratic effect of pupil size on n-back accuracy rate was not significant $b = 0.04, SE = 0.08, t(352.3) = 0.49, p = .313$. A one-tailed linear mixed-effects regression with random intercepts for participants showed there was a significant effect of pupil size on accuracy $b = -0.13, SE = 0.05, t(377.5) = -2.60, p = .005$, corresponding to larger pupil size with lower accuracy.



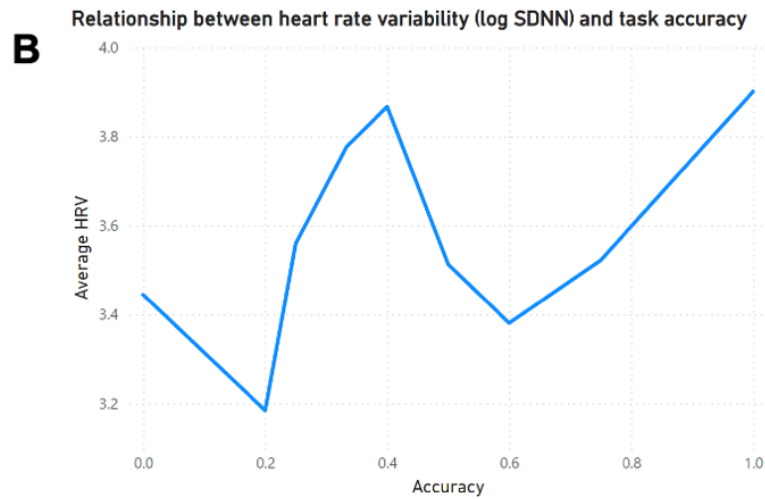


Figure 5. Mean pupil size (A) and HRV (B) vs. mean n-back accuracy rate

The one-tailed quadratic effect of log-transformed SDNN on accuracy was significant, $b = -0.04$, $SE = 0.02$, $t(223.7) = -1.66$, $p = .049$, corresponding to higher SDNN with greater n-back accuracy. This quadratic effect is illustrated in Figure 6.

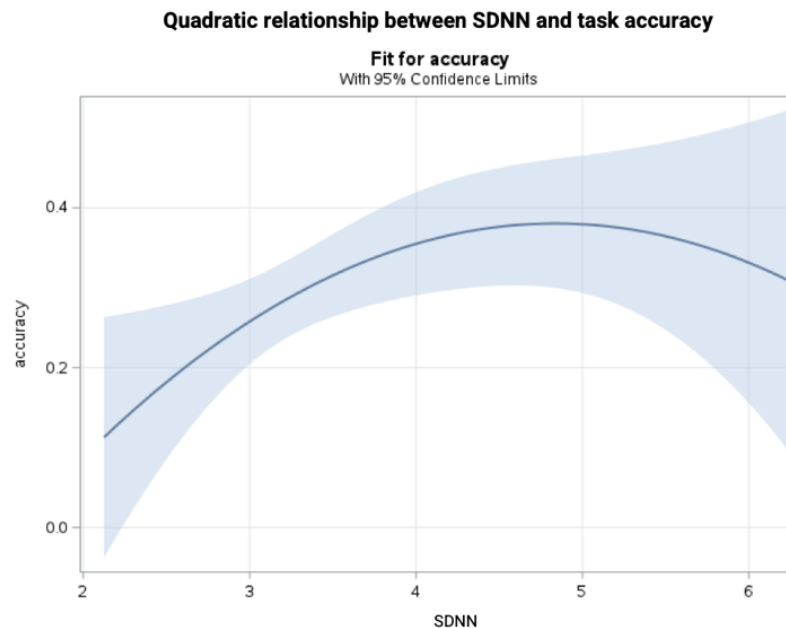


Figure 6. Effect plot of the quadratic relationship between SDNN and mean accuracy rate

The one-tailed quadratic effect of pupil size on reaction time was not significant, $b = 0.01$, $SE = 0.02$, $t(205.1) = 0.74$, $p = .23$. A one-tailed linear mixed-effects regression with random intercepts for participants showed the effect of pupil size on reaction time was not significant, $b = -0.002$, $SE = 0.009$, $t(236.1) = -0.24$, $p = .407$.

The one-tailed quadratic effect of log-transformed SDNN on reaction time was not significant, $b = 0.001$, $SE = 0.006$, $t(175) = 0.16$, $p = .435$. A one-tailed linear mixed-effects regression with random intercepts for participants showed there was a significant effect of log-transformed SDNN on reaction time, $b = 0.009$, $SE = 0.005$, $t(60.83) = 2.03$, $p = .024$, corresponding to higher SDNN with higher n-back accuracy rate.

