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Measuring Pedestrian Stress Response (MPSR) Using Wearable Technologies

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Abstract

Walkability is an essential aspect of urban transportation systems. Properly designed walking paths can enhance transportation safety, encourage pedestrian activity, and improve community quality of life. This, in turn, can help achieve sustainable development goals in urban areas. This pilot study uses wearable technology data to present a new method for measuring pedestrian stress in urban environments and the results were presented as an interactive geographic information system map to support risk-informed decision-making. The approach involves analyzing data from wearable devices using heart rate variability (RMSSD and slope analysis) to identify high-stress locations. This data-driven approach can help urban planners and safety experts identify and address pedestrian stressors, ultimately creating safer, more walkable cities. The study addresses a significant challenge in pedestrian safety by providing insights into factors and locations that trigger stress in pedestrians. During the pilot study, high-stress pedestrian experiences were identified due to issues like pedestrian-scooter interaction on pedestrian paths, pedestrian behavior around high foot traffic areas, and poor visibility at pedestrian crossings due to inadequate lighting.

Keywords

Wearable Technology, Walkability, Built Environment, Pedestrian Safety

1. Introduction

Urban areas consist of multimodal transportation networks, including extensive pedestrian travel. Walkability options not only serve as a key element of the transportation system, but also provide for social interaction and physical activity that align with active lifestyles. Moreover, increased walking contributes to reduced air pollution along with a sense of community identity. For these reasons, a stress-free walkability experience becomes an important consideration for urban planners in designing a healthier and happier city. Developing and validating methods to assess locations of high pedestrian stress is therefore critical to making this sustainable mode of transportation more accessible.

Improving pedestrian comfort and safety involves an understanding of the complexity of the walking experience. In outdoor environments, stress may be due to a variety of environmental factors, such as crowdedness, lighting, visibility, proximity to motor vehicles, and facility design, among others [1] [2]. Measuring the stress that pedestrians experience during their travels can serve as valuable information towards improving the mobility experience and, in particular, mitigating pedestrian safety given the alarming number of pedestrian casualties caused by conflicts with motor vehicles.

Commercially available wearable technologies (personal tracking devices) are capable of recording heart rate data that can be used to determine physiological stress at the geographical location where the wearer is experiencing this effect. When aggregated across a population of wearable technology users, this information can be used to determine "hot spots", locations where pedestrians collectively exhibit the greatest physiological stress response. This provides opportunities for planners to examine the potential for making operational or infrastructure changes at these locations to help mitigate this risk.

This paper describes a pilot project in which wearable technologies were worn by a group of pedestrians to study how they respond to the built environment through physiological stress induced by unsafe conditions. The study methodology and its implementation are presented, along with analysis results utilizing an interactive geographic information system (GIS) map.

2. Background

Traditionally, the study of urban spaces has been heavily dependent on gathering information on human perception of comfort. This information has been typically collected by surveying individuals who are asked about their experience after having navigated through a given situation [3]. While these studies may provide some useful insights, they often lack sufficient detail from which to consider design enhancements. This suggests the need to pursue more interactive and site-specific information on the walkability experience. One potential approach for doing so is to leverage wearable technologies that are capable of capturing physiological stress through changes in heart rate at the precise location where the user is experiencing this effect [4] [5].

Wearable technologies, such as smartwatches, use photoplethysmography (PPG) to measure heart rate. This process involves shining a specific wavelength of light from a pulse oximeter sensor on the underside of the device, which touches the skin on the wrist. As the light illuminates the tissue, the pulse oximeter measures changes in light absorption, and the device uses this data to calculate a heart rate [6] [7].

The human heart rate adapts to the body's level of activity, traditionally slowing down when relaxed and speeding up when active, stressed, or in danger. It can vary depending on breathing patterns and bodily requirements while responding to changes in activity and the environment. The central and peripheral nervous systems work together to synthesize input from the environment to direct and regulate bodily response. In particular, the autonomic nervous system, which operates unconsciously, ultimately directs and mediates changes in heart rate. The autonomic nervous system has two parts, sympathetic and parasympathetic nervous systems, which work together to manage the body's response to stress and relaxation [8].

