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Urban Walkability and Pedestrian Stress: A Sensor-Based Study Across Three Sites

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Abstract

This study investigates the relationship between urban walkability and human stress across three distinct sites, utilizing data collected from wearable sensors. The objective is to assess how urban design and environmental factors influence human stress while walking. Participants were equipped with wearable sensors to monitor physiological indicators of stress (e.g., heart rate variability, etc.) as they walked through different urban environments. Data was collected in real-time to capture fluctuations in stress levels and provide insights into how specific urban design features impact pedestrian well-being. To facilitate data collection and analysis, walking areas were divided into blocks, and urban design features were grouped into six categories such as imageability, enclosure, human scale, transparency, complexity, and safety. Each city has different features, depending on the issues that were considered most pressing for that city. To supplement sensor stress data, the study also utilized surveys to gather participants' perceptions of safety, comfort, and environmental quality. Using regression analysis, researchers identified the urban design categories that have a significant impact on stress scores and their frequency. Machine learning models were built to predict stress scores based on the urban design aspects and air quality data as input features. Results showed that increased stress is correlated with poorly designed walkways, while lower stress was linked to well-maintained paths and green spaces. Transparency and enclosure were identified as significant contributors to pedestrian stress. The findings from one of the three cities add another dimension to the understanding of walkability and stress, highlighting that there are factors beyond basic infrastructure, such as noise levels and tree canopy can play a significant role in influencing pedestrian well-being. Findings from this research can facilitate targeted infrastructure planning and investment, better mobility, and ultimately improve the quality of life in urban areas. Future research should consider a wider range of environmental and social factors and how different factors interact over time to influence stress levels.

Keywords: Sensor-based modeling, empathic design, walkability, human stress, machine learning.

1. Introduction

Walkability is a key element in urban design that profoundly impacts quality of life and fosters community engagement. By promoting physical activity, walkable streetscapes contribute to better physical health while reducing air pollution and supporting environmental sustainability through decreased reliance on motorized transport. Moreover, walkable urban environments alleviate traffic congestion, enhancing mobility and accessibility for all, including vulnerable populations. These features encourage face-to-face interactions, foster social engagement, and stimulate local economies, reflecting thoughtful urban planning and a commitment to long-term sustainability. Walkability encompasses a range of built-environmental features that directly and indirectly enhance population health and well-being. Initially conceptualized in the 1960s through studies of sidewalks and pedestrian safety in U.S. downtown areas, the concept of walkability has evolved into a fundamental pillar of modern urban planning [1]. Jeff Speck, a leading urban planner, articulated the General Theory of Walkability, which posits that walking should be purposeful, safe, comfortable, and engaging to encourage greater pedestrian activity [2]. Building on this framework, Tobin et al. quantified walkability attributes using geospatial data, examining factors such as land use diversity, population and business density, street connectivity, public transit accessibility, traffic-calming measures, and the presence of greenery such as street trees [3]. These elements collectively determine the quality of pedestrian experience and the extent to which urban environments support walkability.

While walkability enhances urban living, it is equally important to consider the impact of environmental factors on human stress. Stress is a physiological and psychological response triggered when individuals perceive that environmental demands exceed their capacity to cope [4], [5]. Though workplace stress is a commonly recognized issue [6], urban environments—such as congested roads, noisy intersections, or poorly designed pedestrian pathways—can also act as stressors during everyday activities like walking or commuting [7]. Stress activates the body's fight-or-flight mechanism, altering emotional states and causing measurable physiological changes. Research has demonstrated that stress manifests in variations in blood pressure, heart rate, skin conductivity, and skin temperature [8-13]. Among these, cardiac activity metrics derived from electrocardiogram (ECG) [14-16], photoplethysmogram (PPG) [17], or blood volume pulse (BVP) [18] recordings are widely used for stress detection, with the standard deviation of normal-to-normal intervals (SDNN) being a common indicator [19].

This study bridges the concepts of walkability and stress by exploring how urban design influences pedestrian well-being. Walkability, defined as the extent to which a built environment supports safe, efficient, and enjoyable walking experiences, is a measure of urban functionality and a determinant of mental and physical health. This research investigates the relationship between pedestrian stress and urban design elements, aiming to identify specific features that exacerbate or alleviate stress levels during walking. The objectives of this research are as follows:

- To examine the impact of environmental factors on pedestrian stress levels and assess the walkability of selected urban routes.
- To compare quantitative stress metrics with qualitative evaluations of the built environment to gain a comprehensive understanding of the pedestrian experience.

By integrating physiological and environmental data, this study contributes to the growing body of knowledge on urban walkability and its effects on human stress. The findings aim to guide urban planners and policymakers in designing more walkable, health-promoting cities that prioritize pedestrian comfort and well-being.

