Final Report

Measuring Pedestrian Psycho-Physiological Well-Being in the Built Environment

Author Name
T. Donna Chen
Phone: 434-924-6224; Email: tdchen@virginia.edu

Author Name
Andrew Mondschein
Phone: 434-924-1044; Email: mondschein@virginia.edu

Date
September 2024

Prepared for the Safety and Mobility Advancements Regional Transportation and Economics Research Center, Morgan State University, CBEIS 327, 1700 E. Coldspring Lane, Baltimore, MD 21251

ACKNOWLEDGMENT

This research was supported by the Safety and Mobility Advancement Regional Transportation and Economics Research Center at Morgan State University and the University Transportation Center(s) Program of the U.S. Department of Transportation.

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, under grant number 69A3552348303 from the U.S. Department of Transportation's University Transportation Centers Program. The U.S. Government assumes no liability for the contents or use thereof.

<table>
<tr><td>1. Report No. SM14</td><td>2. Government Accession No.</td><td>3. Recipient's Catalog No.</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle
Measuring Pedestrian Psycho-Physiological Well-Being in the Built Environment</td><td>5. Report Date
9/13/2024</td></tr>
<tr><td>6. Performing Organization Code</td></tr>
<tr><td colspan="2">7. Author(s) Include ORCID #
T. Donna Chen (0000-0002-7026-3418)
Andrew Mondschein (0000-0002-8454-0463)</td><td>8. Performing Organization Report No.</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name and Address
University of Virginia
Charlottesville, VA, USA</td><td>10. Work Unit No.</td></tr>
<tr><td>11. Contract or Grant No.
69A3552348303</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Agency Name and Address
US Department of Transportation
Office of the Secretary-Research
UTC Program, RDT-30
1200 New Jersey Ave., SE
Washington, DC 20590</td><td>13. Type of Report and Period Covered
Final, September 2024 – September 2024</td></tr>
<tr><td>14. Sponsoring Agency Code</td></tr>
<tr><td colspan="3">15. Supplementary Notes</td></tr>
<tr><td colspan="3">16. Abstract
Pedestrians are some of the most vulnerable road users, and pedestrian fatalities have been increasing over the last 15 years, particularly at night. To create safer infrastructure for pedestrians, it is imperative to understand how pedestrian perception and behavior varies between the daytime and nighttime. Understanding pedestrian behaviors, preferences, and perception of the built environment is essential for creating spaces that promote more active modes of transportation. This study employs mobile eye-tracking glasses and stated preference surveys to examine differences in pedestrian attention and perceptions of comfort and safety along an urban corridor in Charlottesville, VA, USA during the daytime and nighttime. The analysis of gaze data uses an urban typology framework which allows for quantitative differentiation in pedestrian's attention to various urban stimuli, such as transportation elements, built infrastructure, people, and nature. The results indicate that at night, participants paid more attention to vehicles, lighted crossing infrastructure, and lighting features, while attention on unlit transportation infrastructure and nature decreased. Findings from the study also suggest that there is a connection between lighting levels and perception of safety. Locations with the lowest lighting levels along the route were frequently identified by participants as locations they felt the most unsafe at night. The study proposes a comprehensive model of measuring attention, perception, and cognition, and sets the groundwork for future research on the linkages between the experiential dimensions of streets, human-wellbeing, and pedestrian behaviors.</td></tr>
<tr><td colspan="2">17. Key Words: Pedestrians, Safety, Eye-Tracking, Cognition, Behavior, Lighting</td><td>18. Distribution Statement</td></tr>
<tr><td>19. Security Classif. (of this report):
Unclassified</td><td>20. Security Classif. (of this page)
Unclassified</td><td>21. No. of Pages
25 | 22. Price</td></tr>
</table>

Abstract

Pedestrians are some of the most vulnerable road users, and pedestrian fatalities have been increasing over the last 15 years, particularly at night. To create safer infrastructure for pedestrians, it is imperative to understand how pedestrian perception and behavior varies between the daytime and nighttime. Understanding pedestrian behaviors, preferences, and perception of the built environment is essential for creating spaces that promote more active modes of transportation. This study employs mobile eye-tracking glasses and stated preference surveys to examine differences in pedestrian attention and perceptions of comfort and safety along an urban corridor in Charlottesville, VA, USA during the daytime and nighttime. The analysis of gaze data uses an urban typology framework which allows for quantitative differentiation in pedestrian's attention to various urban stimuli, such as transportation elements, built infrastructure, people, and nature. The results indicate that at night, participants paid more attention to vehicles, lighted crossing infrastructure, and lighting features, while attention on unlit transportation infrastructure and nature decreased. Findings from the study also suggest that there is a connection between lighting levels and perception of safety. Locations with the lowest lighting levels along the route were frequently identified by participants as locations they felt the most unsafe at night. The study proposes a comprehensive model of measuring attention, perception, and cognition, and sets the groundwork for future research on the linkages between the experiential dimensions of streets, human-wellbeing, and pedestrian behaviors.

Introduction

After decades of declining pedestrian fatalities in the United States, the numbers have been increasing over the last 15 years, mostly due to nighttime fatalities (*1*). Federal data on roadway fatalities depict a shift in peak times for pedestrian fatalities throughout the year. This suggests that darkness is more of a threat to pedestrians than their routines (*1*, *2*). Even though there are often more pedestrian trips during the day than at night, a disproportionate 76% of pedestrian fatalities occur when it is dark (*3*). While the cause of this has yet to be determined, it highlights the need to analyze pedestrian perception and behavior at night. The condition of the surrounding lighting influences not only the safety of roads but also people's perception of safety. Creating safe and pleasant pedestrian conditions is necessary to protect vulnerable road users and promote more active mobility use. When people feel that conditions are not safe, they will often forgo walking, so it is necessary to consider pedestrian perception when making decisions about a built environment (*4*). To that end, understanding the effect of time of day and lighting conditions from the pedestrian perspective can inform decision-makers about the types of infrastructure and environmental conditions that are both objectively and subjectively safer for pedestrians at all times of day. Driver behavior has often been the focus when examining nighttime crashes that involve pedestrians, but mobile eye-tracking glasses present an opportunity to study these elements from the pedestrian perspective and in real-world settings.

Pedestrians observe many elements when navigating urban environments. Visual behavior is closely associated with underlying cognitive processes, such as attention and memory, and is connected to our actions in the world (*5*). Mobile eye-tracking technology, a sensor that detects eye movements and points of focus, can be used to provide insight into people's perception, cognition, and emotional state. Studies on visual behavior as it relates to the built environment and transportation have previously only been possible in laboratory settings due to technological constraints and the complexity of monitoring tasks in their natural environments (*6–10*). Mobile eye-tracking technology allows researchers to identify which urban streetscape elements capture individuals' attention, offering valuable data on how people perceive their surroundings while navigating streets. This represents a significant advancement over previous methods, such as static scenes, simulated screen-based environments, or virtual reality approaches (*6*, *11*, *12*). This technology presents opportunities for new research into how pedestrians and other road users interact with their surroundings when using different types of infrastructure and in different environmental conditions.

The ability to study more dynamic environments comes with new challenges, as the methodological and analytical approaches for this emerging technology are still being developed. By integrating mobile eye-tracking glasses and pre- and post-experiment surveys, this within-subject study explores how to better understand pedestrian responses to changes in urban infrastructure design and environmental conditions. By having participants walk along the same urban corridor during both the day and night, this study examines shifts in pedestrian attention as conditions change to evaluate pedestrians' perspectives. While this study compares day and nighttime conditions, this technology has the potential to be applied to various types of environmental conditions in order to evaluate how pedestrians and other users interact with and perceive their surroundings.

Literature Review

This section summarizes existing literature related to pedestrian safety and perception, eye-tracking analysis, and eye movements. The existing gaps and contributions of this study are then presented based on the review of existing literature.

Pedestrian Perception and Safety

Pedestrian wayfinding requires attention to traffic signs and signals, traffic rules, and social norms (*13*). The characteristics of the built environment can influence the amount of attention these elements require, as well as the stress and anxiety associated with a pedestrian's surroundings. There has been a great deal of research that focuses on the physical factors that impact pedestrian safety, such as number of lanes, visibility, raised medians, street trees, and land-use patterns (*14–16*). One study that examined factors impacting nighttime fatalities found that there was also a strong correlation between infrastructure factors, including unmarked intersections and road width, and fatal nighttime pedestrian crashes (*17*). The same paper found that the age of pedestrians involved in fatal pedestrian crashes increased more than the national average, suggesting the importance of understanding the behavior of older pedestrians (*17*). However, there is limited research on the perception of safety and environmental conditions, and studies that have examined perception often rely on participant surveys (*18*). Understanding subjective perception of safety with respect to environmental conditions and infrastructure is critical for creating walkable spaces that do not cause fear and anxiety and promoting walking as a chosen mode of transportation.

Previous studies that have examined nighttime crashes have focused on the driver's perspective. Most of the studies that have focused on the pedestrian perspective have used either videos of traffic or virtual reality (VR) simulation to gauge when pedestrians felt the last safe moment to cross was or measure the timing of their movements (*3*). A review of factors affecting pedestrian perception of safety and comfort found a positive correlation between pedestrians feeling safe and public space lighting intensity (*19*). Although some studies suggest that this is a dose-response relationship, where light intensity beyond certain levels does not lead to increased safety perception (*19*). One study found that reduced glare and uniform lighting increases comfort (*20*).

