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Multisensory Comfort in Public Open Spaces: Predicting Perceived Comfort from Environmental Conditions

Ni Putu Amanda Nitidara[1]*, Joko Sarwono[2], Suprijanto[3]
[1,2] Built Environment Performance Engineering Research Group, Bandung Institute of Technology
Jl. Ganesha No.10, Lb. Siliwangi, Kecamatan Coblong, Kota Bandung, Jawa Barat 40132, Indonesia
[3] Instrumentation Control and Automation Research Group, Bandung Institute of Technology
Jl. Ganesha No.10, Lb. Siliwangi, Kecamatan Coblong, Kota Bandung, Jawa Barat 40132, Indonesia

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Corresponding Author:
Ni Putu Amanda Nitidara
Built Environment Performance Engineering Research Group, Bandung Institute of Technology,
Jl. Ganesha No.10, Lb. Siliwangi, Kecamatan Coblong, Kota Bandung, Jawa Barat 40132, Indonesia
Email: amandanitidara@itb.ac.id

Abstract

This study investigates comfort in public open spaces in Bandung by linking measured environmental conditions with visitor perceptions collected through questionnaires. Logistic regression was applied to model the relationship between the two data sets. The model achieved good discriminatory power for predicting comfort, with Area Under the Curve (AUC) of 0.752, accuracy of 0.679, precision of 0.884, and sensitivity of 0.686. Five parameters emerged as significant predictors of comfort: L_{90}, relative humidity, DGI, wind speed, and temperature. Higher comfort is associated with lower values of L_{90}, DGI, and temperature, while increasing relative humidity and wind speed improves comfort. These results confirm that overall comfort in outdoor urban environments arises from multisensory interactions. Understanding these interactions provides urban planners and architects with a practical basis for developing strategies to improve the quality and livability of public open spaces.

INTRODUCTION

Comfort is a feeling of satisfaction with the quality of the surrounding environment; therefore, it is an essential factor that influences the use of space (Lai et al., 2020; Rohde et al., 2020). Our environment consists of various physical conditions that cause numerous sensations, ranging from thermal sensations (hot, cold, humid, dry), visual sensations (brightness, glare, color), audio sensations (loudness, pitch, timbre), and also olfactory sensations (aroma, scent, smell). We feel all these sensations simultaneously, leading us to determine whether the space we occupy is comfortable. Overall comfort refers to our overall assessment of the combined sensations experienced due to environmental conditions (Du et al., 2023; Yang & Moon, 2019).

Research on comfort begins by examining the relationship between comfort perception and objective physical parameters, defining comfort as a measurable variable (Mamani et al., 2022; Riffelli, 2021). The research typically evaluates a single sensory modality, isolating its effects on comfort perception from interference by other sensory modalities. Many studies primarily focus on auditory, thermal, and visual aspects as the main stimuli. Several indices have also been produced and widely used to assess environmental quality (ANSI/ASHRAE, 2013; Hopkinson, 1972; Kep-48/MENLH/11, 1996; Wienold & Christoffersen, 2006).

Noise indices have been developed to assess the quality of the sound environment and are widely used in regulatory frameworks. A study comparing perceived sonic environmental quality in city parks and suburban parks concluded that, for city parks to be perceived as having sonic quality equivalent to suburban parks, noise levels (L_{eq}) should not exceed 50 dB(A) (Nilsson & Berglund, 2006). Other studies have also examined factors influencing soundscapes in urban environments (Acun & Yilmazer, 2019; Cao & Kang, 2021). Some studies have also used the concept of sound masking to improve auditory comfort (Axelsson et al., 2014; Lu et al., 2025; Puyana-Romero et al., 2021). It demonstrates how soundscapes have a role in shaping auditory comfort by a combined approach with noise evaluation.

Visual comfort indices related to photometric and colorimetric have also been developed and widely used for indoor environments. Metrics such as illuminance, luminance, and glare quantify the amount of light and its quality. These indices have been adopted as standards for indoor lighting along with discomfort glare index from the CIE (CIE 117, 1995) and the IES Lighting Handbook (Illuminating Engineering Society of North America, 2000). Outdoor visual comfort, on the other hand, is often assessed based on visual preferences and qualitative aspects. Glare, however, is an important factor not only indoors but also outdoors (Spieringhs et al., 2022; Tyukhova, 2024). It evaluates the contrast between different surfaces and vocal point in the environment. Research also shows that other factors, such as daylighting, shading factors, and light uniformity in pedestrian areas, contribute to visual comfort and enhance the experience in urban public spaces (Wänström Lindh & Jägerbrand, 2021).