2. Relevant Literature

Upon appraisal of the potential impact of urban design on individuals, various research studies have been conducted on this aspect. Roe et al. investigated how walking in different urban environments impacts cognitive health and emotional well-being [20]. They considered two contrasting urban environments: A busy, built-up commercial street and a quieter, green residential area, and integrated real-time environmental data (e.g., air quality and noise levels) and physiological data (e.g., heart rate variability), and cognitive reaction times. Additionally, they also assessed participants' emotional well-being (via survey). It was found that walking in the green district significantly improved happiness and reduced physiological stress ($p < .05$) (measured by heart rate variability), accompanied by faster cognitive reaction times, and higher noise levels and urban conditions were linked to increased stress activation. Nur Sipahioglu adopted a data analytic approach to investigate which attributes make a street walkable [21]. Attributes were divided into nine categories: Street, Sidewalk, Obstacles, Urban Blocks, Amenities, Transportation, Attractiveness, People, and Vehicles. Overall walkability was defined through personal ratings and analyzing physical attributes measured via Remote Sensing in QGIS provides insights into the broader factors influencing walkability. Mutual Information and Correlation matrices effectively revealed relationships and dependencies between walkability attributes. Nancy Averett assessed the impact of the built environment on a long-term health outcome (hypertension) in a population-based sample [22]. It was found that people who moved from a low-walkability neighborhood to a high-walkability neighborhood had a 54% lower likelihood of developing hypertension compared to those who moved between two low-walkability neighborhoods. Choi et al. investigated how human-centered design affects pedestrian satisfaction and community walkability [23]**.** They reviewed existing research on pedestrian-friendly design and conducted interviews with pedestrians about urban street features and found that pedestrians value planting strips as the most significant design feature for enhancing satisfaction. Keat et al. focused on evaluating walkability at the University Malaya

(UM) by surveying students for their perceptions of walkability features, potential, and policies, and conducting direct observations and measurements of existing conditions, such as vehicular and pedestrian circulation and street elements [24]. Key findings reveal that most students perceive the walkability environment at UM as inadequate, with limited user-friendly street elements despite some positive aspects like traffic calming devices near pedestrian crossings.

3. Research Methodology

The study was conducted in three sites: Louisville, KY, South Bend, IN, and Youngstown, OH. Eligibility criteria for participants, with age ranges from 16 to 64, include smartphone access and the ability to walk 1.4 miles (based on their informed consent). The study was approved by the IRB of the University of Notre Dame.

Data collection and analysis

This study used Polar OH1+ Optical Heart Rate Sensors to collect participants' heart rate data during walking. The Strava App was utilized to connect sensor devices to individual phones and ensured the real-time collection of heart rate data and the tracking of GPS coordinates. The MPATH app was used to calculate the stress score automatically from the heart rate data and visualize the integrated geolocation data and stress scores. This empathic engine watches for early indicators of emotional stress, and the algorithm filters out linear increases in heart rate due to physical stress. However, the qualitative data, such as street audit data, were collected by different groups in different ways.

Youngstown Site: Youngstown group collected data on *sidewalk quality*, on a scale of 0 to 5 (non-existent sidewalk to excellent walkability), i.e., if there is any cracking on the sidewalk, uneven ground, and vegetation, *sidewalk infrastructure*, on a scale of 0 to 1 (non-existent surrounding infrastructure to excellent surrounding infrastructure), i.e., if the surroundings contain street barriers or free of obstacles, shade trees or benches, curb out ramp, and consistency in the building materials, and *sidewalk infrastructure excludes* that identifies the specific features missing in the surroundings. Sidewalks' combined rating scores were calculated on a scale of 1 to 10. Then, the sidewalks with the same rating score were categorized.

The group collected data on crosswalks as well such as *crosswalk quality* on a scale of 0 to 5, i.e., if the traffic lights/stop signs existed and were visible at the intersections, if the crosswalk is there at all and visible, if there is signage alerting drivers to pedestrians, raised crosswalks, pedestrian islands, etc., *quality of the pedestrian crossing signals* on a scale of 0 to 5, if the signals are working, if "push to walk" mechanism and audible prompts are there, if the time to cross is adequate or not, etc. Additionally, data was collected on what, among the specific features mentioned above, are missing in the crosswalk and the crossing signals. Similar to the sidewalks, crosswalks' combined scores were calculated, and then crosswalks were categorized.

Corresponding average, median stress scores, and standard deviations for different sidewalks and crosswalks with different rating scores were determined. For visualization, the stress data corresponding to the same combined rating scores were layered with the different sidewalks and crosswalks separately.

Louisville Site: The Louisville group assessed 13 blocks in Downtown Louisville on 57 features of the built environment, such as sidewalk width, curb height, curb ramps, speed limit, street buffer, bicycle lane, parking meters, street width, crossing distance, speed bumps, lane count, lane width, etc. The features were categorized into six categories: imageability, enclosure, human scale, transparency, complexity, and safety. To investigate which features are the most significant contributing to the stress score, a regression analysis was performed with the stress score as the dependent variable and the six categories of features are independent variables. Moreover, this group layered stress data with design scores per block for analysis of pedestrian user experience. The group additionally considered dynamic features in the environment that could affect pedestrian stress. Therefore, they collected air quality data using the Air Quality app. Integrating both stress score and air quality data, several machine learning models were developed to predict stress score based on the block and air quality data as input features.

South Bend Site: The South Bend group considered two different streets, one received recent renovations, and the other had not been updated, and compared the two streets. To precisely measure the difference between these streets, sidewalk data from the city, including metrics such as sidewalk width and uplifts, were collected. After participants finished their walk, they were instructed to complete a post-walk survey to include the subjective experience of the participants, giving context for their stress levels. This data was then aggregated into an ArcGIS map to visualize spatial patterns influencing walkability metrics, leading to the development of an ArcGIS Story Map that layered sidewalk quality data with stress level results. Two-sample t-tests with average stress scores in the two different streets were run for comparative analysis. A machine-learning model was built to predict stress levels at a given point based on the sidewalk conditions.

4. Results and Analysis

Youngstown site

Visualization of the sidewalk and crosswalk data points (see Figures 1 and 2, respectively) on maps with color coding depending on the rating scores of different sidewalks and crosswalks indicates that most of the sidewalks were rated as excellently designed, whereas most of the crosswalks were rated as poorly designed.