Collectively, these results suggest a nuanced relationship between cognitive load and task performance. While increased pupil size and decreased SDNN were both associated with lower n-back accuracy rate, effects on reaction time were not significant. Therefore, H2: Cognitive Load is negatively associated with Performance was partially supported.

3.4.5 Lighting Conditions: Intensity and Directional Angle

A repeated measures ANOVA indicated that the peripheral light intensity did not exert a significant negative moderating effect on the relationship between task complexity and pupillometric measures of cognitive load., $F(1, 328) = 2.12$, $p = .147$. A pairwise comparison from a one-tailed linear mixed-effects model with random intercepts showed that, in the 1-back task, the main effect of intensity of peripheral light on pupil size was significantly higher in the far-low condition compared with the close-low condition, $t(185.7) = 2.79$, $p_{adj} = .023$, $d = .20$. Whereas, no significant difference was found between far-high and close-high, $t(185.7) = 0.30$, $p_{adj} = .401$, $d = .04$. In the 3-back task, the differences between far-low and close-low ($t(186) = 1.57$, $p_{adj} = .119$, $d = 0.23$) was not significant, although the differences between far-high and close-high ($t(186.4) = 1.96$, $p_{adj} = .091$, $d = 0.29$) were marginally significant. Average adjusted pupil size by lighting condition and n-back level by intensity is presented in Figure 7.

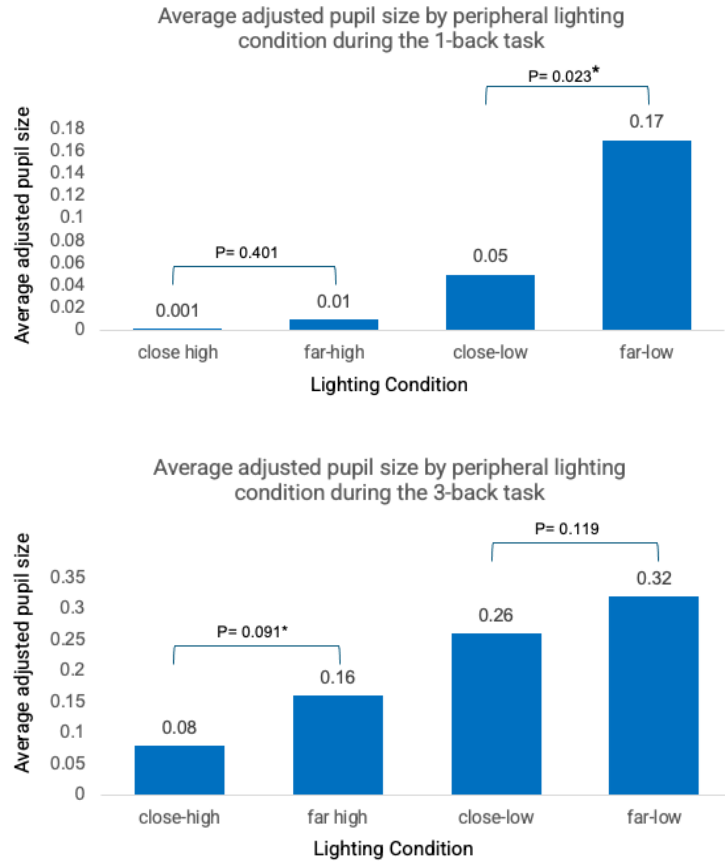


Figure 7. Average adjusted pupil size by intensity lighting condition and n-back level

A repeated measures ANOVA indicated that the directional angle of peripheral light did not significantly moderate the relationship between task complexity and pupillometric measures of cognitive load, $F(1, 328) = 0.00$, $p = .946$. Pairwise comparisons from a two-tailed linear mixed-effects model with random intercepts revealed that, in the 1-back task, the main effect of directional angle of peripheral light on pupil size was significantly different between the far-low and far-high conditions, $t(185.7) = 3.67$, $p_{adj} = .0029$, $d = .27$, whereas the difference between close-low and close-high was not significant, $t(185.7) = 1.18$, $p_{adj} = .801$, $d = .09$. In the 3-back task, the main effect of directional angle of peripheral light on pupil size was significantly different between the far-low and far-high condition, $t(186) = 3.85$, $p_{adj} = .0013$, $d = .28$, and the close-low versus close-high comparison, $t(186.2) = 4.28$, $p_{adj} < .001$, $d = .31$. Average adjusted pupil size by lighting conditions and n-back levels is presented in Figure 8.

