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Advancing Neuro-Urbanism: Integrating Environmental Sensing and Human-Centered Design for Healthier Cities

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Abstract:
Rapid urbanization presents complex challenges to the well-being of city inhabitants. This study reevaluates historical urban design paradigms within the context of contemporary urban growth, emphasizing the need for sustainable and psychologically enriching environments. It explores regenerative design strategies through the emerging framework of Neuro-Urbanism, an interdisciplinary field integrating urban design, neuroscience, and psychology. Employing a multi-method approach, this study combines human experience sensing, remote sensing, and atmospheric environmental sensing to assess urban spaces. A key methodological innovation is the use of voxel-based assessment, a 3D spatial analysis technique that quantifies physical and architectural attributes. Machine learning algorithms analyze emotional responses, while data loggers record microclimatic conditions such as temperature, humidity, and air quality. Empirical findings reveal that temperature and humidity strongly correlate with physiological arousal and perceived comfort levels, underscoring the direct impact of urban microclimates on user experiences. This study contributes valuable insights into the relationship between environmental factors and mental well-being, informing evidence-based urban design strategies to foster inclusive, resilient, and health-supportive urban environments.

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1. Introduction

Throughout history, the role of nature in shaping human well-being has been a central theme across scientific, philosophical, and cultural traditions. Contemporary research underscores the crucial influence of natural environments on physical and mental health, emphasizing their role in providing resources, stabilizing climate, and enhancing quality of life [1]. Urban planning, as a multidisciplinary field, integrates technical and political processes to improve human welfare, regulate land use, design built environments, and foster sustainable interactions with nature [2]. However, as urbanization accelerates, projected to reach 68% of the global population by 2050 [3], the challenges of maintaining human well-being in rapidly expanding cities become increasingly complex.

Neuro-Urbanism, an emerging interdisciplinary approach, seeks to bridge urban design and neuroscience by examining how built environments influence cognitive and emotional states. Architectural design, including landscape architecture, extends beyond functionality to engage with human perception, emotions, and psychological responses. While recent advancements in technology allow for real-time analysis of urban experiences through biometric and sensory data, these tools remain underutilized in evidence-based design [2]. Developing frameworks that integrate empirical findings from neuroscience with urban design principles is crucial to addressing the gaps between theory and practice in fostering human-centered cities.

A growing body of research focuses on regenerative design as a paradigm for sustainable urban development. Initially conceptualized by Regenesis in 1995, regenerative development emphasizes the co-evolution of human and ecological systems, recognizing environmental challenges as manifestations of fractured human-nature relationships rather than solely technological shortcomings [4]. This approach advocates for design processes that restore and renew natural and social systems through holistic and adaptable strategies.

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Despite recognizing environmental stewardship as fundamental to urban planning, integrating human psychological responses within ecological frameworks remains an ongoing challenge [5]. While ecological models have traditionally been applied to urban ecosystems, human communities' distinct social and cultural attributes necessitate a more nuanced understanding of the reciprocal relationship between individuals and their surroundings. Cognitive science plays a critical role in this discourse by investigating how environmental perception shapes mental and emotional states. Research suggests a meaningful correlation between sensory experiences and physiological responses, highlighting the potential for urban environments to either support or hinder mental health [6]. The increasing prevalence of mental health issues further underscores the urgency of designing restorative urban environments. A study conducted in Fars province in 2022 found that 46% of participants exhibited symptoms of mental distress—double the prevalence reported in 2015—with higher rates among women [7-10]. Recent research in Neuro-Urbanism emphasizes the role of cognitive neuroscience in shaping urban environments that enhance human well-being. Makanadar [11] introduces the concept of neuro-adaptive architecture, where buildings and city designs dynamically respond to human emotions, utilizing real-time biometric feedback to optimize environmental conditions. This study underscores the potential of adaptive urban spaces to mitigate stress and improve overall mental health.

Elsayed et al. explores the intersection of environmental neuroscience and urban planning, demonstrating how sensory-rich environments positively influence cognitive function and emotional well-being [12]. This research highlights how urban design interventions—such as increasing green space, incorporating natural materials, and designing human-centered streetscapes—can foster psychological resilience in city dwellers.

Furthering this perspective, Yang provides a bibliometric analysis of restorative environments, identifying key trends and emerging hotspots in research on urban well-being. Their study reveals a growing emphasis on the role of multi-sensory engagement in designing environments that promote psychological restoration, particularly through biophilic elements and immersive public spaces [13].

Lee expands on the concept of sustaining embodied experience in the built environment, arguing that the way people interact physically and emotionally with urban spaces significantly impacts their well-being [14]. His findings suggest that tactile and spatial stimuli, such as texture variations in materials and dynamic lighting, contribute to deeper cognitive and emotional engagement in urban settings.

These findings align with ongoing initiatives by Neuro-Landscape, an organization dedicated to bridging neuroscience and landscape architecture. Their research supports the integration of evidence-based urban design strategies to create environments that not only sustain ecological balance but also enhance mental and emotional health.

Such findings highlight the necessity of urban planning strategies that prioritize psychological resilience alongside environmental sustainability (Figure 1). Although urban life presents inherent stressors, strategic design interventions informed by neuroscience and psychology may mitigate these adverse effects and foster well-being [15].

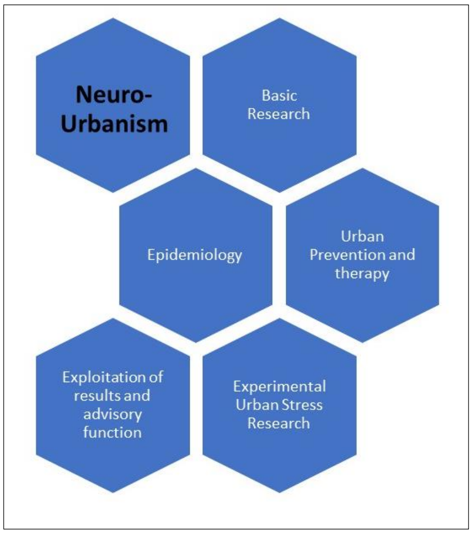

Figure 1. Structural Framework in Interdisciplinary Studies of Neuro-urbanism in Urban Planning (Authors based on Adli et al. [15])

This study proposes an integrative framework that synthesizes principles from Neuro-Urbanism and regenerative design to evaluate urban environments' impact on well-being. Drawing on insights from neuroscience, architecture, and environmental psychology, this approach aims to establish a systematic methodology for assessing urban spaces' physiological and cognitive effects. The study seeks to address the following research questions:

1. How can principles of Neuro-Urbanism inform evidence-based design strategies for enhancing urban well-being?

2. In what ways can regenerative design be applied to foster holistic and adaptive urban environments?

3. How do sensory and cognitive responses to urban spaces influence mental health and overall quality of life?

By integrating these perspectives, this research aims to advance interdisciplinary discourse on the intersection of urban planning, neuroscience, and ecological sustainability. The proposed framework offers a structured approach for incorporating human-centered considerations into urban design, ultimately contributing to more resilient and health-supportive cities.

