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Understanding the Effect of Luminance Conditions in Mobile Augmented Reality: Impact on Visual Discomfort, Legibility, and User Experience

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M.Sc. User Experience

Mémoire présenté en vue de l'obtention
du grade de maîtrise sciences en gestion
(M. Sc.)

August 2024

HEC MONTRĒAL

Comité d'éthique de la recherche

Le 13 février 2023

À l'attention de :
Pierre-Majorique Léger
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 # Projet : 2023-5269

Titre du projet de recherche : Confort visuel et expérience utilisateur

Source de financement : 32 153 300 22 - R2997 - Contrat de recherche

Titre de la subvention : Confort visuel - Essilor

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La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet d'une évaluation en matière d'éthique de la recherche avec des êtres humains et qu'il satisfait aux exigences de notre politique en cette matière.

Projet # : 2023-5269

Titre du projet de recherche : Confort visuel et expérience utilisateur

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Date d'approbation du projet : 13 février 2023

Date d'entrée en vigueur du certificat : 13 février 2023

Date d'échéance du certificat : 13 février 2024

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Signé le 2023-02-13 à 15:07

Abstract

This thesis explores the influence of luminance conditions on visual discomfort, legibility, and overall user experience in mobile augmented reality (AR) environments. Specifically, the research investigates how varying screen and ambient luminance ratios impact users' visual comfort, affective states, and task performance during AR interactions. The study is grounded in the Stimulus-Organism-Response (SOR) model and takes principles from cognitive theories such as the Cognitive Theory of Multimedia Learning (CTML) and Cognitive Load Theory (CLT).

Results indicate that higher luminance ratios significantly enhance legibility, contributing to more positive affective states and improved user satisfaction. However, contrary to expectations, varying luminance ratios did not significantly affect visual discomfort, suggesting that other factors may play a more critical role in influencing visual user comfort in mobile AR environments. Nonetheless, the findings reveal that visual discomfort negatively impacts perceived task performance and task duration, while legibility contributes to a more positive emotional experience but does not significantly alter perceptions of task time or accuracy.

The most significant contribution of this thesis is the empirical evidence supporting the application of the SOR model in AR contexts, demonstrating the importance of optimizing luminance conditions to improve legibility and enhance user satisfaction. From a practical perspective, these insights are valuable for AR application developers and designers, particularly in educational and informational settings where clear and comfortable viewing is crucial for effective learning and interaction.

Keywords: luminance, visual discomfort, legibility, mobile augmented reality, user experience, cognitive load, affective state, task performance, SOR model

Research methods: This study employs a quantitative research design, using a 2x2 within-subject experiment where participants were exposed to different lighting conditions while performing AR tasks. The variables measured include visual discomfort, legibility, affective state, task performance, perceived learning outcomes, and their hedonic motivation to use the AR artifact. Data were analyzed using statistical techniques such as logistic and linear regression models to determine the significance of the relationships between the variables.

This thesis is organized into seven chapters. It begins with an introduction, followed by a detailed literature review that establishes the theoretical framework. The third chapter presents the research methodology, followed by the results and a discussion of the findings. The thesis concludes with a comprehensive conclusion that integrates the study's contributions, practical implications, and suggestions for future research.

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List of abbreviations and acronyms

- AR - Augmented Reality
- VR - Virtual Reality
- SOR - Stimulus-Organism-Response
- VAC - Vergence-Accommodation Conflict
- GPS - Global Positioning System
- EVD - Electronic Visual Displays
- CVS - Computer Vision Syndrome
- STEM - Science, Technology, Engineering, and Mathematics
- OST-HMD - Optical See-Through Head-Mounted Display
- CLT - Cognitive Load Theory
- CTML - Cognitive Theory of Multimedia Learning
- AL - Ambient Luminance
- SL - Screen Luminance
- IILP - Informal Institutional Learning Places
- REB - Research Ethics Board
- CD/m² - Candelas per Square Meter
- LX - Lux
- DES - Digital Eye Strain

Acknowledgements

I would like to extend my heartfelt gratitude to all those who have supported me throughout the journey of completing my thesis.

First and foremost, I am immensely grateful to MITACS for their generous grant of $10,000 CAD, which made this research possible. Their financial support was invaluable in facilitating my study. I also want to express my sincere appreciation to Essilor for their interest in my study. Their on-site visits to ensure the smooth running of the research and the meetings to discuss our findings were crucial to the success of this project. I am grateful to the Insectarium of Montreal, considered among the most important museums dedicated entirely to insects in North America, for providing the resources and environment necessary for my research.

I am deeply thankful to my family for their unwavering moral support. Your encouragement has been my backbone throughout this journey.

A special thanks to my directors and professors Constantinos Coursaris, Sylvain Sénécal and Pierre-Majorique Léger, whose guidance and encouragement have been instrumental in shaping my academic path. Your wisdom and feedback have greatly enhanced the quality of my work. To my project partner, Amritam, whom I worked alongside since the very beginning of this arduous project. To my friends from the UX program - Rachel, Jasmine, Maya and Astrid - who have walked this challenging path alongside me, your camaraderie and understanding have been a source of strength and motivation. I could not have asked for a better support system.

Lastly, I would like to extend my gratitude to my employer, Tecsys, for their remarkable understanding and support. Specifically, I am thankful to my former manager, Ruben Reid, and my current manager, Daniel Vanier, for their flexibility and encouragement, which allowed me to dedicate the necessary time and effort to this project.

Thank you all for your invaluable support and belief in me.

Chapter 1: Introduction

The concept of Augmented Reality (AR) emerged in the late 20th century, envisioning a future where digital information seamlessly integrates with the physical world. Early experiments in the 1960s laid the groundwork for AR technology (Billinghurst, 2021). However, it was not until the late 20th and early 21st centuries that significant advancements in hardware and software paved the way for practical applications.

In the 1990s, AR gained traction with pioneering systems like the Virtual Fixtures platform by Louis Rosenberg, which allowed users to interact with virtual objects overlaid onto real-world environments (Rosenberg, 2022). The subsequent development of wearable AR devices, such as the MIT Media Lab's "SixthSense" system developed by Pranav Mistry, further advanced AR technology by integrating gesture-based interfaces and wearable technology (Mistry & Maes, 2009). In 1994, Milgram and Kishino introduced the Virtual-Reality Continuum, a framework that includes four systems: the real environment, augmented reality, augmented virtuality, and virtual environment (Cipresso et al., 2018). Positioned within this continuum, AR represents the seamless integration of virtual objects into the real world in real-time. Delineating this definition further, the key features of an AR system emphasize the integration of real and virtual objects, interactivity, real-time functionality, and precise registration of real and virtual objects (Azuma et al., 2001).

The advent of smartphones and tablets in the late 2000s marked a transformative period for AR, transitioning it from a niche research area to a mainstream technology accessible to millions. The release of mobile applications such as "Pokemon Go" in the summer of 2016 marked a significant milestone, attracting over 750 million downloads and sparking unprecedented user engagement (Goff et al., 2018). This phenomenon captured the attention of the academic community, leading to research exploring its potential as a treatment for social disorders and its ability to promote physical activity. For many, "Pokemon Go" served as an introduction to mobile augmented reality on a large scale, highlighting its potential for transforming the mobile gaming industry and educational technology.

Projections indicate significant growth in AR adoption, with over 100 million users expected in the United States by 2024 (Adrian & Wurmser, 2022). This growth is fueled by substantial investments in AR technologies, driving advancements in display technology, vision sensors, and interactive interfaces. As a result, AR experiences are becoming increasingly immersive, offering users a heightened sense of presence within virtual environments. This immersive quality has the potential to revolutionize various industries and redefine how individuals interact with digital content in their everyday lives.

This rapid development and integration of AR technology has significantly transformed various facets of everyday life, particularly in education, medicine, and entertainment. Given its mainstream accessibility, mobile AR lies within one of the most promising applications of its field. Mobile AR allows for the superimposition of digital information onto the real world, creating an interactive and immersive experience that can be accessed anywhere and anytime (Perez-Sanagustin et al., 2014).

Traditionally, learning has been confined to formal classroom settings, where structured environments and direct instruction prevail. In these settings, AR can be meticulously tailored to synchronize with specific educational objectives, thereby bolstering learning outcomes and fostering immersive educational experiences. For instance, Ibáñez, Di Serio, Villarán, and Delgado Kloos (2014) crafted an AR application for teaching basic electromagnetism concepts, allowing students to delve into magnetic field effects using mobile devices like tablets. This application not only enhances academic achievements but also provides real-time feedback, demonstrating the substantial benefits of AR in formal education settings (Bacca Acosta et al., 2014).

Indeed, AR applications have emerged as invaluable tools for enhancing learning experiences, including content comprehension, memory retention, and learning motivation (Cipresso et al., 2018). Applications like Aurasma enable interactive exploration of subjects such as astronomy through solar system maps (Paine, 2018). In the medical domain, AR has revolutionized surgical training, patient education, and medical data visualization (Liao et al., 2020). Surgeons benefit from real-time guidance and anatomical visualization during procedures, resulting in enhanced accuracy and reduced risks. Patient education is significantly enhanced through interactive AR experiences that improve comprehension of medical conditions and treatment plans (Liao et al., 2020).

Moreover, the use of AR extends beyond formal settings into non-formal learning environments, such as museums, city tours, and everyday interactions. For example, the Starmap application overlays a map of constellations onto the real stars in the sky, enriching the real world with contextualized data and enhancing learning experiences outside traditional classrooms (Perez-Sanagustin et al., 2014). Researchers have explored the potential of AR and smartphones to facilitate learning in various settings, transforming forests, cities, and museums into digitally enhanced spaces that support and scaffold learning (Perez-Sanagustin et al., 2014).

Mobile technologies, equipped with advanced sensors like cameras and GPS, empower educators to augment any environment with interactive digital information, facilitating contextualized learning experiences. This transformative capability not only supports learning in real-world contexts but also redefines traditional field trips as dynamic, interactive activities, igniting students' motivation and technological curiosity. Furthermore, the integration of AR into blended learning initiatives bridges the gap between formal, non-formal, and informal learning settings, fostering seamless data flow and enhancing the overall formality of learning experiences (Perez-Sanagustin et al., 2014).

As previously mentioned, augmented reality technology offers several advantages that enhance the user experience. AR improves spatial comprehension by seamlessly integrating digital data into the physical environment, providing users with a deeper understanding of space and context (Wedel et al., 2020). Additionally, AR fosters engagement by enabling users to interact with digital content within their real-world surroundings. This interactivity creates immersive and captivating experiences, promoting active participation and exploration. Moreover, AR blurs the boundaries between physical and digital worlds by smoothly integrating virtual components into reality (Craig et al., 2013). This integration offers new ways to interact with information and products, enriching user experiences and expanding the possibilities of interaction design.

Nonetheless, despite these advantages, there are numerous challenges in crafting proficient AR experiences (Kruijff et al., 2021). One primary challenge is achieving perceptually correct augmentation, ensuring that digital content aligns accurately with real-world objects and facilitates correct interpretation of spatial relationships. Depth and illumination issues also pose significant challenges, impacting depth interpretation, scene distortions, and visibility, which can lead to incorrect perception and hinder task performance (Kruijff et al., 2010).

Ergonomic challenges become prominent with handheld devices, involving variables such as screen dimensions, brightness, and contrast, which can hinder perception, especially in outdoor environments (Kruijff et al., 2010). The development of AR faces complications due to varying field of view, screen size, and the capacity to validate real-world cues across head-worn and handheld devices, influencing the extent of perceptual difficulties users might face (Kruijff et al., 2010). Disparities in sensor and processing technologies among platforms can impact perceptual compromises and the appropriateness of a specific platform for distinct tasks, underscoring the intricate nature of optimizing AR experiences. Usability concerns arise from the reliance on user position and orientation, often resulting in misalignment between real and digital objects due to the limited accuracy of GPS sensors and magnetometers (Kurkovsky et al., 2012). Moreover, interaction design complexities emerge when users move their devices while walking, adversely affecting the quality of AR imagery. Open research problems persist in areas such as navigation, context-awareness, visualization, and content creation, posing significant hurdles in the development of handheld AR applications.

Furthermore, the quality of AR imagery can be compromised by users' movement, particularly while walking, causing distortion or lag in the augmented content. This movement-related impact on quality is a notable concern in handheld AR applications (Kurkovsky et al., 2012).

Additionally, the optical quality of device lenses, often wide-angle with short focal lengths, can introduce aberrations such as blurring, reduced contrast, and color misalignment (Kruijff et al., 2010). These optical issues detract from the realism and visual quality of the augmented content, affecting user immersion and engagement.

Moreover, technical limitations in processing power, sensor accuracy, and real-time rendering capabilities pose challenges in delivering complex and sophisticated AR experiences on handheld devices (Kruijff et al., 2010). Designing intuitive and user-friendly AR interfaces is also crucial but can be challenging due to the need for precise interaction, effective spatial mapping, and seamless integration of digital content with the real-world environment. Addressing these challenges requires continuous advancements in hardware capabilities, software optimization, ergonomic design considerations, and user experience research.

AR technology offers multiple mediums of immersive experiences through head-worn devices like smart glasses, handheld devices such as smartphones and tablets, and projector-camera systems that project digital content onto physical surfaces (Kruijff et al., 2010). However, these advancements bring significant challenges that must be addressed to enhance the effectiveness and usability of AR applications.

AR systems require a camera to track user movements and integrate virtual objects, along with a visual display like glasses for users to perceive virtual elements overlaid onto the real world (Cipresso et al., 2018). There are two main display systems: video see-through (VST) and optical see-through (OST) AR systems. The VST system shows virtual objects by capturing real scenes with a camera and overlaying virtual elements on a video or monitor display. Conversely, the OST system integrates virtual objects onto transparent surfaces like glasses, enabling users to view the added elements directly. The primary difference between these systems is latency, as OST systems may experience delays in displaying virtual objects compared to VST systems, resulting in a time lag between user actions and system responsiveness (Cipresso et al., 2018).

The motivation for our study stems from the insufficient literature addressing the effects of visual discomfort, user experience, and task performance specifically related to AR on mobile devices. While there is growing interest and research in wearable AR technologies like optical see-through (OST) displays, such as Google Glass, there is a notable gap in understanding the ergonomic effects and user interactions concerning mobile AR, which is the most prevalent form of AR in widespread use today. This gap drives the need for comprehensive studies that investigate the impacts of visual discomfort and explore user experiences in mobile AR environments to enhance usability and user satisfaction.

Our study specifically focused on manipulating luminance ratios because this factor has been identified as a significant contributor to eye strain and visual discomfort. By examining the impact of luminance ratios on user experiences and task performance in augmented reality on mobile devices, I aimed to shed light on an essential aspect that directly influences the comfort and usability of these technologies.

Despite the clear benefits, AR's effectiveness can be influenced by various external factors, including luminance, and internal factors (directly tied to the user), such as visual fatigue. These factors are critical in understanding how AR affects user experience, particularly in mobile environments where lighting conditions can vary significantly. Thus, investigating the impact of luminance and visual fatigue on user experience in mobile AR environments is necessary for optimizing these technologies and enhancing their potential.

This thesis explores how different luminance ratios affect visual discomfort and, consequently, user experience in mobile AR settings. The study addresses the following research question: **To what extent do phone luminance, ambient luminance and visual fatigue impact user experience during visual tasks?**

The experimental design followed a 2x2 within-subject framework, spanning over 30 minutes and divided into four distinct blocks. The first experimental factor manipulated was ambient luminance (AL), and the second factor was screen luminance (SL), each set to two levels (low and high). The experiment took place in a controlled laboratory environment to simulate conditions similar to those found in informal institutional learning places (IILPs) like museums.

As seen in this first chapter, we introduce augmented reality technology, highlighting its historical development and transformative impact on sectors like education, medicine, and entertainment, with a focus on mobile AR. Chapter 2 provides a comprehensive literature review, covering AR's factors influencing user experience. We identify gaps in research, particularly on visual discomfort and user interaction in mobile AR, using theories such as the Stimulus-Organism-Response (SOR) model, Cognitive Load Theory (CLT), and the Cognitive Theory of Multimedia Learning (CTML) to understand how information is received and processed by users. Chapter 3 details the experimental method and findings on how luminance ratios affect visual discomfort, legibility, affective state, task performance, and hedonic motivation in mobile AR environments. Finally, chapter 4 concludes the thesis by summarizing the main findings, discussing theoretical and practical implications, and suggesting future research directions

Student's Contributions and Responsibilities in the Completion of This Thesis

This thesis was developed in close partnership with my thesis co-directors. The purpose of Table 1 below is to outline my individual intellectual contribution to each part of the thesis. In line with the standards established for our collaboration, the student is expected to contribute at least 50% overall. In areas where my personal contribution surpasses 50%, it reflects leadership and a strong sense of ownership over that particular phase

*Note: the percentages reflect the student's independent work and do not include the guidance and input provided by the project supervisors. The entire study was conducted in 3 phases, of which Phase 1 was the student’s responsibility.

Table 1 - Student's Contributions and Responsibilities in the Completion of This Thesis

Step in the Process	**Contribution**
Problem Identification	Conducted a comprehensive literature review to identify gaps and define the research problem: 80%
Research Question	Formulated a precise research question: 60%
	● Identified key constructs for investigation
Literature Review	Performed extensive literature research and wrote the review section - 100%
Experimental Design	Developed the experimental protocol and design for Phase 1: 60%
	● Crafted the detailed experimental design
Smituli	Selected and prepared the operational stimuli: 50%
	● Collected and edited stimuli images for consistency, along with corresponding textual descriptions
Instrument Development	Created detailed study questionnaires: 80%
	● Designed questionnaires based on identified research constructs: 50%
Ethical Approval	Prepared and submitted all necessary documentation for Research Ethics Board (REB) approval: 80%
Pre-testing	Managed and executed pre-tests to refine the experimental protocol : 70%
Participant Recruitment	Provided criteria and guidelines for participant recruitment: 30%
Data Collection	Was present during the collection of data throughout the experiment at the Insectarium of Montreal: 70%
Data Analysis	Conducted detailed statistical analyses and interpreted the results: 50%
	● Performed data analysis using statistical software (SAS OnDemand)
	● Collaborated with the Tech3Lab statistician for data formatting and preparation
Thesis Writing	Authored the thesis and related articles - 75%

	● Incorporated feedback from supervisors to refine and enhance the thesis

Chapter 2: Literature Review

This chapter consists of two main sections. In the first section, titled "Understanding how information is processed and how it affects the user experience," we will explore the foundational concepts that underpin user behavior and experience. Our exploration will begin with a thorough examination of the Stimulus-Organism-Response (SOR) model, a theoretical framework that delineates the interplay between external stimuli, internal psychological states, and subsequent behavioral responses. Within this context, we will explore the Stimulus (S) aspect, which encompasses external factors that influence an individual's psychological or perceptual state such as features of digital devices, marketing strategies, and technological interfaces. Moving forward, our analysis will extend to the Organism (O) component of the SOR model, which represents an individual's internal state comprising perceptions, emotions, and cognitive processes when exposed to stimuli. We will particularly focus on how these internal processes interact with external stimuli (S) to shape user experiences. Furthermore, the Response (R) aspect of the SOR model will be evaluated, encompassing various outcomes and behavioral responses triggered by the interaction between stimuli (S) and internal states (O). Specifically, we will investigate the response component in terms of task performance, assessing how users' cognitive processes and emotional states influence their ability to perform tasks effectively and efficiently.

Next, we will briefly explore the principles of Cognitive Load Theory (CLT) and the Cognitive Theory of Multimedia Learning (CTML). Cognitive Load Theory, which focuses on the limitations of human working memory and emphasizes the importance of optimizing instructional design to enhance learning efficiency, is particularly relevant in the context of learning. We will examine how different types of cognitive load—intrinsic, extraneous, and germane—affect user experience and task performance within AR environments. The Cognitive Theory of Multimedia Learning builds on these principles by proposing that individuals understand content better when it is presented through a combination of words and images rather than words alone. This theory’s principles are essential in designing effective AR learning experiences that minimize cognitive load and maximize user engagement and comprehension.

Moving on to the second section, "Understanding what influences the user experience within AR settings," we will explore specific factors that significantly impact user experiences within augmented reality environments. One of the primary focuses will be on factors contributing to visual discomfort, including luminance and illuminance. Still relating to the SOR model, these factors play a critical role in shaping how users perceive and engage with AR content, impacting their comfort levels, visual clarity, affective state, and overall satisfaction and performance. By examining these influential factors comprehensively, we aim to uncover insights into how AR design and implementation can be optimized to enhance user comfort, minimize visual discomfort, and create more immersive and enjoyable AR experiences.

Finally, we will explore the impact of different learning settings, such as formal and non-formal environments, on the effectiveness of AR applications. Formal learning environments, like classrooms, have structured objectives and clear educational goals, whereas non-formal settings, such as museums or self-guided tours, offer more flexibility and learner autonomy. Understanding how AR can be tailored to suit these different contexts will provide valuable insights into optimizing its use for educational and informational purposes.

2.1 Understanding how visual information is processed and how it affects the user experience

2.1.1 The SOR Model

The SOR model, an acronym for Stimulus-Organism-Response, stands as a cornerstone in understanding user behavior across various domains, particularly in consumer psychology and technology adoption (Huang, 2023). This model maps the interplay between external stimuli, internal psychological states, and subsequent behavioral responses, shedding light on how individuals interact with stimuli like smartphones, mobile apps, marketing strategies, and digital devices (Huang, 2023). Comprising three essential components – Stimulus (S), Organism (O), and Response (R) – the SOR model explains the complex processes that underlie user experiences and decision-making.