Pedestrian Eye-Tracking Analysis

Mobile eye-tracking is an advancement of lab-based eye-tracking technology that allows researchers to measure eye movements and attention in real-world settings, including outdoor urban environments (*11*, *21–26*). Eye tracking data provide insight into pedestrians' perception and cognition by indicating how visual information is processed (*25*). Research has found that pedestrian viewing behavior seeks information from the environment that allows for safe navigation (*23*). When walking on a typical car-occupied street, visual attention is mostly focused on the side of the street where the pedestrians are actively traveling. However, if the street is pedestrianized, then the visual attention is distributed nearly equally between both sides of the street (*24*). Another study found that the path walked is also important, and that most of the visual attention on the target path happens at close distances (*26*). Overall, these studies demonstrate that pedestrians utilize visual information to interact with their surroundings and move safely along the street. However, these studies do not examine how attention varies under different conditions, when vehicles are present and when lighting conditions differ at different times of day. One study examined the visual behavior of pedestrians at night by having participants walk along 3 different residential routes. The authors concluded that pedestrians spend between 40-50% of their time looking at the footpath. While there were no conclusive lighting level results, the authors highlighted the importance of examining illuminance of the route (*27*).

The emergence of mobile wearable sensor technology has allowed studies on visual behavior to move outside the laboratory setting and collect first-person perspective data in real-world settings (*28*). Despite this, research that considers the built environment from the perspective of pedestrians in the real-world is still limited (*29*). Applying mobile eye-tracking technology in outdoor environments provides a deeper understanding of how people relate to real-life environments. This element is especially important when studying topics related to transportation and the built environment. One 2022 study found that most research on pedestrian safety using sensors and augmented reality focuses on a specific domain, and are not always suitable for real-world settings (*30*). While VR simulations and other lab-based methods are a useful tool for focusing on specific domains and evaluating infrastructure without the risk associated with being in the real world, there may still be differences in people's interaction and the decisions people make in the real world. It is important to be cautious about generalizing lab-based findings in the real-world due to some of the limitations associated with laboratory studies. Lab based studies are unable to expose participants to the same level of visual and non-visual stimuli as they would experience in the real world (*5*). As we are still exploring which elements are connected to pedestrian decision-making, this limitation could lead to different results. The use of smart glasses has been identified as an important tool for collecting reliable data on pedestrian behavior and understanding pedestrians' changes in cognition and focus during their walking experience (*29, 31*).

Eye Movements and Metrics

High visual acuity is restricted to the fovea, a small area at the center of the retina, so for humans to gather quality visual information, eye movement is essential. Visual acuity significantly decreases beyond the fovea, so tracking a visual target necessarily requires eye movement to center the target within the fovea (*32*). The "point of gaze" is defined as where one is looking, and can be analyzed with eye tracking data with respect to the visual scene (*33*). The two fundamental components of eye movements are saccades and fixations. A visual fixation is essentially a period when the gaze remains focused on a specific location (*32*). This paper focuses on fixation data and video recordings in order to determine the relationship between participants' attention and the environment while walking in the two different scenarios.

Saccades are the rapid movements of the eyes that abruptly change the point of fixation. Due to this fast movement, the eyes are not able to acquire new information. The average duration of a saccade is between 20 and 40 ms, whereas fixations occur when the eyes remain in one place and are able to acquire new information from the visual array (*34*). Fixations usually last between 50 to 600 ms and can be used to make inferences about cognitive processes and attention (*34*). When working with dynamic stimuli in real-world settings, eye movements beyond fixations and saccades need to be considered. Vergence eye movements align the fovea on visual targets at different distances. When trying to focus on moving objects, smooth pursuit movements keep the fovea aligned with the visual target. Finally, Vestibular Ocular Reflex (VOR) compensates for head movements by stabilizing the fovea on an element of interest even when the head or body is moving (*35*). When eyes are stabilizing, they are still gathering information. These movements are attempts to stabilize the fovea on an object of interest and can potentially extract information. Understanding these movements is important when determining the velocity threshold to filter the recorded eye tracking data (as discussed in the methodology section).

While the increasing use of eye-tracking devices in experiments related to vulnerable road users speaks to the promise of this type of data, there are some inconsistencies in the metrics used in the literature (*36*). While there are numerous approaches used to analyze eye-tracking data, too few studies have been conducted for standardized metrics to emerge. Metrics can be categorized into two types: general metrics and AOI-related (Area of Interest) metrics. General metrics, fixation duration and fixation dispersion being two of the most common, can be used to infer mental workload and stress levels (*36*). Whereas, AOI-related metrics, such as fixation duration and fixation count, provide insight about attention, visual search patterns, and hazard detection (*36*).

Summary of Literature Review

This review of literature focused on pedestrian perception of their surroundings, the use of eye-tracking technology, and the analysis of eye movement patterns and metrics. While the use of eye-tracking has been used across disciplines for many years, there is a distinct lack of literature analyzing eye tracking data in real-world built environment conditions due to the novelty of mobile eye-tracking technology. However, the technology shows great potential for improving the understanding of pedestrian perception and cognition in real-world settings. Many of the studies that have begun to incorporate this technology with the built environment in transportation-related studies have focused on the driver perspective, and far fewer have focused on the pedestrian perspective (*37–39*). This study contributes to the current state of knowledge by using mobile eye-tracking data to evaluate changes in pedestrian behavior with changing urban infrastructure and environmental conditions. In doing so, it explores potential analytical approaches that can contribute to the development of a more standardized process for this type of research. A better understanding of pedestrians' interactions with infrastructure and their perception of urban spaces can assist engineers, planners, and decision makers in creating safer spaces and promoting more active modes of transportation.

Methodology

Experimental Design

This naturalistic pedestrian within-subject study involved participants walking up and down four blocks of an urban corridor (Water Street between 2nd Street SW and 4th Street SE) in Charlottesville, Virginia in daytime and nighttime conditions. The 2018 Virginia Department of Transportation Pedestrian Safety Action Plan identified the Water Street corridor as a priority corridor due to pedestrian crash risks (*40*). Water Street is a two-lane corridor with permitted parallel parking along the north side, as shown in **Figure 1.** Daytime experiments occurred between the hours of 9am-4pm, and nighttime experiments occurred between the hours of 5:30pm-9pm. Experiments took place on weekdays, Tuesday to Thursday, over the course of six weeks in November and December of 2023. These days were chosen for data collection to minimize operational differences that might occur during weekend days. Participants were scheduled for both daytime and nighttime experiments.

Figure 1: Water Street Corridor with the Study Route Highlighted

As a quasi-experiment occurring across multiple days, environmental conditions such as weather, traffic conditions, and pedestrian volumes varied. While some outdoor conditions were impossible to control for entirely, experiments were not carried out on rainy days given that rain would obstruct the view through the smart glasses' lenses. Data about the environmental condition was also tracked for each participant. This included audio, lux (lighting) level, temperature, and air quality. While this paper focuses on the eye tracking data, all sensors and data tracked during the experiment can be found in **Figure 2.** Although smart glasses were worn for the entire duration of the experiments, gaze data was not continuously recorded throughout and was impacted by factors such as environmental conditions (e.g., glare from the sun) and the fit of the glasses. Due to the influence of the sun and glare, there is a large difference in validity between the daytime and nighttime scenarios. The mean data validity across all recordings was 73.5% (SD = 17.13), with a mean of 63.8% (SD = 18.81) validity during the daytime and 83.2% (SD = 6.89) at night.

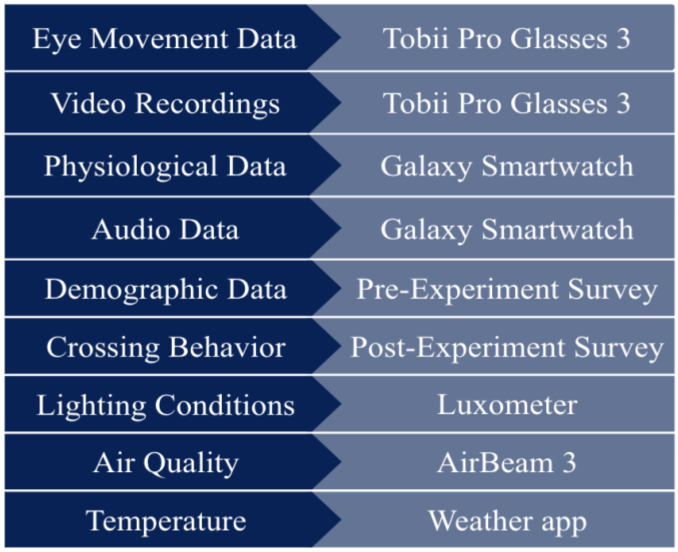

Figure 2: The type and method of data collection

Participants were instructed to meet the researchers at the Meeting Point (**Figure 3**) to prepare for the experiment, about 300 ft from the study's route on Water Street. Prior to the first experiment, participants filled out a pre-experiment survey eliciting information related to socio-demographics, activity (e.g. walking, driving, or time dedicated to physical activity), and familiarity with the area. Participants then put on the wearable sensors, including the Tobii Pro Glasses 3 and a Galaxy smartwatch, and were briefed on their proper use. The glasses recorded video, audio, and eye-tracking data, while the smartwatch gathered participants' heart rates. Before leaving the meeting point to start the experiment, the smart glasses were calibrated to each participant to ensure data collection accuracy. Data collection from the smart watch was started at the starting point of the route.