2. Methodology

The methodology employed in this study aimed to comprehensively collect and analyze data on environmental parameters, physiological responses, and emotional experiences, using a multi-faceted approach.

To achieve these objectives, the methodology consisted of three main steps: human experience sensing, environmental atmospheric sensing, and remote sensing of urban objects. For the first two steps, sensor selection and setup were considered to establish a consistent framework for real-time data acquisition. Additionally, specific procedures were implemented to collect data.

Ten participants were recruited for the pilot study. They provided informed consent, and inclusion criteria were defined to ensure a representative sample of urban dwellers. Each participant completed experimental sessions, ensuring the collection of all exposure data. Participants experienced an 18-hectare urban zone in the Farhangshahr zone in Shiraz (see Figures 2 and 3). While the modest sample size may limit statistical power, it provided initial insights into urban environmental impacts, and we acknowledge this limitation while suggesting that future research expand the sample size to enhance generalizability.

Figure 2. The location of the site and the selected zone of the experimental research on Human Experience Sensing

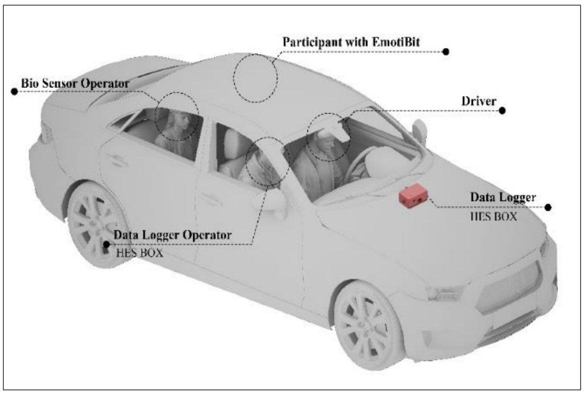

Figure 3. The settings of the test environment in riding mode are set by operators to control the data of the data logger and the physiological sensor

A custom-designed data logger was used to continuously record environmental parameters such as temperature, humidity, air pollution, light intensity, and sound levels. The logger was built using an Arduino Nano microcontroller coupled with dedicated sensors (e.g., AM2311 for temperature and humidity, MQ-135 for air pollution, BH175 for light intensity). A Bluetooth module (HC-06) transmitted the sensor data in real time to a streamlined mobile application developed with Flutter and Dart. Technical details of the application were minimized to emphasize the environmental insights critical to urban design outcomes.

Physiological data were acquired using the EmotiBit wearable sensor, which records multiple modalities including Electrodermal Activity (EDA/GSR) and Heart Rate (HR). The sensor was attached to the proximal portion of the participant's index finger, a placement supported by previous studies van Dooren and Janssen [16] , to optimize the reliability of the skin conductance measurements.

2.1. Data Analysis Techniques

The collected data were systematically analyzed using statistical methods. Pearson and Spearman correlation analyses evaluated associations among environmental factors, physiological responses, and self-reported emotional states. Correlation matrices and regression models were developed to quantify the strength and direction of these relationships, providing insights into key determinants of urban well-being.

1. Machine learning techniques were employed to classify emotional states based on physiological data. The Random Forest algorithm was selected for its robustness, ability to handle high-dimensional and noisy data, and superior performance in similar affective computing studies by Ahmad and Khan [17] and Joy et al [18]. The process involved:
2. Feature Extraction and Selection: Relevant features (e.g., average HR and GSR) were extracted from the raw physiological data.
3. Preprocessing: The data were cleaned to remove motion artifacts using Python's Pandas library and Neurokit2.

Model Training and Evaluation: Using the International Affective Picture System (IAPS) as a labeled database, we trained the Random Forest model on 80% of the data, with the remaining 20% used for testing. Performance metrics, such as classification accuracy, were computed to validate the model.

2.2. Experimental Tool

The Emotibit wearable sensor was used in this study as a biological monitoring device to capture high-precision physiological and motion data. This scientifically validated hardware allows wireless or direct recording onto internal memory, supporting diverse experimental setups. Built on Arduino technology, Emotibit enables project expansion and customization, making it highly adaptable for research purposes. The device collects 16 physiological and motion-related data points, including Electrodermal Activity (EA), Electrodermal Response (ER), Photoplethysmography (PPG), Temperature (T0 and TH), Acceleration (A) and Gravity (G) in X, Y, and Z directions, Skin Conductance (SA), Skin Conductance Response (SCR), Skin Conductance Level (SCL), Skin Conductance Frequency

(SF), Heart Rate (HR), Interbeat Interval (BI), and Skin Humidity (HO).

For this experiment, Heart Rate (HR) and Galvanic Skin Response (GSR) were selected as key physiological indicators to assess participant arousal variations. These parameters were chosen due to their established effectiveness in psychophysiological research for measuring emotional responses.

2.3. Heart Rate (HR)

Heart rate is a long-standing psychophysiological indicator of cognitive load [19, 20]. Cardiovascular indicators such as Heart Rate Variability (HRV) are also evaluated alongside heart rate. However, due to time constraints in data processing, HRV may not be suitable for tests requiring rapid results. Hence, given the short-term changes and momentary focus of this research, heart rate is employed as a feature to assess emotional-arousal changes in users. Cardiovascular activity is correlated with other information regarding user arousal capacity and the level of pleasantness or unpleasantness associated with emotions to differentiate between negative arousal emotions like anxiety and positive emotions like excitement.

2.4. Galvanic Skin Response (GSR)

GSR, also known as Electrodermal Activity (EDA), reflects sympathetic nervous system responses influenced by cognitive and emotional states. EDA metrics are applied to various issues in basic research, such as attention and emotion. These signals can be analyzed alongside Skin Conductance Level (SCL), representing tonic activity, and Skin Conductance Response (SCR), measuring phasic activity [21]. SCR typically measures physiological responses to distinct events, while SCL is useful for measuring overall arousal over a longer timeframe. Previous studies have successfully utilized SCL and SCR as stress indicators during various stress-inducing stimuli [22].