Taken together, these results indicate that peripheral light intensity did not exert a significant negative moderating effect on the relationship between task complexity and pupillometric measures of cognitive load, thereby not supporting H3a: Intensity of peripheral light negatively moderates the relationship between task complexity and cognitive load, such that higher peripheral light intensity reduces changes in pupil size associated with increases in task complexity. Furthermore, the directional angle of peripheral light did not significantly moderate the relationship between task complexity and cognitive load, thereby not supporting H3b: Directional angle of peripheral light moderates the relationship between task complexity and cognitive load, such that changes in directional angle alter the magnitude of pupil-size changes associated with increases in task complexity. However, consistent main-effect differences were still observed in average adjusted pupil size.

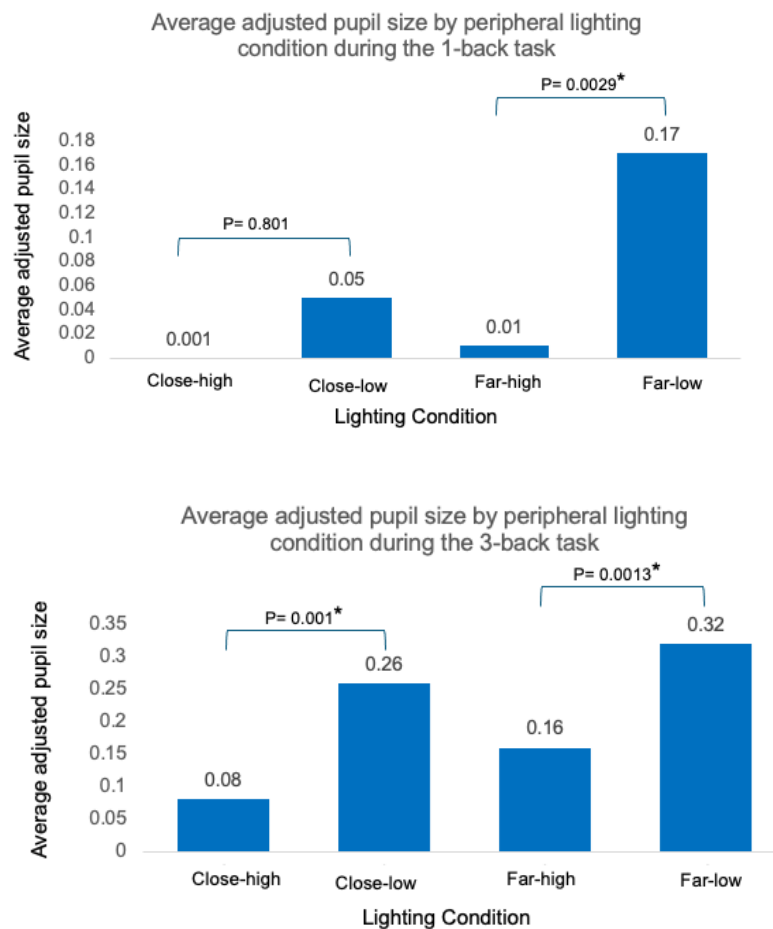


Figure 8. Average adjusted pupil size by directional angle lighting condition and n-back level

Below, Table 6 consists of a table summarizing the results of the hypothesis tests relevant to my research model and their validity.

Table 6. *Validity Test Results*

Hypothesis	IV	DV	Moderator	P-value	Status
H1_1	Task complexity	Lived CL (pupil)		$p < .001^{***}$	Supported
H1_2	Task complexity	Lived CL (HRV)		$p = .038^*$	Supported
H2_1	Lived CL (pupil)	Performance (Accuracy)		$p = .005^{**}$	Supported
H2_2	Lived CL (pupil)	Performance (RT)		.407	Not Supported
H2_3	Lived CL (HRV)	Performance (Accuracy)		.049*	Supported
H2_4	Lived CL (HRV)	Performance (RT)		.024*	Supported
H3a	Task complexity	Lived CL (pupil)	Intensity	.147	Not Supported
H3b	Task complexity	Lived CL (pupil)	Directional Angle	.946	Not Supported

3.5 Discussion

3.5.1 Summary of Findings

The goal of this study was to examine the impact of varying peripheral light intensities and directional angles on the precision of pupillometric assessment of cognitive load during an N-back working-memory task of varying complexities. Consistent with prior research (Beatty, 1982; Van Der Wel & Van Steenbergen, 2018), higher task complexity significantly increased pupil dilation, suggesting that greater working-memory demands elicit stronger TEPRs (H1). Furthermore, Higher task complexity also significantly decrease HRV, suggesting heightened sympathetic arousal during cognitively demanding tasks (H1). Behaviorally, greater pupil dilation was associated with lower task accuracy rate (H2), suggesting a cost to performance when cognitive load exceeds optimal processing capacity.