Similarly, thermal comfort is also typically assessed in indoor settings. Thermal comfort indices, such as PMV and PPD (International Organization for Standardization, 2005), evaluate conditions based on microclimatic variables (temperature, humidity, and solar radiation) and human physiological factors. Several studies have demonstrated modifications of thermal comfort indices such as UTCI (Jendritzky et al., 2012), PET (Höppe, 1999), and SET (Zhang & Lin, 2020) for use in outdoor environments. Moreover, thermal comfort has become an increasingly important aspect to observe due to climate change (Bartesaghi-Koc et al., 2021; Lehnert et al., 2021). Several studies have shown that cities are beginning to use landscape elements such as plants, water features, and shading to improve thermal comfort in public open spaces (Gachkar et al., 2021; Nasrollahi et al., 2021; Triyuly et al., 2021).

While existing research has provided fundamental knowledge of comfort perception, it requires more research on the interaction between sensory modalities and how these interactions affect overall comfort. Several studies have examined bimodal interactions, such as audio-thermal, visual-thermal, and the more common audio-visual interactions. For example, research on streetscapes found that auditory aspects produced a more significant restorative effect than visual aspects, and observing their interaction provides a more comprehensive understanding (Lu et al., 2025). Other research also examined the interaction of audio-visual-thermal aspects in urban parks and produced a model of overall comfort that combines all three aspects (Nitidara et al., 2022). These studies provide initial evidence of a multisensory relationship between the auditory, visual, and thermal comfort aspects.

The study explained in this paper is interested in observing multisensory interactions, especially for public open spaces in urban areas. While most research has primarily focused on indoor settings, outdoor environments present more challenges as they cannot be controlled or modified to the same extent. Creating comfortable outdoor spaces is thus more challenging. This study proposes that a multisensory approach may offer a better framework for understanding overall comfort in public open spaces.

This study builds on our previous research that objectively measured the conditions of public open spaces in Bandung and compared these with visitor perceptions collected via a questionnaire. That earlier work described the existing conditions of public open spaces in the city (Nitidara, 2022) and a Structural Equation Model that explains the relationship and interaction between audio–visual–thermal aspects and overall comfort (Nitidara et al., 2022). In this paper, we utilize those data to create and validate a predictive model that connects objective parameters with overall comfort perceptions using logistic regression. Furthermore, we also identify which objective parameters most strongly influence changes in overall comfort. Finally, we present case studies demonstrating the model's applicability and its design implications.

METHODS

Data Sources and Study Design

This study used the same dataset as the initial study. This dataset contains environmental conditions derived from measurements and visitors' perceptions obtained from questionnaires. Details of the data collection process are described in that study (Nitidara, 2022), while this paper provides more detail on the data modelling process. The main aim of this paper is to capture visitors' overall comfort perception and connect them with the environmental conditions that affect these perceptions.

A total of 420 data were collected from eight public open space locations in Bandung. Data were collected only when visitors were present at each location, at different times of day during the rainy season (October–December) and the dry season (June–August). Data collection times were not standardized across locations because our goal was to observe the conditions under which people reported overall comfort rather than to compare raw parameter values across locations. Variability in the environmental conditions (audio, visual, and thermal) was therefore essential for the analysis.

Objective Measures and Target Variable

This study simultaneously observed environmental conditions, including audio, visual, and thermal aspects. Audio aspects were observed using environmental noise parameters L_{10}, L_{50}, L_{90}, and L_{eq} (dB(A)). The parameter values were obtained from soundscape recordings taken at the visitor's location on site. Visual aspects were observed using glare index parameters, namely DGP and DGI (–). These parameters were derived using pixel-based techniques on calibrated HDR images from the data collection site. Thermal conditions were assessed using air temperature (°C), relative humidity (%), and wind speed (m/s). These parameters were measured at the observation site with an environmental meter and an anemometer. The detailed process of field data collection and processing is described in the initial study (Nitidara, 2022). In total, these nine objective parameters served as predictors in the modeling.

The target parameter in this study was overall comfort perception, obtained from visitor questionnaires. Overall comfort was expressed as a binary condition: comfort (1) and discomfort (0). Details regarding the questionnaire can also be found in the initial study (Nitidara, 2022). All questionnaires and environmental parameters were collected at the same time.