In addition to a verbal explanation by the researchers, participants were shown a map of the experiment route and a member of the research team walked with them to the starting point of the route (**Figure 3**). The study route required participants to walk eastbound from the intersection of Water Street and 2nd Street SW to the intersection of Water Street and 4th Street SE on the north sidewalk, cross Water Street at that intersection, and then walk westbound along the corridor to the initial intersection of Water Street and 2nd Street SW. After the initial crossing at Water Street and 4th Street SE, participants were instructed to cross back over Water Street at any point of their choosing and return to the starting point. The total route was approximately 8 city blocks and took most participants between 6-10 minutes to complete. The predefined walking path and participants' ability to cross the street at any point of their choosing remained constant throughout both daytime and nighttime experiment scenarios. The order in which participants walked the daytime and nighttime scenarios was kept random to avoid any bias that might emerge from a change in familiarity of the route and the novelty of participating in such an experiment. After the completion of each scenario, participants were asked to complete a post-survey upon returning to the meeting point. The post-experiment survey assessed the participants' subjective safety ratings of the daytime and nighttime conditions. It also asked them to identify locations where they felt particularly safe or unsafe along the route, indicate where they chose to cross back across Water Street, and provide their reasoning for their choice.

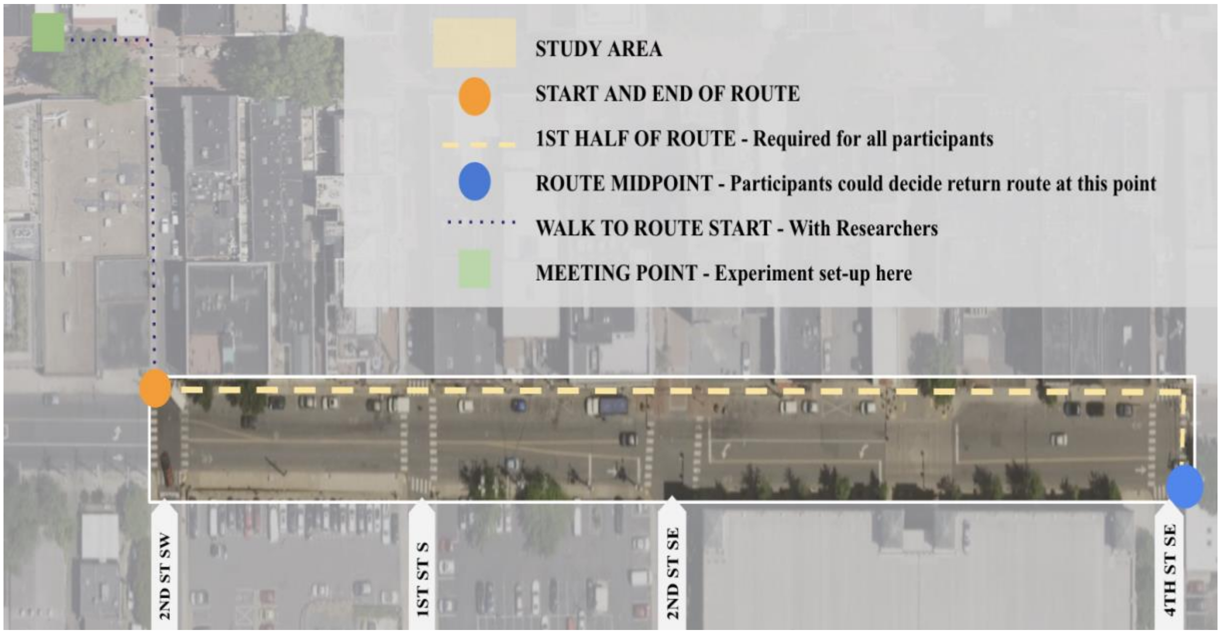

Figure 3: Water Street Study Area and Route

In total, 63 participants completed both scenarios of the experiments. Recruitment for the experiment was done via email, flyers, and word of mouth. Identified interest groups within the local area, university community, city staff, and other community members served as the recruitment base for participants. Participants were required to be at least 18 years of age and could not wear glasses on the days of the test (contact lenses were allowed) as the smart glasses could not be put on over regular eyewear. All participants received compensation in the form of a gift card for their time. **Table 1** shows descriptive statistics of all participants.

Table 1: Descriptive Statistics of Participants

	TOTAL SAMPLE (N=63)	
	Frequency	%
GENDER		
Male	28	44.4%
Female	35	55.6%
RACE AND ETHNICITY [a]		
White/Caucasian	49	77.8%
Asian/Pacific Islander	9	14.3%
Hispanic/Latino	3	4.8%
Black/African American	2	3.2%
American Indian/Native American	1	1.6%
Other	2	3.2%
AGE		
18-29	21	33.3%
30-39	11	17.5%
40-49	14	22.2%
50-59	9	14.3%
60+	8	12.7%
EDUCATION LEVEL		
High School/GED	2	3.2%
Some College (no degree)	3	4.8%
Associate's degree	1	1.6%
Bachelor's degree	20	31.7%
Graduate degree	37	58.7%
EMPLOYMENT [a]		
Full-time	26	41.3%
Part-time	9	14.3%
Student	18	28.6%
Self Employed	10	15.6%
Unemployed	3	4.8%
Stay-at-Home Spouse	2	3.2%
Retired	7	11.1%
INCOME		
Less than $25,000	6	9.5%
$25,001 - $50,000	15	23.8%
$50,001-$75,000	8	12.7%
$75,001-$100,000	10	15.9%
$100,001-$150,000	7	11.1%
$150,001-$200,000	9	14.3%
More than $200,000	6	9.5%
No answer	2	3.2%

[a] Participants were able to select all that apply

Framework and Analysis Approach

Urban Typology Framework

Urban environments are made up of physical and social elements that make cities and streetscapes dynamic spaces. For this study, these elements are identified as Urban Typologies that help to categorize and understand the role different types of urban stimuli play within the urban fabric of cities. The identified Urban Typologies can be found in **Figure 4**. Specific categories (seen in **Figure 5** and **Table 2**) were specified based on the research question. While this research focuses on behavioral differences during different times of the day, this framework could be applied to various other conditions in urban spaces and tailored to the specific research questions.

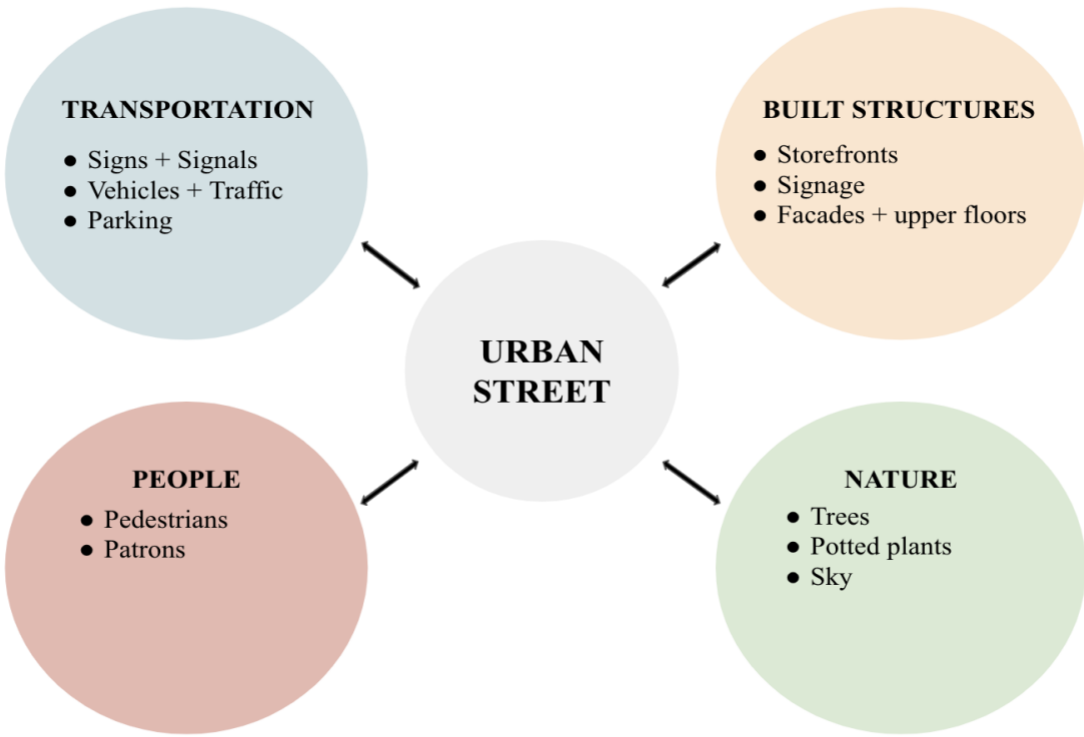

Figure 4: Urban Typology of Stimuli

Eye-Tracking Glasses

Identified categories based on the Urban Typologies were used to better understand which elements were gaining pedestrian attention and how this differed between daytime and nighttime scenarios. This was done by assigning fixation data collected from the mobile eye-tracking glasses as an Area of Interest (AOI). An AOI, defined as the region that may be observed in a scene or object, allowed eye tracking data to be linked to those categories (*21*). The Tobii Pro Glasses 3 were used for both studies.