2.5. Sensor Attachment Location on the Body

To ensure optimal data acquisition, the Emotibit sensor was placed on the proximal part of the index finger, a standard location for skin conductance measurements [16]. Participants were instructed to minimize movement during the experiment to reduce motion artifacts. They were seated in the rear seat of a stationary car to control for external environmental factors (Figure 3). Researchers monitored physiological and environmental data in real time to ensure the validity of recorded signals (Figure 4).

2.6. Machine Learning Algorithms for Arousal and Valence Classification.

A machine learning approach was employed to analyze physiological data and classify emotional states based on arousal and valence levels. The classification process involved four key steps:

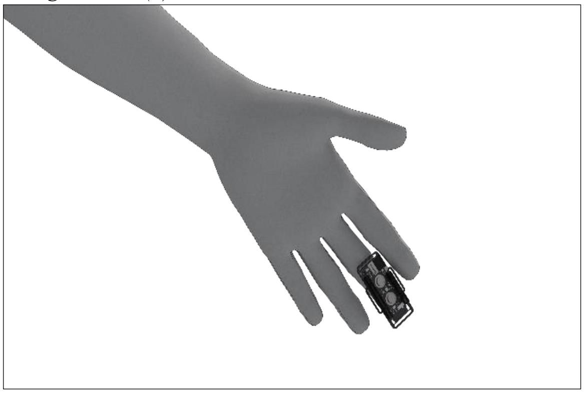

Figure 4. Location of the sensor on the fingers

1. Feature Extraction and Selection: Relevant physiological features, including average HR and GSR values, were extracted to serve as input for the classification model.
2. Preprocessing of Physiological Signals: Data were cleaned by removing motion artifacts and noise using Python's Pandas library and Neurokit2 [23]. Any missing or inconsistent data points were addressed to ensure data integrity.
3. Selection of Emotion Database: The International Affective Picture System (IAPS) database [24] was utilized to provide standardized emotional stimuli. A subset of 24 images was selected from predefined emotional zones, and a 20-minute video was created, displaying each image for 30 seconds followed by a 20-second neutral task (Figure 5).
4. Emotion Classification and Model Evaluation: Various machine learning algorithms were tested for classification accuracy, including decision trees, k-nearest neighbors, support vector machines, and neural networks [17, 18]. The Random Forest algorithm was ultimately selected due to its high precision and robustness in handling high-dimensional physiological data.

2.7. Machine Learning Algorithms for Arousal and Valence Classification

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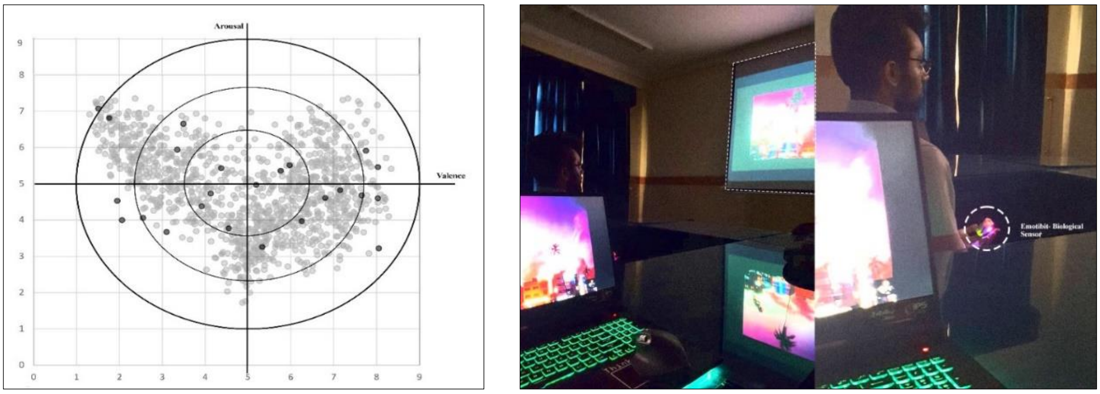

Figure 5. Left: Scatter plot of the results from the IAPS database photos. The gray color corresponds to all the photos, and the black circles represent the photos selected for the present test. Right: Test environment settings considered for displaying IAPS photos

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2.8. Emotion Classification and Model Evaluation

Feature extraction from HR and GSR data allowed emotion classification using the Random Forest algorithm. To evaluate model performance, the dataset was split into 80% training and 20% testing subsets. Emotional states were classified based on arousal and valence dimensions, with a binary labeling system: a score of 1 indicated high arousal or pleasantness, while 0 represented low arousal or unpleasantness. This approach aligns with standard affective computing and psychological research methodologies, providing a simplified yet effective framework for analyzing emotional responses.

2.9. Environmental Atmospheric Sensing

Environmental atmospheric data were recorded to account for external variables influencing emotional responses to complement physiological measurements. A custom portable data logger was developed to collect environmental indicators relevant to urban design and human well-being. This system was specifically tailored to ensure systematic data collection under varying environmental conditions, contributing to the broader applicability of this study's findings.

The experimental framework combining physiological sensing, machine learning classification, and environmental monitoring provides a comprehensive methodology for assessing emotional responses in dynamic settings. The integration of wearable sensing technology and artificial intelligence enhances the precision and reliability of emotional state analysis, offering valuable insights for applications in affective computing, human-computer interaction, and urban design.

2.10. Data Logger Design

The data logger was meticulously designed utilizing an Arduino Nano microcontroller and a selection of sensors tailored for precise weather-related data collection. Careful consideration was given to the choice of sensors to ensure accurate data gathering. A Bluetooth sensor module, HC-06, was also integrated for seamless wireless data transmission.

The HES (Hybrid Environmental Sensing) box incorporates multiple sensors to monitor the environment comprehensively (Figure 6). Temperature and humidity sensors (AM2311) provide real-time data on environmental conditions, while an air pollution sensor (MQ-135) enables monitoring of harmful gases in the atmosphere. Furthermore, a lux meter (BH175) measures ambient light intensity. These sensors collaborate to offer a holistic view of the surrounding environment, empowering users to make informed decisions regarding air quality and energy efficiency. The HES box features a patented recording system for real-time data capture. The Arduino microcontroller facilitates data collection from the sensors, which is then transmitted to a Bluetooth module. This module seamlessly sends data in real-time to a dedicated application.

2.11. Application Design

The application's primary objective was to control, record, and store data collected from a Bluetooth module on the data logger. This was achieved using the Flutter framework and the Dart programming language to provide a user-friendly interface for future use.