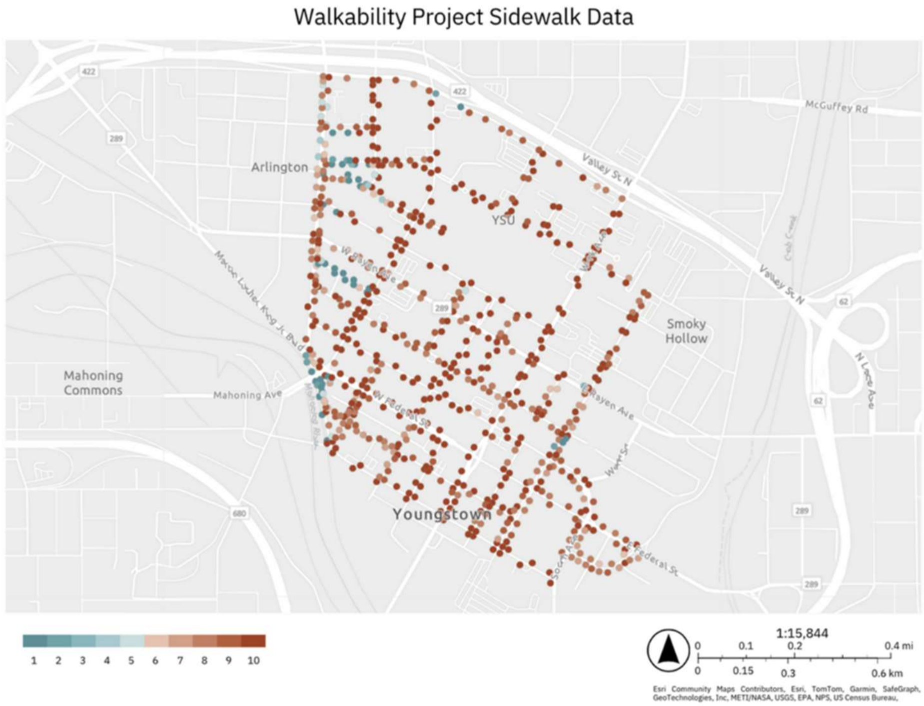

Figure 1. Sidewalk data points with colors indicating sidewalk rating score.

Figure 2. Crosswalk data points with colors indicating crosswalk rating score.

This is more clearly represented by the distribution of sidewalk ratings by count and the distribution of crosswalk ratings by count, demonstrating the number of data points counted under different rating scores (Figures 3 and 4).

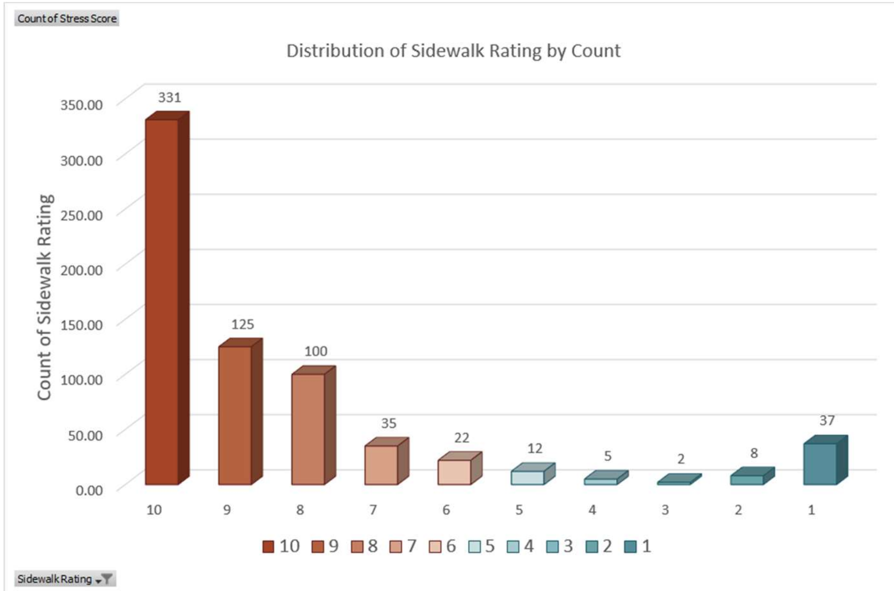

Figure 3. A plot of the distribution of sidewalk ratings by count.

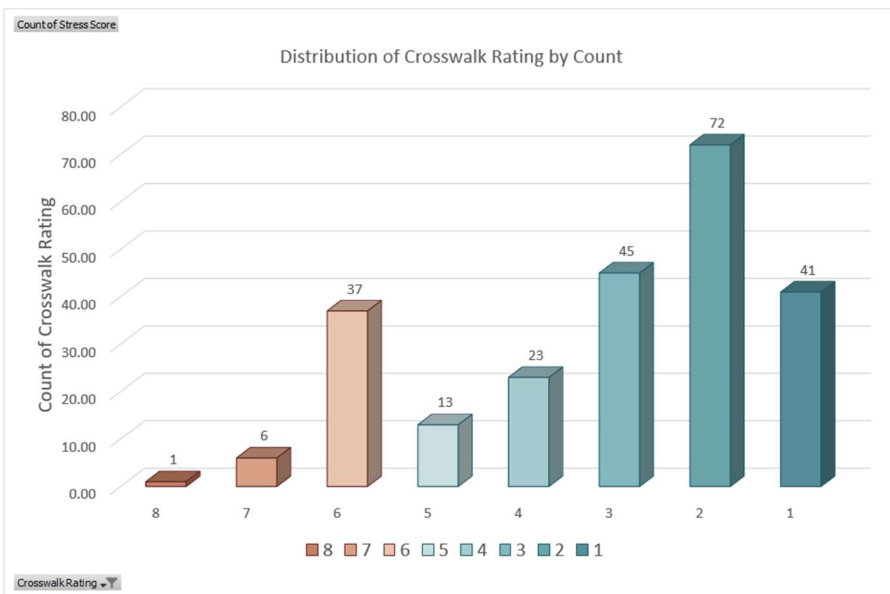

Figure 4. A plot of the distribution of crosswalk ratings by count.