The sympathetic nervous system, responsible for the "fight-or-flight" response, increases heart rate and blood pressure in emergency situations, preparing the body for physical action. It also dilates pupils, increases sweating, and diverts blood from non-essential organs to muscles. The parasympathetic nervous system, in contrast, serves to mediate a 'rest and relax' response. It slows down the heart rate and blood pressure, reducing tension in muscles, helping with digestion, and slowing down breathing. The interplay between these two systems helps manage the body's response to stress and relaxation, keeping heart rate and blood pressure in check, and ensuring the body is prepared to respond to any situation. If danger, fear, anxiety, or startlement occurs, the sympathetic nervous system is activated, releasing adrenaline to enable faster reactions and increasing heart rate for potential physical activity. Once the stressor is gone, the parasympathetic nervous system slows heart rate and lowers blood pressure, relaxing the body's systems [9] [10] [11].

Autonomic function can be quantified non-invasively by examining change in beat-to-beat variability of heart rate (heart rate variability). Root Mean Square of Successive Differences (RMSSD) is a widely used time-based heart rate variability (HRV) metric that measures the degree of variation in successive heart rates over time. Traditionally, RMSSD is said to specifically reflect the parasympathetic activity [12] [13]. In cases of stress, it is believed that the parasympathetic nervous system, indexed by RMSSD, withdraws to allow for the sympathetic (fight or flight) branch to take over [14] [15]. This withdrawal or downregulation of parasympathetic function would be quantified by a reduction in HRV.

RMSSD is calculated as follows:

$$\text{RMSSD} = \frac{\sqrt{\sum_{i=1}^{i=n-1} D_i^2}}{n-1}$$

where:

i = interval index

n = number of total intervals

$n-1$ = number of interval differences

D = the successive heart rate differences (e.g., RR_1 - RR_2 = D_1; RR_2 - RR_3 = D_2; RR_3 - RR_4 = D_3; … RR_{n-1} - RR_n = D_{n-1}), where RR is 60,000/Heart Rate (the reciprocal of Heart Rate)

Conventional methods measure RMSSD in increments of 5 minutes, although ultra-short term calculations have been proposed [16]. However, in order to maintain the granularity of pedestrian stressful locations, a method for capturing immediate, short term variability would be necessary. Thus in the current study, a calculation of RMSSD for every consecutive time period (2-frame) was employed. However, since we are squaring the difference in RMSSD, one is unable to identify the directional change in heart rate. Hence, we introduce slope analysis, which is derived as the difference between the average heart rate differences from each successive heart rate difference *i.e.*, $-1*\left\{D_i-\left(\frac{\sum_{i=1}^{i=n-1}D_i}{n-1}\right)\right\}$. By doing so, we are able to identify the directional change in the heart rate from its central tendency. Thus, by combining the two approaches (RMSSD and slope analysis) we can specifically identify high stress locations for pedestrians.

3. Methodology

The methodology employed in this study involved pedestrians aged 18 and older (*i.e.*, faculty, staff, and students) who walk within or around the perimeter of the Vanderbilt University campus. The methodology is shown in a flowchart in **Figure 1**. All participants owned or were provided with wearable technology capable of recording heart rate and location data. Participants were asked to share their smartwatch heart rate and location data during the study. Data collection was geofenced such that information was only recorded for trips occurring within or on the perimeter of the Vanderbilt campus (see **Figure 2**). The data collection period spanned from February to May 2023 [17]. In accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki), all study procedures were approved by the Vanderbilt Institutional Review Board, and informed written consent was obtained from all participants. All data collected was anonymized to protect personal information, in accordance with Institutional Review Board guidelines.

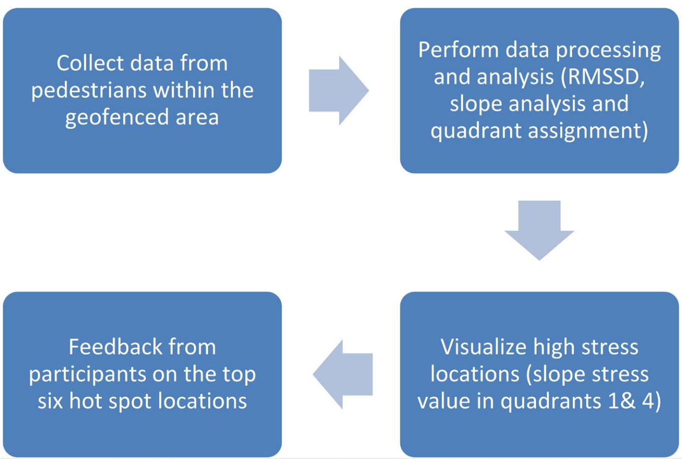


Figure 1. Flowchart of study methodology.