Stimulus (S):

The stimulus component encompasses external factors that exert an influence on an individual's psychological or perceptual state (Jin et al., 2021). In the context of consumer technology like smartphones, stimuli can include features of the device, design elements, user interface, marketing campaigns, and pricing strategies (Huang, 2023). These stimuli serve as triggers that capture the attention and interest of users, prompting them to engage with the product or service.

Organism (O):

The organism represents the internal state of the individual, encompassing perceptions, emotions, cognitive processes, attitudes, beliefs, motivations, and prior experiences (Huang, 2023). When exposed to external stimuli, the organism processes and interprets these stimuli based on individual characteristics and internal psychological factors. For instance, two users encountering the same smartphone features may have different responses based on their unique perceptions, preferences, and past experiences.

Response (R):

The response component signifies the observable behavioral outcomes or reactions elicited by the interaction between stimuli and the organism's internal state (Huang, 2023). This can include actions such as purchasing a product, using a mobile app, recommending a service to others, expressing satisfaction or dissatisfaction, and forming brand loyalty (Wang & Wang, 2021). Responses can also extend to non-behavioral aspects such as emotional reactions, cognitive evaluations, and decision-making processes (Wang & Wang, 2021).

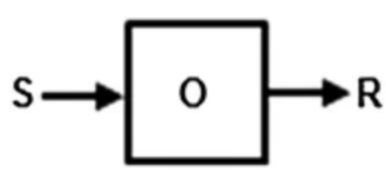


Figure 1 - SOR Model

Buxbaum, O., & Buxbaum, O. (2016). The SOR-model. Key insights into basic mechanisms of mental activity, 7-9.

Many researchers, such as Huang (2023), Jin et al. (2021), Wang and Wang (2021), and Do et al. (2020), have highlighted the versatility of the SOR framework in understanding and explaining consumer behavior across various domains, including mobile app adoption, retail settings, online shopping environments, and technology usage contexts. It offers valuable insights for designing effective user experiences, enhancing product adoption rates, and encouraging user engagement and satisfaction (Huang, 2023; Jin et al., 2021; Wang & Wang, 2021).

In the realm of augmented reality, the SOR model finds practical application (Do et al., 2020). A comprehensive study analyzing 479 valid samples was conducted by Do et al. to understand how mobile AR apps influence tourist impulse buying behavior within the tourism industry. Their findings underscored the pivotal role of utility, ease-of-use, and interactivity of mobile AR apps in shaping user enjoyment and satisfaction, ultimately driving increased impulse buying behavior among tourists. These insights align with the core principles of the SOR model, which emphasizes the dynamic relationship between external stimuli, internal psychological states, and subsequent behavioral outcomes.

Moreover, the study investigated the perceived interactivity of mobile AR apps, revealing a strong correlation between user enjoyment and the interactive features of these apps (Do et al., 2020). This observation further reinforces the SOR model's emphasis on the role of stimuli in evoking positive organismic responses and subsequent behavioral reactions. Over time, the SOR model has evolved and been expanded upon by various researchers in consumer behavior, psychology, and human-computer interaction (Wang & Wang, 2021). Rightfully so, the SOR model has gained prominence due to its flexibility, adaptability, and relevance in capturing complex psychological processes underlying user behaviors (Huang, 2023).

2.1.2. Perception and Visual Perception

Perception is the brain's ability to interpret and make sense of sensory information received from the environment. It involves recognizing and processing various stimuli, such as visual, auditory, tactile, and olfactory cues, to form a coherent understanding of the surroundings (Kruijff et al., 2010). This process is intricate and multifaceted, as different sensory modalities contribute distinct types of information that are integrated to create a unified perception of reality (Kruijff et al., 2010). Perception serves as the foundation for all cognitive processes, facilitating the recognition, organization, and interpretation of sensory inputs to create mental representations and comprehend the external world (Efron, 1969); it plays a vital role in philosophy and science, acting as the fundamental mechanism through which individuals acquire knowledge and engage with their environment. In essence, it enables individuals to distinguish between different stimuli such as colors, shapes, sounds, and textures, leading to adaptive behavior and informed decision-making in various contexts (Efron, 1969). Thus, perception serves as a cognitive bridge that integrates distinct sensory modalities to form a unified perception of reality, allowing individuals to navigate and interact with their surroundings effectively.

Visual perception, a subset of the broader concept of perception, encompasses the brain's intricate process of interpreting visual stimuli received through the eyes. This cognitive operation involves a series of steps aimed at organizing and comprehending visual information to construct a coherent representation of the surrounding environment (Yuen et al., 2011). Through visual perception, individuals can identify objects, navigate spatial surroundings, and interact effectively with their surroundings. Visual perception plays a pivotal role in the realm of augmented reality, particularly concerning the challenges posed by incorrect illumination conditions or the decoupling of vergence and accommodation in human vision (Zhdanov et al., 2019). Accurate depth perception and realistic visual experiences are critical factors in AR environments, where virtual elements are overlaid onto the real world (El Jamiy & Marsh 2019). Depth perception is a critical aspect in mixed reality and augmented reality environments (Cidota et al, 2016). This facet greatly enhances user experiences and interactions by allowing for realistic spatial engagements with virtual objects overlaid on the real world. Accurate depth perception is vital for creating immersive and believable virtual elements within the physical environment, contributing significantly to the overall sense of presence and realism in AR systems (El Jamiy & Marsh, 2019).

2.1.3 Vergence-Accommodation Conflict

Exploring visual perception within augmented reality environments requires an examination of the coordination between vergence and accommodation, commonly referred to as the Vergence-Accommodation Conflict (VAC) (Erickson, et al., 2022). The concept of vergence-accommodation is crucial in understanding how depth perception operates, particularly in the context of stereoscopic displays such as 3D movies, VR headsets and AR.

Vergence refers to the inward rotation of our eyeballs when focusing on an object, ensuring that the point of interest aligns on both retinas for a clear image (Hoffman et al., 2008). This natural process is fundamental to everyday vision. Accommodation, on the other hand, involves the adjustment of crystalline lenses to focus light from objects at varying distances, akin to camera lenses focusing for a clear picture. In normal vision, vergence and accommodation work harmoniously to provide accurate depth perception. (Frey et al., 2015).

In stereoscopic displays, such as headworn virtual reality, the discrepancy arises as these systems can simulate vergence by sending distinct images to each eye, creating a sense of depth (Erickson, et al. 2022). However, they cannot replicate accommodation accurately since their focal plane remains fixed, irrespective of virtual object distances. This incongruity between required vergence and fixed accommodation leads to the vergence-accommodation conflict (VAC), causing visual discomfort and fatigue if prolonged or pronounced (Lambooij et al, 2009).

Addressing the VAC is a significant challenge in designing comfortable and effective stereoscopic displays, highlighting the importance of understanding how our eyes perceive depth and the implications for immersive visual experiences (Frey et al., 2015). Of course, in stereotypical technologies like 3D displays or virtual reality headsets, the VAC becomes pronounced. These technologies present separate images to each eye to create a sense of depth (vergence), but they cannot replicate the natural accommodation process accurately (Lambooij et al., 2009). As a result, users may experience visual discomfort and fatigue due to the mismatch between the required vergence and fixed accommodation.

Nonetheless, in AR environments, where digital objects are superimposed onto the real world through a display, this natural coordination can also be expected to be disrupted. The display remains fixed at a certain distance, while the virtual objects may appear at different depths (Erickson et al, 2022). As a result, our eyes may be accommodated to one distance while the virtual stimuli require a different vergence distance (Hoffman et al. 2008). This discrepancy can lead to visual discomfort and symptoms, such as eye strain and headaches, as the eyes struggle to reconcile the conflicting depth cues presented by the AR environment (Erickson et al, 2022).

One notable effort to address the VAC in AR was made by Magic Leap Inc. in 2018 with their AR display product (Zabels et al., 2019). This device attempted to mitigate VAC by using a varifocal design, featuring two discrete image focal planes that switch based on eye-tracking data (Zabels et al., 2019). Although this approach doesn't provide a completely life-like experience, the addition of a second focal plane at a closer distance significantly improves the sharpness of 3D images (Zabels et al., 2019). Increased interest in wearable display technologies could drive the development of faster, more integrated reflective spatial light modulators (SLMs), potentially leading to improved VAC-corrected displays (Adrian, P., & Wurmser, Y. 2022).

Interestingly, while the VAC has been extensively studied in relation to stereotypical technologies, its impact on augmented reality remains relatively unexplored (Erickson et al., 2022). AR overlays digital content onto the real world, presenting unique challenges in terms of visual perception. Unlike 3D displays, AR maintains a fixed focal plane regardless of the virtual object's distance, potentially affecting the VAC though with a lower intensity (Kruijff et al., 2010). Nonetheless, the interaction between visual perception, accommodation, and the AR environment requires further investigation to understand the potential conflicts and their implications for user experience.

2.1.4 Visual Discomfort vs Visual Fatigue

Transitioning from the discussion on visual perception and the Vergence-Accommodation Conflict (VAC), we now turn our attention to two critical phenomena that can arise from prolonged or intense exposure to digital visual environments: visual discomfort and visual fatigue. These conditions highlight the intricate relationship between human vision, technological interfaces, and user experience, shedding light on the challenges and considerations essential for designing immersive and comfortable augmented reality experiences.

Visual discomfort refers to any subjective sensation or discomfort experienced by an individual due to visual factors. It is closely correlated to visual fatigue, which is defined as a decrease in the performance of the human vision system that can be objectively measured (Lambooij et al., 2009). Symptoms of visual discomfort and fatigue include changes in pupil size, accommodation and vergence adaptation disorders, ocular issues such as dried mucus of the eyes, tears around the eyelid, changes in blinking rate, and a reduction in the speed of eye movements (Urvoy et al., 2013).

A study conducted by Zhou et al. (2021) investigates Computer Vision Syndrome (CVS), also known as digital eye strain, encompassing a spectrum of eye and vision-related challenges resulting from prolonged utilization of digital devices such as computers, tablets, e-readers, and cell phones. These challenges include visual discomfort, visual fatigue, blurred vision, and eye strain, among other symptoms, indicating a widespread prevalence of CVS among digital device users globally (Zhou et al., 2021). The findings from this study are particularly significant within the domain of mobile AR as they emphasize the symptoms of visual discomfort and visual fatigue. Considering that mobile devices can commonly act as platforms for AR experiences, users who engage in prolonged AR interactions may experience comparable eye and vision-related challenges. Furthermore, the study accentuates the critical role of environmental factors, particularly ambient illuminance and screen luminance, in contributing to the severity of CVS. These factors, categorized as environment-related and screen-related, respectively, exert an influence on the overall user experience and comfort levels during interactions with digital screens, including those integrated into mobile AR platforms.

Diagnosing visual fatigue involves both subjective and objective methods. For its subjective counterpart (visual discomfort), self-report questionnaires such as the Visual Fatigue Subjective Assessment Scale (Heuer et al., 1989), allow individuals to report their experiences of visual discomfort. Objective measures include optometry tests like the Critical Fusion Frequency (CFF) test (Katsuyuki et al., 1996), which evaluates the ability of the visual system to distinguish between rapidly flickering light, providing a quantifiable measure of visual performance. These diagnostic tools are crucial for identifying the presence and severity of visual fatigue, enabling the development of strategies to mitigate its impact on users, especially in contexts involving prolonged use of digital devices and augmented reality environments. This is why understanding the nuances of visual discomfort and fatigue is essential for improving the design of AR systems, since it ensures that users engage with AR content comfortably and effectively.

2.2 Factors influencing the user experience within mobile AR environments

2.2.1 The Role of Lighting: Luminance and Illuminance

Illuminance, as defined by King (1973), is the measure of light flux falling onto a surface, regardless of factors like the light source's direction, number, position, type, or the characteristics of the surface. This concept is particularly relevant in the realm of mobile augmented reality where the effectiveness of illuminating virtual objects in real-world environments is crucial for creating immersive AR experiences (Kruijff, et al, 2010). For instance, developers must consider how various lighting conditions, such as natural light outdoors or artificial lighting indoors, affect illuminance levels on mobile AR displays to ensure that virtual content remains visible and engaging across different environments (Kruijff, et al, 2010).

Conversely, luminance refers to the amount and concentration of light flux emitted from a surface, determining how vividly an object is perceived visually (King, 1973). In the context of mobile AR, luminance plays an important role in enhancing the realism of virtual objects by influencing their brightness and appearance relative to the surrounding environment (Kruifjj et al, 2010). Factors such as the direction of incident light on mobile AR devices, the viewing angle of users, and the reflective properties of virtual objects collectively contribute to the overall luminance experienced by AR users.

A study by Benedetto et al. (2014) provides insights into the impact of luminance on visual fatigue and arousal in the context of Electronic Visual Displays (EVDs). The study distinguishes between internal symptoms, often stemming from individual anomalies like refractive, accommodative, or vergence issues, and external symptoms linked to dry eye conditions (known scientifically as keratoconjunctivitis sicca or xerophthalmia). These external symptoms arise from decreased tear production or reduced blinking, resulting in increased tear film evaporation, which is often exacerbated by higher light intensities and can be observed through changes in eye blink rate (Tsubota & Nakamori, 1993; Rosenfield, 2011).

Moreover, Benedetto et al. (2014) highlight the role of light intensity, specifically screen luminance and ambient illuminance, in influencing visual fatigue and arousal during interactions with EVDs. Screen luminance, measured in candelas per square meter (cd/m2), refers to the light emitted by a display, while illuminance, measured in lux (lx), represents the incident light on a surface. Studies referenced by these same authors demonstrate a direct relationship between screen luminance and visual fatigue, where higher luminance levels correlate with increased visual fatigue and reduced performance metrics such as reading speed and search accuracy (Chi et al., 2013; Kim et al., 2012; Rosenfield, 2011). Additionally, Benedetto et al's study is supported by ISO standards (ISO 9241-303, 2011), emphasizing the need for a balance between screen luminance and visual comfort to optimize user experience and performance with EVDs. This balance is crucial as higher luminance levels, while enhancing arousal and alertness, can also lead to elevated levels of visual fatigue.

2.2.2 Task Performance

Task performance within augmented reality systems is influenced by various factors (Yang et al., 2019). One critical consideration is the complexity of assembly tasks, which plays a pivotal role in determining the effectiveness of AR assistance. The study emphasizes that different levels of task complexity can either augment or hinder task performance when utilizing AR systems (Yang et al., 2019). This underscores the importance of tailoring AR solutions to the specific intricacies of assembly tasks to optimize user performance and outcomes.

Visual interference and sensitivity emerge as critical factors affecting task performance in AR environments, particularly during information-related activities within assembly tasks (Yang et al, 2019). The latter authors draw attention to challenges such as visual interference from augmented information, sensitivity to dislocation, delays in information processing, and potential conflicts with physical components. Addressing these issues is essential for optimizing task performance and user experience in AR-enhanced assembly scenarios, necessitating careful design considerations and technological interventions.

Furthermore, the technological capabilities and limitations of the AR system used significantly impacted task performance, as noted by Yang et al. (2019). For instance, the study discusses the utilization of a desktop AR system, which inherently imposes constraints such as fixed assembly visual angles. Overcoming these technological limitations and leveraging advanced AR systems with greater flexibility and functionality can substantially enhance task performance, providing users with more intuitive and efficient tools for assembly tasks within AR environments.

The legibility of text in augmented reality head-worn displays (HWDs) is a critical factor influencing task performance, as highlighted by Gattullo et al. (2015). This legibility is intricately influenced by various factors such as the background environment, display technology, and text style employed within AR interfaces. Additionally, constraints imposed by color-coding practices and workplace lighting conditions further contribute to the complexity of text legibility in AR environments.

The choice of text style emerges as a significant determinant of response time, particularly in industrial settings, as noted by Gattullo et al. (2015). Their study reveals that different text styles, including billboard, outline, and plain text styles, can significantly impact the speed of user responses during tasks. Interestingly, while text style influences response time, it does not exert a substantial effect on error rates, suggesting that text legibility variations primarily affect task efficiency rather than accuracy in industrial AR contexts.

In terms of background environments, the engine background yielded the fastest response times among the tested backgrounds (Gattullo et al., 2015). This finding is attributed to factors such as the luminance profile of the engine background, which may enhance visual contrast and readability of text elements. However, despite the notable impact on response time, the chosen backgrounds did not significantly influence error rates in task performance (Gattullo et al., 2015). Additionally, there was no observed interaction effect between background types and text styles, contrary to previous findings in outdoor AR environments, indicating context-specific nuances in text legibility and task performance within AR systems.

Moreover, a review evaluating the cognitive load and task performance in AR contexts found a positive correlation between effects on mental workload and task performance (Jeffri et al., 2021). A screening of 101 papers was performed, 63 of which were retained, focusing on AR and task performance. From these papers, patterns emerged, indicating that positive effects on mental workload often translate into improved task performance (Jeffri et al., 2021). However, these improvements in performance are not necessarily a direct result of reduced mental workload. Instead, they may stem from the efficient allocation of cognitive resources, such as working memory, when using AR (Huang, 2023; Jin et al., 2021; Wang & Wang, 2021; Do et al., 2020). This reallocation can free up mental resources, allowing users to focus more on task execution, thereby enhancing performance. According to Cognitive Load Theory (CLT), reducing extraneous cognitive load enables users to direct more cognitive resources towards problem-solving and task execution, ultimately leading to better performance (Do et al., 2020).

This finding underscores the importance of designing AR systems that minimize cognitive load to optimize task performance.

2.2.3 Learning Setting: Formal vs Non-Formal

AR technology has demonstrated remarkable versatility across various sectors, showcasing its transformative potential. In formal learning environments like classrooms or training sessions, AR can be tailored to align with specific educational objectives. In the realm of education, AR applications have emerged as invaluable tools for enhancing learning experiences and knowledge retention (Cipresso et al., 2018). Research highlights the positive impact of AR on content comprehension, memory retention, and learning motivation (Cipresso et al., 2018). For example, applications like Aurasma have revolutionized learning paradigms, enabling interactive exploration of subjects such as astronomy through solar system maps and real-time visualization of musical notations (Paine, 2018). Another example of current AR applications in education is an AR tool designed by Ibáñez, Di Serio, Villarán, and Delgado Kloos (2014) for teaching basic electromagnetism concepts. This application allows students to explore magnetic field effects by using mobile devices like tablets to recognize experimental components (cables, magnets, batteries, etc.). Through the tablet's camera, students can view superimposed information such as electromagnetic forces and circuit behavior. The study found that this AR application enhanced academic achievement and provided immediate feedback (Acosta et al, 2014). A further illustration of AR's capability to enhance learning is the iPhone application, Starmap. This app overlays a map of constellations onto the real stars observed in the sky, demonstrating AR's ability to superimpose digital information onto physical settings. This enrichment of the real world with contextualized data has prompted researchers to explore AR and smartphones for facilitating learning outside traditional classrooms, incorporating digital layers into informal and non-formal learning environments (Perez-Sanagustin et al., 2014). By enabling learning to take place anytime and anywhere, AR and mobile technologies create new opportunities for educational experiences outside the classroom, enhancing both knowledge acquisition and retention (Perez-Sanagustin et al., 2014).

Recent national initiatives have emphasized the importance of increasing interest and engagement in STEM (science, technology, engineering, and mathematics) disciplines to meet future workforce demands (Goff et al., 2018). While much of this focus has been on traditional classroom settings, non-formal learning environments have also been recognized for their vital role in fostering STEM interest (Jensen & Lister, 2016). Non-formal science education (ISE), which includes diverse settings like science centers, after-school programs, and makerspaces, offers unique opportunities for engagement. Additionally, many studies have underscored the importance of museums and similar settings in promoting non-formal learning (Goff et al., 2018). Nonetheless, there is a pressing need for updated reviews to incorporate new technological advancements, like augmented reality, that can further enhance educational outcomes (Goff et al., 2018).

Moving beyond education, AR has made significant strides in architecture, construction, and facility management, assisting in a new era of visualization and operational efficiency (Chi et al., 2013). In the architecture sector, AR enhances spatial understanding and design decision-making by superimposing virtual models onto real-world environments (Chi et al., 2013). This capability streamlines the design process and improves spatial comprehension. Additionally, AR aids construction workers by providing real-time guidance, displaying plans, and facilitating communication among stakeholders, leading to improved efficiency and coordination throughout projects (Chi et al., 2013).

In the medical domain, AR has revolutionized surgical training, patient education, and medical data visualization (Liao et al., 2020). Surgeons benefit from real-time guidance and anatomical visualization during procedures, resulting in enhanced accuracy and reduced risks (Liao et al., 2020). Patient education is significantly enhanced through interactive AR experiences that improve comprehension of medical conditions and treatment plans. Furthermore, AR-based medical training provides realistic simulations for trainees, enhancing surgical skills and knowledge retention (Liao et al., 2020). The integration of AR technology across these sectors underscores its potential to transform industries, enhance learning experiences, and improve operational workflows.

Conversely, non-formal learning is characterized by learners having the autonomy to choose what they want to learn, while the methods to achieve this learning are decided by others (Perez-Sanagustin et al., 2014). It takes place in environments that are more organized than informal settings but not as formal as traditional educational institutions, such as museums or specialized training programs. This type of learning strikes a balance between learner independence and structured support, providing opportunities for skill development and knowledge acquisition outside conventional educational contexts (Perez-Sanagustin et al., 2014). Recognizing the differences between informal and non-formal learning is essential for creating effective educational strategies that accommodate various learning preferences and environments.