The Tobii Pro Glasses 3 sample participants' eye movements at 100 Hz and are equipped with a forward-facing point-of-view camera with recording resolution of 1920 x 1080 pixels, a sampling rate of 25 frames per second, and a diagonal field of view of 106 degrees. Even though it has a slightly smaller field of view than the human eye, the glasses can portray which elements gain pedestrians' attention. Further recording capabilities of the glasses include 16-bit mono audio recording, and gyroscope and accelerometer movements sampled at 100 Hz. The resulting data outputs include the users' gaze and fixations, pupils' position, pupils' diameters, video with sound from the smart glasses' camera, linear acceleration, and rotational velocity, among other metrics.

Eye-Tracking Software and Analysis

From the video recordings with eye-tracking data collected via the glasses, physical elements that attracted participants' visual attention were manually classified into one of seventeen areas of interest (AOI) for analysis, based on the urban typologies identified in **Figure 4.** The seventeen categories used for analysis are listed in **Table 2**. With this segmentation, the duration that individual elements were fixated upon can be assessed (*21*). Examples of the AOI classification used in this study within Tobii Lab can be seen in **Figure 5.**

Table 2: AOI Classifications

Vehicles	*Parked Vehicles*
	Moving Vehicles
Transportation + Crossing Infrastructure	*Non-Pedestrian Transportation Infrastructure*
	General Pedestrian Infrastructure
	Lighted Crossing Infrastructure
	Unlighted Crossing Infrastructure
Lighting	*General Lighting Features*
People	*Pedestrians*
	Bicyclists
	Other People (Patrons, Waiting for a bus, etc.)
Storefronts and Buildings	*Storefronts*
	External Store Infrastructure
	Non-Storefront Buildings

	Public Art
Other	*Nature (Trees, Sky, etc.)*
	Miscellaneous Infrastructure (garbage bins, newsracks, etc.)
	Blurry or Undetermined

While reviewing the recordings, the Tobii Pro Lab software uses the Gaze Filter, an eye movement classification algorithm, to process and classify the gaze data, which is then superimposed on the videos (*41*). The Velocity-Threshold Identification (I-VT) fixation classification algorithm uses velocity of the directional shifts of the eye to classify the data and is measured in visual degrees per second. When samples are above a determined threshold, they are classified as a saccade. Similarly, when samples fall below the threshold, they are classified as fixations. The algorithm can be customized to the needs of researchers; however, the recommended presets available are the Tobii I-VT (Attention), Tobii I-VT (Fixation), and Raw Gaze Filters. The Tobii I-VT (Attention) filter is optimized for wearable eye trackers and created for dynamic situations when the subject is moving (*42*). Thus, the Attention filter, with a threshold of 100 degrees/second, was used in this study. This threshold allows VOR and smooth pursuit movements to be included instead of limiting analysis to fixations. As discussed in section 2.3, people are still gathering information with these movements. Therefore, using the Attention filter means that any fixation metrics in this study could be described as "foveal stabilization" metrics. However, the term fixation will be used throughout this study.

The Tobii Pro Lab software identifies the location of fixations that fall within the threshold (described above) for each relevant frame and superimposes it on the forward-looking video recordings**.** From the video recordings, physical elements that attracted participants' visual attention were manually classified into one of thirteen areas of interest (AOI) for analysis. In static studies, AOIs can be identified on the image themselves. However, with dynamic studies like this one, the fixations within the video must be remapped as an AOI on a static image to be able to analyze the fixations. The gaze data mapping in Tobii Pro Lab allows researchers to map gaze data onto a snapshot with AOIs. The AOIs of each study were added to a snapshot with the AOI tool, and fixations were manually remapped as AOIs for analysis on the frequency and duration of each category. For both studies, all recordings were manually analyzed by one researcher to limit the influence of different interpretations and human bias on the AOI classification between participants and scenarios. After all fixations have been remapped, metrics, such as fixation duration and fixation count, can be exported from the software for analysis.

Figure 5: Examples of AOI Classification Categories

Results and Discussion

All eye movements within the attention threshold were remapped in the Tobii software to identify the urban elements that gained participant's attention. Participant attention when walking the corridor during the day and at night was compared using the seventeen AOI categories. On average, 52.8% of the total route time was associated with fixations. The initial analysis includes the mean share of fixation duration across all participants, the mean share of fixation duration disaggregated by age, and the mean total fixation duration (normalized to account for differences in data validity).

Average Fixation Duration

The share of total fixation duration was calculated from 'Total Fixation Duration' to visualize the differences between daytime and nighttime scenarios (**Figure 6**). Analyzing the data using this metric showed that the largest increases in attention at night were on moving and parked vehicles, lighted crossing infrastructure, and general lighting features. The other transportation infrastructure categories, all of which were unlighted, all experienced decreases. Storefronts and other buildings all experienced an increase in attention at night as well, likely due to the lighting in storefront windows. There was also a large decrease in attention on natural elements, such as trees and the sky, at night. While the share of fixation duration that was determined to be too blurry to classify was minor, it should be noted that there was a large increase in frames that were within the I-VT threshold that were too blurry to determine at night due to the dark conditions of the video.

Daytime Mean	Nighttime Mean	
4.41%	7.23%	Moving Vehicles
5.36%	6.65%	Parked Vehicles
30.21%	24.95%	General Ped Infrastrucutre
6.14%	4.97%	Non-Ped Transportation Infrastructure
8.53%	7.93%	Non-Lighted Crossing Infrastrucutre
3.29%	5.16%	Lighted Crossing Infrastrucutre
0.75%	5.06%	Lighing Features
6.78%	7.12%	Pedestrians
0.47%	0.30%	Cyclists
0.84%	0.50%	Other People
11.73%	13.75%	Storefronts
3.88%	1.91%	Sidewalk boards and setups
3.76%	4.71%	Other Buildings
0.95%	0.59%	Public Art and Banners
6.02%	2.08%	Nature Elements
6.09%	5.80%	Miscellaneous Infrastructure
0.79%	1.28%	Blurry and Undetermined

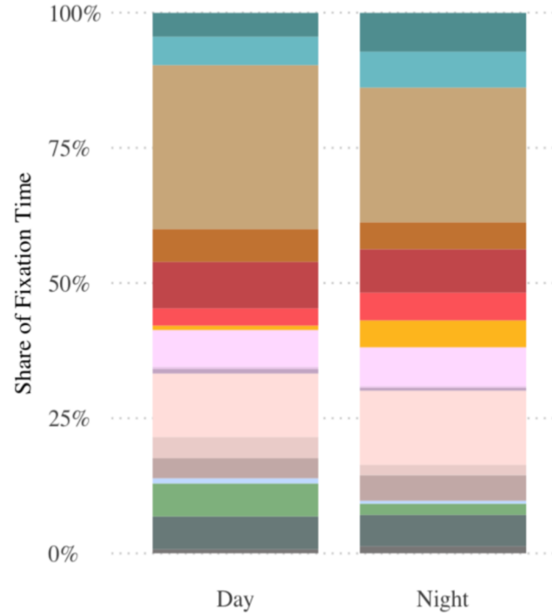

Figure 6: The mean share of fixation duration for all participants during the Day and Night Scenarios