Figure 5 represents the boxplot of stress scores in the sidewalks with different rating scores. It's noticeable that well-designed sidewalks with rating scores of 8, 9, or 10 incur lower stress scores than poorly designed sidewalks with rating scores of 1, 2, 3, or 4. Additionally, the high standard deviation in stress scores in the poorly designed sidewalks indicates inconsistent presence of or missing quality in the sidewalks and the surrounding infrastructures. Similarly, Figure 6 represents the boxplot of stress scores in the crosswalks with different rating scores, which shows that well-designed crosswalks with rating scores incur lower stress scores than poorly designed crosswalks with rating scores. Moreover, these crosswalks incur a high standard deviation in stress scores, indicating their poor design.

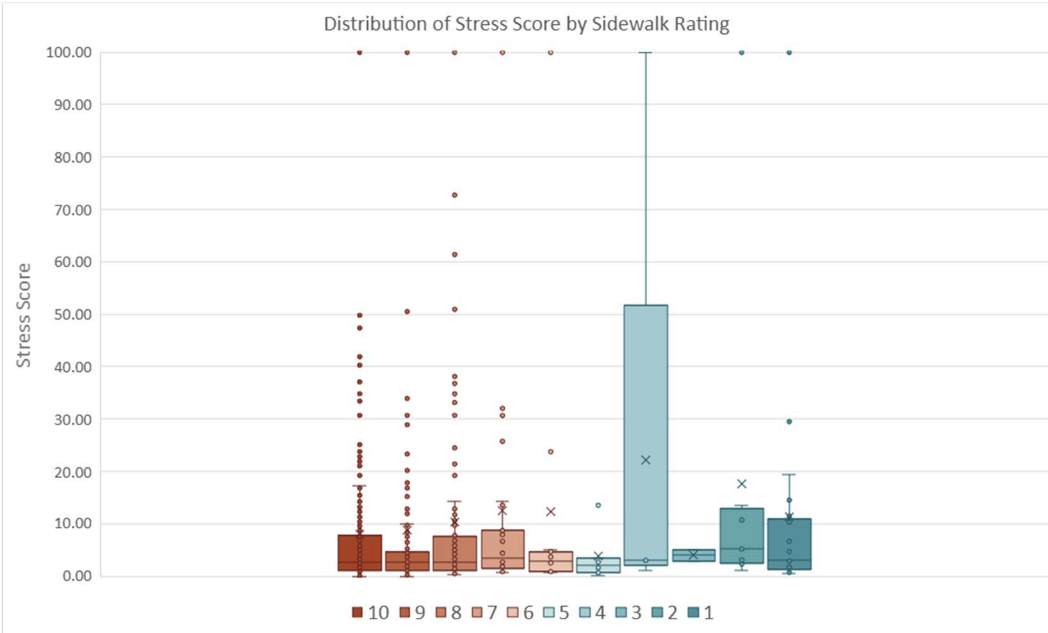

Figure 5. Box and whisker plot of the distribution of stress scores by sidewalk rating.

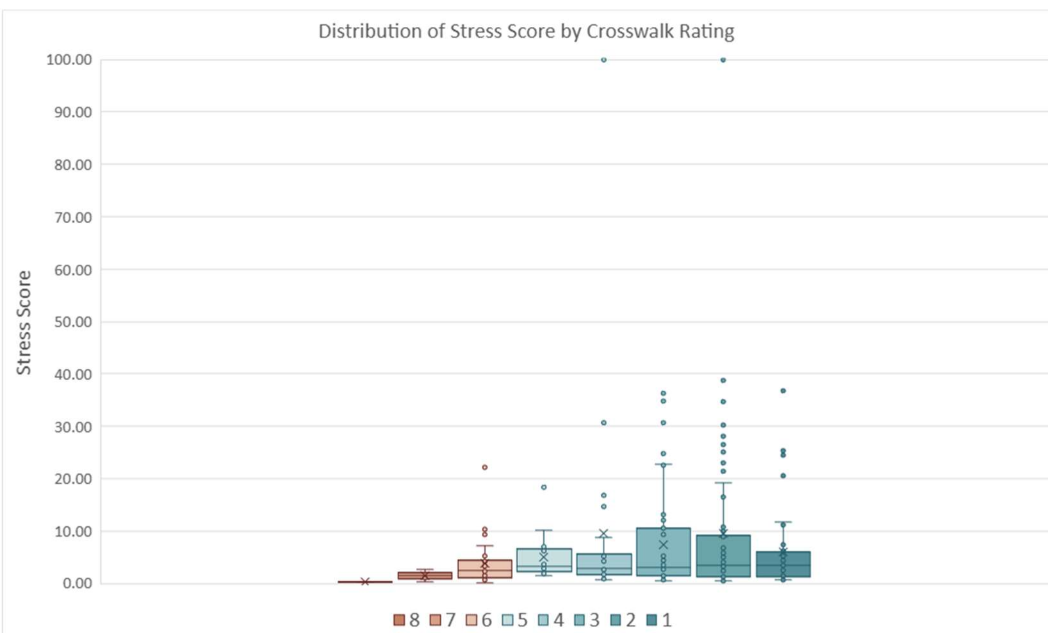

Figure 6. Box and whisker plot of the distribution of stress scores by crosswalk rating.