In non-formal learning environments, such as museums, galleries, or for personal use, AR has demonstrated a significant impact on knowledge acquisition and retention, outperforming non-AR exhibits (Sommerauer & Müller, 2014). These settings provide a more relaxed and self-directed approach to learning, allowing users to explore at their own pace. This technology aligns with cognitive theory principles, thereby enhancing the efficiency and effectiveness of learning processes (discussed further in section 2.2.4). AR applications in these environments can offer interactive, exploratory experiences that capture users' interest and curiosity, making learning more engaging and enjoyable (Sommerauer & Müller, 2014). By integrating AR into non-formal learning settings, learners can experience a more engaging and immersive learning environment, leading to improved learning outcomes and a deeper understanding of the subject matter.

The NMC Horizon Report 2012 predicted that AR would see widespread adoption by 2015, highlighting its potential impact on teaching and learning (Sommerauer & Müller, 2014). However, despite this potential, there has been limited active exploration into how mobile, context-aware AR can enhance educational experiences in non-formal settings. Most existing empirical research on AR in education has been qualitative, concentrating on the affordances and constraints of AR within learning environments (Sommerauer & Müller, 2014).

2.2.4 Cognitive Load and Cognitive Multimedia Learning Theory

2.2.4.1 Cognitive Load and AR

While a deep dive into cognitive load theory (CLT) is beyond the scope of this literature review, understanding its basic principles provides a framework for designing effective AR learning experiences. At its core, CLT focuses on the limitations of human working memory and emphasizes the importance of optimizing instructional design to enhance learning efficiency (Sweller, 2011). Understanding the different types of cognitive load is crucial for evaluating the effectiveness of AR in an educational setting. Cognitive load theory, as outlined by Sweller (2011), categorizes cognitive load into three distinct types:

1. **Intrinsic Cognitive Load** refers to the inherent complexity of the material being learned. This complexity is determined by the nature of the task and the learner's existing knowledge levels. Changes in intrinsic cognitive load can only be achieved by modifying the content or enhancing the learner's prior knowledge.

2. **Extraneous Cognitive Load** is associated with the way information is presented and the instructional design itself. Unlike intrinsic load, it is not inherent to the material but is imposed by the instructional environment. Reducing extraneous cognitive load involves optimizing instructional design to minimize unnecessary cognitive demands on learners.

3. **Germane Cognitive Load** focuses on the cognitive effort required for schema acquisition and automation. This involves the mental effort directed towards organizing and integrating new information into existing cognitive structures, which is essential for deeper learning and schema development.

Building on this understanding of cognitive load, while previous studies have addressed various challenges of using AR in education, such as technological issues and usability concerns, the issue of cognitive load has not been systematically investigated (Buchner et al, 2022). Indeed, research on the effects of augmented reality on cognitive load in formal education presents mixed results. Some studies suggest that AR can lower cognitive load compared to traditional methods, though these studies often lack performance data (Buchner et al, 2022). Conversely, other research indicates that cognitive load is higher in AR groups than in control groups, yet this higher cognitive load is linked to better performance outcomes (Buchner et al, 2022; Do et al., 2020). Furthermore, eight studies found no significant differences in cognitive load between AR and other instructional methods, with two of these comparing AR to multiple alternatives. These findings highlight the variability in AR's impact on cognitive load and emphasize the need for additional research to better understand the complex relationship between AR technology and cognitive load in educational contexts (Buchner et al., 2022).

However, to provide a clearer picture, it is essential to explore the studies that have shown a reduction in cognitive load when using AR, shedding light on the potential benefits of this technology for learning efficiency. It is important to note that, in these studies, they indeed differentiated the different branches of the cognitive load theory; that is, intrinsic, extraneous and germane loads.

A novel psychometric tool designed by Leppink, et al. (2014) aimed to differentiate between intrinsic, extraneous, and germane cognitive load. This tool is a questionnaire, measuring the distinct types of cognitive load during learning tasks, offering a more nuanced understanding of the cognitive processes involved in learning. In their first study, which involved 108 participants engaged in language learning and 174 participants attending a statistics lecture, a consistent three-factor structure was identified across these different contexts. Notably, a negative correlation was found between statistics exam scores and the cognitive loads identified as intrinsic and extraneous, suggesting that higher levels of these cognitive loads are associated with poorer academic performance.

In the second study, university freshmen were divided into four groups to study applications of Bayes' theorem: 18 students in the example–example condition, 18 in the example–problem condition, 18 in the problem–example condition, and 20 in the problem–problem condition. The freshmen demonstrated better posttest performance when studying through example–example or example–problem formats compared to problem–example or problem–problem formats. Additionally, a modified version of the psychometric tool was effective in differentiating between intrinsic and extraneous cognitive loads. These findings support a revised understanding of germane cognitive load as the working memory resources dedicated to managing intrinsic cognitive load (Leppink et al., 2014).

Lai et al. (2018) summarized that the AR-based science learning approach positively impacted students' learning motivations across four dimensions: attention, relevance, confidence, and satisfaction. In examining cognitive load, the study differentiated between "mental load" and "mental effort." T-tests were conducted to assess the effects of the AR-based learning approach on intrinsic and extraneous cognitive load. The results showed no significant difference in intrinsic cognitive load between the two groups ($t = -1.55$, $p > .05$), indicating that the AR-based approach did not significantly affect students' intrinsic cognitive load. However, a significant difference was observed in the mental effort dimension ($t = -2.07$, $p < .05$), suggesting that the AR-based approach did influence students' perceptions of mental effort.

Importantly, the study highlighted that reducing extraneous cognitive load through the use of AR can provide contextual information directly in the learner's field of view (Lai et al., 2018). This reduces the need for students to switch their attention between different sources of information, thereby lowering cognitive demands and potentially enhancing the learning experience by making it more seamless and integrated (Lai et al., 2018).

2.2.4.2 Cognitive Multimedia Learning Theory and AR

The Cognitive Theory of Multimedia Learning (CTML) and Cognitive Load Theory (CLT) are closely intertwined and work together to understand how learners process information and optimize learning experiences (Mayer, 2009; Sweller, 2011). CTML, proposed by Mayer (2009), builds on the principles of CLT and extends them to multimedia learning environments.

CTML posits that individuals understand content better when it is presented through a combination of words and images rather than words alone (Haridas et al., 2017). This emphasizes the importance of designing multimedia content in ways that align with how the human brain processes information. Recently, augmented reality technologies have introduced a new dimension by combining virtual elements with physical, real-world elements (Kruger & Bodemer, 2022). Instructional materials can now include various representation modes, such as text and graphics, sensory modalities like visual and auditory, and different realities, such as physical and virtual. However, merely adding words to pictures isn't sufficient to enhance learning; instead, instructional media should be designed considering the workings of the human mind (Haridas et al., 2017). This forms the foundation of Mayer's cognitive theory of multimedia learning, which is built on three core assumptions:

1. Information is processed through two distinct channels: auditory and visual.
2. Each channel has a limited capacity for processing information.
3. Learning involves an active process of filtering, selecting, organizing, and integrating new information based on existing knowledge.

CTML includes several principles designed to enhance learning by optimizing how information is presented (Tugtekin & Odabasi, 2022). Mayer (2009) explains that the key principles include the Coherence Principle, which suggests that extraneous information should be eliminated to focus on essential content; the Signaling Principle, which emphasizes the use of cues to highlight important information; the Spatial Contiguity Principle, which advocates for placing related text and images close together; the Temporal Contiguity Principle, which recommends presenting corresponding words and pictures simultaneously; and the Modality Principle, which posits that people learn better from graphics and narration than from graphics and text. Each of these principles aims to reduce cognitive load and improve the integration of new information into the learner’s existing knowledge base (Mayer, 2009).

While all these principles contribute to effective multimedia learning, certain principles are particularly pertinent to the use of AR in educational contexts:

- Spatial Contiguity Principle: This principle suggests that learners gain more from multimedia content when related text and images are placed close together on the page or screen, as this minimizes the split-attention effect (Mayer, 2009). AR environments excel in this aspect by placing virtual annotations and explanatory text near the relevant real-world objects. This minimizes the need for learners to shift their focus between disparate sources of information, thus reducing cognitive load and enhancing comprehension (Geng & Yamada, 2020).

- Modality Principle: This principle posits that people learn better from graphics and narration than from graphics and on-screen text. AR can leverage this principle by incorporating audio explanations along with visual elements, reducing the cognitive load on the visual channel and making the learning process more efficient (Mayer, 2009). For example, in biology lessons, students who received information through auditory narration alongside visual elements performed better than those who relied solely on text and visuals (Harskamp et al., 2007).

- Signaling Principle: This principle suggests that learning improves when cues are used to highlight the structure of essential information within a learning environment (Sommerauer & Müller, 2014). AR can apply this principle by using geographic location data and visual prompts to direct and guide individuals through learning environments (Sommerauer & Müller, 2014).

A study by Sommerauer and Müller (2014) tested CTML principles in the context of AR in museums, focusing on the signaling, modality, and spatial contiguity principles. The researchers hypothesized that visitors would learn more effectively from augmented museum exhibits compared to traditional physical displays like boards, posters, or screens. They argued that AR inherently incorporates CTML principles, including multimedia, spatial contiguity, temporal contiguity, modality, and signaling. The empirical results supported their hypothesis, showing that museum visitors learned significantly more from augmented exhibits, valued AR as a beneficial addition to the exhibition, and expressed a desire for more AR technologies in museums (Sommerauer & Müller, 2014).

The principles of Spatial Contiguity, Modality, and Signaling are particularly relevant, as they help in reducing cognitive load and improving learning outcomes (Sommerauer & Müller, 2014). By aligning AR design with CTML principles, we can optimize educational experiences, making them more effective and enjoyable for learners.

2.3 User Experience and Motivation in AR

The study conducted by Benedetto et al. (2014) primarily focuses on the effects of light intensity, specifically screen luminance and ambient luminance, on visual fatigue and arousal during interactions with Electronic Visual Displays (EVDs). While their research contributes valuable insights into the relationship between light intensity and visual discomfort within the context of EVDs, there exists a notable gap in the literature concerning the application of these findings to augmented reality environments. The scarcity of comprehensive and rigorous studies on AR experiences in informal settings likely stems from the complexity of these environments rather than a lack of interest in researching visitors' learning processes, outcomes, and perceptions (Orr et al, 2021). Although some research has explored the impact of extended reality experiences on visitor enjoyment and engagement (He et al., 2018; Leopardi et al., 2020), there are few studies that specifically examine how these experiences affect visitors' learning processes and outcomes. Typically, learning activities in informal contexts are low-structured and involve open-ended interactions with objects and, potentially, other learners.

Unlike traditional EVDs, AR systems introduce virtual elements into the user's visual field, creating a blended reality experience. This unique interaction between digital content and the physical environment raises questions about how factors like screen luminance and ambient luminance, as discussed by Benedetto et al. (2014), impact visual comfort, and overall user experience in AR settings.

As evidenced by the diverse applications of AR in education, architecture, medicine, and other domains, the technology's pervasive influence underscores the need to understand and address issues related to visual discomfort and fatigue within AR environments. It is therefore worth exploring the transferability and applicability of findings from studies like Benedetto et al. (2014) to augmented reality is crucial for advancing our understanding of visual discomfort and fatigue in contemporary digital environments. This exploration can provide valuable insights into optimizing AR systems to enhance user comfort, minimize visual fatigue, and improve overall usability, thereby addressing an important gap in the existing literature.

2.4 Summary of Literature Review

In this chapter, we explored the complex mechanisms that shape user experiences in augmented reality environments, using foundational theories and models as our guide. Our exploration began with the Stimulus-Organism-Response (SOR) model, which provided a robust framework to understand the interaction between external stimuli, internal psychological states, and resultant behaviors. By dissecting the Stimulus (S), Organism (O), and Response (R) components, we gained insights into how features of digital devices, marketing strategies, and technological interfaces impact user perceptions, emotions, and cognitive processes, ultimately shaping their experiences and task performance.

We then examined the principles of Cognitive Load Theory (CLT) and the Cognitive Theory of Multimedia Learning (CTML), both of which emphasize the importance of optimizing instructional design to enhance learning efficiency. These theories highlight the challenges and opportunities within AR environments, particularly regarding cognitive load management and the presentation of multimedia content. Our analysis underscored the necessity of reducing extraneous cognitive load and leveraging multimedia principles to create engaging and effective AR learning experiences.

The second section of this chapter focused on specific factors influencing user experiences in AR settings. Visual discomfort and visual fatigue emerged as critical issues, particularly due to the Vergence-Accommodation Conflict (VAC) and the impact of screen and ambient luminance.

Understanding these factors is essential for designing AR systems that minimize visual strain and enhance user comfort. Additionally, we explored the role of different learning settings, such as formal and non-formal environments, in determining the effectiveness of AR applications. Our findings revealed that AR can significantly enhance learning outcomes by providing immersive and interactive experiences tailored to various educational contexts.

Moreover, we discussed the importance of task performance and the technological capabilities of AR systems. Factors such as visual interference, text legibility, and the complexity of assembly tasks were identified as crucial determinants of task efficiency and user satisfaction. Our review of the literature indicated that well-designed AR systems could positively impact cognitive load and task performance, highlighting the need for further research to optimize these technologies.

In conclusion, our study provides a comprehensive understanding of the factors that influence user experiences within AR environments. By integrating theoretical frameworks with empirical evidence, we have identified key areas for improvement in AR design and implementation. Future research should continue to explore the complex interplay between cognitive load, visual perception, and user behavior to develop more effective and user-friendly AR applications. This thesis contributes to the growing body of knowledge in the field of AR and offers practical insights for enhancing user experiences and educational outcomes through thoughtful design and innovative technology

Chapter 3: Theoretical Foundations

The following section explores how various factors within mobile AR environments influence user experience. It begins by examining how different luminance ratios impact visual discomfort and legibility, subsequently affecting affective state and task performance. The aim is to identify the specific characteristics within these AR environments that predict these outcomes.

3.1 Visual Discomfort and Legibility in Mobile AR

Luminance ratios are critical in AR environments, as they can significantly affect visual comfort and content legibility. Luminance ratios refer to the relative brightness levels between different light sources or surfaces in a given environment. In handheld AR settings, this typically involves the contrast between the brightness of the AR display and the ambient lighting conditions. Research indicates that visual discomfort can negatively impact user experience and task performance (Hoffman et al., 2008; Lambooij et al., 2009). Higher luminance ratios have been associated with improved legibility, enhancing the clarity and readability of content displayed on screens (King, 1973). Understanding these effects is crucial for optimizing AR applications, particularly in educational settings.

H1: Luminance ratio has a significant effect on visual discomfort.
H2: Luminance ratios are positively associated with legibility.

3.2 Impact of Visual Discomfort on Affective State and Task Performance

Visual discomfort not only affects physical comfort but also has significant implications for users' emotional states and performance. When users experience visual discomfort, it can lead to negative affective states, reducing their overall satisfaction and engagement (Rosenfield, 2011). Additionally, visual discomfort can detrimentally impact both actual and perceived task performance, as well as increase the time required to complete tasks (Chi et al., 2013).

H3: Visual discomfort is negatively associated with affective state.
H4a: Visual discomfort is negatively associated with actual task performance.

H4b: Visual discomfort is negatively associated with perceived task performance.
H4c: Visual discomfort is positively associated with task time.
H4d: Visual discomfort is positively associated with perceived time.

3.3 Role of Affective State in Task Performance and Learning Outcomes

Affective states, which include emotions and mood, play a significant role in determining user performance and learning outcomes. Positive affective states are associated with better task performance and shorter task completion times, as they enhance motivation and cognitive engagement (Kim et al., 2012). Conversely, negative affective states can impair performance and prolong task duration.

H7a: Affective state is positively associated with actual task performance.
H7b: Affective state is positively associated with perceived task performance.
H7c: Affective state is negatively associated with task time.
H7d: Affective state is negatively associated with perceived time.

3.4 Affective State and Hedonic Motivation

Hedonic motivation refers to the enjoyment and pleasure derived from using a product or service. Positive affective states are likely to enhance hedonic motivation, making the user experience more enjoyable and engaging (Perez-Sanagustin et al., 2014).

H8: Affective state is positively associated with hedonic motivation.

3.5 Task Performance and Learning Outcomes

Effective task performance is crucial for positive learning outcomes in AR environments. Both actual and perceived task performance can significantly influence users' perceptions of their learning achievements (Kazemi et al. 2018). Additionally, the time taken to complete tasks, whether actual or perceived, can impact learning outcomes.

H9a: Actual task performance is positively associated with perceived learning outcome.
H9b: Perceived task performance is positively associated with perceived learning outcome.
H9c: Task time is negatively associated with perceived learning outcome.
H9d: Perceived time is negatively associated with perceived learning outcome.

The proposed research model and hypotheses provide a comprehensive guide for examining the complex relationships between luminance ratios, visual discomfort, affective states, task performance, and learning outcomes in mobile AR environments. The subsequent sections will detail the methodology and empirical analysis used to test these hypotheses.

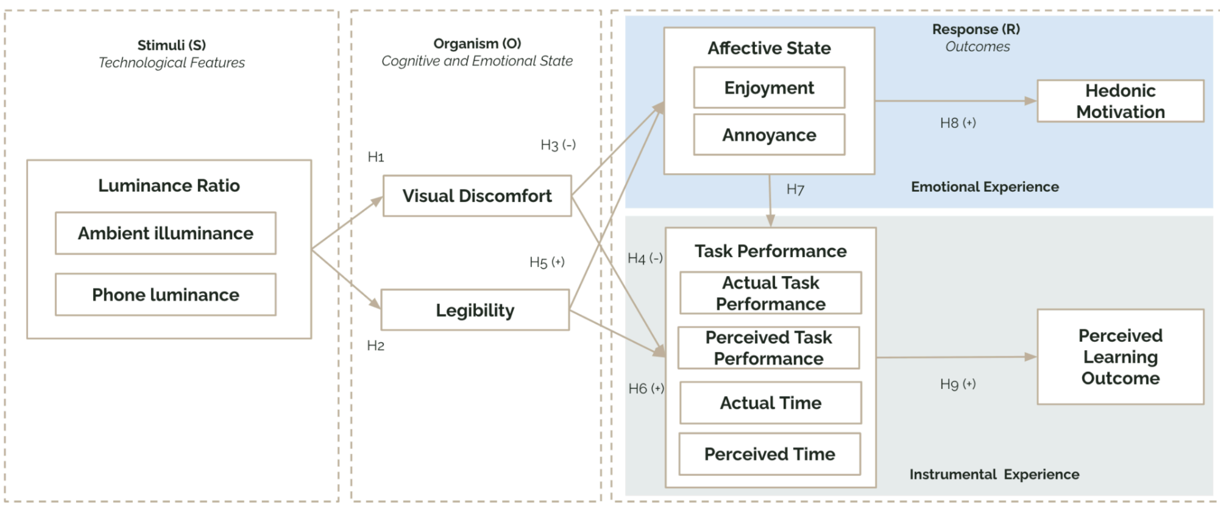


Figure 2 - Proposed Research Model

Chapter 4: Methodology

This section outlines the methodology used in this study, involving manipulating lighting conditions in a controlled laboratory environment. This study was carried out in two distinct phases. The first phase involved a pre-test to verify the manipulation of the predictor variables, ensuring their validity before the main study. The second phase focused on the main study, which aimed to assess the impact of these variables on various outcomes, including visual discomfort, legibility, affective state, task performance, and learning outcomes.

4.1 Pre-Test

During the pre-test phase, 5 participants were engaged to help refine the experimental protocol and survey structure. Due to some technical difficulties encountered during this phase—such as issues with the AR task not functioning as expected or errors in data collection—these participants' responses were not considered valid for the final analysis. As a result, these participants were treated as part of a preliminary test, rather than included in the main study. The pretest entailed the same tasks and questionnaires as in the real experiment.

The insights gained from the pretest were invaluable in troubleshooting and adjusting the experimental setup, which ensured a smoother experience for subsequent participants. Following these adjustments, the main study was conducted with 24 valid participants, who were selected from an initial pool of 29 recruited through the HEC research panel and public social media postings.

4.2 Experimental Design

The experimental design followed a 2x2 within-subject framework, spanning over 30 minutes and divided into four distinct blocks. The first experimental factor manipulated was ambient luminance (AL), and the second factor was screen luminance (SL), each set to two levels (low and high), as detailed in Table 2.

The study was conducted in a controlled laboratory environment to simulate conditions similar to those found in informal institutional learning places (IILPs) like museums. This controlled setting allowed for systematic manipulation of ambient and screen luminance levels to mimic real-world scenarios (Engineering ToolBox, 2004). Participants interacted with AR content on smartphones under different lighting conditions, and the pre-test results informed adjustments to the experimental setup.

Participants were exposed to two different insects per block, repeated across four blocks, each with distinct lighting conditions. The following table outlines the specific lighting conditions applied during each block of the experiment.

The experiment took place in a controlled laboratory-like environment to simulate and optimize the conditions found in informal institutional learning places (IILPs), such as museums. This setup allowed for systematic isolation and manipulation of lighting conditions, specifically adjusting ambient and screen luminance to closely mimic real-world scenarios.

This research adhered to ethical guidelines set by the institution's Research Ethics Board (REB), and ethical approval was obtained. Participants were compensated $50 for their participation.