Regarding lighting conditions, peripheral light intensity (H3a) did not exert the expected significant negative moderating effect on task complexity's association with pupillometric measures of cognitive load. Similarly, the directional angle (H3b) did not significantly moderate the relationship between task complexity and cognitive load. Nonetheless, both variables produced robust main-effect differences in average adjusted pupil size. The results suggest that directional angle plays the most consistent role in shaping baseline pupil size. Far-angled lighting reliably produced larger diameters than close-angled lighting, especially in the far-low versus far-high comparisons, which held across both N-back levels. Close-angle effects were weaker, emerging only in the 3-back task where close-low exceeded close-high. Intensity effects followed a similar but less robust pattern, differences appeared mainly under low-intensity conditions, with far-low producing larger pupils than close-low in the 1-back task, while high-intensity contrasts were minimal and only marginal in the 3-back task. Overall, these patterns indicate that lighting geometry and intensity both shift tonic pupil size, though angle exerts the more reliable influence.

3.5.2 Theoretical Implications

The present study makes two theoretical contributions to existing models of cognitive load and pupillometry. First, the results reinforce core predictions of Cognitive Load Theory (Sweller, 1988) and classic pupillometry research (Beatty, 1982; Kahneman & Beatty, 1966). As hypothesized, task complexity was positively associated with cognitive load, reflected in larger TEPRs ($p < .001$) and lower HRV ($p = .038$). These findings replicate the well-established pattern that higher working-memory demands elicit greater sympathetic activation within the LC-NE system, accompanied by diminished parasympathetic activity indexed through reduced HRV (Cao et al., 2019; Kim et al., 2018). The convergence of pupil dilation and HRV as task difficulty increased provides strong psychophysiological support for models linking working-memory load to autonomic arousal.

Behaviorally, the findings also confirmed that cognitive load was negatively associated with performance. Greater pupil dilation predicted lower task accuracy ($p = .005$), and HRV was associated with slower reaction times ($p = .024$) and reduced accuracy ($p = .049$). These performance costs are consistent with the Yerkes-Dodson law

(1908), suggesting that as cognitive demands intensify, individuals exceed their optimal processing capacity (Cohen, 2018). This pattern aligns with empirical findings from cognitive pupillometry studies showing that increased load produces both larger dilations and reduced accuracy (Van der Meer et al., 2010).

Second, this study contributes to a clearer understanding of the pupillary light response in cognitive research by addressing an area that remains relatively underexplored and characterized by mixed findings. Incorporating illumination parameters into this framework offers an additional theoretical insight. We hypothesized that intensity of peripheral light negatively moderates the relationship between task complexity and cognitive load, such that higher peripheral light intensity reduces the precision of pupillometric estimates of cognitive load. Results showed that intensity did not negatively moderate this relationship ($p = .147$) suggesting that within the tested range, increased illumination did not significantly impair cognitive load detection. This outcome is consistent with older studies (Bradshaw, 1969; Pomplun & Sunkara, 2003; Xu et al., 2011) reporting minimal illumination effects on TEPR-based load estimation, yet contrasts with more recent studies (Bao et al., 2021; Peysakhovich et al., 2015, 2017; Shahidi et al., 2025; Shelton et al., 2022) suggesting that high-brightness environments compress the dynamic range of pupil responses.

Additionally, this work introduces directional angle of peripheral illumination as a theoretically meaningful aspect of light-pupil interaction. We hypothesized that directional angle would moderate the relationship between task complexity and cognitive load, such that changes in directional angle alter the precision of pupillometric estimates of cognitive load. Although directional angle did not significantly moderate this relationship in the present study ($p = .946$), this null finding suggests that the accuracy of pupillometric cognitive load assessment may not depend on lighting geometry within the tested range. However, the observed main effects on baseline pupil diameter demonstrate that directional angle systematically influences tonic pupil size. This is theoretically important because studies show that TEPR amplitude is constrained by the baseline operating range defined by the pupillary light reflex (Mathôt, 2018; Sirois & Brisson, 2014). Demonstrating that lighting geometry affects baseline diameter, therefore refines existing models of light-pupil interaction by showing that illumination geometry, not only

intensity, shapes the physiological limits in which cognitive load is expressed. This interpretation is consistent with studies showing that off-axis illumination can induce glare, visual strain, and baseline constriction (Shahidi et al., 2025; Williamson et al., 2023).

3.5.3 Methodological Contributions

This study makes two primary methodological contributions to pupillometry and cognitive load research. First, it introduces the Luminosity Dome, a novel apparatus that enables precise manipulation of peripheral light intensity and directional angle. Prior pupillometry studies have typically relied on tightly controlled laboratory environments with stable lighting conditions. (Hayes & Petrov, 2016; Mahanama et al., 2022; Pan et al., 2022; Sirois & Brisson, 2014), limiting the field's ability to examine pupil dynamics under ecological lighting configurations. The Dome overcomes this constraint by providing systematic, reproducible, and spatially differentiated lighting that does not interfere with the primary task. This innovation allows researchers to isolate subtle lighting effects that conventional laboratory setups cannot capture, thereby bridging the divide between internal and ecological validity in pupillometric measurement.