Statistical Data Processing and Logistic Regression Modeling

We combined environmental condition data obtained from field measurements with the perception score of overall comfort from questionnaires to create a predictive model. The modeling was performed using logistic regression because the target parameter, overall comfort, is a binary condition between comfort (score = 1) and discomfort (score = 0). Thus, a complete data set consisting of nine objective parameters (L_{10}, L_{50}, L_{90}, L_{eq}, DGP, DGI, temperature, relative humidity, and wind speed) and one overall comfort score.

We start with data preprocessing, taking into account missing data, multicollinearity, and data standardization. The model used 321 complete data sets obtained from a total of 420 questionnaire surveys, after removing some missing data. The nine objective parameters were then tested for multicollinearity using Pearson correlation. Parameters with high correlations (greater than 0.65) were reduced and represented by one of the stronger parameters. Due to a high correlation to L_{90}, we discarded parameters L_{eq}, L_{10}, and L_{50} from the model. DGP and DGI also show a strong correlation, so the DGI parameter was selected as a representative parameter because its scale is more comparable to the ranges of the other parameters. As a result, the total number of parameters was decreased from 9 to 5. Additionally, the values for these five parameters were z-standardized before modeling.

All data processing was performed using Orange software with a workflow as shown in Figure 1. Logistic regression was performed using the logistic regression widget with the ridge (L2) regularization method. Due to the unequal distribution of the target variable, where approximately 80% of the data indicates comfort, we applied balanced class weight during model fitting in the logistic regression widget. Performance of the model was evaluated using the test and score widget with a 10-fold stratified cross-validation method. We then report the results of the Receiver-operating characteristic curve (ROC) and its Area under the curve (AUC), specificity, accuracy, precision, and sensitivity. We also observed the nomogram to visualize the contribution and direction of each predictor to overall comfort. Additionally, we utilized FreeViz widget to assess location-wise patterns and illustrate the influence/direction of the contributing objective parameters.

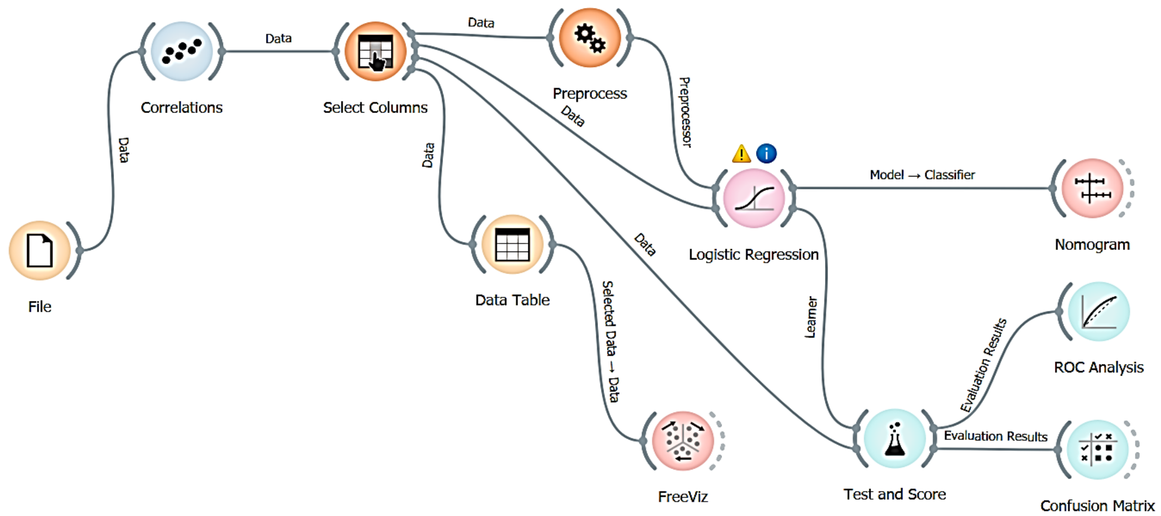

Fig. 1. Orange workflow
(Source: author)

RESULTS AND DISCUSSION

On-site measurements showed that public spaces in Bandung had temperatures ranging from 24–34 °C, humidity levels between 40–65%, in the dry season, temperature ranged between 27–34 °C with relative humidity between

40–55%, while in the rainy season, temperature was lower (24–26 °C) and relative humidity higher (55–65%). Wind velocities are relatively similar in both seasons at 0–3 m/s. L_{eq} values range from 55–85 dBA, and visual discomfort is noticeable within 50% of the data. Many of these conditions exceeded common standards for thermal, acoustic, and visual comfort. However, our earlier study found that about 80% of visitors still reported feeling comfortable in these spaces (Nitidara, 2022). This mismatch between objective indicators and subjective evaluations underscores the need for a predictive approach that accounts for the interaction of multiple factors. The following sections present the performance of the logistic regression model, identify the most influential predictors, and discuss their implications for design.