Figure 2. Study area.

A total of 190,664 data points from 62 unique activities were recorded at various times of the day. Data processing, analysis, and visualization, including the generation of interactive maps, were done using Python 3.

Five RMSSD calculations (cumulative, 2-frame, 5-frame, 10-frame, and 30-frame) and slope analyses were performed for each activity. RMSSD values were normalized [100*(RMSSD-min RMSSD)/(max RMSSD-min RMSSD)] to obtain the stress score values. The slope value sign was inversed for ease of interpretation where values of less than zero indicate comfort (*i.e.*, decrease in heart rate) and values of greater than 0 indicate physiological stress (*i.e.*, increase in heart rate).

Figure 3 displays the RMSSD stress score value, slope stress score, and heart rate for one pedestrian activity. Note that the 2-frame stress score closely follows the changes in heart rate, but is unable to address the directional change in heart rate as the RMSSD method squares the differences in heart rate. However, by using slope analysis, we can address the directional fluctuations in heart rate, as explained above. By calculating the consecutive difference between the 2-frame RMSSD stress score and heart rate values, we can identify where each value increased or decreased and assign them to quadrants. The quadrant assignment helps to identify regions of interest, where heart rate increased, possibly either by sympathetic activation, parasympathetic withdrawal, or a combination of both (Quadrants 1 and 4). Quadrant 1 is where the heart rate and 2-frame RMSSD stress score are increasing, and Quadrant 4 is where the heart rate is increasing, but the 2-frame RMSSD stress score is decreasing (see **Figure 4**). It is critical to note that because RMSSD largely represents parasympathetic (rest and relax) function, an increase in the RMSSD score (Quadrant 1) suggests *more* autonomic calming response, while a decrease (Quadrant 4) suggests *less* autonomic calming response. In this case, Quadrant 4 strongly suggests a significant stress response, given the increase in heart rate and decrease in autonomic calming response (decreased RMSSD). However, Quadrant 1 is still relevant given that events in this Quadrant resulted in an increase in heart rate despite an increase in the autonomic calming response. There are 138 instances where the heart rate has changed by more than +/−20. As such magnified changes are typically