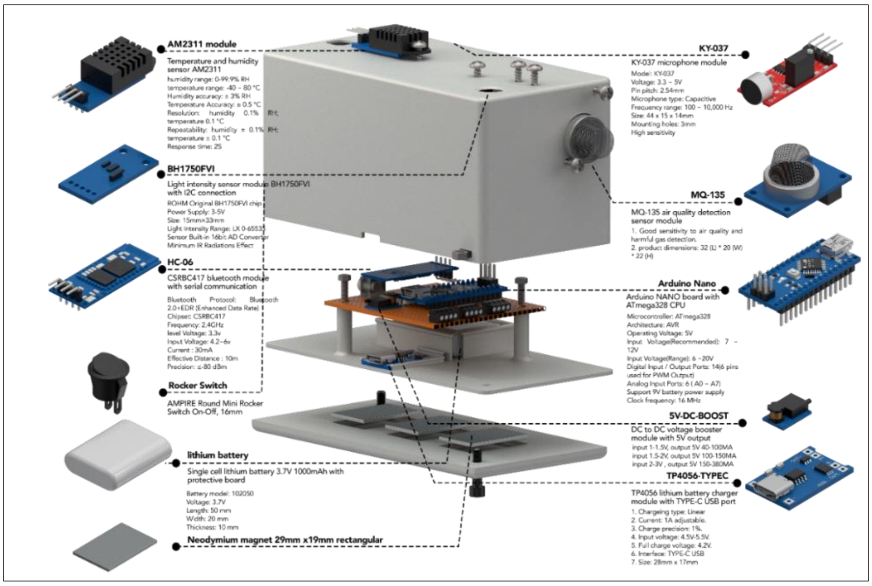


Figure 6. The HES datalogger box is designed with the display of the sensors on the board and the specifications of the sensors used

To record sound intensity data, the application utilizes the phone's microphone. Permission is requested from the user to access the microphone, a standard requirement for applications utilizing audio input. The application receives data sent via Bluetooth from the data logger as a JSON string, which is then converted into a Uint8List buffer for further processing. This conversion process requires using appropriate libraries and packages in the application code to manage the conversion and manipulation of data. Subsequently, the data is converted into a continuous textual line, and the textual data is separated and stored in a Float format.

2.12. Remote Sensing of Urban Objects

An innovative approach for creating and analyzing qualitative and quantitative data for urban zones was adopted, employing voxel-based assessment (VBA). The six-stage process for collecting and categorizing data includes:

1. Aerial Imagery Acquisition: High-resolution aerial imagery of the study zone is obtained.
2. GIS-Based Separation: Land parcels and street networks are separated using available GIS data.
3. Semantic Segmentation: Advanced segmentation algorithms (e.g., U-Net architecture trained on ISO 37120-aligned datasets) are employed to classify urban materials (stone, brick, concrete, soil, natural green materials, and composite materials).
4. 3D Modeling: A 3D volumetric model of the zone is constructed.
5. Texture Attachment: Textural information is assigned to corresponding voxels.
6. Voxelization and Classification: The 3D model is voxelized (with a resolution of 1 m^3) to quantify the spatial distribution of materials and land uses. Voxels are further classified into "stationary" (e.g., built infrastructure with minimal movement) and "mobile" (areas of active transit) based on additional data such as traffic sensor outputs and land-use maps. This approach integrates with our physiological and environmental data to provide a comprehensive picture of urban conditions relevant to Neuro-Urbanism.

VBA is a vital component of a systematic approach to urban analysis. The voxelized representation of cities enables a deeper and more comprehensive evaluation of the materials, locations, sizes, and functions of urban structures and objects (Figure 7).

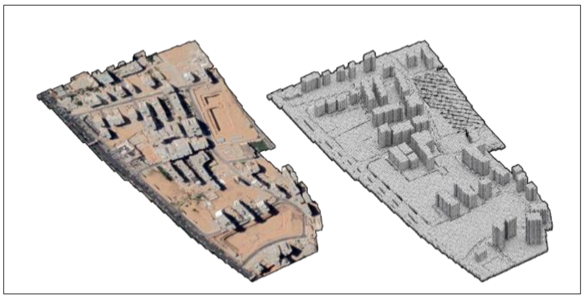


Figure 7. The final voxelized model of the studied zone, coupled with the sensors used and the results of VBA analysis, offers valuable insights into city features and development, informing urban planning decisions and future design considerations.

3. Results

3.1. Statistical Analysis

The statistical analysis conducted in this study aimed to elucidate the intricate relationships between environmental variables, physiological responses, and emotional experiences. Employing a multifaceted approach, the analysis incorporated correlation analysis, significance testing, and regression modeling to comprehensively explore the associations among the diverse datasets.

Initially, correlation analysis was undertaken to scrutinize the pairwise relationships among different environmental factors, physiological measures, and emotional indices. Pearson correlation coefficients were computed to quantify the strength and direction of these associations. Significance testing was then applied to discern the reliability of the observed correlations, with p-values indicating the statistical significance of the relationships.

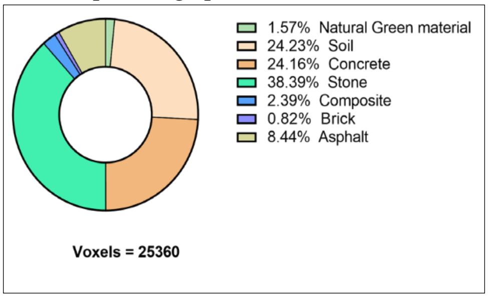
Furthermore, regression modeling was employed to investigate the predictive capacity of environmental variables on physiological responses and emotional experiences. Multiple regression analyses were conducted to assess the collective influence of multiple predictors on the dependent variables. Coefficients of determination (R-squared) were computed to evaluate the proportion of variance in the dependent variable explained by the independent variables.

Overall, the statistical analysis yielded valuable insights into the complex interplay between environmental factors, physiological responses, and emotional experiences. By employing rigorous analytical techniques, this research contributed to a deeper understanding of the mechanisms underlying human-environment interactions in urban settings. The statistical analysis findings have important implications for urban planning, public health, and well-being, informing evidence-based strategies for creating healthier and more sustainable urban environment.

3.2. Voxel-Based Assessment and Material Classification

The voxel-based assessment (VBA) approach provides a multidimensional framework for urban analysis by integrating spatial, environmental, and physiological data. Rooted in Neuro-Urbanism, VBA allows for a granular understanding of how built environments influence human cognition, stress levels, and overall well-being. This method captures micro- and macro-scale features that impact mobility, material composition, and environmental quality by partitioning the urban landscape into uniform volumetric units. The six-stage VBA process encompasses voxel grid generation, material classification, activity mapping, environmental color analysis, physiological data correlation, and integration with machine learning for predictive insights.

The study employed a voxel grid with a resolution of 1 cubic meter to systematically classify urban elements. Material classification followed ISO 37120 urban spatial quality standards, categorizing voxels into stone, brick, concrete, soil, natural green materials, and composite materials (Figure 8).