Model Performance

The logistic regression model showed an AUC value of 0.752, as shown in the ROC curve in Figure 2. This AUC value indicates that the model provides good performance and discriminatory power to separate comfortable and uncomfortable conditions. Table 1 shows the confusion matrix of the 321 data points used for modeling. The model has an accuracy of 0.679, a precision of 0.884, and a sensitivity of 0.686. Accuracy indicates the overall proportion of correctly predicted cases across both comfortable and uncomfortable conditions. Precision shows how reliable the model is when it predicts a space as comfortable, while sensitivity measures the ability of the model to correctly identify uncomfortable conditions. Based on our model, higher precision than sensitivity values indicates that the model is better at predicting comfortable conditions than uncomfortable ones. The class imbalance between comfortable and uncomfortable is the leading cause of the lower sensitivity, even though the modeling process included a class-balancing algorithm. For the application of the model in environmental design and prediction, both precision and sensitivity metrics are equally important. Precision enables us to create guidelines for conditions considered comfortable, while sensitivity ensures we do not overlook conditions that cause discomfort.

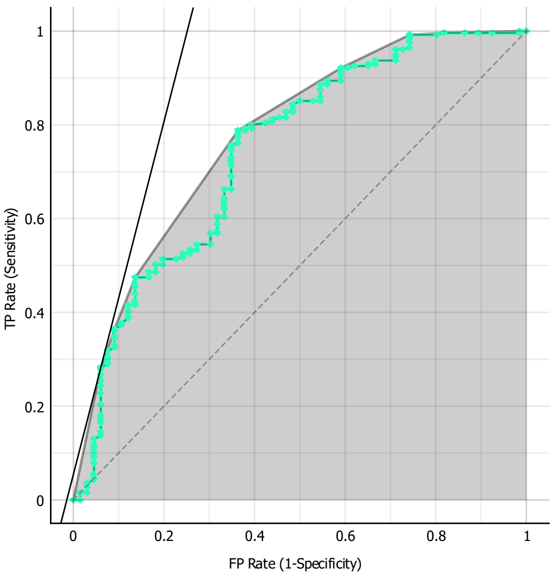

Fig. 2. ROC curve from logistic regression model with AUC = 0.752

Table 1 Confusion matrix of the logistic regression model

		Actual	
		0	**1**
Predicted	**0**	43	23
	1	80	175

Predictor Importance and Interaction

In addition to observing the model's performance, we were also interested in determining which environmental parameters significantly influence comfort. The nomogram in Figure 3 displays the five predictors ranked by their influence on comfort, along with the direction of that influence. In order of most influence, they are as follows: L_{90}, relative humidity, DGI, wind speed, and temperature. L_{90}, DGI, and temperature all show a decreasing trend. As the values of these three parameters decrease, the likelihood of comfort increases. Meanwhile, relative humidity and wind speed show an increasing trend, meaning that increasing the values of these two parameters also increases the likelihood of achieving comfort. By using this nomogram, we can better observe that overall comfort is indeed a multisensory interaction.