Second, the integration of multimodal physiological measurement, pupillometry with HRV, provides a more comprehensive assessment of autonomic responses to cognitive load. By combining TEPRs and SDNN, this study demonstrates how these complementary indices capture both reduced parasympathetic influence and heightened sympathetic arousal during cognitively demanding tasks (Cao et al., 2018). This multimodal approach strengthens the interpretability of pupillometric data and provides a richer account of underlying autonomic dynamics (Alshanskaia et al., 2024).

3.5.4 Practical Implications

The present findings contribute three practical implications. First, they highlight the importance of systematically documenting illumination parameters when using pupillometry in both laboratory and operational environments. As noted in prior work, inconsistent or underreported lighting conditions may partly explain the contradictory results observed in earlier studies examining illumination effects on pupillometric cognitive load assessment (Bradshaw, 1969; Holmskär et al., 2023; Ong et al., 2018;

Pomplun & Sunkara, 2003). Although neither peripheral light intensity nor directional angle significantly moderated the relationship between task complexity and cognitive load, both variables produced systematic shifts in baseline pupil size. This demonstrates that environmental lighting can distort the precision of cognitive load estimates even when it does not alter the underlying physiological response, reinforcing the need for consistent illumination control and reporting. Accordingly, researchers should quantify illuminance, color temperature, and light-source geometry using objective tools, such as light meters and digital inclinometers. Expanding reporting guidelines in cognitive pupillometry to include the position, angle, and stability of light sources would improve methodological transparency and ensure that TEPRs are interpreted in relation to the precise illumination conditions in which they were recorded. Such standardization is essential for improving replicability across studies and for preventing lighting-related confounds from obscuring genuine cognitive load effects.

Second, beyond laboratory settings, the results have implications for applied User Experience and Human-Computer Interaction environments where pupillometry is increasingly used to evaluate workload, interface complexity, and the quality of user interaction. Because peripheral lighting conditions seem to shift baseline pupil diameter, practitioners conducting usability studies should ensure that testing environments maintain consistent lighting across sessions, especially when comparing prototypes or conducting longitudinal studies. Furthermore, when portable or naturalistic testing environments introduce unavoidable variability in environmental light, workload estimates may require normalization procedures or model-based corrections that account for illumination-driven changes in tonic pupil size. This is particularly relevant for research conducted with mobile eye-tracking systems, where variation in peripheral lighting is more difficult to control.

The results also hold relevance for safety-critical and training environments such as aviation, driving, and healthcare simulation, where physiological workload monitoring is increasingly integrated into human-system interfaces. Because illumination influenced baseline pupil diameter did not disrupt sensitivity to cognitive load, real-time workload estimation may remain viable in dynamic lighting contexts provided that systems incorporate adaptive baseline correction or integrate environmental light sensors into their

light sensors into their workload-estimation systems. Designers of training simulators and control-room interfaces may therefore benefit from standardizing lighting configurations or embedding environmental sensing to maintain stable workload measurements across scenarios.

Third, the results contribute insights relevant to emerging computational systems that incorporate pupillometry into adaptive and intelligent interfaces. As extended-reality devices, multimodal AI assistants, and wearable technologies increasingly rely on pupil-based signals to infer user states, illumination awareness will be crucial for preventing systematic misinterpretation of cognitive load. Integrating environmental light monitoring, and illumination-informed normalization into device algorithms would improve the robustness of cognitive load estimation in everyday environments. More broadly, these results motivate treating illumination not as an incidental background condition but as a design variable that fundamentally shapes the measurement range available for pupillometric indicators of cognitive load.

3.5.5 Limitations and Future Research

This study has five primary limitations, each of which offers a distinct opportunity for future research. First, the experiment relied exclusively on the N-back task, which restricts generalizability to other cognitive contexts. Tasks involving more dynamic visual exploration or emotional stimuli may elicit different PLRs. Future research should therefore examine how peripheral illumination influences pupillometric assessment in a broader range of paradigms, and naturalistic HCI scenarios to determine whether the patterns observed here hold across more ecologically valid cognitive environments.

Second, the task required minimal eye movement, likely reducing retinal adaptation to changing peripheral light. In real-world settings, frequent gaze shifts continuously reposition peripheral illumination across the retina, which may modulate both tonic and phasic pupil responses (Mâthot, 2018). This constraint suggests that the current findings may underestimate the contribution of oculomotor movement to light-pupil interactions. Future work should incorporate tasks with greater visual exploration to model how gaze shifts shape the pupillary light reflex and cognitive dilation.