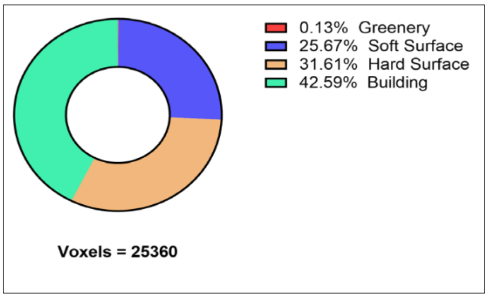
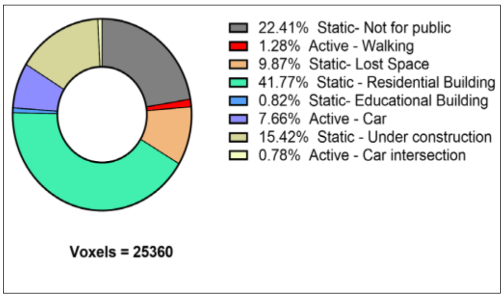


Figure 8. The percentage of each material and type of voxels available on the site

This classification, visualized in Figure 12, reveals that stone is the predominant material, accounting for 34% of voxels, while brick is the least represented at only 0.82%. Additionally, green elements cover merely 0.13% of the area, suggesting an urgent need for enhanced green infrastructure. Figure 8 illustrates zoning classification based on these material distributions.



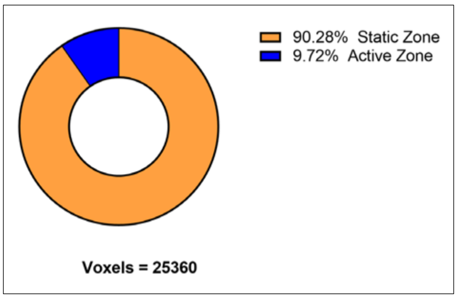


Figure 9. The results obtained from the ratio of voxels to express the potential of a voxel being active or static

Voxel-based activity classification distinguished between "stationary" and "mobile" spaces, integrating traffic sensor outputs and land-use data. Analysis revealed that 90.28% of voxels were associated with stationary activity, while only 9.72% supported mobility. Furthermore, only 1% of voxels were deemed pedestrian-friendly, with the majority allocated to roadways. These findings underscore the scarcity of walkable spaces and the necessity for urban interventions to enhance pedestrian accessibility and mobility behaviors (Figure 9). The environmental color assessment further emphasized the dominance of neutral hues, highlighting a lack of diversity in visual stimuli. This homogeneity in urban color palettes can contribute to lower cognitive stimulation and reduced wayfinding efficiency. Figure 10 illustrates the proportional use of various colors throughout the study zone, supporting the call for a more vibrant and visually engaging urban environment.

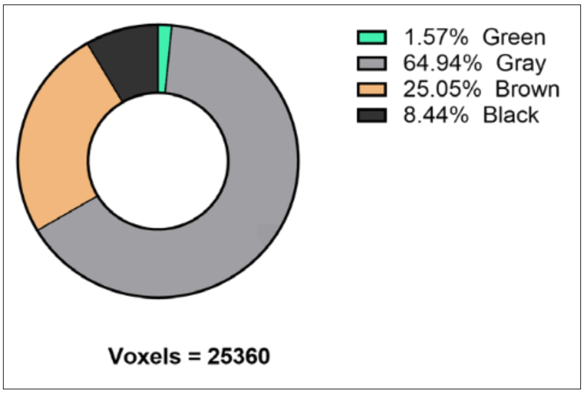


Figure 10. **The ratio of using each color in the studied zone**

Physiological responses were analyzed through EmotiBit sensors deployed on two pilot groups to measure Electrodermal Activity (EDA), Galvanic Skin Response (GSR), and Heart Rate (HR). The results, displayed in Figure 11, indicated that heart rate peaked at the beginning of the path, along steep sections, and near the highway, suggesting heightened stress levels in these areas.

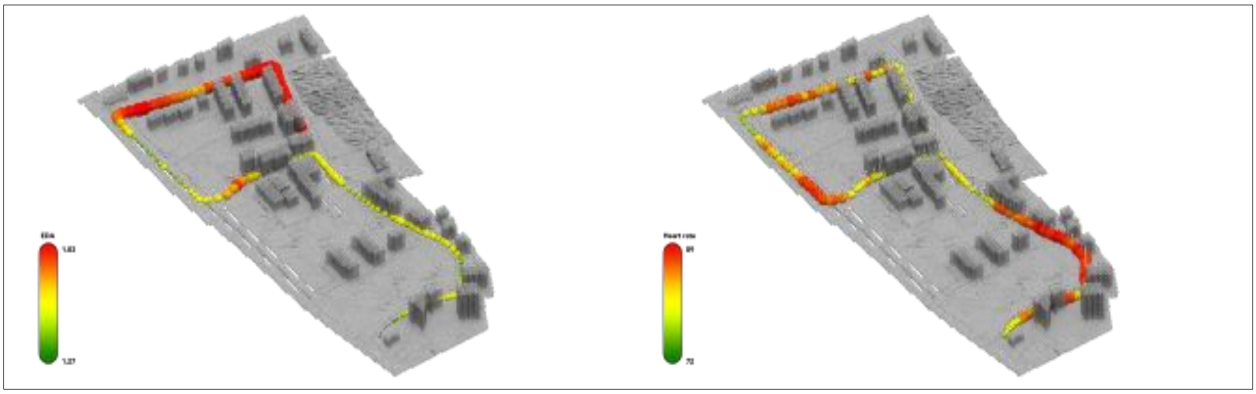


Figure 11. **Average heart rate (left) and galvanic skin response (right) of pilot test participants**

Conversely, GSR data showed a notable decline near the highway in the second sample, potentially reflecting reduced cognitive load or emotional engagement. Applying machine learning models, particularly the Random Forest algorithm, further refined these insights by mapping arousal and valence levels across spatial points (Figures 12 and 13). These results align with theories in Neuro-Urbanism, reinforcing the connection between spatial configurations and psychological well-being.