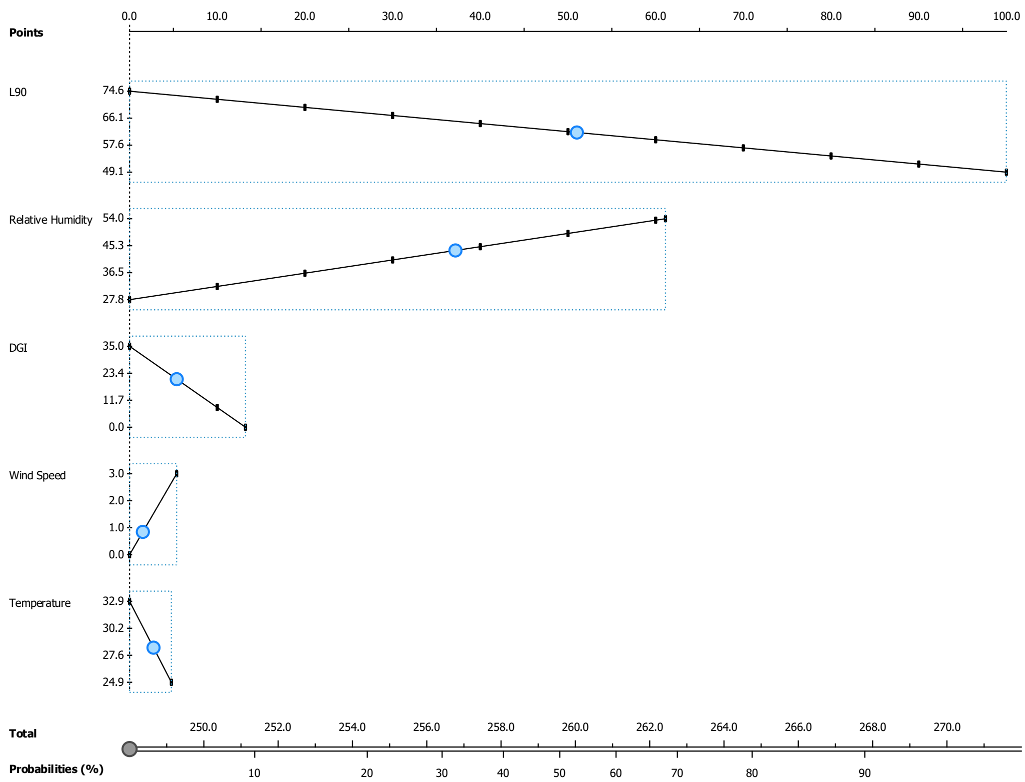

Fig. 3. Nomogram of the Logistic Regression Model, Showing Scale of Importance and Direction of Influence for Each Predictor

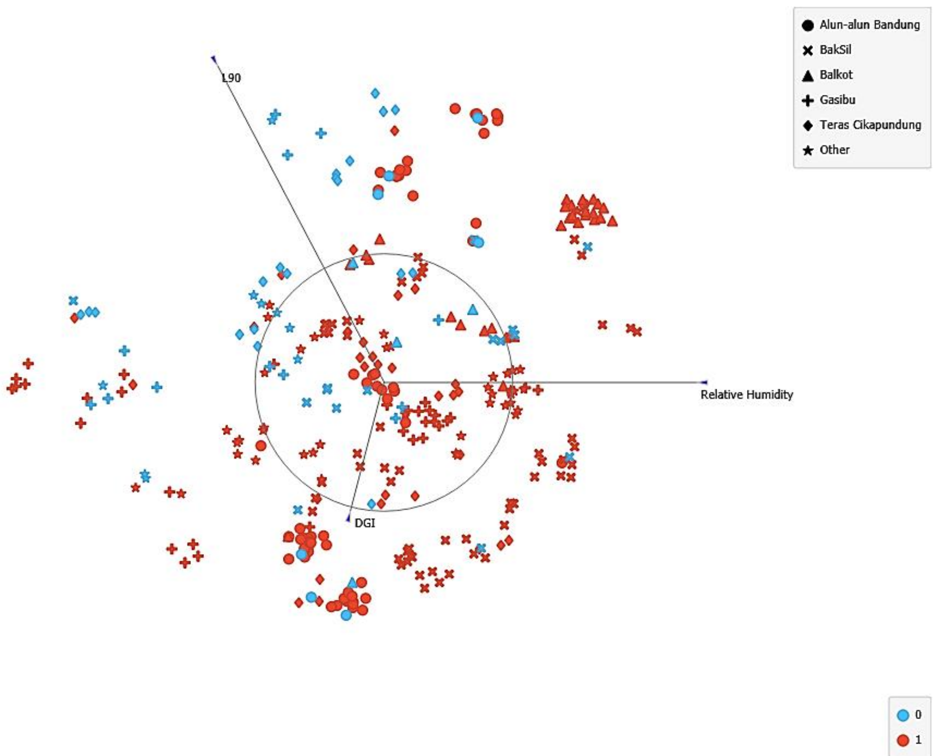

Fig. 4. Analysis of the Overall comfort based on observed locations

To further explore the interactions between predictors, we visualized the data using FreeViz (Figure 4). The top three parameters (L_{90}, relative humidity, and DGI) are depicted as axes. Wind speed and temperature are included in the model, but they have a lesser impact and are therefore not plotted as additional axes in the diagram. This decision helps maintain a clear visual representation of the directionality of each parameter, making the data easier to interpret.