Third, this study examined adjusted pupil size without decomposing tonic and phasic components. Although this approach simplified interpretation, it may obscure

subtle distinctions between cognitively driven and light-driven responses. To better isolate these mechanisms, future studies should apply algorithmic approaches, such as Index of Cognitive Activity (ICA) (Mahanama et al., 2022; Marshall, 2002), the Index of Pupillary Activity (IPA) (Duchowski et al., 2018), or other derivative-based methods, that can separate task-evoked changes from the underlying pupillary light reflex. Doing so would clarify how illumination alters the temporal profile of TEPRs and improve the precision of cognitive load estimation.

Fourth, the frequency of NASA-TLX administration limited our ability to model the evolving relationship between perceived and physiological load. Future research should employ a trial-level subjective workload assessment strategy to examine whether perceived load and physiological load change in tandem or diverge over time.

Fifth, the findings are tied to the technical parameters of the laboratory environment and the 600 Hz eye tracker used in this study. Different sampling rates, or device characteristics may introduce varying levels of noise, or change sensitivity to lighting. To address this limitation, future research should conduct validation studies comparing pupil metrics across a range of sampling frequencies to identify the minimum threshold required for reliable measurement and determine whether certain frequencies are more susceptible to illumination-related interference.

Beyond these limitations, several broader research avenues emerge from this work. Future studies should continue to explore wider ranges of peripheral light intensities and directional angles to determine the precise thresholds at which illumination begins to suppress or enhance TEPR amplitude. Dynamic peripheral lighting, where intensity or angle changes in synchrony with task demands, represents a promising direction for developing adaptive lighting systems that support cognitive efficiency. Extending the Luminosity Dome to operational HCI contexts may reveal how subtle lighting adjustments influence operator fatigue, vigilance, and performance. Finally, incorporating distraction as an explicit construct may help disentangle lighting-related cognitive effects from attentional shifts due to variations in lighting across, offering a more comprehensive account of how peripheral illumination shapes cognitive control in visually complex settings, and complementing the subjective dimension of this study.

3.6 Conclusion

The present study investigated how variations in peripheral light intensity and directionality affect the precision of pupillometric measurements of cognitive load during a working-memory task. Motivated by the need to strengthen the ecological validity of pupillometry, the study investigated how lighting conditions interact with autonomic indicators of mental effort. The findings demonstrate that task complexity reliably increases cognitive load, while neither lighting intensity nor direction moderated this relationship, suggesting that illumination may influence baseline pupil size without altering load reactivity itself. Methodologically, the introduction of the Luminosity Dome represents a meaningful step toward controlled yet realistic simulation of lighting environments, offering a foundation for future studies to better isolate and model illumination effects. Looking forward, expanding pupillometric research to incorporate spatial lighting geometry and multimodal autonomic measures may strengthen theoretical models of cognitive load and support the development of more robust, context-aware human-technology systems.

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Chapter 4

Conclusion

This thesis set out to: (1) to determine how variations in peripheral lighting intensity and directional angle influence the reliability of pupillometric cognitive load assessment, (2) to refine the conceptual understanding of illumination as a confounding factor in physiological measurement, and (3) to generate methodological and design recommendations for researchers and practitioners who rely on pupillometry in complex or dynamically lit environments. These aims were guided by the following research question:

To what extent can varying intensities and directional angles of peripheral light impact pupillometric measurements of cognitive load?

To address this question, an experimental study was conducted using the Luminosity Dome, a custom-built illumination apparatus capable of manipulating peripheral lighting with high spatial and luminance precision. By integrating pupillometric, cardiovascular, behavioral, and subjective workload measures within an N-back working-memory paradigm, the study provided a multimodal view of how cognitive load and lighting conditions interact during task performance. This concluding chapter synthesizes the primary findings, discusses their theoretical, methodological, and practical implications, and outlines promising avenues for future research.

4.1 Main Findings

The results reinforce several well-established patterns in cognitive load literature while also highlighting important constraints. Consistent with foundational work on task-evoked pupillary responses (Beatty, 1982; Van der Wel & van Steenbergen, 2018), higher task complexity elicited larger pupil dilations and decreased HRV, confirming the sensitivity of these physiological indices to working-memory demands. The inverse relationship between pupil dilation and task accuracy further underscores the behavioral costs of cognitive overload, consistent with CLT (Sweller, 1988; Wigert & Sutton, 2023) and Yerkes-Dodson law (1908). The effects of peripheral lighting conditions offer a more

nuanced contribution. Although neither intensity nor directional angle significantly moderated the relationship between task complexity and cognitive load, both produced robust main-effect differences in pupil size. The pattern suggests that directional angle plays the strongest role in shaping baseline pupil size, far-angled lighting reliably produced larger diameters than close-angled lighting across both N-back levels. Intensity showed a similar but weaker trend, appearing mainly under low-intensity conditions and only modestly in the 3-back task. These findings indicate that illumination alters tonic pupil diameter even when it does not distort the cognitive signal itself, largely consistent with established findings on the pupillary light response (Beatty, 1982; Mathôt, 2018).