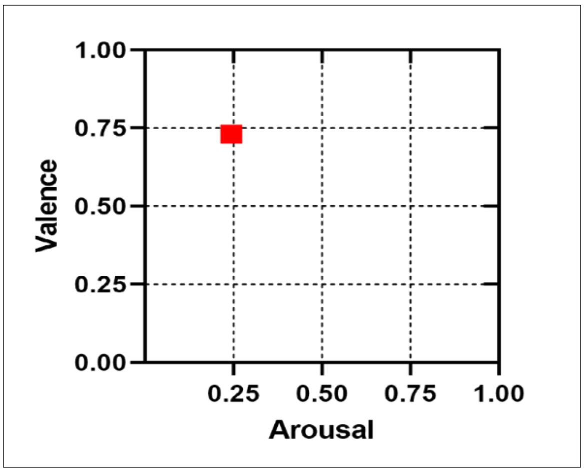


Figure 12. **The Emotional state of the study zone in the Arousal-Valence model**

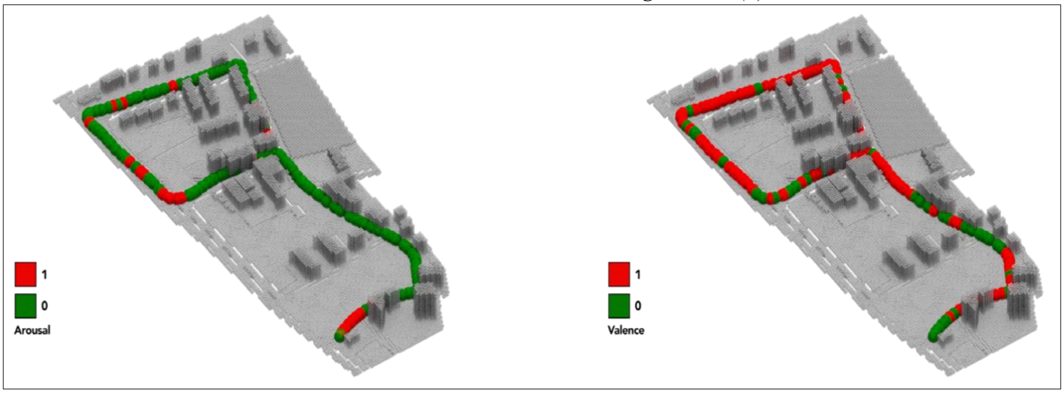


Figure 13. **Point-by-point display of Arousal and Valence resulting from the prediction of the Random Forest algorithm**

Environmental datalogger analysis provided additional context by capturing air quality, sound levels, relative humidity, and temperature variations along the study route. The findings, visualized in Figure 14, revealed an average temperature of 15.22°C, relative humidity of 34%, particle concentration of 1734 PPM, and an average sound intensity of 77 dB. Notably, pollution levels were elevated near major streets, reinforcing the necessity for green infrastructure, pedestrian walkways, and shaded areas to mitigate thermal discomfort and air quality concerns.

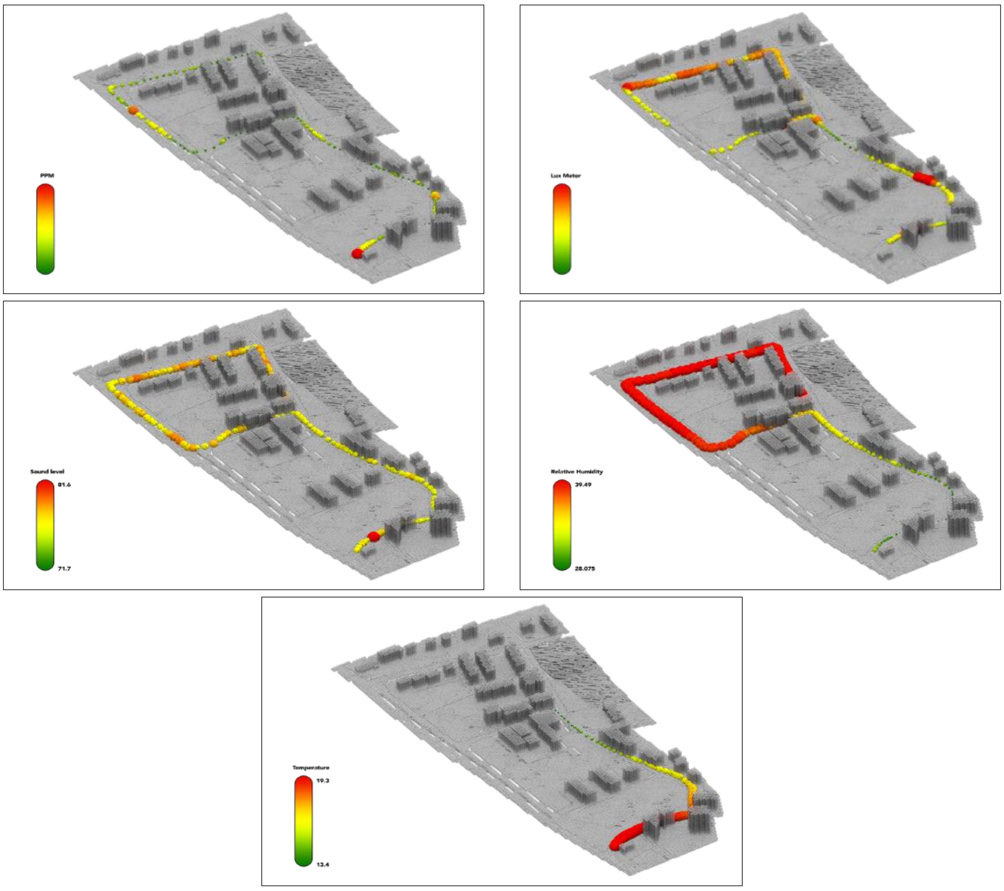


Figure 14. **Point-by-point visualization of the data logger results for the average of the pilot study - a) temperature chart, b) humidity chart, c) air pollution, d) light intensity chart, e) sound intensity chart**

To translate these findings into actionable urban design recommendations, strategic planning should prioritize green buffers, tree-lined streets, and noise-reducing materials to enhance environmental quality. Moreover, integrating physiological and voxel-based spatial analytics underscores the potential for data-driven urban design interventions that promote cognitive well-being and environmental sustainability.

4. Discussion

The study collected environmental and physiological data through various indices, including heart rate (HR), electrodermal activity/galvanic skin response (EDA/GSR), temperature, relative humidity, sound levels, pollution (ppm), and light intensity. The objective was to explore their correlations with emotional states, namely arousal and valence, and to investigate their implications for urban design. The results revealed varying strengths of relationships among these variables, with some correlations exhibiting practical significance and others presenting weak or negligible relationships.