Each point represents measurement data plotted on the axes based on the environmental conditions of each parameter. Red indicates comfortable conditions, while blue indicates uncomfortable conditions. Different shapes represent different data collection locations. From this diagram, we can observe several things: 1. The number of uncomfortable data is indeed smaller than the number of comfortable data. 2. Uncomfortable data appear in areas with high L_{90} and DGI values. 3. Comfortable data are primarily found in areas with high relative humidity. This visualization reinforces the nomogram results and illustrates how multiple predictors interact to shape perceived comfort.

Site Patterns and Design Implications

The interactions between parameters, as shown in Figure 4, also help us identify which locations visitors generally describe as comfortable or uncomfortable. Among the eight site locations, Babakan Siliwangi is considered comfortable because its microclimate has a relatively high relative humidity with a low L_{90}. Although it is surrounded by main roads, the traffic is not as heavy, and the area is covered with trees and vegetation, which reduces noise by acting as a sound barrier while also enhancing the microclimate conditions. Conversely, Lapangan Gasibu and Teras Cikapundung are often considered uncomfortable, primarily due to their high L_{90} values and low relative humidity. These areas, particularly the Lapangan Gasibu, are exposed to heavy traffic.

The analysis presented earlier reveals that human perception of overall comfort is not a simple, single-dimensional concept but encompasses multiple aspects. If we look at these aspects in isolation, we will find that in some conditions the environmental conditions do not comply with the standard. However, when asked to evaluate their overall experience, visitors will report feeling comfortable in the public open space. This result indicates that visitors' assessment of the environment is holistic and does not isolate any particular aspect. Each physical aspect contributes to overall comfort, meaning that trade-offs are likely to occur; if one aspect of the environment is lacking, it can be compensated for by improvements in other areas.

In the case of Lapangan Gasibu, for example, rather than viewing this exclusively as an environmental noise problem, we can adopt a comprehensive approach using the multimodal principle. If high noise levels are difficult to avoid in Lapangan Gasibu and adding a sound barrier might negatively affect the area's aesthetics, we should instead focus on improving overall comfort by altering the microclimate in the vicinity. These solutions include adding more vegetation (Gachkar et al., 2021; Van Renterghem, 2019; Van Renterghem & Botteldooren, 2016) or incorporating water features into the area (Axelsson et al., 2014; Puyana-Romero et al., 2021). By understanding this multisensory interaction, city planners and architects can develop alternative strategies to address various issues.

Limitation and Future Work

This study has several limitations. First, the environmental measurements and questionnaire responses were not fully time-synchronized across sites. This limitation makes it difficult to compare sites directly. However, it does reflect the actual dynamics of public spaces: visitors have the freedom to choose whether to stay or leave, which in itself serves as an indicator of comfort. This dynamic also explains the class imbalance in the dataset, with comfort reported more often than discomfort. While this skews model sensitivity, it also underscores the ecological validity of the data. In this study, the model has already achieved high precision, and future work could aim at improving the sensitivity to achieve a more balanced predictive performance. Second, the study did not account for contextual variables such as activity type, duration of stay, or social setting, all of which may shape comfort perceptions. Their omission may limit the explanatory power of the model. Lastly, while measurement data were collected during both the dry and rainy seasons, the perceived comfort data for the rainy season were not sufficient to build a separate model. Therefore, the current model may be more representative of dry season conditions, and future studies should aim to validate it across different seasonal contexts.

Future research should address these gaps through controlled experiments where conditions and responses are measured in real time. Multisensory virtual environments provide a controlled way to vary thermal, visual, and acoustic conditions, while also allowing for the recording of physiological and perceptual data. Such environments could also help rebalance the representation of uncomfortable conditions, ensuring models capture the full spectrum of comfort. In addition, incorporating contextual information about activities and social interactions would provide a more comprehensive understanding of comfort in urban spaces.

CONCLUSION

This study developed a logistic regression model to link environmental conditions with perceived comfort in urban public spaces in Bandung. The model achieved good discriminatory power (AUC = 0.752) and identified five key predictors of comfort: L_{90}, relative humidity, DGI, wind speed, and temperature. Higher comfort was associated with lower L_{90}, DGI, and temperature, while higher relative humidity and wind speed contributed positively to comfort. These results confirm that outdoor comfort emerges from multisensory interactions rather than single-domain parameters.

Despite some limitations, this study presents a new insight for urban designers and architects. The model provides a framework for identifying design strategies that combine the influences of audio, visual, and thermal conditions. It emphasizes multisensory observations to assess overall comfort in their projects and explores how interactions between different sensory modalities can help mitigate certain shortcomings. Future studies should validate the model under different temporal and spatial contexts to strengthen its applicability in diverse urban settings.

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