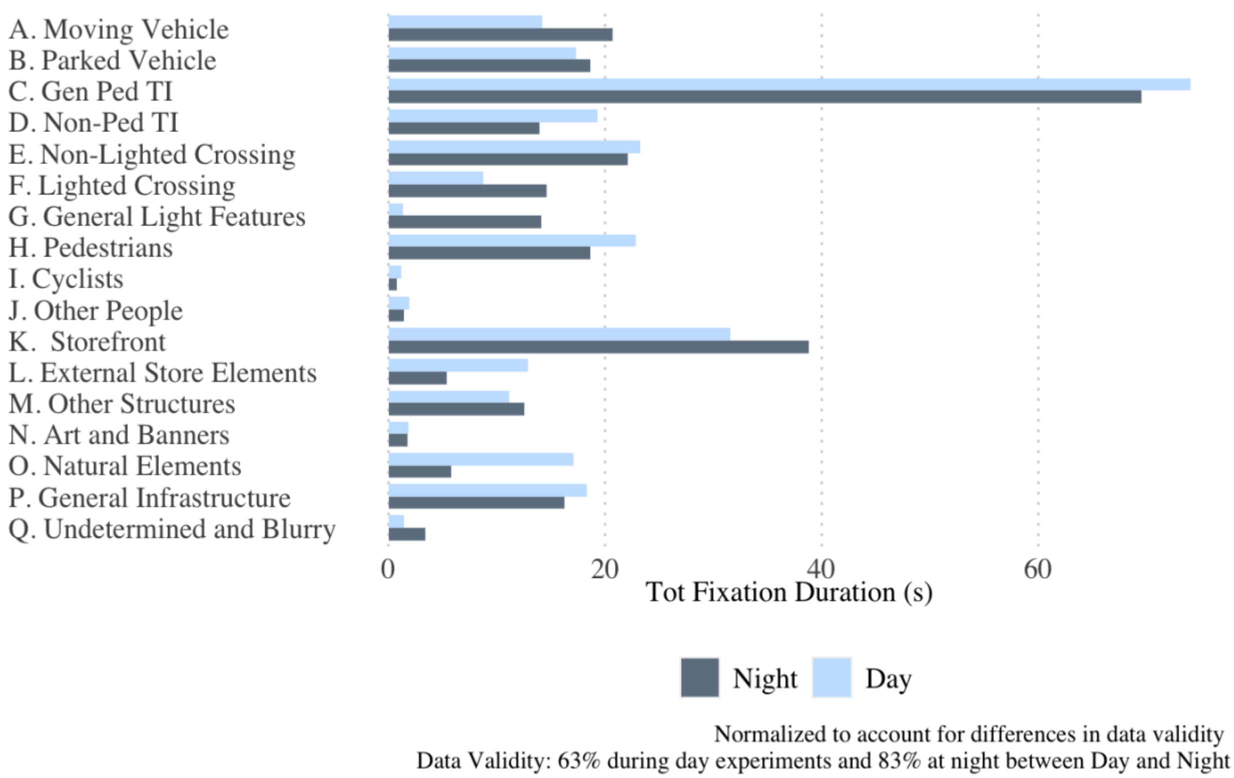

Figure 7: The mean total fixation duration for participants by Day and Night (normalized for differences in data validity)

While share of fixation duration is one of the most commonly used metrics to look at visual attention, total fixation duration was also analyzed in order to further examine the extent of the variation between the scenarios. As mentioned previously, there was a large difference in data validity between the day and night scenarios. The glare from the sun led to a lower data validity rate of 63% during daytime experiments. While it was more common for the video to be blurry at night, the eye-tracking data had a higher validity rate of 83% at night due to the absence of the sun glare. Thus, the mean total fixation duration data was normalized in order to compare this data, as seen in **Figure 7**. Similar to mean share of fixation duration, on average, a shift from daytime to nighttime scenarios experienced a notable increase of total fixation duration on moving and parked vehicles, lighted crossing infrastructure, general lighting features, and storefronts. Meanwhile, all other (non-lighted) transportation infrastructure also experienced a decrease in total fixation duration at night compared to daytime. The only category that varied differently between mean share of fixation duration and total fixation duration was pedestrians, which showed an increase in attention at nighttime when using the total fixation duration metric. While further analysis is needed, the data begins to demonstrate trends of attention and focus between the day and night conditions.

Variation by Age

Participant ages ranged from 20 to 88 years old, and the fixation duration data was disaggregated by age group to explore differences across this range, which can be seen in **Figure 8.** Most notably, there was an increase in attention to general pedestrian infrastructure (mostly consisting of sidewalks) with age. Based on conversations with participants, one possibility for this increase is a greater concern about sidewalk conditions and the possibility of tripping as people get older. Previous studies have also found that the sidewalk conditions and the fear of falling is a concern for middle-aged and senior adults and can impact their sense of safety (*43–45*). While it is expected that this concern would grow at night, it is also possible that additional safety concerns beyond sidewalk conditions corresponded to an increase in attention at night. There was little variation when data was analyzed by gender.

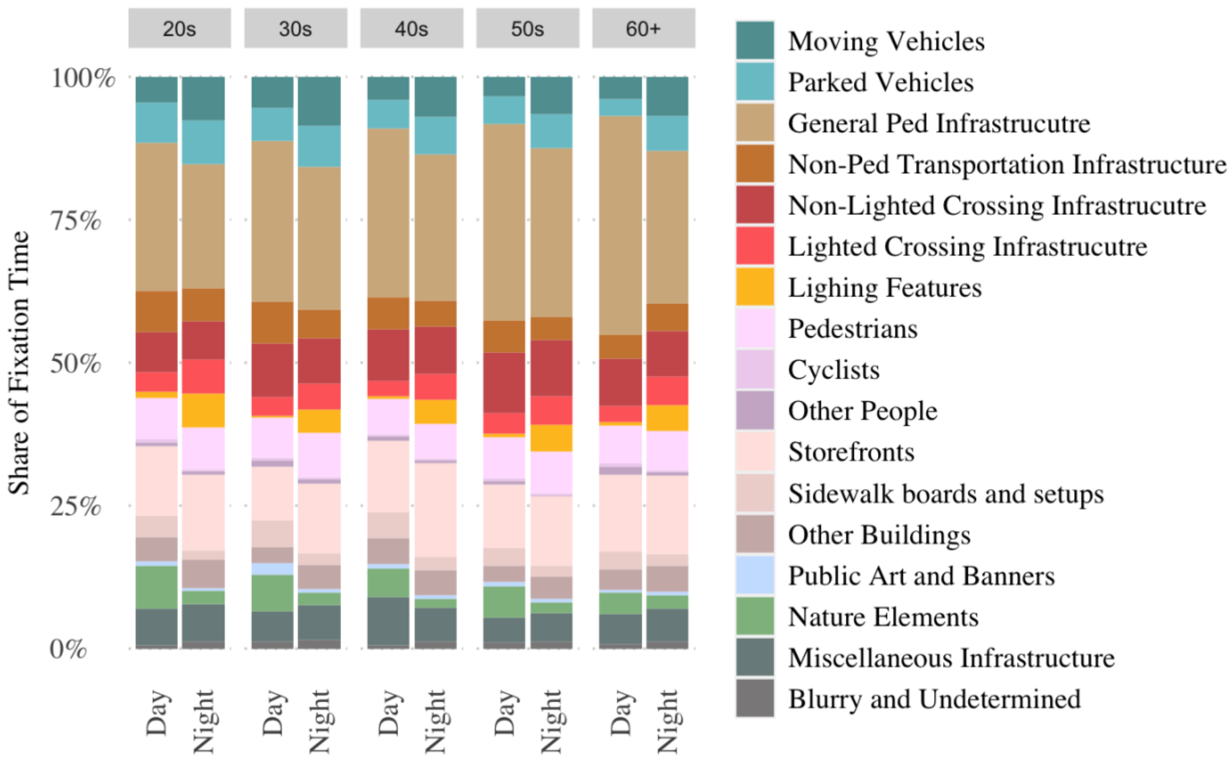

Figure 8: The mean share of fixation duration by age group during the Day and Night Scenarios

Perception of Safety

In addition to the eye-tracking data collected, the post-experiment survey asked participants about their safety perception (using a Likert scale from 1 [not at all safe] to 5 [very safe] for the entire route as well as identifying specific locations) along the route. After each experiment, participants marked how safe they felt while walking along the corridor and crossing Water Street. On average, participants felt safer during the day (walking = 4.70 and crossing = 4.43) compared to the nighttime scenario (walking = 3.97 and crossing = 3.87). They were also asked to mark up to three locations along the route where they felt the safest and/or comfortable and up to three locations where they felt the most unsafe and/or uncomfortable. During the day, there were 117 locations marked as safe and 66 locations marked as unsafe. At night, 113 locations were marked as safe, and 98 locations marked as unsafe. It is important to note that all participants walked the northside of the street, but not as many participants walked the entire southside of the route given that participants could cross back to the northside at any point. This could contribute to the lower number of identified locations towards the end of the route. Based on the explanations of why they chose these locations, some of the main reasons participants highlighted were related to lighting levels, interaction with vehicles, infrastructure conditions, people, and design elements.