4.2.1 Experimental Stimuli

Participants were exposed to AR content on a smartphone under different lighting conditions. The content included lifelike images of insects and accompanying textual descriptions averaging 150 words each. The stimuli pool comprised 12 different insect-related QR codes, with 8 randomly selected for each participant. These QR codes, when scanned through the smartphone's camera, revealed the corresponding 3D insect models and textual content. Participants were exposed to 2 different insects per block, repeated across 4 blocks, each with distinct lighting conditions.

The lighting conditions encompassed ambient luminance from the room's artificial illumination (Great Video Maker studio lights, model GVM-672S-B) and screen luminance from the smartphone's brightness (Google Pixel 7). These conditions were randomized to prevent order effects and ensure robust examination of the variables.

Figure 3 - Experimental stimuli being developed at the Tech3Lab

Figure 4 - High ambient luminance with low screen luminance VS low ambient luminance with high screen luminance

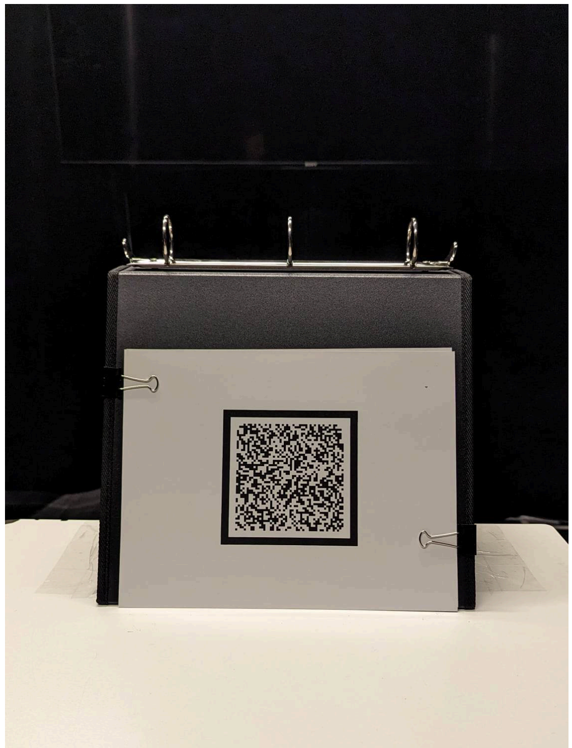


Figure 5 - QR code

Table 2 outlines the specific lighting conditions applied during each block of the experiment. The study examined phone luminance, with high phone luminance set at 100% screen brightness and low phone luminance set at 20% screen brightness. Ambient luminance conditions were also manipulated, with high ambient luminance achieved by turning on all four studio lights to their maximum brightness (100%) and low ambient luminance achieved by turning on only the two back studio lights at 20% brightness.

These luminance levels were selected through a combination of practical trials and real-world comparisons (see Figure 6)

Activity	Illuminance (*lx, lumen/m^2*)
Public areas with dark surroundings	20 - 50
Simple orientation for short visits	50 - 100
Areas with traffic and corridors - stairways, escalators and travelators - lifts - storage spaces	100
Working areas where visual tasks are only occasionally performed	100 - 150
Warehouses, homes, theaters, archives, loading bays	150
Coffee break room, technical facilities, ball-mill areas, pulp plants, waiting rooms,	200

Figure 6 - Recommended light levels for different types of work spaces (Engineering ToolBox, 2004)

In particular, we conducted a series of trial-and-error sessions , testing various combinations of ambient and screen luminance to identify settings that would be realistic yet challenging for participants. For example, while the low ambient lighting condition (at 10-20 lux) might appear quite dim based on its numeric value, our tests revealed that it closely approximated the lighting levels found in the Insectarium's low-light exhibits, which are specifically designed to enhance visibility of delicate displays without causing glare or visual discomfort.

Similarly, the low phone luminance level (20% brightness) was selected because it provided sufficient readability under all tested ambient conditions. Our research assistants did not report any extreme difficulty in reading the AR text under these conditions, suggesting that the chosen settings were within a comfortable range for typical mobile device use, even if the numeric lux readings might suggest otherwise.

Overall, the chosen luminance levels were intended to reflect realistic conditions that users might encounter in various environments, from dimly lit rooms to brightly illuminated spaces, while also ensuring that the AR content remained visible and legible. The systematic manipulation of these levels allowed for a controlled investigation of how different lighting conditions affect visual discomfort, legibility, and user experience in augmented reality (AR) environments.

Figure 7 - Low ambient luminance (only the two studio lights in the back turned on)

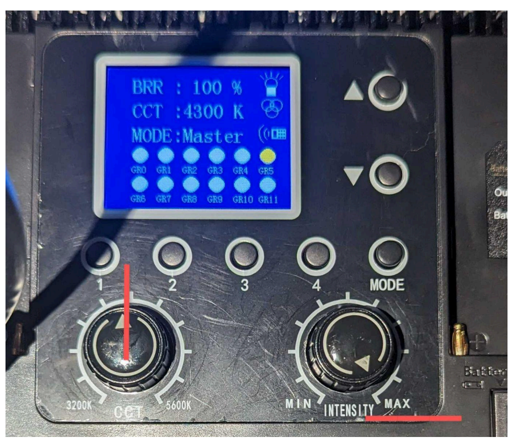


Figure 8 - High ambient luminance (all four studio lights turned on)

This 2x2 within-subjects design was designed to systematically manipulate ambient luminance and screen luminance across four distinct blocks. Each block featured a unique combination of low and high ambient and phone lighting conditions, allowing for a comprehensive assessment of the impact of these variables on participants' visual discomfort, legibility, affective state, and task performance.

Table 2 - Ambient and Phone Lighting Conditions per Block

Block Number	Ambient Condition	Phone Condition
1	Low (20%)	Low (20%)
2	High (100%)	Low (20%)
3	Low (20%)	High (100%)
4	High (100%)	High (100%)

Lux Values

The following tables provide detailed measurements of luminance ratios for two ambient lighting conditions, low and high ambient luminance.

Table 3 presents the luminance values for the low ambient lighting condition, measured in lux (lx). The ambient luminance was set at 20.4 lx. The screen luminance, determined by the phone's brightness settings, was measured at two levels: 20% and 100%. At 20% brightness, the screen luminance was 8.34 lx, and at 100% brightness, it was 319.82 lx. These values indicate the contrast in luminance participants experienced between low and high screen brightness under low ambient lighting conditions.

Table 3 - Luminance For Low Ambient Luminance With Respective Low/High Screen Luminance

Ambient Luminance	**Lux Value (lx)**
Low	20.4

Screen Luminance	**Lux Value (lx)**	**Phone Brightness (%)**
20	8.34	20%
100	319.82	100%

Table 4 outlines the luminance values for the high ambient lighting condition, with an ambient luminance set at 153.6 lx. Similar to the low ambient condition, the screen luminance was measured at two levels: 20% and 100% phone brightness. At 20% brightness, the screen luminance was 9.5 lx, and at 100% brightness, it was 323.02 lx. These values highlight the differences in screen luminance under high ambient lighting, providing a comprehensive understanding of the experimental lighting conditions.

Table 4 - Luminance For High Ambient Luminance With Respective Low/High Screen Luminance

Ambient Luminance	**Lux Value (lx)**
High	153.6

Screen Luminance	**Lux Value (lx)**	**Phone Brightness (%)**
20	9.5	20%
100	323.02	100%

Luminance ratios

The following table presents the luminance ratios under different conditions of ambient and screen luminance. These ratios provide insights into the relative brightness levels experienced by participants during the experiment. This table details the lux values and corresponding luminance ratios for both low and high ambient lighting conditions.

It is important to note that during the experiment, light measurements were taken in lx using a light meter. However, moving forward, the unit used to express brightness levels will be in candelas per square meter (cd/m²). This unit of measure of luminance describes the amount of light that is emitted, transmitted, or reflected from a surface in a particular direction (King, 1973). **Luminance directly relates to how bright an object appears to the human eye**, making it a more relevant measure for studies focused on visual perception and comfort. In AR environments, where the perception of virtual elements overlaid on real-world scenes is critical, luminance (cd/m²) provides a better representation of visual conditions as experienced by users.

For each ambient lighting level, the screen luminance was measured at two levels: low (20% brightness) and high (100% brightness).

Ambient Luminance Measurement

The ambient luminance was measured by following the radius around the phone. Specifically, four measurements were taken at each corner perimeter of the phone. This approach ensured a comprehensive assessment of the ambient light levels surrounding the device, providing an accurate representation of the lighting conditions participants experienced.

Phone Luminance Measurement

The phone luminance was measured using a five-point protocol to capture the brightness levels accurately. Measurements were taken at each of the four corners of the phone's screen and one at the center. This method, based on the protocol described by Yu & Akita (2020), allowed for a thorough evaluation of the screen's luminance distribution, ensuring that the brightness settings were consistent and reliable throughout the experiment.

Table 5 - Luminance Ratios for Low and High Ambient Luminance and Phone Luminance

Condition	**Ratio**
Low Phone/Low Ambient	8.34/20.4 ≈ 0.41:1
High Phone/Low Ambient	319.82/20.4 ≈ 15.68:1
Low Phone/High Ambient	9.5/153.6 ≈ 0.06:1
High Phone/High Ambient	323.02/153.6 ≈ 2.10:1

To ensure precise and consistent lighting conditions during the experiment, a systematic measurement protocol was implemented for both phone and ambient luminance (see Figure 9).
The number in the picture indicates the chronological placement of the object (i.e., the light meter tool) (Yu & Akita, 2020). The following annotation refers to the measurements in Figure 9: AL1 = Ambient luminance 1; AL2 = Ambient luminance 2; AL3 = Ambient luminance 3;

AL4 = Ambient luminance 4; PL1 = Phone luminance 1; PL2 = Phone luminance 2; PL3 = Phone luminance 3; PL4 = Phone luminance 4.

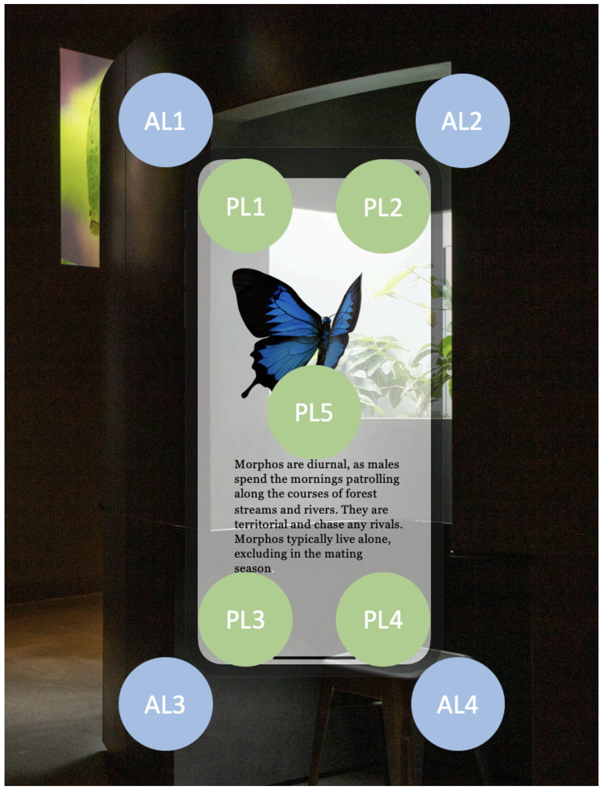


Figure 9 - Ambient Luminance and Screen Luminance Measurements

4.2.2 Sample

A total of 29 participants were initially involved in this study. However, data from the final 24 participants were considered valid for analysis due to adjustments made to the experimental protocol, survey structure, and task duration, rendering the initial five participants' results incomparable to the remaining participants. These 5 participants were used as pretests, and their results will be presented in the measures section.

Participants were recruited through PanelFox, the university’s student participant panel, and public social media platforms. All participants held at least a bachelor's degree and were familiar with smartphone usage. Inclusion criteria required participants to be above 18 years old, fluent in French, and have unaided perfect vision or vision corrected via contact lenses. Exclusion criteria included a history of laser vision correction, astigmatism, presbyopia, epilepsy, or a pronounced phobia of insects, particularly butterflies. Participants were also informed of their right to discontinue participation at any time. This research adhered to the ethical guidelines set by the institution's Research Ethics Board (REB), with ethical approval obtained. Participants received a compensation of $50 upon completing the study.

Figure 10 - First iteration of environment set-up

4.2.3 Procedure

Upon arrival in the room demonstrated in Figure 10, participants were welcomed and briefed on the study's purpose and procedures. They were then required to complete a consent form. Before beginning the main study, the Research Assistant (RA) conducted a series of pre-tests.

One of the initial tests was the Dominant Eye Test. In this test, participants were asked to focus on an object positioned approximately 3 meters away. They were instructed to extend their arms and create a triangular shape with their palms. Starting by closing their right eye, the RA inquired whether they could still see the object. Following this, participants repeated the procedure with their left eye closed. The dominant eye was determined based on which eye allowed the object to appear most centrally within the triangular frame.

Figure 11 - Dominant Eye Test

The second assessment involved the Worth Light test. During this test, participants were provided with two-tone glasses (green/red). The RA positioned a flashlight at a distance of 40 cm from the participants. Subsequently, the RA inquired about the colors the participants perceived. The RA documented both the colors observed by the participants and, when relevant, noted the position of these colors.

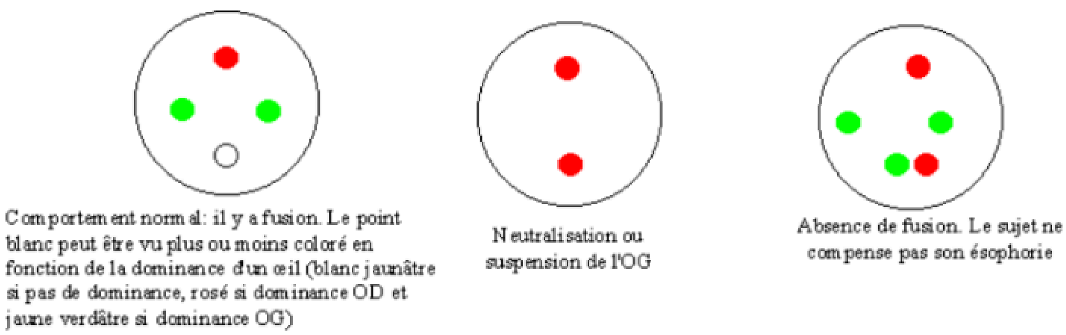
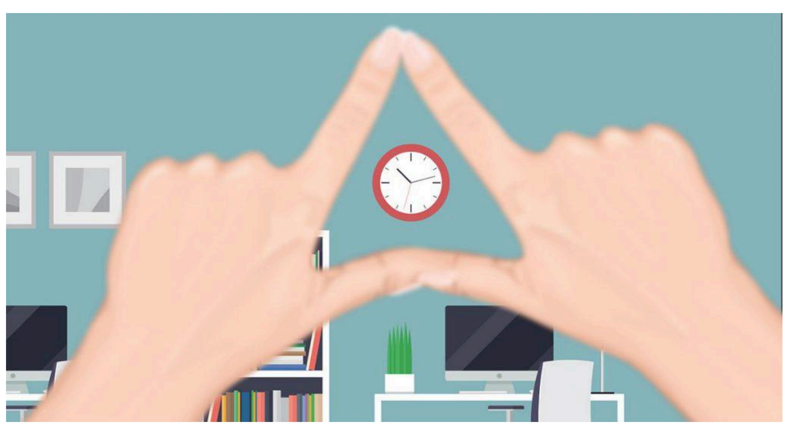


Figure 12 - Worth Light Test



The main task sequence followed a structured pattern. Participants were prompted to read the assigned text displayed on the smartphone and verbally indicate when they had finished reading by saying the phrase "I'm ready." Subsequently, quiz questions related to the text were projected onto the TV screen. Each block included two insects, and each question had four possible answer options (A, B, C, D). Participants had a maximum of 30 seconds to respond aloud, and they were allowed to look back at the smartphone to answer the question if needed. To alleviate potential stress, the countdown timer remained hidden from participants' view. If participants did not answer within the allotted time, the screen automatically transitioned to the next question.

Participants were seated comfortably in a desk chair pre-set at a specific height to ensure their eyesight was at 1 meter from the floor. The backrest to the phone was set at 60 cm, and the chair to the TV was set at 2.5 meters. A preliminary area was set by black curtains to isolate the participant and eliminate visual clutter. Four studio lights were positioned at each corner of this area, each 2 meters apart and 2 meters high. Participants were instructed not to physically touch the screen during the task. Instead, research assistants changed the QR codes, adjusted the phone brightness, and manipulated the studio lights. At the end of each block, participants were given a 1-minute rest period and instructed to close their eyes. This approach aimed to isolate the outcomes specific to each condition, ensuring clear delineation of results across different blocks.

Room and Equipment Measurements:

The distance between the studio lights was set at 2 meters. The lighting equipment used was from the brand Great Video Maker, model GVM-672S-B. The smartphone used in the study had a screen size of 6.36 inches (161.6 mm) diagonal with a resolution of 2400 x 1080 pixels and was a Google Pixel 7. The height of the lights was 2 meters. The distance from the chair to the TV was set at 2.5 meters, and the backrest to phone distance was 60 centimeters. The chair height was set at 1 meter. The table, where the phone was set up, measured 59 centimeters in width, 79 centimeters in length, and 66 centimeters in height. The TV measurements were 83 centimeters in width and 1.45 meters in length.

Tasks:

Each participant was presented with eight different insects, each represented as an augmented reality (AR) image displayed on a smartphone, accompanied by a textual description averaging 150 words. These AR insects were displayed on the Google Pixel 7 smartphone, accessed by scanning QR codes through the phone's camera. The QR codes were printed on non-glossy, high-quality photography paper (see Figure 5). The QR codes were displayed on a Binder Easel, and research assistants changed the QR codes after each block during a 1-minute rest period for the participant. Each participant interacted with a randomized selection of eight insects out of the total pool of twelve available stimuli.

The task sequence was designed to be repetitive but varied across multiple blocks. There were four blocks in total, with each block representing a different luminance ratio condition, randomized across participants (e.g., Block 1 = [Low Ambient Luminance (AL) and High Screen Luminance (SL)], Block 2 = [High AL and High SL], etc.). Within each block, participants first read the textual description associated with the first insect and then answered four multiple-choice quiz questions related to that description. This process was then repeated for the second insect within the same block. Participants had 30 seconds to vocalize their answer for each quiz question, with the next question appearing automatically if they did not respond within the allotted time. To minimize stress and distractions, no timer was displayed, though the 30-second limit was explained during the initial task instructions at the beginning of the experiment.

After completing the tasks in each block—reading two insect descriptions and answering four quiz questions per insect—participants provided their responses via a Qualtrics questionnaire (see Annex D), followed by a 1-minute rest period with their eyes closed. During this 1-minute rest, the lighting conditions were adjusted. The sequence of the four luminance conditions (2 x 2 manipulation) was fully randomized, resulting in 24 different possible arrangements

The sequence of the four conditions (2 x 2 manipulation) was fully randomized. There were 24 different arrangements possible

Figure 13 - Low ambient luminance and high screen luminance

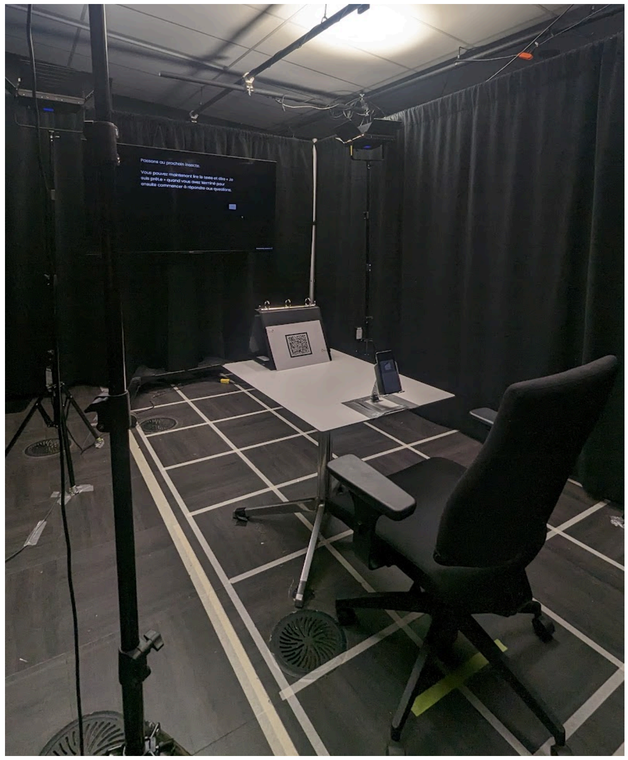


Figure 14 - High ambient luminance and low screen luminance

4.2.4 Measures

The following table summarizes the various constructs measured in this study, their operationalization/purpose, the measurement tools and scales used, and the administration methods employed in this study. It details the subjective measures taken to evaluate the impact of different luminance conditions on participants' visual discomfort, legibility, affective state, task performance, and learning effectiveness. The constructs were assessed through a combination of self-report scales and performance metrics, ensuring a robust approach to understanding the effects of smartphone augmented reality in varying lighting conditions. The administration of these measures occurred throughout the experiment, capturing data at specific intervals.