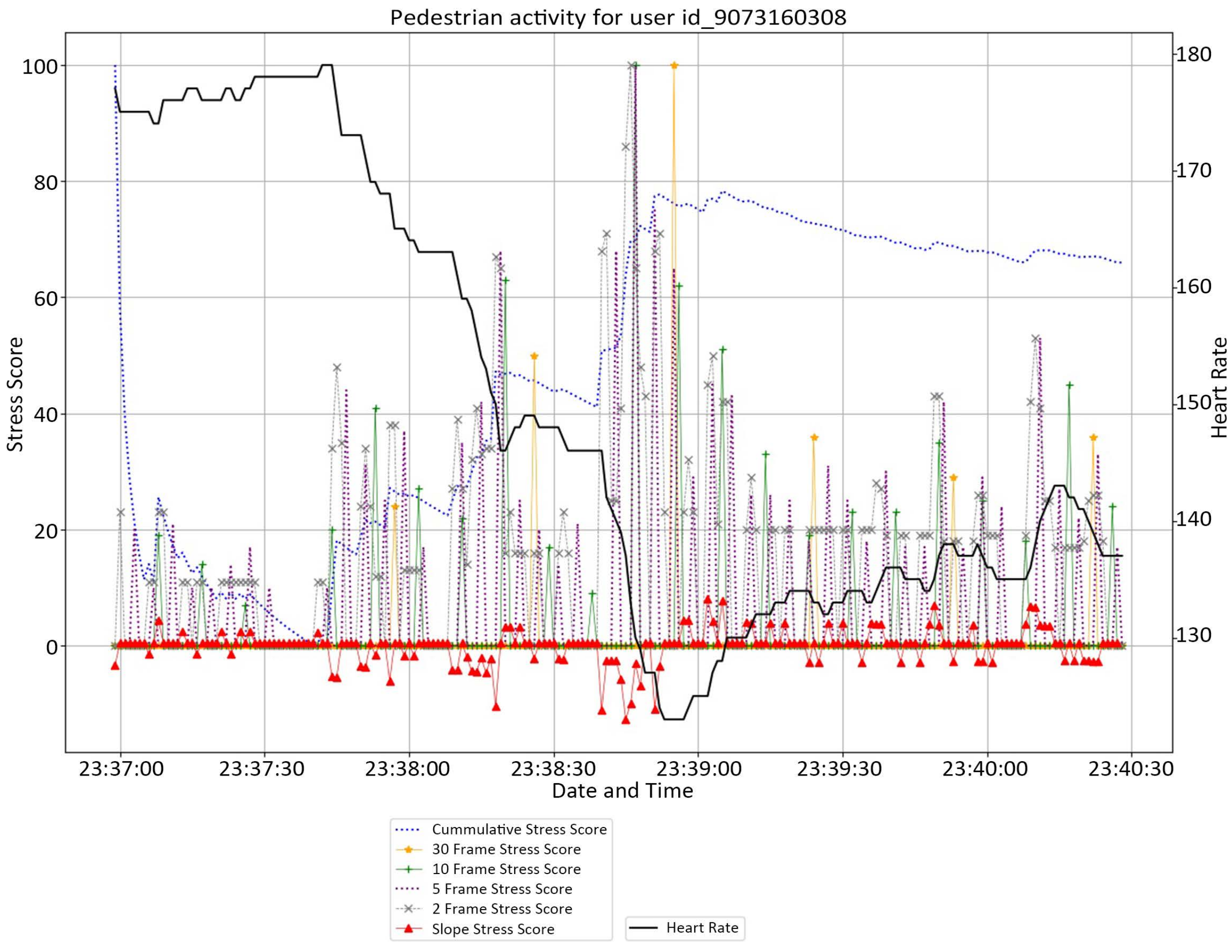


Figure 3. RMSSD stress score value, slope stress score, and the heart rate for one pedestrian activity.

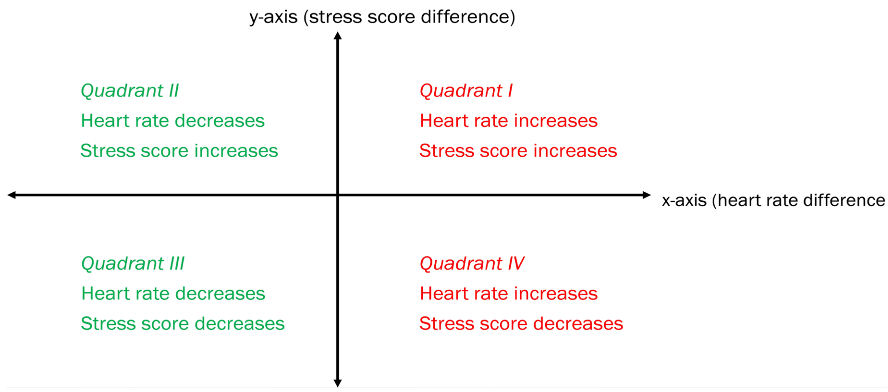


Figure 4. Quadrant assignment using heart rate and 2-frame RMSSD stress score.

unlikely, as even in conditions of significant heart rate change, such as moving from sitting to standing, average increase is only 10 - 20 beats per minute [18]. Therefore, it is more likely these magnified changes could be attributed to recording errors and thus these instances were dropped.

The next step was identifying likely pedestrian stress locations by plotting the latitude and longitude of the data points on a map[1] where the slope stress value

[1]Vanderbilt Pedestrian Stress Map - Feb to May 2023

(slope_sign_inv) falls within Quadrants 1 and 4. Average stress levels were determined within a 5-meter radius of the reported location. In Figure 5a the height of the hexbins indicates the number of data points recorded within a 5-meter radius, with taller columns representing more data points (*i.e.*, greater pedestrian activity), whereas in Figure 5b the hexbin height is shown as the average of the slope stress values within the 5-meter radius, thus revealing locations with high-stress levels regardless of the number of data points. For both the data representation approaches in Figures 5a & Figures 5b, the color of the hexbins corresponds to the average stress value, as indicated in the legend. To prioritize areas for improvement, it is desirable to select high-stress locations with higher activity levels (*i.e.*, where the height equals the point count, Figure 5b).