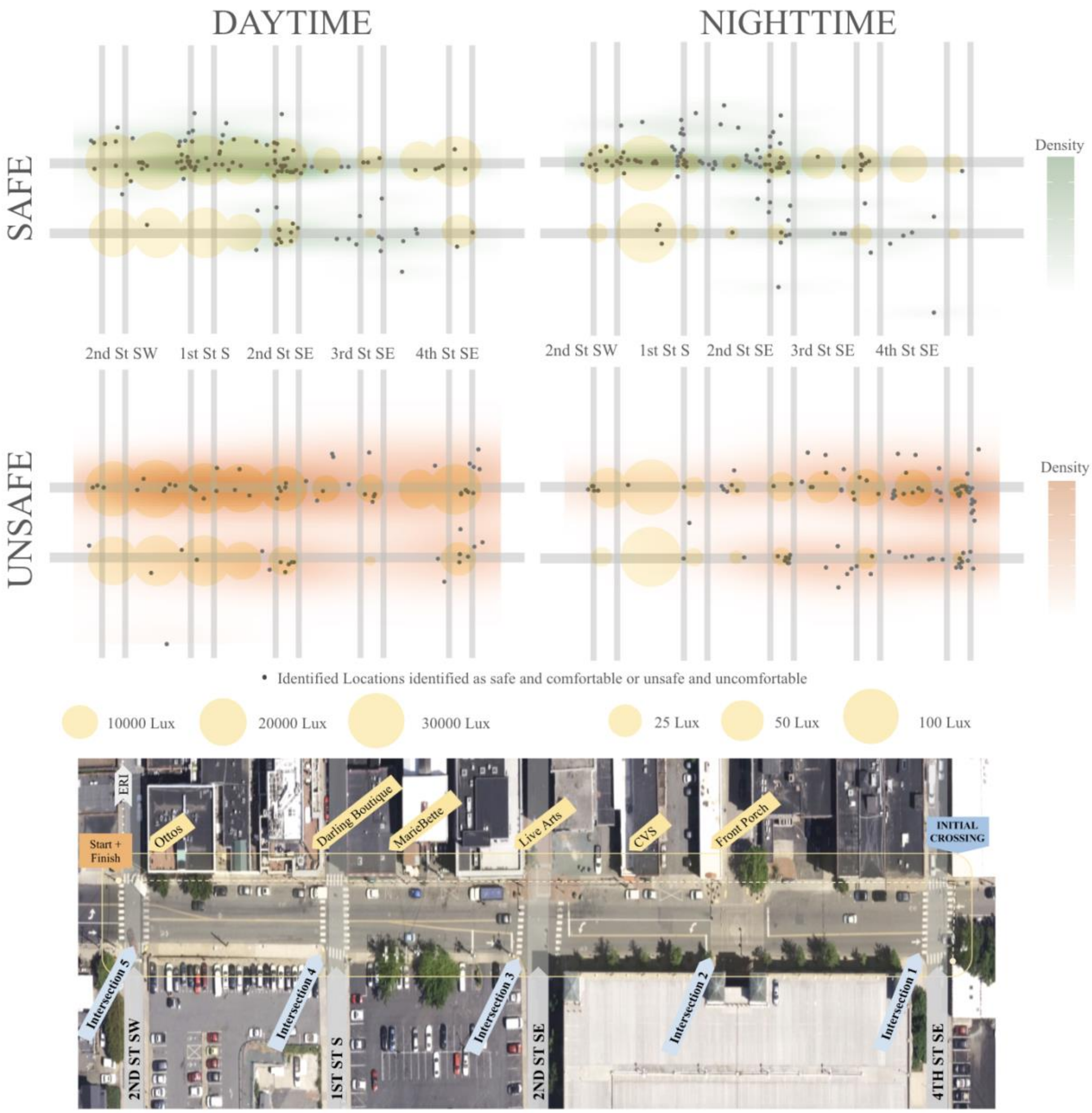

Figure 9: Locations identified safest and the most unsafe during the day and night overlaid with the average lighting levels (aerial view map for reference)

The connection between lighting conditions and perceived safety is illustrated by **Figure 9**. Locations marked unsafe were more frequently on the eastern side of the route at the 4th St SE crossing, which had poorer lighting at night compared to the western side of the route. The comments reflect this pattern as well, with many of the safe locations being described as well-lit and many of the unsafe locations being described as dark, with a few participants noting that they felt unsafe as a woman.

The comments also showed a lot of anxiety and feelings of vulnerability with vehicle interactions during both day and night, but particularly at night. These comments typically related to uncertainty around vehicle behavior and limited sight distance. Many cars did not stop for pedestrians or give them right-of-way even when they were already in the crosswalk. Even idling cars caused some participants to be uneasy not knowing what the vehicle's next move would be. There were also mentions of higher traffic volumes and speeds contributing to unsafe perceptions. These qualitative comments, combined with the increased pedestrian attention to vehicles at night in the gaze analysis, show that lighting conditions at night not only affect general perceived safety, but can impact the physiological responses of pedestrians as their attention shifts to stimuli that they perceive as threats to safety.

The conditions of the sidewalk were mentioned frequently as a contributing factor to safety and comfort perceptions. The unevenness and narrowness of the sidewalk on the north side of the route was of particular concern. Further, almost all of participants who mentioned the sidewalk conditions were over the age of 40. This supports the possibility that concern about sidewalk conditions could be the reason attention to the ground increased with age in the gaze analysis. Some of the locations identified as unsafe were associated with intersections, and comments called out the lack of a pedestrian signal or a confusing signal, lack of crosswalk marking, and the duration of the pedestrian signal being too short all as safety concerns. On the other hand, sidewalks buffered from the road by trees and textured pavement were mentioned as elements contributing to a feeling of safety.

There were multiple comments related to the impact of the building design. Not having an active street front contributed to some participants feeling less safe. It is notable that in the gaze analysis, participants paid slightly more attention to storefronts at nighttime compared to daytime. The section of the walking path with well-lit store display windows (north sidewalk between 2nd St SW and 2nd St SE) also contains the locations most identified as "feeling safe and comfortable" at night. Rundown or bland buildings were associated with not feeling as comfortable, but the main building design element was the parking garage block that has a recessed walkway. There were concerns that the columns in front of the parking garage could serve as a hiding spot for people. The gaze analysis also showed that participants paid more attention to "other buildings/structures" at night compared to the day.

Some negative interactions with people included witnessing altercations between people, loud people outside bars, strangers staring, and having a police presence. That said, interactions with people often correlated with feeling safer when it came to higher foot traffic, activity around the stores, and the type of people around (i.e. people they knew, families, commuters). As previously mentioned, the difference between attention on other pedestrians during day and night was unclear from the gaze data analysis, as the two metrics analyzed (mean share of fixation duration and total fixation duration) yielded opposite results.

Conclusion

Summary of Results

The study explores the pedestrian experience on an urban corridor at daytime and nighttime by utilizing gaze data from mobile eye-tracking glasses and stated preference surveys. This study presents AOI classifications based on the Urban Typology framework. These classifications can adapt to the conditions and research questions of each study as needed. Since this study compares daytime and nighttime scenarios, it was important to separate lighted features for the classification and analysis.

The initial analysis suggests that vehicles and lighted elements experienced the largest increase in attention from pedestrians when shifting from daytime to nighttime conditions. Comparing the lighting levels along the route during the daytime and nighttime and the stated preference survey responses demonstrated the connection between lighting, perceived safety, and shifts in attention. Participants identified more locations where they felt unsafe in unlit areas, particularly at night. Specific infrastructure conditions, interactions with vehicles, interactions with people, and building design were cited as factors influencing perceptions of safety. Alongside the gaze analysis, the results suggest that lighting conditions at night influence both perceived safety and pedestrian attention, where pedestrians shift attention to stimuli that they perceive as potentially unsafe.

There is a need for a more comprehensive model of measuring attention to better understand linkages between pedestrians' attention, perceptions, and cognition (*25*), which could improve our understanding of urban mobility and behavior. This study contributes to the current knowledge by proposing the design of an on-site naturalistic walking experiment and the use of wearable sensors to assess real-life settings in an urban environment from the pedestrian viewpoint. Being able to capture the pedestrian perspective in a real-world setting, identified in previous research as challenging to capture and quantify (*24*), is a strength of this technology and research. The first-person view of the video recordings allows the environment to be interpreted from their point of view. On-site real-world data collection is advantageous since it has been shown to describe behavior more accurately than that collected in a laboratory setting (*13*). Understanding pedestrian behavior and perception is essential for enhancing urban spaces and infrastructure, and the study provides a framework and initial analysis that can be used in future research. With the increase in nighttime pedestrian fatalities that the US is experiencing, the need for creating safer spaces and infrastructure for pedestrians and other vulnerable road users is greater than ever. The results from these studies, and future work that builds on this framework, can help inform the choices of communities and decision makers.

Limitations

This study demonstrates the type of research that mobile eye tracking glasses makes possible and provides a framework for future research. However, there are some limitations related to the study and the tracking technology that are important to acknowledge.

Some of the main limitations identified for this type of study are the small sample sizes and the demographic representation among the samples. The study was able to recruit 63 participants, a relatively large sample size for this type of experimental study, but still presents challenges for robust statistical analysis. Reaching proportional representation across age demographics was a challenge. First, people who require corrective lenses are ineligible for the study, unless they can wear contact lenses. Personal glasses do not fit properly under the mobile glasses, and the sensors are unable to track eye movements through the personal lenses. This hindered the ability to find eligible participants, especially those over forty years old. Many people in their forties also found it difficult to take time from their children and families, or to find childcare, in orderto participate in the studies, especially during the nighttime experiments. While seniors were often enthusiastic, they were more likely to have vision or mobility issues which made it impractical for them to participate.

While the days selected for the study were intentionally chosen to minimize the differences in the environment beyond the condition being studied, there remained differences that were impossible to control for entirely in the real-world setting. In the study, experiments were only completed on Tuesdays, Wednesdays, and Thursdays to minimize any differences that might be seen between weekdays and weekend days. The main difference is the time of day and lighting, but there was still some natural variation related to the people and vehicles present along the study route.

It is also important to note the impact that the sensors and the awareness of being in a study might have had. While participants mostly indicated that the glasses were comfortable and did not impact their behavior, the wearable sensing devices could be a potential stress for some participants (*46*). It is difficult to entirely ensure that participant behavior is not impacted by the mechanics of the study itself. Similarly, possible survey fatigue should also be considered when examining stated preference survey results.