Table 6 - Summary of variable measurements & tools

Construct	Operationalization	Measurement Tools/Scale	Administration	Scale Items
Visual Discomfort (MV)	**Subjective Measure**: 7-point Likert scale with self-report items ranging from 1 (strongly disagree) to 7 (strongly agree)	Visual Fatigue Subjective Assessment Scale (Heuer et al., 1989)	At the end of block 1,2,3,4	Totally disagree, Disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Agree, Totally agree
Legibility	**Subjective Measure**: 4 bipolar items, 7-point Liker scale with self-reported items. Ranges differ per question (See Annex 6D)	Selected questions from Questionnaire for legibility (Yu & Akita)	At the end of block 1,2,3,4	L1: the phone screen is… [Hard to see - Easy to see] L2: the text is… [Hard to read - Easy to read] L3: it is easy to… [Lose focus - Stay focused] L4: there are reflections on the screen [Totally disagree - Totally agree]
Annoyance (DV)	**Subjective Measure:** The extent to which the AR task is annoying under the different circumstances	100-point Annoyance scale (Pawlaczyk-Łuszczyńska et al., 2005)	At the end of block 1,2,3,4	Slider: 0 to 100
Enjoyment (DV)	**Subjective Measure:** The extent to which the AR task is enjoyable under the different circumstances	Affective slider (Betella & Verschure, 2016)	At the end of block 1,2,3,4	Slider: 0 to 100
Task Performance (DV)	**Objective Measure:** Evaluate the efficacy of the participant to complete the tasks under different circumstances (independent variables). Perceived vs actual	Time taken to complete each block (seconds); Accuracy of responses (correct number of answers)	During block 1,2,3,4	Actual task performance: time taken (s) to complete the task and accuracy of answers Perceived task performance: perceived correct number of answers and

				perceived time elapsed
Hedonic Motivation (DV)	**Subjective Measure:** 7-point Likert scale with self-report items ranging from 1 (strongly disagree) to 7 (strongly agree)	Selected questions from Hedonic motivation questionnaire by Shen et.al	At the end of block 1,2,3,4	Not at all; Very little; A little; Moderately; Enough; A lot; Enormously
Learning Effectiveness (DV)	**Subjective Measure:** 7-point Likert scale with self-report items ranging from 1 (strongly disagree) to 7 (strongly agree)	Selected questions from Pallud (2017)	At the end of block 1,2,3,4	Not at all; Very little; A little; Moderately; Enough; A lot; Enormously

Chapter 5: Analysis and Results

We aimed to evaluate the impact of various luminance conditions on visual discomfort, legibility, affective state, task performance, and hedonic motivation within a mobile AR environment. The results of the hypothesis testing are detailed below, as well a summarized table of the results.
The research model tested is illustrated in Figure 13.

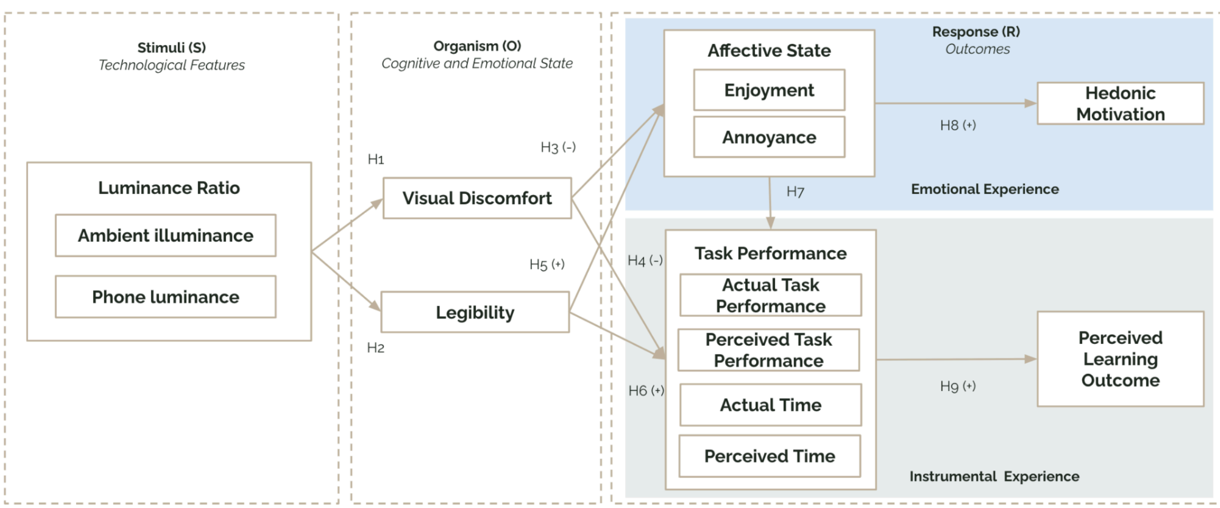


Figure 13 - Research Model

To test the hypotheses, a series of regression analyses were performed. The specific hypotheses, the type of analysis conducted, and the details of the procedures used are described below:

Hypothesis 1 (H1): Luminance ratios have a significant effect on visual discomfort.

The first hypothesis examined the effect of ambient luminance and screen luminance on visual discomfort (VD). This hypothesis was tested using logistic regression with a random intercept. The dependent variable (VD) was treated as binary after a median split due to its heavily skewed distribution. The SAS procedure proc glimmix with a binary distribution was utilized for this analysis.

Hypothesis 2 (H2): Luminance ratios are positively associated with legibility.

The second hypothesis explored the relationship between ambient luminance, screen luminance, and legibility (Legi). A linear regression with a random intercept was conducted for this analysis. The dependent variable (Legi) had a bell-shaped distribution and was treated as a normal variable. The SAS procedure proc glimmix was used.

Hypothesis 3 (H3): Visual discomfort is negatively associated with affective state.

The third hypothesis assessed the impact of visual discomfort (VD) on affective state (Aff). This hypothesis was tested using linear regression with a random intercept. The dependent variable (Aff) had a bell-shaped distribution and was treated as normal. The SAS procedure proc glimmix was employed.

Hypothesis 4 (H4):

This hypothesis was divided into multiple sub-hypotheses to evaluate the effect of **visual discomfort** (VD) on various performance metrics:

- H4a: The relationship between VD and actual task performance (perform) was analyzed using logistic regression with a random intercept. The dependent variable (perform) was binary, transformed via a median split due to its heavily skewed distribution.
- H4b: The impact of VD on perceived task performance (pPerform) was also tested using logistic regression with a random intercept and binary distribution.

- H4c: The effect of VD on task time (time) was examined using linear regression with a random intercept, treating the dependent variable (time) as normal due to its bell-shaped distribution.
- H4d: The relationship between VD and perceived task time (pTime) was analyzed using linear regression with a random intercept, treating the dependent variable (pTime) as normal.

The SAS procedure proc glimmix was used for these analyses, with appropriate transformations applied to the dependent variables as needed.

Hypothesis 5 (H5): Legibility is positively associated with Affective State

The fifth hypothesis examined the effect of legibility (Legi) on affective state (Aff). This hypothesis was tested using linear regression with a random intercept. The dependent variable (Aff) had a bell-shaped distribution and was treated as normal. The SAS procedure proc glimmix was employed for this analysis.

Hypothesis 6 (H6):

This hypothesis was also divided into several sub-hypotheses to examine the effect of **legibility** (Legi) on affective state (Aff) and performance metrics:

- H6a: The relationship between Legi and **actual task performance** (perform) was analyzed using logistic regression with a random intercept, treating the dependent variable (perform) as binary after a median split.
- H6b: The effect of Legi on **perceived task performance** (pPerform) was tested using logistic regression with a random intercept and binary distribution.
- H6c: The impact of Legi on **task time** (time) was examined using linear regression with a random intercept, treating the dependent variable (time) as normal.
- H6d: The relationship between Legi and **perceived task time** (pTime) was analyzed using linear regression with a random intercept, treating the dependent variable (pTime) as normal.

The SAS procedure proc glimmix was employed for these analyses, ensuring the appropriate transformations and distributions for each dependent variable.

Hypothesis 7 (H7)

This hypothesis examined the influence of **affective state** (Aff) on various **performance** metrics. H7a and H7b were analyzed using logistic regression with a random intercept and binary distribution. H7c and H7d were examined using linear regression with a random intercept, treating the dependent variable (time) as normal. The SAS procedure proc glimmix was used for these analyses.

Hypothesis 8 (H8): Affective state is positively associated with Hedonic Motivation

This hypothesis assessed the relationship between affective state (Aff) and hedonic motivation (HM). This hypothesis was tested using linear regression with a random intercept. The dependent variable (HM) had a bell-shaped distribution and was treated as normal. The SAS procedure proc glimmix was employed for this analysis.

Hypothesis 9 (H9):

This hypothesis was divided into multiple sub-hypotheses (H9a, H9b, H9c, H9d) to evaluate the effect of task performance and related factors on perceived learning outcomes. Each sub-hypothesis was tested using linear regression with a random intercept, where the dependent variables were treated as a dependent variable as normal and employing the proc glimmix procedure on SAS.

Impact of Luminance Ratio on Visual Discomfort and Legibility

H1: The hypothesis that luminance ratio has a significant effect on visual discomfort was tested using logistic regression with a random intercept (SAS procedure: proc glimmix, dist = binary). The results ([$F(1, 65) = -1.16$, $p = 0.2487$]) indicate that changes in luminance ratio did not significantly impact visual discomfort experienced by participants.

H2: The hypothesis that luminance ratios are positively associated with legibility was tested using linear regression with a random intercept (SAS procedure: proc glimmix). The results ([$F(1, 65) = 3.56$, $p = 0.00035$]) show a significant positive relationship between luminance ratios and legibility, suggesting that higher contrast between screen luminance and ambient luminance enhances the clarity with which participants can read text and view images on the phone.

To understand the effect of different luminance ratios on legibility, the mean legibility score was calculated for each luminance ratio condition. A bar chart was created to visualize these mean scores, comparing the legibility of text under varying levels of ambient and screen luminance (Figure 14). The four luminance ratio conditions tested included combinations of low/high ambient luminance with low/high screen luminance. The results show a clear trend where legibility improves as the luminance ratio increases. In other words, as the contrast between ambient and screen luminance becomes more pronounced, the clarity with which participants could read text on the smartphone improves.

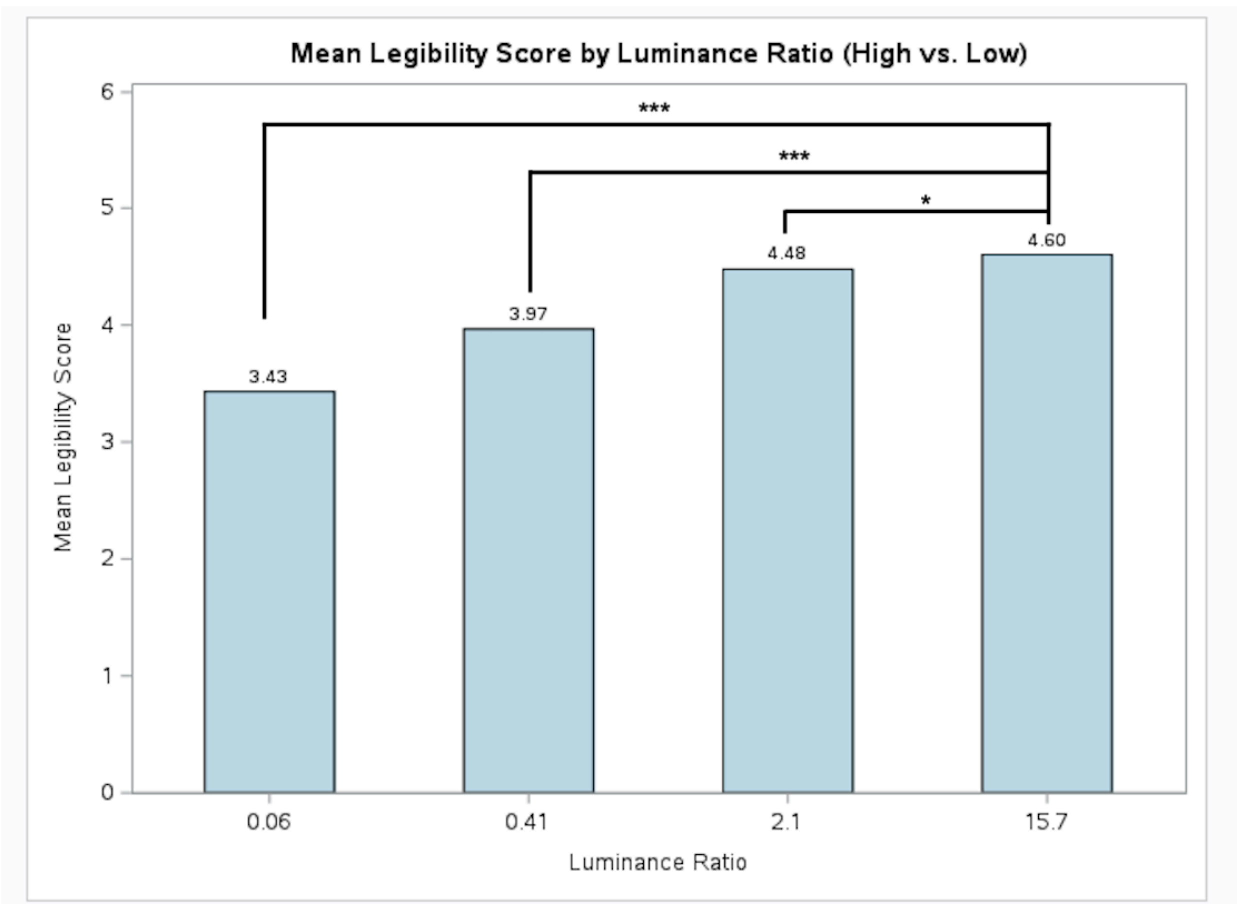


Figure 14 - Mean Legibility Score by Luminance Ratio (High vs Low)

Luminance Ratio 0.06 (high ambient luminance, low screen luminance): The mean legibility score is approximately 3.43. This represents the lowest legibility score among all the luminance ratios tested.

Luminance Ratio 0.41 (low ambient luminance and low screen luminance): The mean legibility score increases to about 3.97. This is a marginally significant improvement in legibility compared to the lowest luminance ratio.

Luminance Ratio 2.1 (high ambient luminance and high screen luminance): The mean legibility score jumps to around 4.48, showing a significant improvement in legibility as the luminance ratio increases.

Luminance Ratio 15.7 (low ambient luminance and high screen luminance): The highest luminance ratio results in a mean legibility score of approximately 4.60, which is the highest score observed in the chart.

The analysis reveals a clear positive relationship between luminance ratio and legibility. As the luminance ratio increases, the mean legibility score correspondingly rises. The results demonstrate that the **relationship between luminance ratio and legibility is highly significant ($p < 0.01$).** This finding is visually supported by the bar chart, which shows that higher contrast between ambient and screen luminance (i.e., higher luminance ratio) significantly enhances participants' ability to read text and view images clearly.

Influence of Visual Discomfort and Legibility on Affective State

H3: Visual discomfort's impact on affective state was tested using linear regression with a random intercept (SAS procedure: proc glimmix). The results ([$F(1, 64) = -2.61$, $p = 0.00565$]) indicate a significant negative association, meaning increased visual discomfort leads to a less positive affective state among participants.

H5: Legibility's effect on affective state was also tested using linear regression with a random intercept (SAS procedure: proc glimmix). The results ([$F(1, 64) = 2.91$, $p = 0.00245$]) show that improved legibility contributed to a more positive affective state.

To investigate the relationship between legibility and participants' affective state, a bar chart was generated to compare the mean affective state across different levels of legibility (Figue 10). Affective state was measured on a continuous scale and was analyzed in relation to legibility, which was treated as a binary variable. The chart illustrates how varying levels of legibility impact the affective state of users during mobile AR interactions. Additionally, significance levels were annotated on the chart to highlight statistically significant differences between the legibility levels, providing a clearer understanding of how improvements in legibility can positively influence user emotions and overall experience.

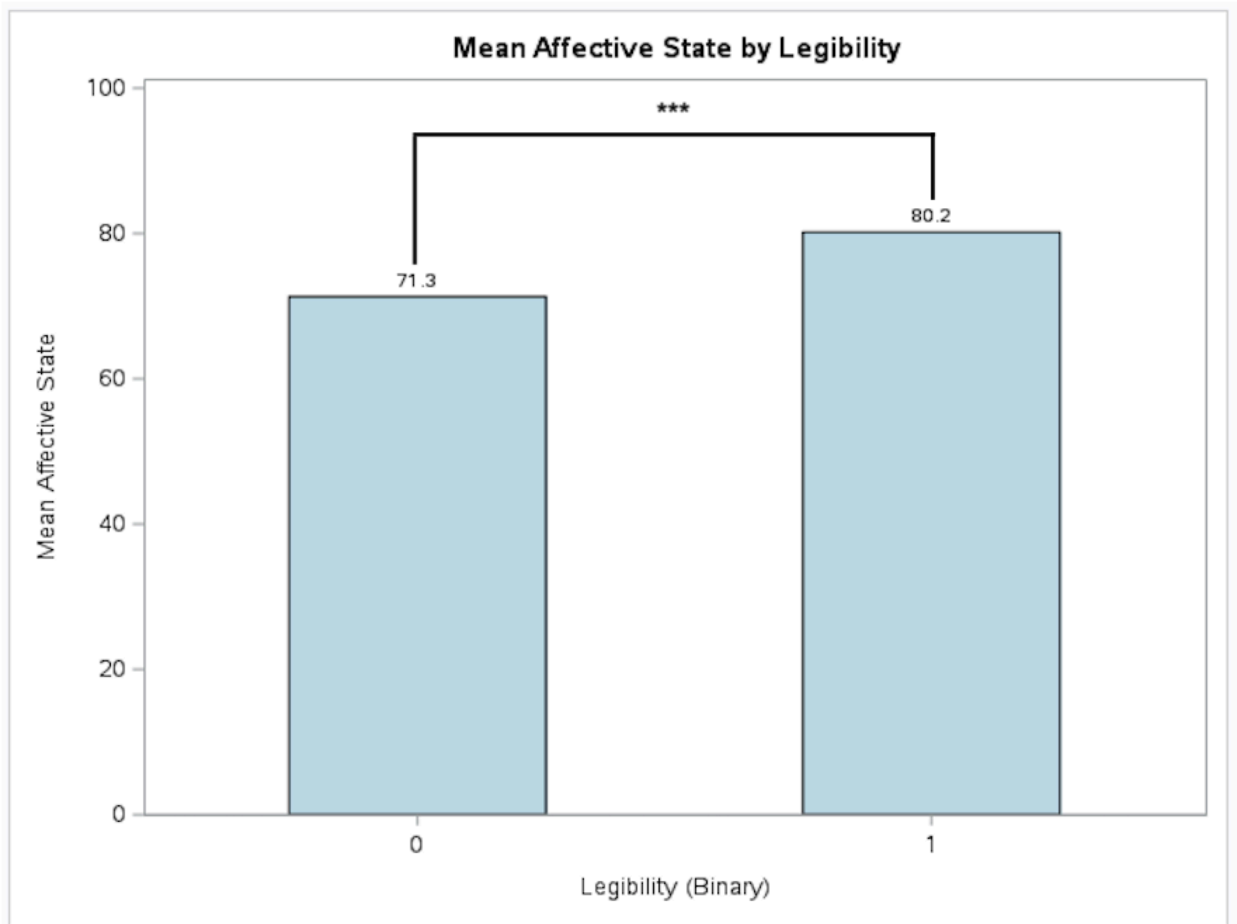


Figure 15 - Mean Affective State by Legibility

Effects of Visual Discomfort on Task Performance and Perception

There is a **significant positive relationship** between legibility and affective state ($p < 0.01$). **As legibility improves, participants report a more positive affective state.** This suggests that when text and images are easier to read and view, participants feel more positive about the task. Improved legibility contributes to a better overall emotional experience, enhancing user satisfaction in the augmented reality environment.

H4a: The relationship between visual discomfort and actual task performance was examined using logistic regression with a random intercept (SAS procedure: proc glimmix, dist = binary).

The results ([$F(1, 65) = -0.37$, $p = 0.35655$]) suggest no significant impact of visual discomfort on actual task performance.

H4b: Visual discomfort's impact on perceived task performance was analyzed using logistic regression with a random intercept (SAS procedure: proc glimmix, dist = binary). The results ([$F(1, 65) = -1.79$, $p = 0.0388$]) show a significant negative association.

H4c: The effect of visual discomfort on task time was tested using linear regression with a random intercept (SAS procedure: proc glimmix). The results ([$F(1, 63) = 2.26$, $p = 0.0135$]) indicate a significant positive association, meaning participants took longer to complete tasks when they experienced higher visual discomfort.

H4d: The relationship between visual discomfort and perceived task time was tested using linear regression with a random intercept (SAS procedure: proc glimmix). The results ([$F(1, 65) = -0.6$, $p = 0.72415$]) indicate no significant impact.

Influence of Legibility on Task Performance and Perception

H6a: Legibility's impact on actual task performance was examined using logistic regression with a random intercept (SAS procedure: proc glimmix, dist = binary). The results ([$F(1, 65) = -0.02$, $p = 0.50805$]) suggest no significant effect.

H6b: The relationship between legibility and perceived task performance was tested using logistic regression with a random intercept (SAS procedure: proc glimmix, dist = binary). The results ([$F(1, 65) = 0.74$, $p = 0.22965$]) show no significant impact.