(a)

(b)

Figure 5. (a) Stress locations for all pedestrians (in Quadrants 1 & 4) – The height scale is the point count. (b) Stress locations for all pedestrians (in Quadrants 1 & 4) – The height scale is the average of the slope score (slope_sign_inv).

4. Results

The analysis shows that a significant portion (75%) of the slope score value is at or below 0, which indicates that pedestrian comfort levels are generally high (see Figure 6). However, around 25% of the slope stress scores are above 0, indicating moderate to high stress levels. Upon closer inspection, one observes that 13% of the slope stress scores fall within Quadrants 1 and 4, where the heart rate increases and the 2-frame RMSSD stress score value increases or decreases, and therefore implies a possible stress response (see Figure 7).

We conducted a thorough investigation on the pedestrian stress map of Quadrants 1 and 4, and based on our findings, we identified the top 5 percentile stressful locations. The pedestrian stress map and the identified hot spots are shown in Figure 7 and Figure 8, respectively. Among the top hot spots (see Figure 9), we have selected six locations that require further analysis, and the

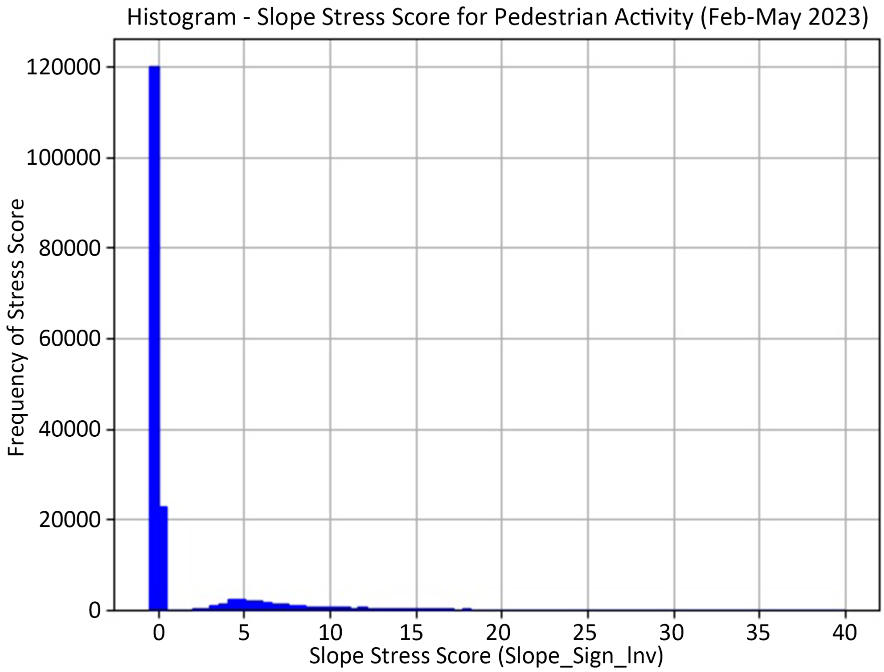


Figure 6. Histogram of all pedestrian slope stress scores.

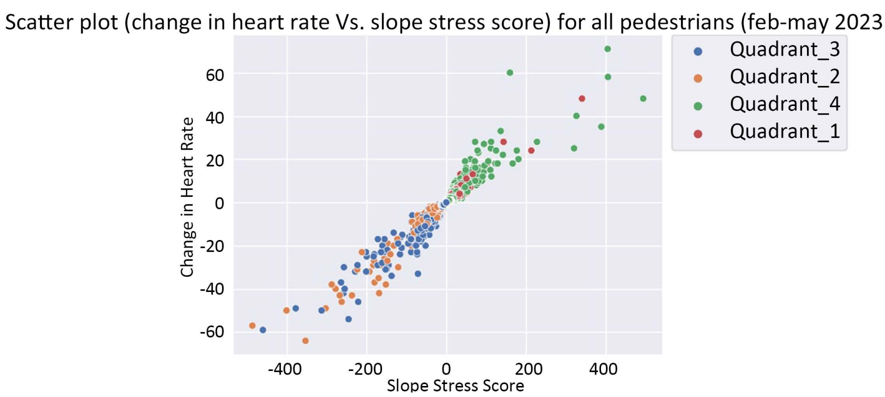


Figure 7. 13% of the slope stress score value in Quadrants 1 & 4 for all pedestrian activity.