Beyond this specific study, there are also some general limitations related to the data collection and analysis methods. One aspect to consider is that the use of smart glasses with cameras poses potential privacy concerns for individuals not involved in the experiment who are passively recorded (*47*). The validity of eye movement data collection also varies with some environmental conditions, such as glare from the sun. The study also relied on manual remapping of the fixations as one of the identified AOI classifications, which introduces potential researcher bias. While the eye movement detection validity rates were higher during the nighttime experiments, the video imagery was often more difficult to interpret. The approach used within this study accounts for many issues often experienced within mobile eye-tracking experimentation, yet there is still a significant need for the development of more robust detection algorithms (*48*, *49*). Additionally, the manual remapping of fixations as AOIs is not an efficient method. In order for this technology to be scalable and usable for larger sample sizes, an automated classification process is necessary.

Future Work

While some of the limitations identified above are unavoidable realities of this type of study, others can inform the direction of future research. This study presents an application of mobile eye-tracking technology and provides a framework for future research of this type. Eye-tracking data can provide insight about pedestrians' attention, however further research is necessary to make the connection among attention, perception, cognition, and the behaviors that impact mobility choices and economic activity on urban streets (*25*). This section highlights some potential directions for further study.

There is currently no standardized data processing technique or methodology for this type of analysis that would prove valid across multiple experiments. Further research should define standardized methodologies for data analysis and interpretation in the urban planning domain. The study focuses on initial findings related to attention data, but further analysis is required to fully reveal comprehensive results related to the eye-tracking data. This work can assist in identifying the best analytical approach when using this technology for naturalistic studies related to the built environment. The elements that gained attention, based on the I-VT attention threshold, were classified into the AOI categories related to the Urban Typologies identified. However, some fixations are more significant than others, and identifying these can provide insight into a person's cognitive processes and how they perceive their environment (*50*). The initial analysis completed for the study has not distinguished between types of fixations, such as distance of the elements, that could lead to different levels of cognition and potentially an increased need to detect safety hazards (*51*, *52*). It may be important to identify elements that gained attention from fixations that were passive or continued. The eye-tracking glasses include gyroscope and accelerometer sensors and record Inertial Measurement Unit data that could be helpful in identifying these differences.

There are also eye-tracking metrics unrelated to AOI identification, such as Mean Fixation Duration and Horizontal and Vertical Gaze Variability, that can provide additional information related to stress and anxiety. Stationary Gaze Entropy and Gaze Transition Entropy are additional metrics that could be considered. Further analysis could also focus on pupil diameter, a physiological factor that relates to emotional states and stress.

The attention filter used in this analysis was created for dynamic situations when subjects are moving to include "foveal stabilization" movements. However, there has been limited validation of using this threshold in various types of studies, and this should be examined further given the differences in cognitive processing with different movements. It would also be useful to compare and validate real-world experiments with those done in a virtual setting. Few studies examining human perception of the built environment have used mobile eye-tracking in an outdoor setting, and significant differences between laboratory and outdoor environments have been found when using mobile eye-tracking glasses (*24*, *50*, *53*, *54*).

Mobile wearable sensors are a promising technology in improving the understanding of vulnerable road users by providing easy-to-obtain data and being flexible in their application. Developing the methodology and analytical approach further would allow for the expansion of mobile eye-tracking technology studies. The methods utilized in this study have the potential to allow planners, engineers, designers, and policy makers to directly identify how their designs, such as street lighting, landscaping, and pedestrian infrastructure, alter the urban experience.

References

1. Emily Badger, Ben Blatt and Josh Katz. Why Are So Many American Pedestrians Dying at Night? *New York Times*, Dec 11, 2023.

2. NHTSA. Fatality Analysis Reporting System (FARS). .

3. Subramanian, L. D., E. E. O'Neal, S. Mallaro, B. Williams, R. Sherony, J. M. Plumert, and J. K. Kearney. A Comparison of Daytime and Nighttime Pedestrian Road-Crossing Behavior Using an Immersive Virtual Environment. *Traffic Injury Prevention*, Vol. 23, No. 2, 2022, pp. 97–101.

https://doi.org/10.1080/15389588.2021.2023738.

4. Alfonzo, M. A. To Walk or Not to Walk? The Hierarchy of Walking Needs. *Environment and Behavior*, Vol. 37, No. 6, 2005, pp. 808–836. https://doi.org/10.1177/0013916504274016.

5. Uttley, J., J. Simpson, H. Qasem, J. Uttley, J. Simpson, and H. Qasem. Eye-Tracking in the Real World: Insights About the Urban Environment. *https://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-5225-3637-6.ch016*. https://www.igi-global.com/gateway/chapter/www.igi-global.com/gateway/chapter/198172. Accessed Mar. 15, 2024.

6. Pelz, J. B., and R. Canosa. Oculomotor Behavior and Perceptual Strategies in Complex Tasks. *Vision Research*, Vol. 41, No. 25–26, 2001, pp. 3587–3596. https://doi.org/10.1016/S0042-6989(01)00245-0.

7. Land, M., and B. Tatler. *Looking and Acting: Vision and Eye Movements in Natural Behaviour*. Oxford University Press, 2009.

8. Babcock, J. S., and J. B. Pelz. Building a Lightweight Eyetracking Headgear. Presented at the the Eye tracking research & applications symposium, San Antonio, Texas, 2004.

9. Foulsham, T. Eye Movements and Their Functions in Everyday Tasks. *Eye*, Vol. 29, No. 2, 2015, pp. 196–199. https://doi.org/10.1038/eye.2014.275.

10. Pelz, J. B., R. L. Canosa, D. Kucharczyk, J. S. Babcock, A. Silver, and D. Konno. Portable Eyetracking: A Study of Natural Eye Movements. Presented at the Electronic Imaging, San Jose, CA, 2000.

11. Crosby, F., and F. Hermens. Does It Look Safe? An Eye Tracking Study into the Visual Aspects of Fear of Crime. *Quarterly Journal of Experimental Psychology*, Vol. 72, No. 3, 2019, pp. 599–615. https://doi.org/10.1177/1747021818769203.

12. Babcock, J. S., M. Lipps, and J. B. Pelz. How People Look at Pictures before, during, and after Scene Capture: Buswell Revisited. Presented at the Electronic Imaging 2002, San Jose, CA, 2002.

13. José Aleixo Cruz. Learning Realistic and Safe Pedestrian Behavior by Imitation. Presented at the AAMAS, 2021.

14. Sheykhfard, A., F. Haghighi, S. Bakhtiari, and L. Pariota. Safety Margin Evaluation of Pedestrian Crossing through Critical Thresholds of Surrogate Measures of Safety: Area with Zebra Crossing versus Area without Zebra Crossing. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2677, No. 1, 2023, pp. 396–408. https://doi.org/10.1177/03611981221099510.

15. Sheykhfard, A., F. Haghighi, S. Kavianpour, S. Das, P. S. Farahani, and G. Fountas. Risk Assessment of Pedestrian Red-Light Violation Behavior Using Surrogate Safety Measures: Influence of Human, Road, Vehicle, and Environmental Factors. *IATSS Research*, Vol. 47, No. 4, 2023, pp. 514–525. https://doi.org/10.1016/j.iatssr.2023.11.003.

16. Fonseca, F., P. J. G. Ribeiro, E. Conticelli, M. Jabbari, G. Papageorgiou, S. Tondelli, and R. A. R. Ramos. Built Environment Attributes and Their Influence on Walkability. *International Journal of Sustainable Transportation*, Vol. 16, No. 7, 2022, pp. 660–679. https://doi.org/10.1080/15568318.2021.1914793.

17. Ferenchak, N. N., and M. G. Abadi. Nighttime Pedestrian Fatalities: A Comprehensive Examination of Infrastructure, User, Vehicle, and Situational Factors. *Journal of Safety Research*, Vol. 79, 2021, pp. 14–25. https://doi.org/10.1016/j.jsr.2021.07.002.

18. Kim, Y., B. Choi, M. Choi, S. Ahn, and S. Hwang. Enhancing Pedestrian Perceived Safety through Walking Environment Modification Considering Traffic and Walking Infrastructure. *Frontiers in Public Health*, Vol. 11, 2024, p. 1326468. https://doi.org/10.3389/fpubh.2023.1326468.

19. Trop, T., S. Shoshany Tavory, and B. A. Portnov. Factors Affecting Pedestrians' Perceptions of Safety, Comfort, and Pleasantness Induced by Public Space Lighting: A Systematic Literature Review.

Environment and Behavior, Vol. 55, No. 1–2, 2023, pp. 3–46. https://doi.org/10.1177/00139165231163550.

20. Markvica, K., G. Richter, and G. Lenz. Impact of Urban Street Lighting on Road Users' Perception of Public Space and Mobility Behavior. *Building and Environment*, Vol. 154, 2019, pp. 32–43. https://doi.org/10.1016/j.buildenv.2019.03.009.

21. De La Fuente Suárez, L. A. Subjective Experience and Visual Attention to a Historic Building: A Real-World Eye-Tracking Study. *Frontiers of Architectural Research*, Vol. 9, No. 4, 2020, pp. 774–804. https://doi.org/10.1016/j.foar.2020.07.006.

22. Simpson, J. Three-Dimensional Gaze Projection Heat-Mapping of Outdoor Mobile Eye-Tracking Data. *Interdisciplinary Journal of Signage and Wayfinding*, Vol. 5, No. 1, 2021, pp. 62–82. https://doi.org/10.15763/issn.2470-9670.2021.v5.i1.a75.