Louisville site

Analysis of the data collected revealed similar insights. Figure 7 shows the raw stress scores in different geolocations in the walking area considered in this study. Height represents the number of data points collected in that location. Color represents different ranges of average stress scores. For instance, red indicates the highest level of stress scores, a range of 13.69-28.87, and blue indicates the lowest level of stress score, a range of 0.47-7.72. It's noticeable that there are multiple locations with higher stress scores.

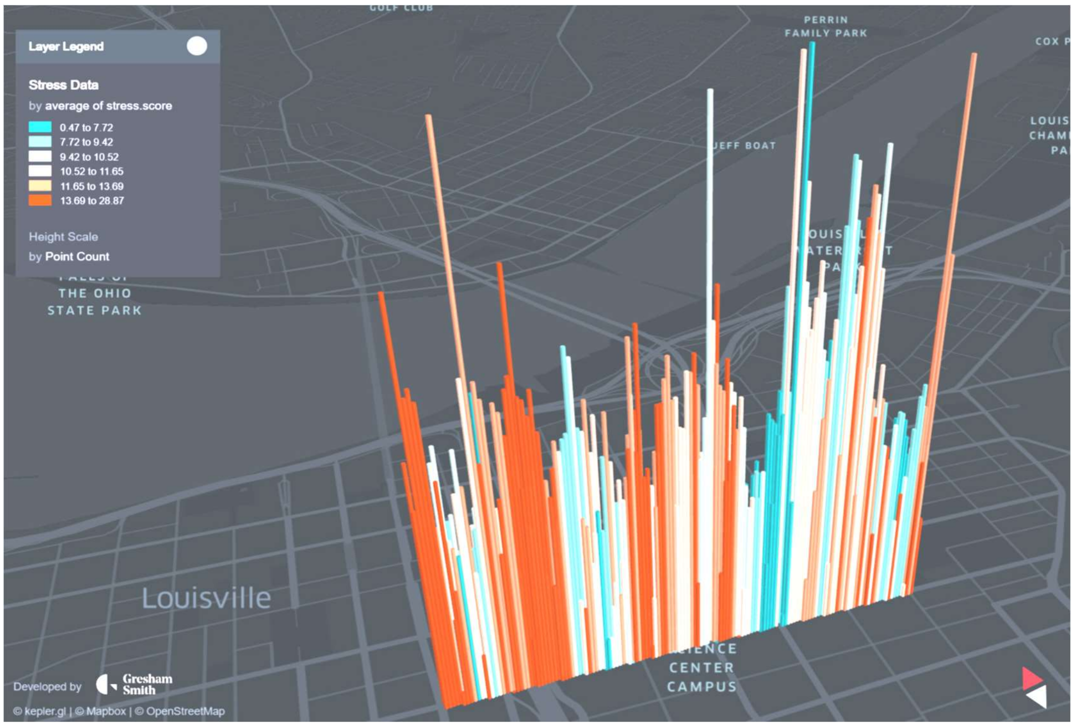

Figure 7. Visual representation of raw stress data.

The boxplot below (Figure 8) represents a clearer view of which specific location, i.e., which blocks incurring more stress than others. South Side Chestnut St 2nd 1st, South Side Chestnut St 1st Brook, South Side Chestnut St Brook Floyd, and South Side Chestnut St Floyd Preston incurred higher stress than other blocks, even than the global median stress score.

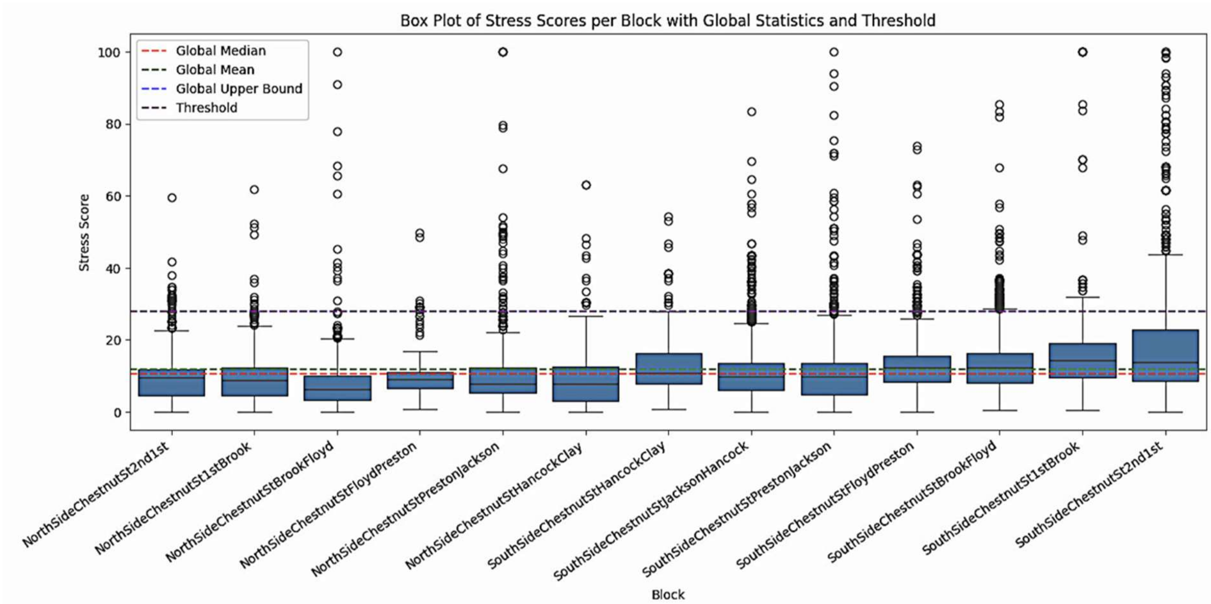

Figure 8. Box Plot of stress scores per block.