Figure 8. Pedestrian stress map from February to May 2023.

Figure 9. Top 5% percent pedestrian stressful locations.

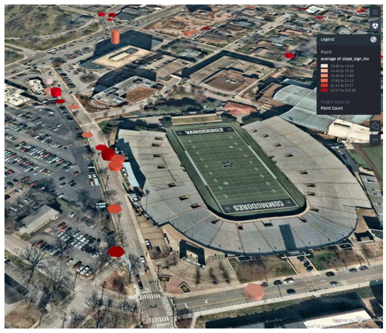
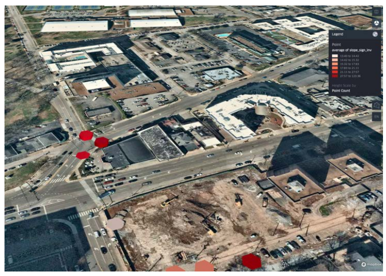
pedestrian feedback for these locations is summarized in Table 1. The six hot spots are: 1. Natchez Trace (between West End Avenue and Vanderbilt Place), 2. Edgehill Ave and Pedestrian Bridge (between 21st Ave S and Magnolia Cir), 3. Elliston Place, 4. The path between Jacobs Hall, Buttrick Hall, Vaughn Home, and Bishop Johnson Black Cultural Center, 5. In front of Stevenson Center Complex, and 6. Garland Ave (near the Eskind Biomedical Library).

The participants provided their feedback on their walking experience at these high pedestrian-stress locations, and the feedback suggests that there is a need for improved visibility and lighting. Additionally, better-controlled interactions with other modes of transportation, such as motor vehicles, scooters, or bicycles, are also required.

5. Conclusion and Outlook

This paper introduced a novel approach to identifying pedestrian stress using

Table 1. Pedestrian high-stress locations on and around Vanderbilt campus.

Location	Stress Map	Experience /Feedback
Natchez Trace (Between West End Avenue and Vanderbilt Place)		High foot traffic during game day, pedestrian behavior, improve pedestrian visibility and lighting
Edgehill Ave and Pedestrian Bridge (Between 21st Ave S and Magnolia Cir)		High foot traffic, incident with scooter users
Elliston Place		Improve pedestrian visibility and lighting
Path between Jacobs Hall, Buttrick Hall, Vaughn Home, and Bishop Johnson Black Cultural Center		High foot traffic, parking area, improve pedestrian visibility and lighting
In front of Stevenson Center Complex		High foot traffic, improve pedestrian visibility and lighting
Garland Ave (Near the Eskind Biomedical Library)		Pedestrian behavior, high foot traffic, two-way traffic for drop off, and pick of staff, faculty, students, and patients in front of the round wing

wearable technologies and applying data analytics based on 2-frame RMSSD and slope analysis. The heart rate variability calculated using 2-frame RMSSD is used to isolate regions or quadrants (1 & 4) where heart rate inscreases but 2-frame RMSSD stress score value may increase or decrease. Additionally, slope analysis addresses directional changes in heart rate that RMSDD is unable to derive. Thus, by isolating quadrants of increased heart rate with a change in the autonomic calming response and using the slope score values in these quadrants (1 & 4), it is possible to identify stressful pedestrian locations.

The pilot project served to demonstrate proof-of-concept of the methodology and its application. Notably, out of the total data recorded, a significant 13% of pedestrian responses were classified as experiencing high stress.

There are several future research directions that can emanate from this initial effort. One possibility is to include images of the hot spots and develop a predictive model to identify high-stress locations in other urban areas. Another direction is to attempt to validate the results by outfitting study participants with cameras (such as Go-Pro). Additionally, one could explore a participant's physiological factors that may enrich the data and better understand the impact of gender, weight, and socio-cultural background on model performance. Also, one might integrate the model with other datasets, such as the impact of precipitation, wind, and other micro-climate variables. Finally, one can extend the research domain by including other vulnerable groups (e.g., bicyclists, scooter users, and mobility-impaired communities).

In summary, this paper introduces an approach to analyze the sensory impact on pedestrians. Study results suggest that the use of wearable technologies offer a promising opportunity to enhance pedestrian comfort and safety, thereby helping to promote greater use of walkability as a transportation mode in urban areas.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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