H6c: The effect of legibility on task time was tested using linear regression with a random intercept (SAS procedure: proc glimmix). The results ([$F(1, 63) = 2.39$, $p = 0.9901$]) indicate a significant positive association.

H6d: The relationship between legibility and perceived time was tested using linear regression with a random intercept (SAS procedure: proc glimmix). The results ([$F(1, 64) = 1.97$, $p = 0.9736$]) suggest a near-significant positive association.

Relationship Between Affective State and Task Performance

H7a: The impact of affective state on actual task performance was examined using logistic regression with a random intercept (SAS procedure: proc glimmix, dist = binary). The results ([$F(1, 64) = -0.02$, $p = 0.50755$]) show no significant effect.

H7b: Affective state's relationship with perceived task performance was tested using logistic regression with a random intercept (SAS procedure: proc glimmix, dist = binary). The results ([$F(1, 64) = -0.15$, $p = 0.558$]) indicate no significant impact.

H7c: The effect of affective state on task time was analyzed using linear regression with a random intercept (SAS procedure: proc glimmix). The results ([$F(1, 64) = -0.72$, $p = 0.76295$]) show no significant effect.

H7d: Affective state's relationship with perceived time was tested using linear regression with a random intercept (SAS procedure: proc glimmix). The results [($F(1, 64) = 2.21$, $p = 0.98475$]) indicate a significant positive effect.

H8: The relationship between affective state and hedonic motivation was tested using linear regression with a random intercept (SAS procedure: proc glimmix). The results ([$F(1, 64) = 2.83$, $p = 0.00315$]) show a significant positive association.

The relationship between affective state and hedonic motivation is **highly significant ($p < 0.01$).** Higher affective state scores (which reflect a positive emotional experience) are associated with increased hedonic motivation. This finding indicates that when participants experience a more positive affective state (1), they are more motivated by the pleasure or enjoyment of the task.

This supports the idea that emotional engagement plays a crucial role in motivating users in augmented reality environments.

Note that "Affective State" was calculated as a composite measure using the formula:

$AffState=[Enj+(100-Ann)]/2$

where:

- **Enj** is the Enjoyment score.
- **Ann** is the Annoyance score.

This formula results in an overall affective state score, which can theoretically range from 0 to 100. We binarized Affective State to simplify the data, making it easier to interpret and analyze, especially since we dealt with regression models. This also helped us understand the effects of a high vs. low affective state.

Perceived Learning Outcome

H9a: The effect of actual task performance on perceived learning outcome was analyzed using logistic regression with a random intercept (SAS procedure: proc glimmix, dist = binary). The results ([$F(1, 64) = -0.03$, $p = 0.51075$]) indicate no significant effect.

Table 7 - Analysis Variable for Perceived Learning Outcome to Task Performance (binary)

Analysis Variable : PLO PLO		
Perfom_bin	N Obs	Mean
0	29	4.6551724
1	59	4.6214689

To further explore the relationship between task performance and perceived learning outcomes, a line chart was generated to compare the mean perceived learning outcome across different levels of task performance. The analysis considered task performance as a binary variable and calculated the mean perceived learning outcome for each level. This visualization aims to illustrate how variations in task performance influence participants' perceptions of their learning outcomes during mobile AR interactions, albeit, non-significantly.

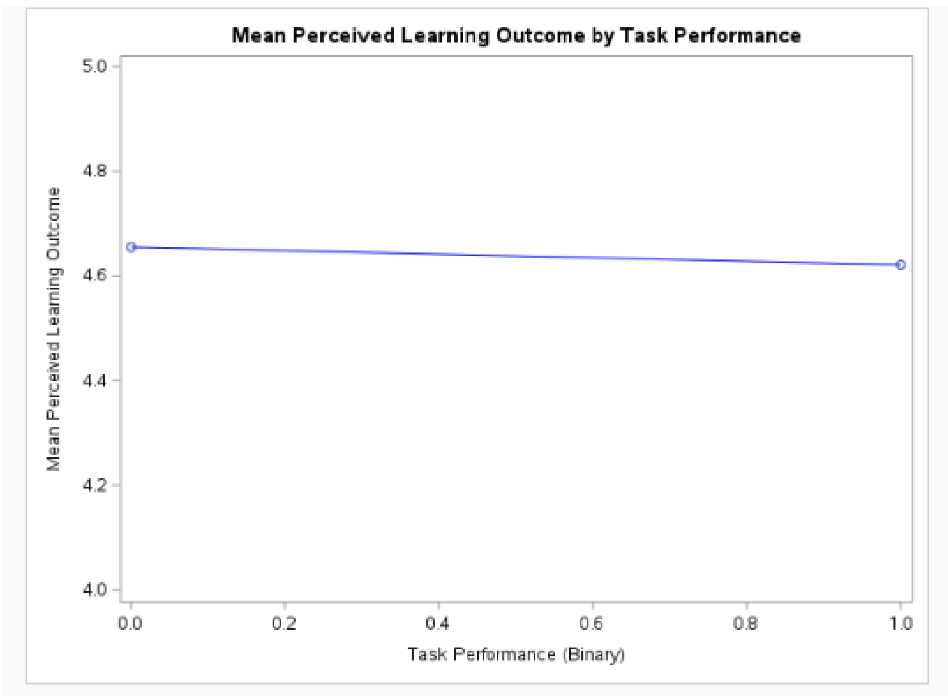


Figure 16 - Mean Perceived Learning Outcome by Task Performance

H9b: The relationship between perceived task performance and perceived learning outcome was tested using logistic regression with a random intercept (SAS procedure: proc glimmix, dist = binary). The results ([$F(1, 64) = 0.06$, $p = 0.47615$]) suggest no significant impact.

H9c: The effect of task time on perceived learning outcome was examined using linear regression with a random intercept (SAS procedure: proc glimmix). The results ([F(1, 64) = 0.28, p = 0.6081]) show no significant effect.

H9d: The relationship between perceived time and perceived learning outcome was tested using linear regression with a random intercept (SAS procedure: proc glimmix). The results ([F(1, 64) = 1.07, p = 0.85465]) indicate no significant impact.

Below is Figure 17, indicating which paths (hypotheses) are significant (*** p<0.01 and in green), which are partially significant (** p<0.05 and in blue) and which were not supported (*p<0.1 and in brown).

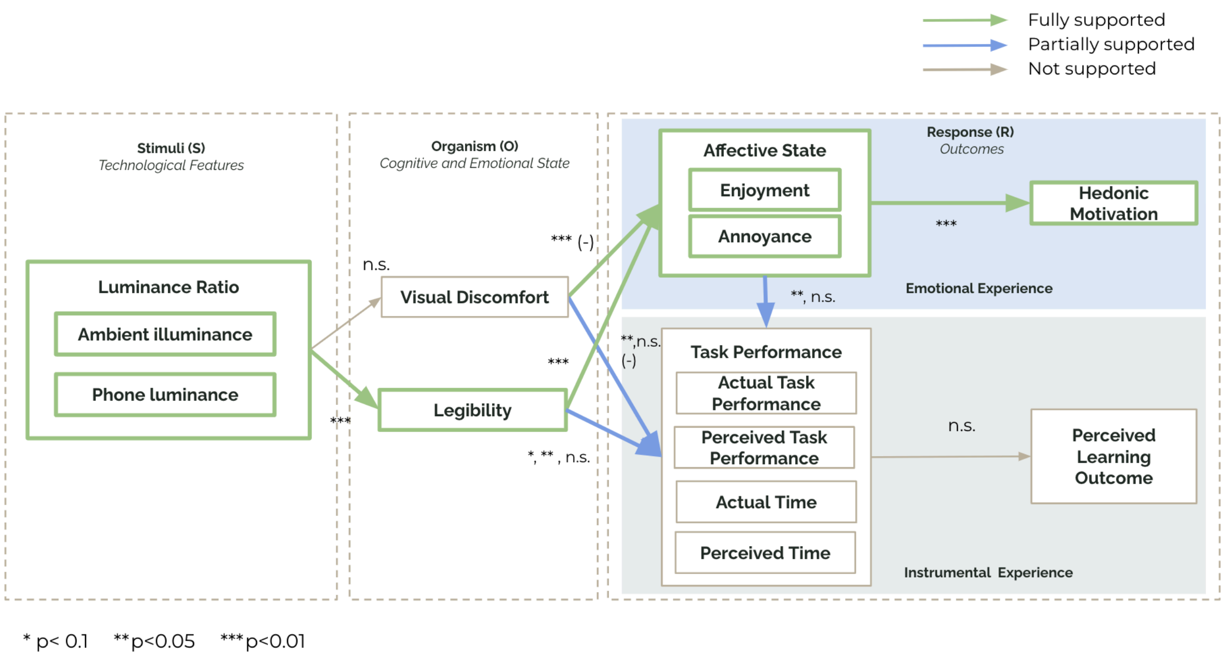


Figure 17 - Validated Research Model

We can now proceed to further expand on these findings in the discussion section, where we will interpret the results, compare them with existing literature, and explore their implications. Below is a summarized table of the results.

Table 8 presents summary statistics for the key variables analyzed in our study. Specifically, it includes the mean, standard deviation, minimum, maximum, and sample size (n) for Visual Discomfort, Legibility, Affective State, Performance, Perceived Performance, Time, Perceived Time, Hedonic Motivation, and Perceived Learning Outcome.

Table 8 - Descriptive Statistics of Tested Constructs

Descriptive Statistics of Tested Constructs

The MEANS Procedure

Variable	Label	Mean	Std Dev	Minimum	Maximum	N
VD_bin	Visual Discomfort	0.55682	0.49961	0.00000	1.00000	88
Legi	Legibility	4.12079	1.21316	1.00000	6.75000	89
Aff	Affective State	76.42045	13.33518	39.00000	98.00000	88
Perfom_bin	Performance	0.67045	0.47274	0.00000	1.00000	88
pPerform_bin	Perceived Performance	0.60227	0.49223	0.00000	1.00000	88
Time	Time	9.22780	2.71971	0.49775	16.25250	86
pTime	Perceived Time	66.38636	18.41441	21.00000	100.00000	88
HM	Hedonic Motivation	4.61742	1.47134	1.00000	7.00000	88
PLO	Perceived Learning Outcome	4.63258	1.69142	1.00000	7.00000	88

Table 9 - Correlation Table of Tested Constructs

Correlation Table of Tested Constructs

The CORR Procedure

9 Variables:	VD_bin Legi Aff Perfom_bin pPerform_bin Time pTime HM PLO

Pearson Correlation Coefficients
Prob > |r| under H0: Rho=0
Number of Observations

	VD_bin	Legi	Aff	Perfom_bin	pPerform_bin	Time	pTime	HM	PLO
VD_bin **VD_bin**	1.00000 88	-0.09611 0.3731 88	-0.13198 0.2230 87	-0.04148 0.7012 88	-0.21086 0.0486 88	0.17107 0.1153 86	0.02507 0.8166 88	-0.11342 0.2927 88	-0.15864 0.1399 88
Legi **Legi**	-0.09611 0.3731 88	1.00000 89	0.37583 0.0003 88	0.00917 0.9324 88	0.06558 0.5438 88	0.20760 0.0551 86	0.13913 0.1961 88	0.19914 0.0629 88	0.02799 0.7958 88
Aff **Aff**	-0.13198 0.2230 87	0.37583 0.0003 88	1.00000 88	0.03894 0.7203 87	-0.02830 0.7947 87	-0.00338 0.9755 85	-0.01891 0.8620 87	0.48229 <.0001 87	0.25634 0.0165 87
Perfom_bin **Perfom_bin**	-0.04148 0.7012 88	0.00917 0.9324 88	0.03894 0.7203 87	1.00000 88	0.41818 <.0001 88	-0.33162 0.0018 86	0.28151 0.0079 88	0.09208 0.3935 88	-0.00942 0.9306 88
pPerform_bin **pPerform_bin**	-0.21086 0.0486 88	0.06558 0.5438 88	-0.02830 0.7947 87	0.41818 <.0001 88	1.00000 88	-0.30173 0.0048 86	0.26062 0.0142 88	-0.21251 0.0468 88	-0.17294 0.1071 88
Time **Time**	0.17107 0.1153 86	0.20760 0.0551 86	-0.00338 0.9755 85	-0.33162 0.0018 86	-0.30173 0.0048 86	1.00000 86	-0.21919 0.0426 86	0.02480 0.8207 86	0.16339 0.1328 86
pTime **pTime**	0.02507 0.8166 88	0.13913 0.1961 88	-0.01891 0.8620 87	0.28151 0.0079 88	0.26062 0.0142 88	-0.21919 0.0426 86	1.00000 88	-0.01018 0.9250 88	-0.00191 0.9859 88
HM **HM**	-0.11342 0.2927 88	0.19914 0.0629 88	0.48229 <.0001 87	0.09208 0.3935 88	-0.21251 0.0468 88	0.02480 0.8207 86	-0.01018 0.9250 88	1.00000 88	0.71726 <.0001 88
PLO **PLO**	-0.15864 0.1399 88	0.02799 0.7958 88	0.25634 0.0165 87	-0.00942 0.9306 88	-0.17294 0.1071 88	0.16339 0.1328 86	-0.00191 0.9859 88	0.71726 <.0001 88	1.00000 88

The correlation table above presents Pearson correlation coefficients between the primary variables analyzed in this study: Visual Discomfort (VD_bin), Legibility (Legi), Affective State (Aff), Performance (perfom_bin), Perceived Performance (pPerform_bin), Time (time), Perceived Time (pTime), Hedonic Motivation (HM), and Perceived Learning Outcome (PLO). The table helps to understand the relationships between these variables and offers insights into how they interact within the context of mobile augmented reality environments.

We see that the correlation table reveals a significant negative correlation between Visual Discomfort (VD_bin) and Legibility (Legi), suggesting that as visual discomfort increases, legibility decreases. This result aligns with the hypothesis that higher visual discomfort negatively impacts the ability to read text effectively on mobile AR devices.

Affective State (Aff) shows a significant positive correlation with both actual Performance (perfom_bin) and Perceived Performance (pPerform_bin). This indicates that a more positive affective state is associated with better task performance and higher perceived performance. These findings underscore the importance of maintaining a positive emotional state to enhance user performance in AR environments.

Significant correlations exist between Time (time) and Perceived Time (pTime) as well. A strong positive correlation indicates that actual task duration is closely related to how long participants perceive the tasks to take. This relationship suggests that participants' perceptions are fairly accurate reflections of the time they spend on tasks.

Hedonic Motivation (HM) has a significant positive correlation with Perceived Learning Outcome (PLO), implying that participants who enjoy the AR experience more tend to report better learning outcomes. This finding highlights the importance of designing engaging and enjoyable AR experiences to enhance educational effectiveness. Nonetheless, these two variables are significantly correlated (p-value <.0001), and also share a high Pearson correlation coefficient of 0.71726. However, by revisiting the Likert scale items (Annex 2D & 5D), at face value, the scales are indeed measuring distinct constructs.

Finally, Several other correlations within the table provide additional insights into the interplay between these variables. For instance, the relationship between legibility and affective state suggests that clearer text can improve users' emotional responses. Similarly, the link between visual discomfort and perceived performance underscores the broader impact of discomfort on users' overall experience.

Table 10 - Hypothesis testing results

Hypothesis	From	To	Estimate	t-Value	p-Value	Significance (p-value)	H Description
H1	Luminance Ratio	Visual Discomfort	-0.057	-1.16	0.2487	Not significant	Different Global Luminance have a significant effect on Visual Discomfort
H2	Luminance Ratio	Legibility	0.0491	3.56	0.00035	Significant	Greater Global Luminance is ratio is positively associated with Legibility
H3	Visual Discomfort	Affective State	-4.1735	-2.61	0.00565	Significant	Visual Discomfort is negatively associated with Affective State
H4a	Visual Discomfort	Actual Task Performance	-0.1052	-0.37	0.35655	Not significant	Visual Discomfort is negatively associated with Actual Task Performance
H4b	Visual Discomfort	Perceived Task Performance	-0.5877	-1.79	0.0388	Significant	Visual Discomfort is negatively associated with Perceived Task Performance
H4c	Visual Discomfort	Task Time	0.7208	2.26	0.0135	Significant	Visual Discomfort is positively associated with Task Time

H4d	Visual Discomfort	Perceived Task Time	-1.1575	-0.6	0.72415	Not significant	Visual Discomfort is positively associated with Perceived Time
H5	Legibility	Affective State	3.2868	2.91	0.00245	Significant	Legibility is positively associated with Affective State
H6a	Legibility	Actual Task Performance	-0.00444	-0.02	0.50805	Not significant	Legibility is positively associated with Actual Task Performance
H6b	Legibility	Perceived Task Performance	0.1832	0.74	0.22965	Not significant	Legibility is positively associated with Perceived Task Performance
H6c	Legibility	Task Time	0.5922	2.39	0.9901	Not significant	Legibility is negatively associated with Task Time
H6d	Legibility	Perceived Time	2.7377	1.97	0.9736	Not significant	Legibility is negatively associated with Perceived Time
H7a	Affective State	Actual Task Performance	-0.00038	-0.02	0.50755	Not significant	Affective State is positively associated with Actual Task Performance

H7b	Affective State	Perceived Task Performance	-0.00318	-0.15	0.558	Not significant	Affective State is positively associated with Perceived Task Performance
H7c	Affective State	Task Time	-0.01629	-0.72	0.76295	Not significant	Affective State is negatively associated with Task Time
H7d	Affective State	Perceived Time	0.2811	2.21	0.98475	Significant	Affective State is negatively associated with Perceived Time
H8	Affective State	Hedonic Motivation	0.0189	2.83	0.00315	Significant	Affective state is positively associated with hedonic motivation
H9a	Actual Task Performance	Perceived Learning Outcome	-0.00145	-0.03	0.51075	Not significant	Actual Task Performance is positively associated with Perceived Learning Outcome
H9b	Perceived Task Performance	Perceived Learning Outcome	0.004296	0.06	0.47615	Not significant	Perceived Task Performance is positively associated with Perceived Learning Outcome

H9c	Task Time	Perceived Learning Outcome	0.04071	0.28	0.6081	Not significant	Task Time is negatively associated with Perceived Learning Outcome
H9d	Perceived Time	Perceived Learning Outcome	0.007445	1.07	0.85465	Not significant	Perceived Time is negatively associated with Perceived Learning Outcome

Chapter 6: Discussion

The results of this study show that lighting conditions did not have a significant effect on visual discomfort, which could be explained by several factors. One key consideration is the duration of the experiment, which lasted only 30 minutes. Research on Digital Eye Strain (DES) has consistently shown that visual discomfort, such as eye fatigue, dry eyes, and blurred vision, tends to develop after prolonged exposure to screens (Kaur et al, 2022; Pavel et al, 2023). For instance, symptoms are generally reported after two hours or more of continuous screen use, making shorter durations insufficient for generating significant levels of discomfort (Kaur et al, 2022; Pavel et al, 2023). Therefore, the relatively short time frame of this study may have contributed to the absence of significant visual discomfort among participants.

Another factor that may have influenced the findings is the high resolution of the Google Pixel 7 used in the study. With a 1080 x 2400 pixel display and a pixel density of 416 ppi, this device produces sharp and clear images that minimize strain on the eyes. Lower-resolution screens are known to increase accommodation lag and contribute to visual fatigue, particularly when viewed for longer periods (Ziefle, 2001). Ziefle's research on monitor resolution found that lower resolutions led to slower reaction times and greater visual fatigue, while higher-resolution displays reduced these effects. Thus, the high-resolution display in the Google Pixel 7 likely mitigated visual discomfort, further diminishing the potential impact of lighting conditions on participant strain.

To support the lack of a link between affective experiences and task performance in our study, several peer-reviewed papers suggest that emotional states don't always directly impact task performance, especially in leisurely or exploratory settings like museums.

For example, research shows that environments designed for exploration often promote low approach-motivated positive affect—such as curiosity or amusement—which can broaden attention and encourage engagement without necessarily improving task performance. This kind of affective state doesn't focus on achieving a specific goal, and thus, participants might be more absorbed in the experience rather than on performance outcomes (Harmon-Jones et al., 2008). In contrast, high approach-motivated positive affect, where individuals are strongly driven to complete a task, tends to narrow attention and improve performance, which is more typical in goal-oriented environments (Harmon-Jones et al., 2008).

In leisurely environments like museums, participants engage in self-paced learning, focusing more on the enjoyment of the activity than on specific performance measures. This can reduce the influence of emotions on task efficiency, as cognitive load and performance pressures are minimized (Stenfors et al., 2019). Additionally, in multimedia learning environments, research shows that affective states (such as enjoyment) improve engagement and motivation but don’t always correlate with better task performance, particularly when the tasks are less cognitively demanding (Liew et al., 2017).

Nonetheless, a noteworthy discovery was the significant positive correlation between luminance ratios and legibility, indicating that greater contrast enhances readability of text on smartphones. This is consistent with existing research which suggests that optimal lighting conditions improve visual clarity and user satisfaction (Benedetto et al., 2014). Further analysis revealed that both visual discomfort and legibility influence affective states. Visual discomfort had a negative effect on the participants' affective states, whereas improved legibility had a positive impact. This highlights the importance of user comfort and readability in fostering positive emotional responses during AR interactions. These findings support the principles of the Stimulus-Organism-Response (SOR) model, emphasizing how external stimuli (luminance conditions) affect internal psychological states (affective states) and subsequent behaviors (Do et al., 2020; Huang, 2023). The study also found that visual discomfort significantly impacts perceived task performance and task duration, suggesting that discomfort can lead to longer task completion times and reduced perceived performance. This aligns with prior studies on the detrimental effects of visual fatigue and discomfort on task efficiency (Zhou et al., 2021).