The regression analysis revealed that Transparency and Enclosure are the most significant ones (Figure 9). The positive coefficient associated with Transparency suggests that as visibility beyond street edges increases and obstructions from trees, walls, or windows decrease, pedestrians tend to experience higher stress levels. On the other hand, the negative coefficient associated with Enclosure means that as street walls and trees increase, reducing a block's openness and sky exposure, pedestrians tend to experience higher stress.

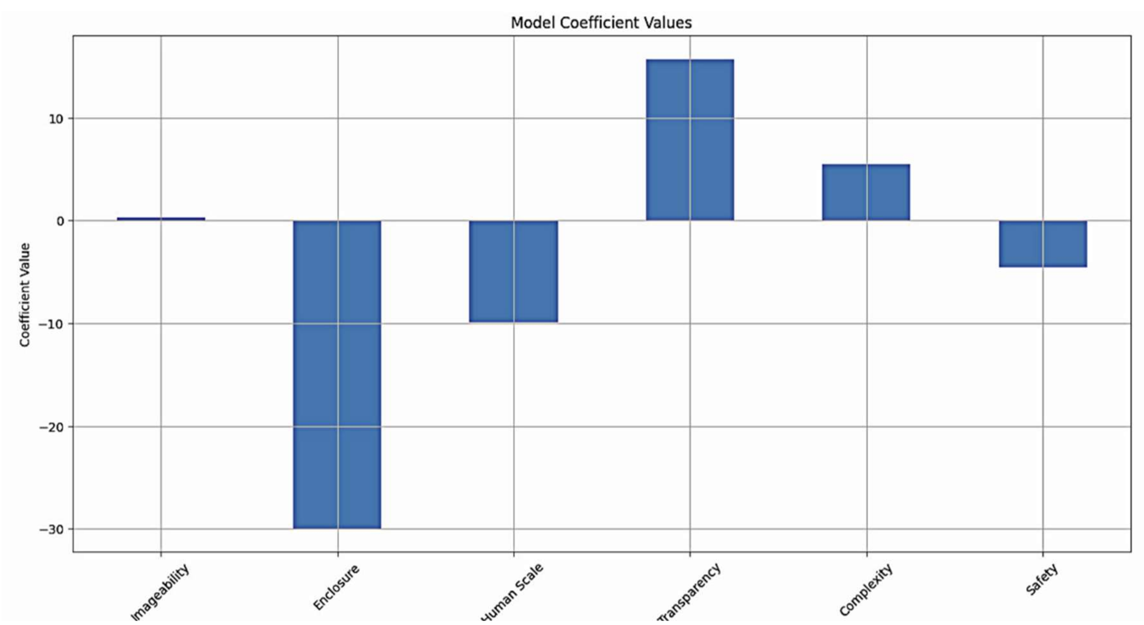

Figure 9. Regression coefficient values represent the significance of the impact of the categories of the street audit on stress.

Among the machine learning models developed in this study (see Figure 10), the random forest model performed the best in predicting stress scores with the lowest mean squared error (MSE) of 4.83.

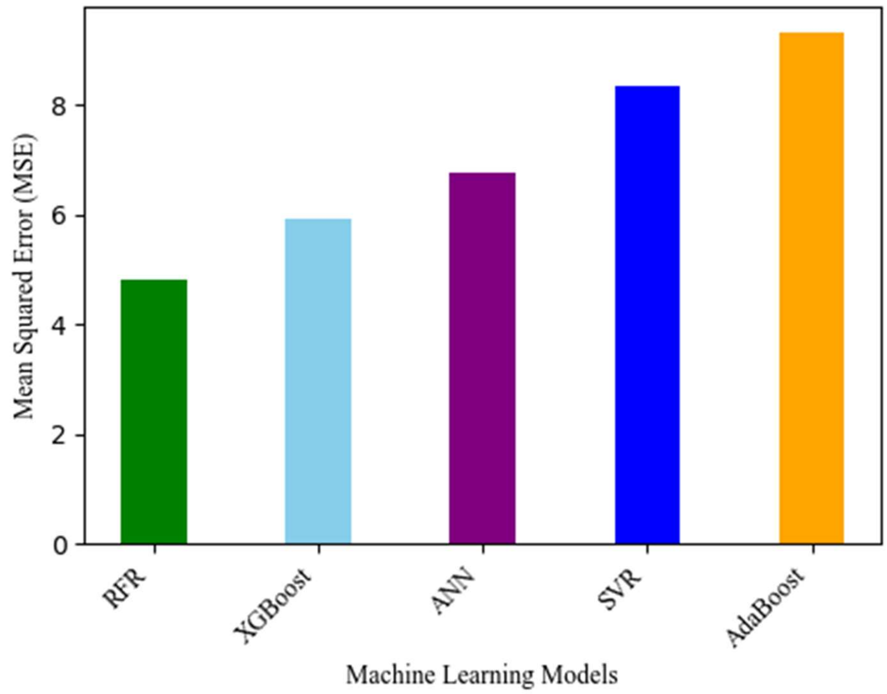

Figure 10. Comparison of MSE values of different machine learning models, including Random Forest Regressor (RFR), XGBoost Regressor, Analytical Neural Network (ANN), Support Vector Regressor (SVR), and AdaBoost Regressor.

South Bend site

Participants walked the streets shown in Figure 11. The color of the lines indicates the stress level, with red showing high stress and green showing low stress.