4.1. Heart Rate and Environmental Factors

The correlation between heart rate and environmental factors, as presented in Table 1, reveals several noteworthy findings:

Table 1. The correlation between heart rate and environmental factors

Index	Variable	R squared	P (two-tailed)	P value summary
EDA/GSR	Temperature	0.4043	<0.0001	****
	Relative Humidity	0.3883	<0.0001	****
	Sound Level	0.153	<0.0001	****
	Pollution (ppm)	0.2205	<0.0001	****
	Light Intensity	0.002047	<0.0001	****
	Heart Rate	0.01232	0.1734	ns
Heart Rate	Light Intensity	0.002047	0.5799	ns
	EDA/GSR	0.01232	0.1734	ns
	Temperature	0.07864	0.0005	***
	Relative Humidity	0.135	<0.0001	****
	Sound Level	0.00223	0.5635	ns
	Pollution (ppm)	0.03516	0.0207	*

The correlation between heart rate and light intensity ($r = 0.002$, p = ns) is exceedingly weak and statistically insignificant, suggesting that changes in light intensity have little to no practical effect on heart rate. This observation implies that light intensity may not be a major factor in regulating physiological responses like heart rate, particularly in relatively stable lighting conditions. Similarly, the correlation between heart rate and electrodermal activity/galvanic skin response (EDA/GSR) ($r = 0.012$, p = ns) is also weak and non-significant. This reflects that while both heart rate and EDA/GSR are related to physiological arousal, they do not exhibit a strong interdependence in the context of this study. This suggests that while both indices might reflect changes in emotional or physiological states, they may not always move in tandem or be influenced by other factors.

On the other hand, the correlation between heart rate and temperature ($r = 0.079$, $p < 0.0001$) shows a moderate positive relationship, indicating that heart rate tends to increase with higher temperatures. This suggests that temperature is an important physiological driver, as warmer environments may increase heart rate. This finding is consistent with previous studies showing that heat stress can lead to elevated heart rates. The implications for urban design are noteworthy, as higher ambient temperatures in city environments could contribute to increased stress and discomfort for inhabitants. A stronger positive correlation is observed between heart rate and relative humidity ($r = 0.135$, $p < 0.0001$), pointing to the impact of moisture in the air on cardiovascular responses. High humidity can affect heat dissipation and cause discomfort, potentially increasing heart rate. This relationship suggests that urban areas with high humidity levels might require thoughtful design solutions, such as improved ventilation and shading, to reduce residents' physiological impact.

In contrast, the weak and non-significant correlation between heart rate and sound level ($r = 0.002$, p = ns) suggests noise may not significantly influence heart rate in this context. While sound levels can influence stress and emotional states, their direct impact on physiological indicators like heart rate may be minimal or overshadowed by other factors. Lastly, the weak positive correlation between heart rate and pollution ($r = 0.035$, p = *) indicates a slight increase in heart rate with higher pollution levels. This may suggest that polluted urban environments have a mild physiological effect on individuals, potentially contributing to stress or discomfort. However, the weak strength of this correlation calls for further investigation into whether pollution is a substantial contributor to stress or if other variables are more influential.

4.2. EDA/GSR and Environmental Factors

Table 2 presents correlations between electrodermal activity/galvanic skin response (EDA/GSR) and various environmental factors. These correlations provide valuable insights into how environmental stimuli affect physiological arousal:

Table 2. The correlations between (EDA/GSR) and various environmental factors

Index	Variable	r	95% Confidence Interval	P (two-tailed)	P value summary	Significant? (alpha = 0.05)
Valence	Light Intensity	0.1442	-0.02015 to 0.3009	0.0764	ns	No
	Pollution (ppm)	-0.2640	-0.4101 to -0.1047	0.0010	**	Yes

	Sound Level	0.3296	0.1752 to 0.4681	<0.0001	****	Yes
	Relative Humidity	0.2762	0.1177 to 0.4210	0.0006	***	Yes
	Temperature	-0.3326	-0.4708 to -0.1785	<0.0001	****	Yes
	EDA/GSR	0.4157	0.2703 to 0.5426	<0.0001	****	Yes
	Heart Rate	-0.0292	-0.1921 to 0.1352	0.7208	ns	No
Arousal	Light Intensity	-0.1213	-0.2795 to 0.04343	0.1367	ns	No
	Pollution (ppm)	0.2627	0.1033 to 0.4089	0.0011	**	Yes
	Sound Level	0.02083	-0.1435 to 0.1840	0.7989	ns	No
	Relative Humidity	0.07284	-0.09209 to 0.2339	0.3725	ns	No
	Temperature	-0.007666	-0.1713 to 0.1564	0.9253	ns	No
	EDA/GSR	-0.2075	-0.3591 to -0.04517	0.0103	*	Yes
	Heart Rate	-0.2255	-0.3754 to -0.06399	0.0052	**	Yes

The correlation between EDA/GSR and temperature ($r = 0.4043$, $p < 0.0001$) indicates a strong positive relationship, suggesting that higher temperatures are associated with increased electrodermal activity/galvanic skin response (EDA/GSR). This is consistent with the body's physiological response to heat stress, where rising temperatures lead to heightened arousal, reflected in increased skin conductivity. This finding suggests that urban design strategies aimed at cooling public spaces could help reduce physiological arousal linked to high temperatures, thereby enhancing comfort in those environments.

Similarly, the positive correlation between EDA/GSR and relative humidity ($r = 0.3883$, $p < 0.0001$) implies increased humidity levels are linked to higher arousal. This suggests that urban environments with high humidity could induce stress or discomfort among residents. As a result, there is a need for design interventions to optimize air quality and reduce humidity in enclosed spaces, which could potentially improve residents' comfort and well-being.

A moderate positive correlation between EDA/GSR and sound level ($r = 0.153$, $p < 0.0001$) suggests that noise levels can contribute to physiological arousal, reinforcing the well-documented effects of noise pollution on stress. This highlights the importance of incorporating strategies to mitigate noise pollution in urban areas, such as soundproofing and the inclusion of green spaces, which can have a calming effect on individuals and improve their overall quality of life.

The correlation between EDA/GSR and pollution ($r = 0.2205$, $p < 0.0001$) further suggests that higher pollution levels can increase physiological arousal. This finding emphasizes the negative impacts of poor air quality on public health and suggests that urban areas with higher pollution levels may need interventions to improve air quality. Potential solutions could include expanding green spaces or enhancing ventilation systems, which would help mitigate the effects of pollution on residents' health.

Finally, the weak and non-significant correlation between EDA/GSR and light intensity ($r = 0.002047$, $p =$ ns) suggests that light intensity may not be a major factor influencing physiological arousal in this study. This reinforces the idea that other environmental factors, such as temperature and humidity, significantly shape physiological responses.