23. De Winter, J., P. Bazilinskyy, D. Wesdorp, V. De Vlam, B. Hopmans, J. Visscher, and D. Dodou. How Do Pedestrians Distribute Their Visual Attention When Walking through a Parking Garage? An Eye-Tracking Study. *Ergonomics*, Vol. 64, No. 6, 2021, pp. 793–805. https://doi.org/10.1080/00140139.2020.1862310.

24. Simpson, J., K. Thwaites, and M. Freeth. Understanding Visual Engagement with Urban Street Edges along Non-Pedestrianised and Pedestrianised Streets Using Mobile Eye-Tracking. *Sustainability*, Vol. 11, No. 15, 2019, p. 4251. https://doi.org/10.3390/su11154251.

25. Leveque, L., M. Ranchet, J. Deniel, J.-C. Bornard, and T. Bellet. Where Do Pedestrians Look When Crossing? A State of the Art of the Eye-Tracking Studies. *IEEE Access*, Vol. 8, 2020, pp. 164833–164843. https://doi.org/10.1109/ACCESS.2020.3021208.

26. Fotios, S., J. Uttley, C. Cheal, and N. Hara. Using Eye-Tracking to Identify Pedestrians' Critical Visual Tasks, Part 1. Dual Task Approach. *Lighting Research & Technology*, Vol. 47, No. 2, 2015, pp. 133–148. https://doi.org/10.1177/1477153514522472.

27. Davoudian, N., and P. Raynham. What Do Pedestrians Look at at Night? *Lighting Research & Technology*, Vol. 44, No. 4, 2012, pp. 438–448. https://doi.org/10.1177/1477153512437157.

28. Zhao, Q., B. Zhang, S. Lyu, H. Zhang, D. Sun, G. Li, and W. Feng. A CNN-SIFT Hybrid Pedestrian Navigation Method Based on First-Person Vision. *Remote Sensing*, Vol. 10, No. 8, 2018, p. 1229. https://doi.org/10.3390/rs10081229.

29. Cruz, J. A., T. R. P. M. Rúbio, J. Jacob, D. Garrido, H. L. Cardoso, D. Silva, and R. Rodrigues. Towards Predicting Pedestrian Paths: Identifying Surroundings from Monocular Video. In *Intelligent Data Engineering and Automated Learning – IDEAL 2020* (C. Analide, P. Novais, D. Camacho, and H. Yin, eds.), Springer International Publishing, Cham, pp. 594–601.

30. Hasan, R., and R. Hasan. Pedestrian Safety Using the Internet of Things and Sensors: Issues, Challenges, and Open Problems. *Future Generation Computer Systems*, Vol. 134, 2022, pp. 187–203. https://doi.org/10.1016/j.future.2022.03.036.

31. Nijholt, A. Experiencing Social Augmented Reality in Public Spaces. Presented at the UbiComp '21: The 2021 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Virtual USA, 2021.

32. Mahanama, B., Y. Jayawardana, S. Rengarajan, G. Jayawardena, L. Chukoskie, J. Snider, and S. Jayarathna. Eye Movement and Pupil Measures: A Review. *Frontiers in Computer Science*, Vol. 3, 2022, p. 733531. https://doi.org/10.3389/fcomp.2021.733531.

33. Chennamma, H. R., and X. Yuan. A Survey on Eye-Gaze Tracking Techniques. 2013. https://doi.org/10.48550/ARXIV.1312.6410.

34. Rayner, K. Eye Movements and Attention in Reading, Scene Perception, and Visual Search. *Quarterly Journal of Experimental Psychology*, Vol. 62, No. 8, 2009, pp. 1457–1506. https://doi.org/10.1080/17470210902816461.

35. Purves, D., and S. M. Williams, Eds. *Neuroscience*. Sinauer Associates, Sunderland, Mass, 2001.

36. Shiyu Ma, Wenwen Zhang, Robert B. Noland, Clinton J. Andrews. Eye Tracking Measures of Bicyclists' Behavior and Perception: A Systematic Review.

37. Vetturi, D., M. Tiboni, G. Maternini, and M. Bonera. Use of Eye Tracking Device to Evaluate the Driver's Behaviour and the Infrastructures Quality in Relation to Road Safety. *Transportation Research Procedia*, Vol. 45, 2020, pp. 587–595. https://doi.org/10.1016/j.trpro.2020.03.053.

38. Cvahte Ojsteršek, T., and D. Topolšek. Eye Tracking Use in Researching Driver Distraction: A Scientometric and Qualitative Literature Review Approach. *Journal of Eye Movement Research*, Vol. 12, No. 3, 2019. https://doi.org/10.16910/jemr.12.3.5.

39. Ahlström, C., K. Kircher, M. Nyström, and B. Wolfe. Eye Tracking in Driver Attention Research—How Gaze Data Interpretations Influence What We Learn. *Frontiers in Neuroergonomics*, Vol. 2, 2021, p. 778043. https://doi.org/10.3389/fnrgo.2021.778043.

40. VDOT. *Pedestrian Safety Action Plan*. 2018.

41. Tobii. Tobii Pro Lab User's Manual. Danderyd Municipality: Tobii Technology, , 2019.

42. TobiiPro. When Do I Use the I-VT Attention Filter? .

43. Lee, S., C. Lee, M. G. Ory, J. Won, S. D. Towne, S. Wang, and S. N. Forjuoh. Fear of Outdoor Falling Among Community-Dwelling Middle-Aged and Older Adults: The Role of Neighborhood Environments. *The Gerontologist*, Vol. 58, No. 6, 2018, pp. 1065–1074. https://doi.org/10.1093/geront/gnx123.

44. Twardzik, E., P. Clarke, S. Judd, and N. Colabianchi. Neighborhood Participation Is Less Likely among Older Adults with Sidewalk Problems. *Journal of Aging and Health*, Vol. 33, No. 1–2, 2021, pp. 101–113. https://doi.org/10.1177/0898264320960966.

45. Van Cauwenberg, J., V. Van Holle, D. Simons, R. Deridder, P. Clarys, L. Goubert, J. Nasar, J. Salmon, I. De Bourdeaudhuij, and B. Deforche. Environmental Factors Influencing Older Adults' Walking for Transportation: A Study Using Walk-along Interviews. *International Journal of Behavioral Nutrition and Physical Activity*, Vol. 9, No. 1, 2012, p. 85. https://doi.org/10.1186/1479-5868-9-85.

46. Sakamoto, K., S. Aoyama, S. Asahara, H. Mizushina, and H. Kaneko. Relationship between Emotional State and Pupil Diameter Variability under Various Types of Workload Stress. In *Ergonomics and Health Aspects of Work with Computers* (B.-T. Karsh, ed.), Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 177–185.

47. Lee, K., D. Sato, S. Asakawa, H. Kacorri, and C. Asakawa. Pedestrian Detection with Wearable Cameras for the Blind: A Two-Way Perspective. 2020. https://doi.org/10.48550/ARXIV.2003.12122.

48. Trabulsi, J., K. Norouzi, S. Suurmets, M. Storm, and T. Z. Ramsøy. Optimizing Fixation Filters for Eye-Tracking on Small Screens. *Frontiers in Neuroscience*, Vol. 15, 2021, p. 578439. https://doi.org/10.3389/fnins.2021.578439.

49. Andersson, R., L. Larsson, K. Holmqvist, M. Stridh, and M. Nyström. One Algorithm to Rule Them All? An Evaluation and Discussion of Ten Eye Movement Event-Detection Algorithms. *Behavior Research Methods*, Vol. 49, No. 2, 2017, pp. 616–637. https://doi.org/10.3758/s13428-016-0738-9.

50. Uttley, J., J. Simpson, H. Qasem, J. Uttley, J. Simpson, and H. Qasem. Eye-Tracking in the Real World: Insights About the Urban Environment. *https://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-5225-3637-6.ch016*. https://www.igi-

global.com/gateway/chapter/www.igi-global.com/gateway/chapter/198172. Accessed Mar. 15, 2024.

51. Von Stülpnagel, R. Gaze Behavior during Urban Cycling: Effects of Subjective Risk Perception and Vista Space Properties. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 75, 2020, pp. 222–238. https://doi.org/10.1016/j.trf.2020.10.007.

52. Zhao, G., J. Orlosky, J. Gabbard, and K. Kiyokawa. HazARdSnap: Gazed-Based Augmentation Delivery for Safe Information Access While Cycling. *IEEE Transactions on Visualization and Computer Graphics*, 2024, pp. 1–10. https://doi.org/10.1109/TVCG.2023.3333336.

53. Foulsham, T., E. Walker, and A. Kingstone. The Where, What and When of Gaze Allocation in the Lab and the Natural Environment. *Vision Research*, Vol. 51, No. 17, 2011, pp. 1920–1931. https://doi.org/10.1016/j.visres.2011.07.002.

54. Hollander, J. B., A. Purdy, A. Wiley, V. Foster, R. J. K. Jacob, H. A. Taylor, and T. T. Brunyé. Seeing the City: Using Eye-Tracking Technology to Explore Cognitive Responses to the Built Environment. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, Vol. 12, No. 2, 2019, pp. 156–171. https://doi.org/10.1080/17549175.2018.1531908.