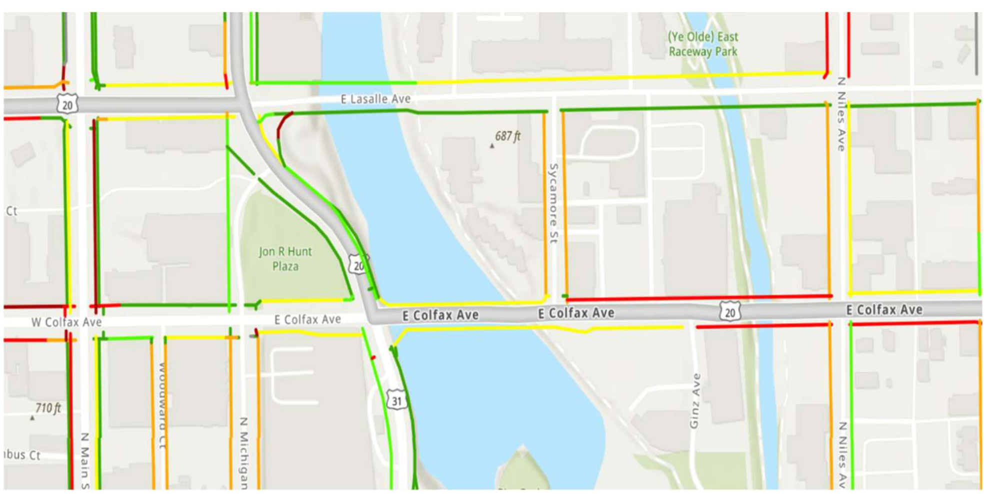

Figure 11. Sidewalk conditions map.

Between the respective average stress scores for the two streets, Colfax and Lasalle, Colfax Street was found to offer a less stressful walking experience (Figure 12) despite worse sidewalk conditions, suggesting that sidewalk quality is a poor predictor of walkability.

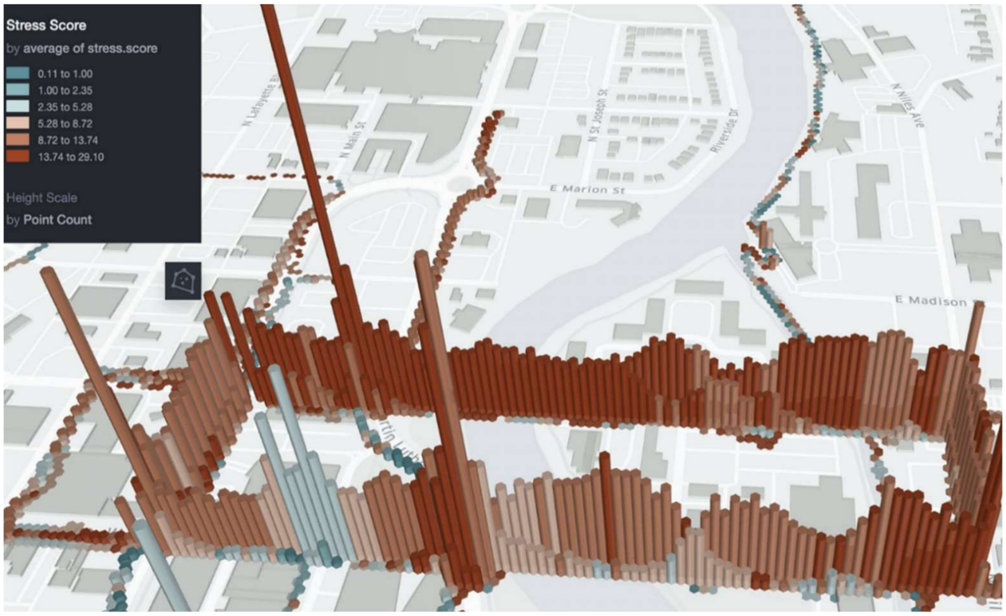

Figure 12. Stress score visualization.

The t-tests revealed that the difference in stress scores of the streets was statistically significant, with LaSalle and Colfax showing an average stress score of 16.6 and 10.4, respectively (Figure 13), showing that walking experiences were drastically different between streets. Even though this was not due to sidewalk data, participants claimed that urban design quality was impacting walkability (Figure 14). Noise level and tree canopy were identified as two of such quality aspects. Although the machine learning model was able to correlate variables with the stress score, the sidewalk quality and stress levels were not correlated.

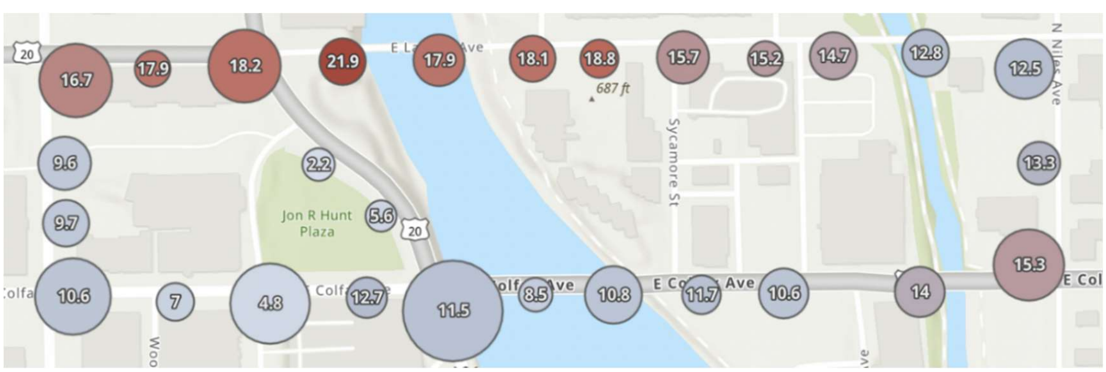

Figure 13. ArcGIS Layer from the South Bend site showing stress scores recorded in LaSalle Street (upper line) and Colfax Street (lower line). Red bubbles indicate higher stress scores, and grey bubbles indicate lower stress scores.