In contrast, affective state positively influenced hedonic motivation but did not significantly affect actual or perceived task performance. This implies that while positive emotions can enhance motivation and enjoyment, they do not necessarily lead to better task outcomes in AR settings. These results highlight the complex relationship between emotional states and performance metrics, a key focus in cognitive load theory and user experience research (Lai et al., 2018; Mayer, 2009).

Additionally, the study found that legibility only partially influenced participants' perceptions of task performance, particularly regarding perceived time. This suggests that while clearer text can improve user experience, it may not significantly alter their perception of task duration or accuracy. This is consistent with previous research on text legibility in AR systems, which found that legibility affects ease of use but not necessarily performance accuracy (Gattullo et al., 2015). Our study also offers several theoretical contributions. First, it underscores the importance of luminance conditions in enhancing legibility and user comfort in mobile AR environments, contributing to our understanding of how lighting affects visual perception and user experience in digital interfaces (Kruijff et al., 2010).

Furthermore, the findings provide empirical support for the application of the SOR model in AR contexts, demonstrating how external stimuli (luminance) influence internal states (visual comfort, legibility) and subsequent behaviors (affective states, task performance) (Huang, 2023). This reinforces the utility of the SOR framework in designing user-centric AR applications that prioritize visual comfort and readability. From a practical standpoint, these insights are valuable for AR application developers and designers. Ensuring optimal luminance conditions can significantly improve text legibility and reduce visual discomfort, leading to better user experiences and higher engagement. This is particularly important for educational and informational AR applications, where clear and comfortable viewing is essential for effective learning and interaction (Sommerauer & Müller, 2014).

However, we acknowledge the study limitations. The measurements relied on subjective reports, which might not fully capture the range of user experiences. Future research should incorporate additional objective measures like eye-tracking and heart rate monitoring to provide a more comprehensive understanding of user responses. Additionally, the study focused on specific tasks and lighting conditions, which may limit the generalizability of the findings. The 30-minute timeframe of the experiment might not have been sufficient to create significant discomfort. Future research should consider longer testing periods to better understand the impacts of prolonged exposure to different luminance conditions, as well as explore a broader range of tasks and environmental settings to validate these results.

To address the contextual nature of our findings, we can consider how different environments impact the user experience in augmented reality (AR) applications

For instance, in informal learning environments like museums, AR experiences are often designed to enhance exploration and self-directed learning, focusing less on task performance and more on engagement and knowledge retention. Studies have shown that in such settings, users are typically motivated by curiosity and the opportunity to interact with digital content in a leisurely manner (Markouzis et al., 2022). This aligns with the fact that affective states like enjoyment or curiosity might not directly translate into improved task performance because the primary goal is learning, not efficiency (Sommerauer & Müller, 2014).

Moreover, the impact of lighting conditions or visual discomfort may differ in outdoor AR environments. For instance, outdoor AR applications—such as tourism or location-based gaming—are subject to more variable lighting conditions, such as glare from the sun, which could exacerbate or mitigate discomfort. In contrast, controlled indoor environments like museums tend to provide stable lighting conditions, making discomfort less likely. Thus, findings related to visual discomfort and legibility may vary significantly depending on whether the AR application is used in a controlled indoor space (like a museum) or in unpredictable outdoor settings (Benedetto et al., 2014).

Additionally, a review of AR usability studies highlights how domain-specific factors, such as the physical environment and the type of AR content being delivered, can greatly influence user experience and the usability of AR systems. For example, outdoor AR systems that require users to remain mobile and aware of their surroundings might emphasize legibility and visibility more than static, indoor experiences where users are focused on interacting with digital content without external distractions (Kruijff et al., 2010). These findings suggest that while our study focused on Mobile AR in a controlled environment, further research could explore how the results might differ in other domain-specific contexts, such as outdoor environments or informal learning settings like museums.

In summary, this study highlights the critical role of luminance conditions in shaping visual perception and user experience in mobile AR environments. By optimizing lighting conditions, developers can enhance legibility and reduce visual discomfort, leading to more positive affective states and improved user engagement. These insights contribute to the development of user-friendly and effective AR applications, underscoring the need for continued research and innovation in this evolving field.

Chapter 7: Conclusion

This study aimed to understand the impact of luminance conditions on visual discomfort, legibility, and user experience in mobile augmented reality (AR) environments. The research employed a 2x2 within-subject design to systematically manipulate ambient and screen luminance levels, assessing their effects on various outcomes including visual discomfort, legibility, affective state, task performance, and learning outcomes.

The central research question guiding this thesis was: To what extent do phone luminance, ambient luminance, and visual fatigue impact user experience during proposed visual tasks? The study found that varying luminance ratios did not significantly impact visual discomfort, suggesting that other factors may play a more critical role in influencing visual discomfort in mobile AR environments. However, there was a significant positive correlation between luminance ratios and legibility, indicating that greater contrast enhances the readability of text on smartphones. This finding underscores the importance of optimal lighting conditions for improving visual clarity and user satisfaction. Visual discomfort negatively affected participants' affective states, highlighting the importance of user comfort in fostering positive emotional responses during AR interactions. Improved legibility had a positive impact on affective state, demonstrating that clearer text can contribute to more positive emotions during AR tasks. Visual discomfort significantly impacted perceived task performance and task duration, suggesting that discomfort can lead to longer task completion times and reduced perceived performance. While affective state positively influenced hedonic motivation, it did not significantly affect actual or perceived task performance, implying that while positive emotions can enhance motivation and enjoyment, they do not necessarily lead to better task outcomes in AR settings. Lastly, legibility only partially influenced participants' perceptions of task performance, particularly regarding perceived time. This suggests that while clearer text can improve user experience, it may not significantly alter their perception of task duration or accuracy.

Our findings revealed that while varying luminance ratios did not significantly impact visual discomfort, higher luminance ratios significantly enhanced legibility. This suggests that optimal lighting conditions, characterized by greater contrast between screen and ambient luminance, can improve the readability of text on smartphones, thereby enhancing user satisfaction. Improved legibility also positively influenced affective states, indicating that clearer text can contribute to more positive emotions during AR interactions. Conversely, visual discomfort negatively affected perceived task performance and task duration, highlighting the importance of user comfort in fostering efficient and effective task completion.

These results underscore the importance of optimizing luminance conditions to enhance user experience and engagement in mobile AR applications. Our study also contributes to the literature by providing empirical evidence on the role of luminance in mobile AR environments, supporting the principles of the Stimulus-Organism-Response (SOR) model. This model illustrates how external stimuli (luminance conditions) affect internal psychological states (visual comfort, legibility) and subsequent behaviors (affective states, task performance).

From a practical perspective, these insights are valuable for developers and designers of AR applications. Ensuring optimal luminance conditions can significantly improve text legibility and reduce visual discomfort, leading to better user experiences and higher engagement. This is particularly important for educational and informational AR applications, where clear and comfortable viewing is essential for effective learning and interaction.

Nonetheless, the study acknowledges certain limitations. The reliance on subjective reports may not fully capture the range of the visual discomfort and overall user experience. Future research should incorporate additional objective measures like eye-tracking to provide a more comprehensive understanding of user responses. Additionally, the study focused on specific tasks and lighting conditions, which may limit the generalizability of the findings. Longer testing periods and a broader range of tasks and environmental settings are recommended to validate these results.

This thesis makes several theoretical contributions to the fields of lighting design, user experience, and educational technology. It demonstrates how lighting conditions can significantly impact various aspects of user experience, providing a framework for future research and practical application in AR environments. The research highlights the importance of managing visual discomfort to improve affective states, perceived learning outcomes, and task performance, contributing to the broader understanding of environmental factors in user experience design.

The findings of this thesis also have practical implications for educators, designers, and developers of AR applications. Educators and institutions should consider investing in optimal lighting solutions to enhance visual comfort, improve learning outcomes, and boost user engagement in mobile AR environments. Designers and developers of mobile AR applications should prioritize user comfort by ensuring that lighting conditions are conducive to reducing visual discomfort and enhancing overall user experience. Furthermore, educational leaders and policymakers should work towards creating guidelines and standards for lighting conditions in mobile AR environments, ensuring that these settings are conducive to effective learning and task performance.

Future research should continue to explore the long-term impacts of lighting on user experience in AR environments, particularly by extending the duration of exposure beyond the 30-minute timeframe used in this study. This would help determine if prolonged exposure to varying luminance ratios results in significant visual discomfort. Additionally, future studies could explore more extreme contrasting lighting conditions, although this might be more applicable to exploratory studies given the rarity of such conditions in typical learning environments. Investigating a broader range of tasks and environmental settings would also help validate these findings and enhance the generalizability of the results.

In conclusion, this thesis has demonstrated the critical role of luminance conditions in shaping user experience in mobile AR environments. While luminance ratios did not significantly impact visual discomfort, they were found to enhance legibility, which in turn positively influenced affective states. By optimizing lighting conditions and managing visual discomfort, developers can create more effective, engaging, and comfortable AR experiences for users, contributing to the development of user-friendly and effective AR applications.

References

Adrian, P., & Wurmser, Y. (2022). US Augmented and Virtual Reality Users Forecast 2022. EMarketer. https://content-na1.emarketer.com/us-augmented-virtual-reality-users-forecast-2022

Azuma, R., Baillot, Y., Behringer, R., Feiner, S., Julier, S., & MacIntyre, B. (2001). Recent advances in augmented reality. *IEEE computer graphics and applications*, *21*(6), 34-47.

Bacca Acosta, J. L., Baldiris Navarro, S. M., Fabregat Gesa, R., & Graf, S. (2014). Augmented reality trends in education: a systematic review of research and applications. *Journal of Educational Technology and Society, 2014, vol. 17, núm. 4, p. 133-149*.

Benedetto, S., Carbone, A., Drai-Zerbib, V., Pedrotti, M., & Baccino, T. (2014). Effects of luminance and illuminance on visual fatigue and arousal during digital reading. *Computers in human behavior*, *41*, 112-119.

Betella, A., & Verschure, P. F. (2016). The affective slider: A digital self-assessment scale for the measurement of human emotions. *PloS one*, *11*(2), e0148037.

Billinghurst, M. (2021). Grand challenges for augmented reality. *Frontiers in Virtual Reality*, *2*, 578080.

Buchner, J., Buntins, K., & Kerres, M. (2022). The impact of augmented reality on cognitive load and performance: A systematic review. *Journal of Computer Assisted Learning*, *38*(1), 285-303

Buxbaum, O., & Buxbaum, O. (2016). The SOR-model. Key insights into basic mechanisms of mental activity, 7-9.

Cidota, M. A., Clifford, R. M., Lukosch, S. G., & Billinghurst, M. (2016, September). Using visual effects to facilitate depth perception for spatial tasks in virtual and augmented reality. In *2016 IEEE International Symposium on Mixed and Augmented Reality (ISMAR-Adjunct)* (pp. 172-177). IEEE.

Cipresso, P., Giglioli, I. A. C., Raya, M. A., & Riva, G. (2018). The past, present, and future of virtual and augmented reality research: a network and cluster analysis of the literature. *Frontiers in psychology*, *9*, 309500.

Chi, H. L., Kang, S. C., & Wang, X. (2013). Research trends and opportunities of augmented reality applications in architecture, engineering, and construction. *Automation in construction*, *33*, 116-122.

Craig, A. B. (2013). Understanding augmented reality: Concepts and applications.

Do, H. N., Shih, W., & Ha, Q. A. (2020). Effects of mobile augmented reality apps on impulse buying behavior: An investigation in the tourism field. *Heliyon*, *6*(8).

Efron, R. (1969, January). What is perception?. In *Proceedings of the Boston Colloquium for the Philosophy of Science 1966/1968* (pp. 137-173). Dordrecht: Springer Netherlands.

El Jamiy, F., & Marsh, R. (2019). Survey on depth perception in head mounted displays: distance estimation in virtual reality, augmented reality, and mixed reality. *IET Image Processing*, *13*(5), 707-712.

Engineering ToolBox, (2004). Illuminance - Recommended Light Level. [online] Available at: https://www.engineeringtoolbox.com/light-level-rooms-d_708.html.

Erickson, A., Kim, K., Bruder, G., & Welch, G. (2022, January). A review of visual perception research in optical see-through augmented reality. In *Proceedings of ICAT- EGVE 2020-International Conference on Artificial Reality and Telexistence and Eurographics Symposium on Virtual Environments*.

Frey, J., Appriou, A., Lotte, F., & Hachet, M. (2015). Estimating visual comfort in stereoscopic displays using electroencephalography: A proof-of-concept. In *Human-Computer Interaction–INTERACT 2015: 15th IFIP TC 13 International Conference, Bamberg, Germany, September 14-18, 2015, Proceedings, Part IV 15* (pp. 354-362). Springer International Publishing.

Gattullo, M., Uva, A. E., Fiorentino, M., & Gabbard, J. L. (2015). Legibility in industrial AR: text style, color coding, and illuminance. *IEEE computer graphics and applications*, *35*(2), 52-61

Geng, X., & Yamada, M. (2020). The Effects of Augmented Reality on Learning Performance and Cognitive Load Using the Spatial Continuity Principle. *International Association for Development of the Information Society*.

Goff, E. E., Mulvey, K. L., Irvin, M. J., & Hartstone-Rose, A. (2018). Applications of augmented reality in informal science learning sites: A review. *Journal of Science Education and Technology*, *27*, 433-447.

Haridas, M., Nedungadi, P., & Raman, R. (2017, December). Incorporating CTML principles in tablet-based learning. In *2017 International Conference on Technological Advancements in Power and Energy (TAP Energy)* (pp. 1-6). IEEE.

Harmon-Jones, E., Gable, P. A., & Price, T. F. (2012). The influence of affective states varying in motivational intensity on cognitive scope. *Frontiers in integrative neuroscience*, *6*, 73.

Harskamp, E. G., Mayer, R. E., & Suhre, C. (2007). Does the modality principle for multimedia learning apply to science classrooms?. *Learning and instruction*, *17*(5), 465-477.

He, Z., Wu, L., & Li, X. R. (2018). When art meets tech: The role of augmented reality in enhancing museum experiences and purchase intentions. *Tourism Management*, *68*, 127-139.

Heuer, H., & Owens, D. A. (1989). Vertical gaze direction and the resting posture of the eyes. Perception, 18(3), 363-377.

Hoffman, D. M., Girshick, A. R., Akeley, K., and Banks, M. S. 2008. “Vergence–Accommodation Conflicts Hinder Visual Performance and Cause Visual Fatigue,” *Journal of Vision* (8:3), pp. 33–33.

Huang, T. (2023). Using SOR framework to explore the driving factors of older adults smartphone use behavior. *Humanities and Social Sciences Communications*, *10*(1), 1-16.

Ibáñez, M. B., Di-Serio, Á., Villarán-Molina, D., & Delgado-Kloos, C. (2014). Augmented reality-based simulators as discovery learning tools: An empirical study. *IEEE Transactions on Education*, *58*(3), 208-213.

Jeffri, N. F. S., & Rambli, D. R. A. (2021). A review of augmented reality systems and their effects on mental workload and task performance. *Heliyon*, *7*(3).

Jensen, E., & Lister, T. (2017). The challenges of ‘measuring long-term impacts of a science center on its community’: A methodological review. *Preparing Informal Science Educators: Perspectives from Science Communication and Education*, 243-259.

Jin, B., Kim, G., Moore, M., & Rothenberg, L. (2021). Consumer store experience through virtual reality: its effect on emotional states and perceived store attractiveness. *Fashion and Textiles*, *8*, 1-21.

Katsuyuki, M., Shunichi, A., Kazuhito, Y., Kohei, Y., Toshihiro, O., & Shinichi, S. (1996). Accumulation of VDT work-related eyestrain assessed by visual evoked potential, near point distance and critical flicker fusion. Industrial Health, 34(2), 61-69.

Kaur, K., Gurnani, B., Nayak, S., Deori, N., Kaur, S., Jethani, J., ... & Mishra, D. (2022). Digital eye strain-a comprehensive review. *Ophthalmology and therapy*, *11*(5), 1655-1680.

Kazemi, R., Choobineh, A., Taheri, S., & Rastipishe, P. (2018). Comparing task performance, visual comfort and alertness under different lighting sources: An experimental study. *EXCLI journal*, *17*, 101

Kim, J. S., Lee, J. H., & Kim, S. Y. (2012). Variation of spatial cognition according to visual perception and psychological responses for lighting environments in rest space. *Korean Journal of Air-Conditioning and Refrigeration Engineering*, *24*(5), 443-453.

King, L. E. (1973). Illuminance versus luminance. *Special Report*, *134*.

Kruijff, E., Swan, J. E., & Feiner, S. (2010, October). Perceptual issues in augmented reality revisited. In *2010 IEEE International Symposium on Mixed and Augmented Reality* (pp. 3-12). IEEE.

Krüger, J. M., & Bodemer, D. (2022). Application and investigation of multimedia design principles in augmented reality learning environments. *Information*, *13*(2), 74.

Kurkovsky, S., Koshy, R., Novak, V., & Szul, P. (2012, June). Current issues in handheld augmented reality. *In 2012 international conference on communications and information technology* (ICCIT) (pp. 68-72). IEEE.

Lai, A. F., Chen, C. H., & Lee, G. Y. (2019). An augmented reality‐based learning approach to enhancing students' science reading performances from the perspective of the cognitive load theory. *British Journal of Educational Technology*, *50*(1), 232-247.

Lambooij, M., IJsselsteijn, W., Fortuin, M., & Heynderickx, I. (2009). Visual discomfort and visual fatigue of stereoscopic displays: A review. *Journal of imaging science and technology*, *53*(3), 30201-1.

Leopardi, A., Ceccacci, S., Mengoni, M., Naspetti, S., Gambelli, D., Ozturk, E., & Zanoli, R. (2021). X-reality technologies for museums: a comparative evaluation based on presence and visitors experience through user studies. *Journal of Cultural Heritage*, *47*, 188-198.

Leppink, J., Paas, F., Van Gog, T., van Der Vleuten, C. P., & Van Merrienboer, J. J. (2014). Effects of pairs of problems and examples on task performance and different types of cognitive load. *Learning and instruction*, *30*, 32-42.

Liao, T., Chang, P. F., & Lee, S. (2020). Augmented reality in health and medicine: a review of augmented reality application for health professionals, procedures, and behavioral interventions. *Technology and Health*, 109-128.

Liew, T. W., Mat Zin, N. A., & Sahari, N. (2017). Exploring the affective, motivational and cognitive effects of pedagogical agent enthusiasm in a multimedia learning environment. *Human-centric Computing and Information Sciences*, *7*, 1-21.

Mayer, R. E. (2009). *Multimedia Learning*. Cambridge University Press.

Mistry, P., & Maes, P. (2009). SixthSense: a wearable gestural interface. In *ACM SIGGRAPH ASIA 2009 Art Gallery & Emerging Technologies: Adaptation* (pp. 85-85)

Markouzis, D., Baziakou, A., Fesakis, G., & Dimitracopoulou, A. (2022). A systematic review on augmented reality applications in informal learning environments. *International Journal of Mobile and Blended Learning*, 14(4), 1-17.

Orr, M., Poitras, E., & Butcher, K. R. (2021). Informal learning with extended reality environments: Current trends in museums, heritage, and tourism. In *Augmented Reality in Tourism, Museums and Heritage: A New Technology to Inform and Entertain* (pp. 3-26). Cham: Springer International Publishing.

Paine, C. (2018). Title of the article. Journal Name, Volume(Issue), Page range.

Pallud, J. (2017). Impact of interactive technologies on stimulating learning experiences in a museum. Information & Management, 54(4), 465-478.

Pavel, I. A., Bogdanici, C. M., Donica, V. C., Anton, N., Savu, B., Chiriac, C. P., ... & Salavastru, S. C. (2023). Computer vision syndrome: an ophthalmic pathology of the modern era. *Medicina*, *59*(2), 412.

Pawlaczyk-Łuszczyńska, M., Dudarewicz, A., Waszkowska, M., Szymczak, W., & Śliwińska-Kowalska, M. (2005). The impact of low frequency noise on human mental performance. *International Journal of Occupational Medicine & Environmental Health*, *18*(2).

Perez-Sanagustin, M., Hernández-Leo, D., Santos, P., Kloos, C. D., & Blat, J. (2014). Augmenting reality and formality of informal and non-formal settings to enhance blended learning. *IEEE Transactions on Learning Technologies*, *7*(2), 118-131.

Rosenfield, M. (2011). Computer vision syndrome: a review of ocular causes and potential treatments. *Ophthalmic and Physiological Optics*, *31*(5), 502-515.

Rosenberg, L. B. (1992). The Virtual Fixtures system: A telerobotic tool for remotely manipulating real-world objects. Proceedings of the 1992 IEEE international conference on robotics and automation (ICRA'92), 65–70. https://doi.org/10.1109/ROBOT.1992.220825).

Sommerauer, P., & Müller, O. (2014). Augmented reality in informal learning environments: A field experiment in a mathematics exhibition. *Computers & education*, *79*, 59-68.

Shen, Shiwei & Xu, Kexin & Sotiriadis, Marios & Wang, Yuejiao. (2022). Exploring the factors influencing the adoption and usage of Augmented Reality and Virtual Reality applications in tourism education within the context of COVID-19 pandemic. Journal of Hospitality, Leisure, Sport & Tourism Education.