4.2 Theoretical contributions

These results contribute to a literature marked by inconsistent findings, with some studies suggesting greater load sensitivity in dim environments (Peysakhovich et al., 2015, 2017; Pfleging et al., 2016) and others reporting stronger modulation under brighter conditions (Steinhauer et al., 2004). Although the present work does not resolve these discrepancies, it suggests that the accuracy of pupillometric cognitive load assessment may be less sensitive to lighting intensity or geometry than previously assumed, at least within the tested range. This finding helps reconcile conflicting evidence by demonstrating that inconsistencies across prior studies may stem from unreported or uncontrolled differences in the spatial distribution of light rather than from true variation in cognitive load sensitivity. Furthermore, the observed main effects may clarify a key theoretical boundary, suggesting that peripheral lighting angle may more consistently influence baseline pupil size independent of cognitive load, than peripheral lighting intensity.

A second theoretical contribution is the introduction of directional angle as a previously untested aspect of illumination in pupillometric cognitive load assessment. The findings show that peripheral lighting geometry, not just its brightness, influences autonomic responses and visual attention, suggesting that pupil-based load measures are shaped by lighting geometry in ways not yet reflected in existing research. This insight points toward a broader model of cognitive load pupillometry that treats spatial lighting

characteristics as key factors in baseline pupil size and the range available for task-evoked dilation.

4.3 Methodological contributions

Methodologically, this study underscores the importance of precision, transparency, and reproducibility in pupillometry research. Some studies fail to report objective illuminance levels or the spatial geometry of lighting, limiting comparability across experiments (Ong et al., 2019). These results reinforce the need for a measurement checklist that includes quantified illuminance, color temperature, light-source position and angle, tonic-phasic decomposition of pupil signals, and automated luminance logging when possible.

A second methodological contribution is the introduction of the Luminosity Dome, which enables controlled manipulation of peripheral light intensity and directional angle. This apparatus bridges the gap between tightly controlled laboratory conditions and the heterogeneous lighting found in cockpits, control rooms, and everyday computing environments.

4.4 Practical contributions

The present findings contribute two practical implications for UX practitioners and designers of adaptive, cognitive-aware systems. First, the results emphasize that peripheral lighting conditions systematically shift baseline pupil diameter, even when they do not alter sensitivity to task-evoked cognitive load. This suggests that illumination can distort workload estimates if not properly controlled. For practitioners, this underscores the importance of conducting usability testing under consistent lighting, particularly when comparing prototypes or running longitudinal studies. In portable or ecological environments where lighting cannot be fully controlled, workload estimates may require normalization procedures that adjust for illumination-driven changes in tonic pupil size. This is especially important for mobile eye-tracking setups and real-world evaluations where lighting variability is unavoidable.

Second, the findings have direct relevance for safety-critical and training domains, such as aviation, driving, and healthcare simulation, where real-time cognitive-state

monitoring is increasingly integrated into human-system interfaces. Because lighting affected baseline diameter but not load sensitivity, real-time estimation remains viable if systems incorporate adaptive baseline correction or embed light sensors. Similarly, emerging technologies such as Extended Reality devices, and AI assistants, should integrate illumination monitoring and light-normalized algorithms to prevent systematic misclassification of cognitive states.

More broadly, these implications reinforce a key message introduced at the outset: in an era where cognitive load measurement is becoming central to human-centered design, decision-support tools, and safety-critical systems, illumination cannot be treated as an afterthought. Instead, it must be managed, or explicitly modeled, as a design variable that shapes the measurement range available for pupillometric indicators of mental effort. Ensuring illumination-aware pupillometry will help advance the development of adaptive interfaces that respond intelligently to users' cognitive states across both controlled and real-world environments.

4.5 Limitations and Future Research

This thesis has several limitations that open pathways for future research. First, relying solely on the N-back task limits the generalizability of the findings. Future studies should incorporate additional cognitive paradigms to determine whether peripheral illumination affects pupillometric load indices across more complex and ecologically valid scenarios.

Second, this study did not decompose tonic and phasic components of the pupil signal to simplify interpretation. However, future analyses should apply decomposition algorithms such as the ICA (Marshall, 2002) or IPA (Duchowski et al., 2018) to separate cognitive-evoked dilation from the pupillary light reflex and improve the precision of load estimation.