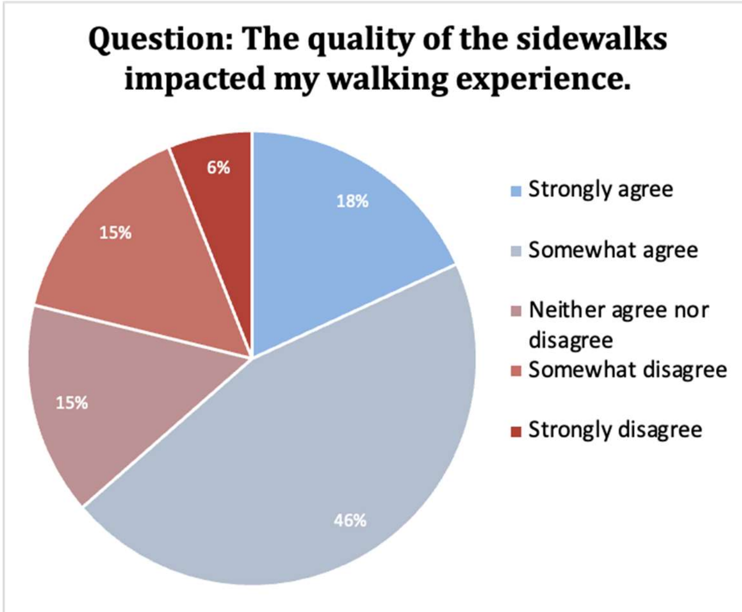

Figure 14. Participants' subjective assessment of the sidewalks.

5. Discussion

The relationship between urban design and pedestrian stress provides valuable insights into the factors influencing walkability across different urban environments. The findings reveal that well-maintained sidewalks and green spaces are critical in reducing stress during walking, as evidenced by the lower stress scores associated with high-rated sidewalks and crosswalks in Youngstown. Poorly designed infrastructure, on the other hand, incurs higher stress scores and exhibits greater variability, reflecting inconsistent or missing quality in the built environment.

In the Louisville site, the study also found that spatial visualization and regression analysis identified transparency and enclosure as significant contributors to pedestrian stress. Blocks with high transparency were linked to increased stress, potentially due to overexposure to traffic or the lack of perceived safety, whereas reduced enclosure was associated with lower stress levels. These results underscore the importance of considering visibility, proximity, and perceived safety when designing urban spaces.

The findings from the South Bend site add another dimension to the understanding of walkability and stress. Despite poor sidewalk conditions, some streets had a less stressful walking experience compared to others, highlighting that there are factors beyond basic infrastructure, such as noise levels and tree canopy, that can play a significant role in influencing pedestrian well-being. The statistically significant differences in stress scores between these streets emphasize the importance of holistic urban design that incorporates sensory and environmental quality alongside structural elements.

Overall, the results reveal that walkability is influenced by a combination of design features, environmental factors, and perceptual elements, rather than infrastructure quality alone. By integrating wearable sensor data, geospatial analysis, and participant feedback, this study provides a comprehensive understanding of how urban design impacts human stress and walkability.

6. Conclusions and Future Work

This research underscores the critical role of urban design in shaping pedestrian experiences and reducing stress during walking. The findings emphasize the importance of well-designed sidewalks, green spaces, and cohesive urban environments that prioritize safety, comfort, and accessibility. Key insights include the significance of Transparency and Enclosure in affecting pedestrian stress, as well as the influence of sensory factors like noise levels and tree canopy on perceived walkability. Besides, the study demonstrates the utility of sensor-based methods in capturing real-time stress data, enabling a more nuanced analysis of urban walkability across diverse environments. These results not only highlight the potential for targeted infrastructure planning but also provide actionable recommendations for improving urban design to enhance pedestrian well-being and overall quality of life.

Future research should expand on the current findings by exploring additional environmental and social factors, such as lighting, crowd density, and traffic flow, and their interactions with pedestrian stress over time. Longitudinal studies could provide deeper insights into how urban design changes impact walkability and stress over extended periods. Moreover, integrating advanced sensor technologies, such as eye-tracking and acoustic sensors, could enhance the granularity of data collection, capturing subtle stress responses and environmental interactions. Exploring cross-cultural differences in walkability and stress perceptions across cities globally could offer a broader understanding of universal versus localized urban design principles. Finally, developing predictive models using machine learning to analyze complex relationships between urban design features and pedestrian stress could provide planners with tools to simulate and optimize urban environments before implementation. By addressing these areas, future studies can contribute to creating more inclusive, sustainable, and stress-free urban spaces.

This study contributes to engineering education by demonstrating a data-driven approach to urban design using wearable sensors, geospatial analysis, and machine learning. It offers practical case studies for courses in smart cities, transportation engineering, and human-centered design, equipping students with skills in sensor-based data collection, predictive modeling, and statistical analysis. By integrating engineering, psychology, and urban planning, the research promotes interdisciplinary learning and hands-on applications of machine learning and physiological signal processing in real-world infrastructure design. These insights support experiential learning and can be incorporated into project-based coursework, fostering data-driven decision-making in engineering education.

Acknowledgments

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