4.3. Emotional States: Arousal and Valence

A critical analysis of emotional states, specifically arousal and valence, is crucial for understanding how the environment shapes emotional experiences. The correlation between arousal and pollution ($r = 0.2627$, $p = 0.0011$) suggests a moderate positive relationship, indicating that higher pollution levels are associated with increased emotional arousal. Pollution can induce discomfort, which in turn can trigger heightened physiological responses, such as increased arousal. This suggests that urban areas with high pollution levels may lead to higher stress and emotional arousal in residents. This finding underscores the need for urban design solutions that address pollution and its potential psychological impacts, including strategies for reducing emissions and enhancing air quality.

In contrast, the weak and non-significant negative correlation between arousal and light intensity ($r = -0.1213$, $p =$ ns) suggests that light levels have little to no impact on emotional arousal within the scope of this study. This finding contradicts other studies that have linked natural light exposure to improved mood and reduced stress. It may indicate that the lighting conditions in the study were not extreme enough to elicit a measurable emotional response, or other factors may have been more influential.

The significant positive correlation between valence and sound level ($r = 0.3296$, $p < 0.0001$) suggests that higher sound levels are associated with more positive emotional experiences. This could indicate that participants in the study responded more favorably to certain types of noise, such as music or ambient sound. This highlights the potential for urban design to enhance emotional experiences in public spaces by carefully considering and controlling soundscapes, potentially using nature sounds or calming music to improve the emotional atmosphere.

On the other hand, the moderate negative correlation between valence and pollution ($r = -0.264$, $p = 0.001$) suggests that higher pollution levels are linked to lower emotional satisfaction. This finding emphasizes the importance of cleaner air for improving emotional well-being. Urban environments with lower pollution levels will likely foster more positive emotional states, enhancing residents' overall quality of life. Cleaner air may create a more pleasant environment and positively influence residents' emotions.

The negative correlation between valence and temperature ($r = -0.3326$, $p < 0.0001$) suggests that higher temperatures are associated with lower emotional satisfaction, aligning with previous studies showing discomfort caused by excessive heat. In light of this, urban design strategies, such as increasing greenery, adding shaded areas, or implementing cooling techniques, could help mitigate the negative emotional effects of high temperatures and improve the comfort of public spaces.

These findings underscore the significance of linking emotional states to urban features. The relationship between green spaces and valence highlights the role of a cleaner, greener environment in promoting positive emotional experiences. Urban areas rich in greenery can reduce the negative effects of pollution, fostering calmness and satisfaction. The relationship between noise and arousal also suggests that urban design can leverage soundscapes to influence emotional states. Designers can create spaces that positively impact residents' emotional well-being by incorporating natural sounds or reducing unwanted noise.

5. Conclusion

This study comprehensively evaluates urban environments by integrating voxel-based assessments, physiological measurements, and environmental data to investigate the intricate relationships between spatial features, human health, and emotional experiences. The voxel-based assessment (VBA) revealed key deficiencies in stationary activity spaces and pedestrian-friendly features, emphasizing the need for urban redesigns that prioritize mobility and human-centric environments. Furthermore, the prevalence of materials such as stone and concrete, alongside the minimal presence of greenery, indicates a missed opportunity for green infrastructure and highlights the potential for improving environmental quality through targeted design interventions.

The physiological data, obtained through EmotiBit sensors measuring Electrodermal Activity (EDA/GSR) and Heart Rate (HR), complement the voxel-based insights by providing physiological evidence of how urban spaces influence emotional and physical states. Notably, higher heart rates and increased arousal levels were observed in areas with environmental stressors such as highways and steep pathways. These physiological responses were closely correlated with environmental variables such as temperature, humidity, pollution, and light intensity, demonstrating the direct impact of these factors on individuals' emotional states and overall well-being.

The voxel-based data and physiological measurements offer a robust framework for understanding the dynamic interplay between built environments and human health. The findings underscore the potential for regenerative urban design, where environmental features such as green spaces and pedestrian-friendly pathways could foster emotional well-being and promote healthier, more sustainable urban living. By considering spatial data and physiological responses, urban planners can create environments that support physical activity and emotional balance, leading to more resilient and people-centered cities.

However, several limitations warrant attention. The small sample size of physiological data presents a significant challenge, as it limits the statistical power of the analysis and the generalizability of the findings. With a larger sample, the robustness of the correlations between environmental factors and physiological responses could be more confidently assessed. Additionally, the sample was collected within a limited timeframe, which may not have captured the full range of seasonal variations or the long-term effects of environmental stimuli. Weather variability and other confounding factors, such as noise or traffic, could have influenced physiological readings, further emphasizing the need for more controlled and longitudinal studies to account for these factors.

The voxel-based assessment’s resolution was another limitation, as it may not have fully captured the fine-grained spatial dynamics of the study zone. Future studies could benefit from higher-resolution data collection methods and more sophisticated spatial analytics to provide deeper insights into urban form and its effects on human experience. Moreover, the analysis did not incorporate socio-economic variables, such as income levels or population density, which could have influenced the participants' emotional responses. Future research should explore how these socio-economic factors interact with the physical environment to shape individuals' experiences in urban spaces.

Future research should build on these findings by addressing the limitations discussed. One critical avenue for future exploration is to investigate the role of green space interventions in altering emotional states and physiological responses. Specifically, how do green infrastructure implementations, such as parks or green rooftops, influence arousal levels and heart rate in similar urban zones? Another important direction is the exploration of specific urban design interventions that could enhance pedestrian experiences, such as traffic calming measures or introducing more shaded areas. Understanding the potential impact of these interventions on human well-being will be crucial for advancing urban planning practices that prioritize health and sustainability.

Longitudinal studies are also needed to assess how environmental factors evolve and how these changes affect human health. For example, tracking seasonal changes in temperature, humidity, and pollution levels could provide valuable insights into how individuals adapt to fluctuating conditions and how urban design can mitigate negative impacts on health. Additionally, incorporating qualitative data from residents, such as perceptions of safety and community well-being, would offer a more holistic view of how urban environments influence emotional experiences.

In conclusion, this study contributes significantly to the growing field of neuro-urbanism by demonstrating the complex relationships between urban environments, human physiology, and emotional experiences. While the current study has limitations, the insights gained provide a foundation for future research that will continue to refine our understanding of how urban design can foster healthier, more resilient communities. We can further develop evidence-based design strategies that prioritize human well-being and environmental sustainability by addressing these limitations and pursuing more targeted research questions.

6. Statements & Declarations

All authors have read, understood, and have complied as applicable with the statement on "ethical responsibilities of authors" as found in the instructions for authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

6.1. Competing Interests

The authors declare no competing interests.

6.2. Funding

There is no funding for this research article.

6.3. Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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