Third, subjective workload was measured after each n-back block to avoid participant fatigue. Future studies should collect workload ratings after each n-back trial to better capture how perceived and physiological load evolve under changing illumination. It would allow more precise characterization of how peripheral illumination may moderate subjective and physiological relationships.

Fourth, the findings are tied to a specific hardware configuration and a 600 Hz sampling rate. Future research should validate the results across different eye-tracker sampling frequencies and device types and evaluate the Luminosity Dome in applied settings such as aviation simulators, control rooms, or VR training environments.

Broader extensions also emerge from this work. Future studies should test wider illuminance ranges, more directional angles, and perhaps dynamic peripheral lighting that adapts to task demands. These steps will help clarify the boundary conditions under which pupillometry remains reliable and support the development of cognitive-load aware systems capable of operating effectively outside tightly controlled laboratory environments.

4.6 Concluding Remarks

This thesis contributes to ongoing efforts in HCI, cognitive ergonomics, and physiological computing to strengthen the conditions under which pupillometry can serve as a reliable indicator of cognitive load. It addresses the central challenge of obtaining accurate cognitive-state measurement in environments where illumination naturally varies. As digital systems, automated interfaces, and AI-enabled decision-support tools become increasingly embedded in safety-critical operations, professional training, and everyday technologies, understanding how environmental lighting shapes physiological signals is vital for maintaining human performance. Despite its limitations, the insights offered here help move the field toward more ecologically grounded and context-aware applications of pupillometry, helping ensure that future adaptive interfaces and human-centered technologies can respond intelligently to users' cognitive states and better support their attentional demands, and overall performance.

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Appendix

Appendix A. Psychometric Scales

Construct Name	Acronym	Measure type	Items	Reference
Task Workload	NASA-TLX	Self-Reported	Slider from Low/High on a scale of 1 -100 • Mental demand: How mentally demanding was the task? • Performance: How successful were you in accomplishing what you were asked to do? • Effort: How hard did you have to work to accomplish your level of performance? • Frustration level: How insecure, discouraged, irritated, stressed, and annoyed were you?	Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. <i>Advances in Psychology</i> , 52, 139-183.
Visual Fatigue	VFS	Self-Reported	1-10 (1 being not at all, 10 being very much) • I have difficulties in seeing. • I have a strange feeling around my eyes. • My eyes feel tired. • I feel numb. • I have a headache. • I feel dizzy looking at the screen.	Heuer H, Hollendiek G, Kröger H, Römer T. Die Ruhelage der Augen und ihr Einfluss auf Beobachtungsabstand und visuelle Ermüdung bei Bildschirmarbeit [Rest position of the eyes and its effect on viewing distance and visual fatigue in computer display work]. <i>Z Exp Angew Psychol</i> . 1989;36(4):538-66. German. PMID: 2576484.
Sleepiness	SSS	Self-Reported	1-7 (choosing one of the seven options) • Feeling active, vital, alert, or wide awake • Functioning at high levels, but not at peak; able to concentrate • Awake, but relaxed; responsive but not fully alert	Hoddes, E., Dement, W. C., & Zarcone, V. (1972). The development and use of the Stanford Sleepiness Scale (SSS). <i>Psychophysiology</i> , 9(150).

			• Somewhat foggy, let down • Foggy; losing interest in remaining awake; slowed down • Sleepy, woozy, fighting sleep; prefer to lie down • No longer fighting sleep, sleep onset soon; having dream-like thoughts	
Visual Sensitivity	L-VISS	Self-Reported	Not at all (0 points), Slightly (1 point), Moderately (2 points), Severely (3 points) and Very severely (4 points). (English Version - Translated from Dutch) • To what extent does sunlight bother you when you're not wearing sunglasses? • To what extent are you bothered by artificial lighting? • To what extent are you bothered by flickering lights (e.g., a flickering lamp, during films or in a nightclub) • When you look at a bright light, is your eyesight worse afterwards (e.g., blurred or distorted vision) • When you look at a computer or TV screen, do you see afterimages? (seeing an image of the pattern elsewhere, such as on a white wall) • When you look at a computer or TV screen, is your eyesight worse? (e.g., blurred or distorted vision)	Perenboom, M. J. L., Zamanipour Najafabadi, A. H., Zielman, R., Carpay, J. A., & Ferrari, M. D. (2018). Quantifying visual allodynia across migraine subtypes: The Leiden Visual Sensitivity Scale. <i>Pain</i>, 159(11), 2375–2382. https://doi.org/10.1097/j.pain.0000000000001343

Appendix B. Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to support tasks such as refining grammar and spelling, brainstorming preliminary ideas for research questions, and identifying potential sources. All content produced with the assistance of this tool was subsequently reviewed, edited, and validated by the authors, including verifying the existence and accuracy of cited sources. The authors take full responsibility for the final content presented in this thesis.