Stenfors, C. U., Van Hedger, S. C., Schertz, K. E., Meyer, F. A., Smith, K. E., Norman, G. J., ... & Berman, M. G. (2019). Positive effects of nature on cognitive performance across multiple experiments: Test order but not affect modulates the cognitive effects. *Frontiers in psychology*, *10*, 1413.

Sweller, J. (2011). Cognitive load theory. In *Psychology of learning and motivation* (Vol. 55, pp. 37-76). Academic Press.

Tsubota, K., & Nakamori, K. (1993). Dry eyes and video display terminals. *New England Journal of Medicine*, *328*(8), 584-584.

Tugtekin, U., & Odabasi, H. F. (2022). Do interactive learning environments have an effect on learning outcomes, cognitive load and metacognitive judgments?. *Education and Information Technologies*, *27*(5), 7019-7058.

Urvoy, M., Barkowsky, M., & Le Callet, P. (2013). How visual fatigue and discomfort impact 3D-TV quality of experience: A comprehensive review of technological, psychophysical, and psychological factors. Annals of Telecommunications - Annales Des Télécommunications, 68(11–12), 641–655

Wang, Y., Ko, E., & Wang, H. (2021). Augmented reality (AR) app use in the beauty product industry and consumer purchase intention. *Asia Pacific Journal of Marketing and Logistics*, *34*(1), 110-131.

Wedel, M., Bigné, E., & Zhang, J. (2020). Virtual and augmented reality: Advancing research in consumer marketing. *International Journal of Research in Marketing*, *37*(3), 443-465.

Yang, Z., Shi, J., Jiang, W., Sui, Y., Wu, Y., Ma, S., ... & Li, H. (2019). Influences of augmented reality assistance on performance and cognitive loads in different stages of assembly task. *Frontiers in psychology*, *10*, 458057.

Yu, H., & Akita, T. (2020). Influence of ambient-tablet PC luminance ratio on legibility and visual fatigue during long-term reading in low lighting environment. Displays, 62, 101943.

Yuen, S. C. Y., Yaoyuneyong, G., & Johnson, E. (2011). Augmented reality: An overview and five directions for AR in education. *Journal of Educational Technology Development and Exchange (JETDE)*, *4*(1), 11.

Zabels, R., Osmanis, K., Narels, M., Gertners, U., Ozols, A., Rūtenbergs, K., & Osmanis, I. (2019). AR displays: Next-generation technologies to solve the vergence–accommodation conflict. *Applied Sciences*, *9*(15), 3147.

Ziefle, M. (2001, October). Aging, visual performance and eyestrain in different screen technologies. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 45, No. 3, pp. 262-266). Sage CA: Los Angeles, CA: SAGE Publications

Zhdanov, A. D., Zhdanov, D. D., Bogdanov, N. N., Potemin, I. S., Galaktionov, V. A., & Sorokin, M. I. (2019). Discomfort of visual perception in virtual and mixed reality systems. *Programming and Computer Software*, *45*, 147-155.

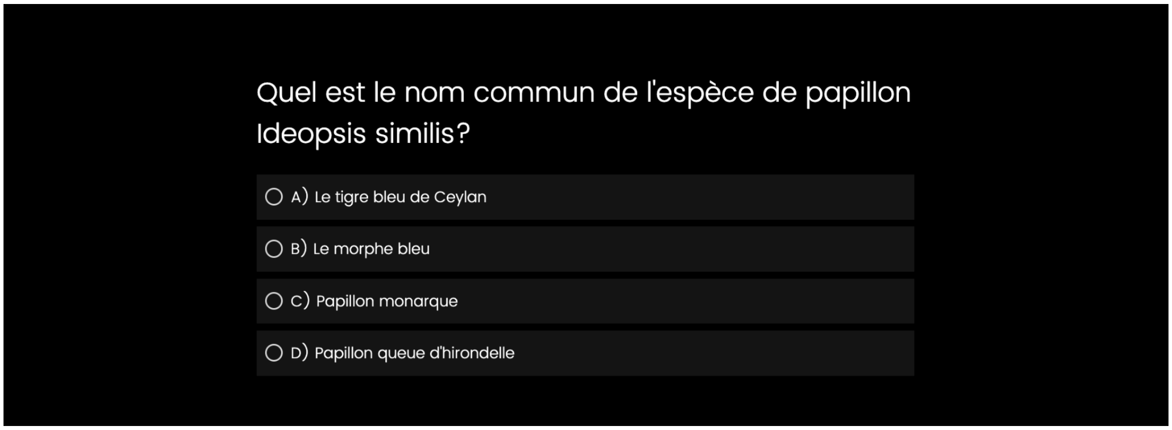
Zhou, Y., Shi, H., Chen, Q. W., Ru, T., & Zhou, G. (2021). Investigation of the optimum display luminance of an LCD screen under different ambient illuminances in the evening. *Applied Sciences*, *11*(9), 4108.

Annexes

Annex A - Participant Block ID, condition and insect sequence

Participant I	Block Letter	Block Seque	Insect Sequence
P05	E	1, 4, 2, 3	7, 3 / 5, 11 / 2, 9 / 8, 1
P06	F	1, 4, 3, 2	6, 4 / 1, 10 / 9, 3 / 12, 5
P07	G	2,1,3,4	2, 11 / 8, 4 / 1, 7 / 6, 12
P08	H	2,1,4,3	9, 5 / 10, 3 / 11, 2 / 8, 6
P09	I	2,3,1,4	12, 7 / 1, 4 / 5, 10 / 6, 9
P10	J	2,3,4,1	3, 6 / 12, 7 / 10, 5 / 9, 1
P11	K	2,4,1,3	4, 8 / 2, 11 / 6, 3 / 12, 7
P12	L	2,4,3,1	10, 2 / 9, 6 / 12, 7 / 4, 3
P13	M	1, 3, 2, 4	5, 1 / 4, 8 / 3, 11 / 7, 10
P14	N	3, 1, 4, 2	11, 10 / 6, 2 / 8, 1 / 4, 9
P15	O	3, 2, 1, 4	7, 12 / 5, 9 / 4, 6 / 1, 3
P16	P	3, 2, 4, 1	3, 8 / 6, 1 / 11, 9 / 10, 5
P17	Q	3, 4, 1, 2	4, 7 / 2, 10 / 5, 12 / 9, 6
P18	R	3, 4, 2, 1	1, 3 / 8, 11 / 7, 6 / 4, 10
P19	S	4, 1, 2, 3	9, 10 / 3, 1 / 8, 4 / 7, 2
P20	T	4, 1, 3, 2	5, 6 / 12, 4 / 2, 9 / 7, 11
P21	U	4, 2, 1, 3	2, 1 / 7, 3 / 9, 6 / 10, 8
P22	V	4, 2, 3, 1	11, 5 / 4, 9 / 10, 7 / 3, 1
P23	W	4, 3, 1, 2	6, 12 / 1, 7 / 8, 4 / 5, 11
P24	X	4, 3, 2, 1	8, 11 / 9, 6 / 7, 5 / 3, 2
P25	Y	1, 2, 3, 4	10, 4 / 3, 5 / 12, 1 / 11, 8
P27	AA	1, 2, 4, 3	5, 9 / 7, 3 / 1, 4 / 2, 12
P28	AB	1, 3, 4, 2	12, 2 / 11, 10 / 6, 5 / 8, 7
P29	AC	1, 4, 2, 3	3, 4 / 9, 1 / 7, 10 / 6, 12

Annex B - Example of quiz question presented to the participant

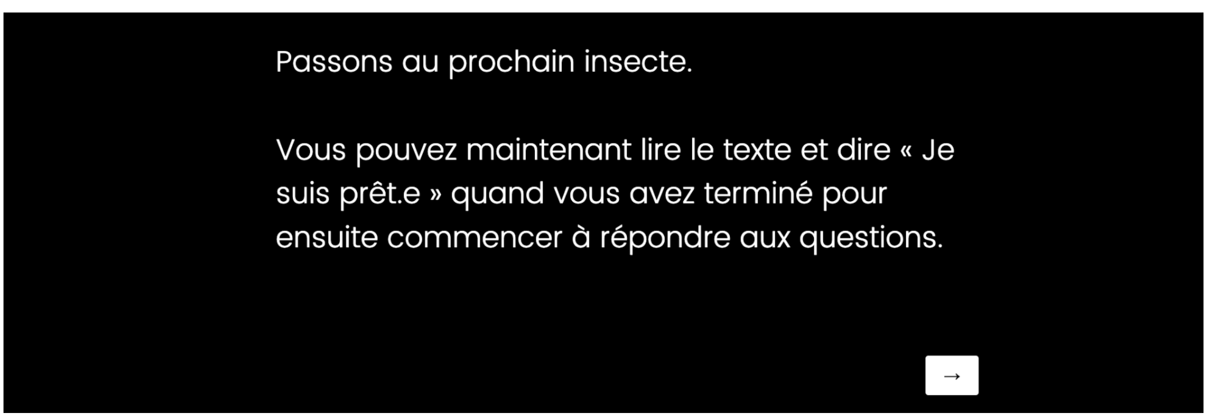


English translation:

“What is the common name for this butterfly species “Ideopsis similis”?

A) The Ceylon blue tiger butterfly
B) The Morpho
C) The Monarch butterfly
D) The Swallowtail butterfly

Annex C - transition slide between insects (i.e., 1 minute break in-between conditions)



English translation:

“Let’s move on to the next insect. You can now read the text and say “I am ready” out loud when you have finished reading to begin answering the questions”

Annex D - Qualtrics Questionnaires:

1D) Visual Discomfort

1a. Visual Discomfort (Heuer et al)

VD

En vous basant sur les tâches que vous venez de compléter, veuillez s'il vous-plaît évaluer votre niveau d'inconfort visuel:

	Totalement en désaccord	En désaccord	Plutôt en désaccord	Ni en accord, ni en désaccord	Plutôt en accord	En accord	Totalement en accord
J'ai des difficultés à voir	○	○	○	○	○	○	○
Je ressens une sensation inhabituelle autour de mes yeux	○	○	○	○	○	○	○
Je ressens de la fatigue occulaire	○	○	○	○	○	○	○
Je me sens engourdi	○	○	○	○	○	○	○
J'ai des maux de tête	○	○	○	○	○	○	○
Je me sens étourdi en regardant l'écran	○	○	○	○	○	○	○

English translation:

“Basing yourself on the tasks that you just completed, please evaluate your visual discomfort level:

- I have difficulty seeing
- I feel an inhabitable feeling around my eyes
- I feel tiredness in my eyes
- I feel numb
- I have a headache
- I feel dizzy watching the screen

Scale: Totally disagree, Disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Agree, Totally agree"

2D) Perceived Learning Outcome

1b. Perceived learning outcome

PL

En vous basant sur votre expérience en Réalité Augmentée (RA), veuillez évaluer vos préférences:

	Pas du tout	Très peu	Un peu	Modérément	Assez	Beaucoup	Énormément
L'utilisation de l'application de réalité augmentée m'a aidé à identifier les principales caractéristiques des insectes.	○	○	○	○	○	○	○
L'application de réalité augmentée m'a aidé à mieux comprendre la couleur, les formes, les habitats et les proies des insectes.	○	○	○	○	○	○	○
L'application de réalité augmentée m'a permis d'approfondir mes connaissances sur les insectes.	○	○	○	○	○	○	○

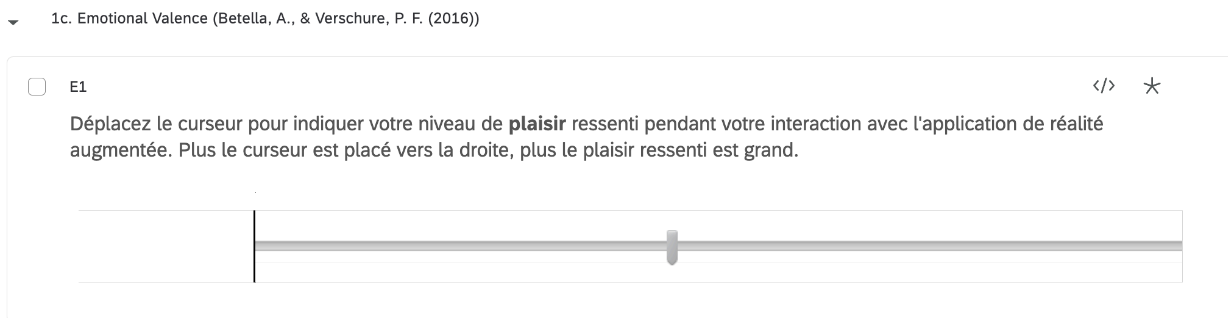
English translation:

"Basing yourself on your Augmented Reality (AR) experience, please evaluate your preference:

- Using the AR application has helped me identify the principle insects' characteristics
- The AR application has helped me understand the colour, the shapes and the preys of each insect
- The AR application has allowed me to deepen my knowledge about insects

Scale: Not at all; Very little; A little; Moderately; Enough; A lot; Enormously"

3D) Emotional Valence


1c. Emotional Valence (Betella, A., & Verschure, P. F. (2016))

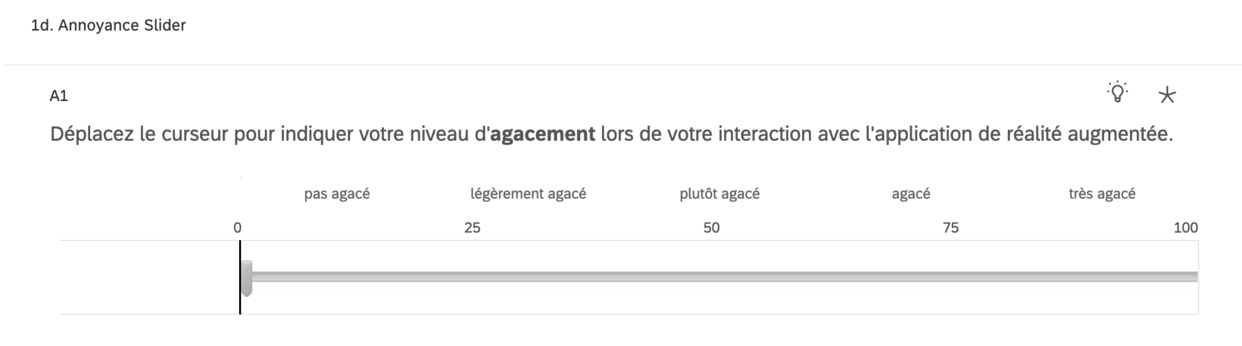
E1

Déplacez le curseur pour indiquer votre niveau de **plaisir** ressenti pendant votre interaction avec l'application de réalité augmentée. Plus le curseur est placé vers la droite, plus le plaisir ressenti est grand.

English translation:

“Move the cursor to indicate the level of **pleasure** during your interaction with the AR application. The more the cursor is towards the right, the greater the pleasure is felt.”

4D) Annoyance Slider


1d. Annoyance Slider

A1

Déplacez le curseur pour indiquer votre niveau d'**agacement** lors de votre interaction avec l'application de réalité augmentée.

pas agacé légèrement agacé plutôt agacé agacé très agacé

0 25 50 75 100

English translation:

“Move the cursor to indicate the level of **annoyance** during your AR interaction.

0 = not annoyed

25 = slightly annoyed

50 = rather annoyed

75 = annoyed

100 = very annoyed”

5D) Hedonic Motivation

1e. Hedonic Motivation (Xu et al 2022)

HM

En vous basant sur votre expérience en Réalité Augmentée (RA), veuillez évaluer vos préférences:

	Pas du tout	Très peu	Un peu	Modérément	Assez	Beaucoup	Énormément
Utiliser l'application RA est amusant.	○	○	○	○	○	○	○
Utiliser l'application RA pour apprendre est appréciable.	○	○	○	○	○	○	○
Utiliser l'application RA pour apprendre est divertissant.	○	○	○	○	○	○	○

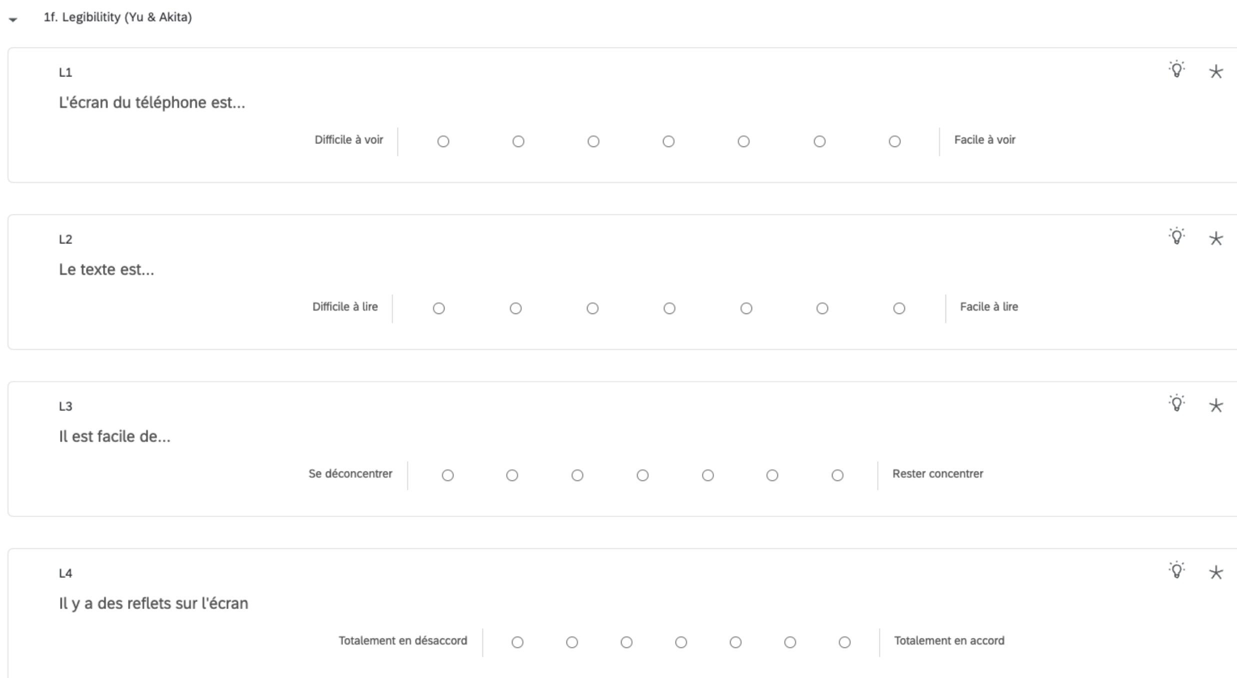
English translation:

"Basing yourself on your AR experience, please indicate your preference:

- Using the AR application is exciting
- Using the AR application for learning is appropriate
- Using the AR application for learning is entertaining

Scale: Not at all; Very little; A little; Moderately; Enough; A lot; Enormously"

6D) Legibility



1f. Legibilitity (Yu & Akita)

L1

L'écran du téléphone est...

Difficile à voir ○ ○ ○ ○ ○ ○ ○ Facile à voir

L2

Le texte est...

Difficile à lire ○ ○ ○ ○ ○ ○ ○ Facile à lire

L3

Il est facile de...

Se déconcentrer ○ ○ ○ ○ ○ ○ ○ Rester concentrer

L4

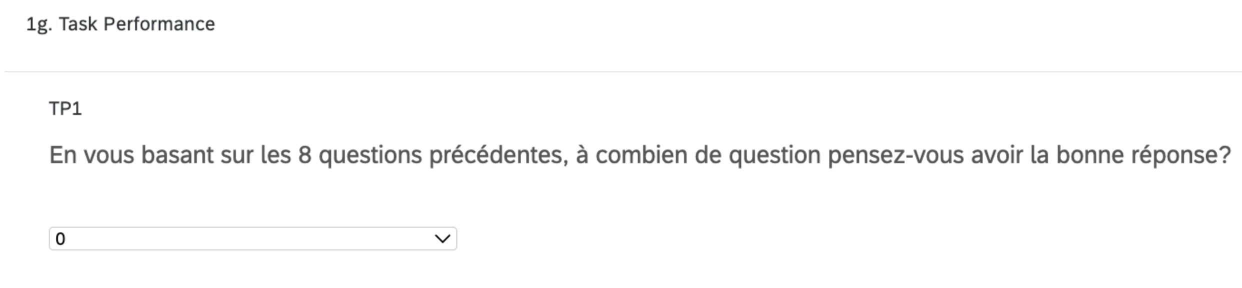
Il y a des reflets sur l'écran

Totalement en désaccord ○ ○ ○ ○ ○ ○ ○ Totalement en accord

English translation:

- L1: the phone screen is… [Hard to see - Easy to see]
- L2: the text is… [Hard to read - Easy to read]
- L3: it is easy to… [Lose focus - Stay focused]
- L4: there are reflections on the screen [Totally disagree - Totally agree]

7D) Perceived Task Performance


1g. Task Performance

TP1

En vous basant sur les 8 questions précédentes, à combien de question pensez-vous avoir la bonne réponse?

0

English translation:

“Basing yourself on the last 8 questions, how many questions do you think you got right?”

Scale: 0 to 8

8D) Perceived Time


TP2

À propos des 2 insectes précédents, veuillez faire glisser le curseur en fonction de votre perception du temps écoulé au cours des deux dernières tâches.

Très lent

Très rapide

English translation:

“About the previous 2 insects, please drag the slider according to your perception of the time elapsed during the last two tasks.”