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People in Cities: Combining subjective occupant feedback with urban-scale data to support indoor and outdoor thermal comfort

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ABSTRACT

The increasing availability of urban-scale, open-access datasets can support decision-making in urban planning, in particular in relation to climate resilience and climate change mitigation. Such data-driven initiatives however often neglect the central role of urban dwellers, whose activities create the demand for energy and mobility in urban areas. This is due in large part due to the difficulty of data collection at this scale, along with privacy concerns arising from any such data collection effort. The use of wearable technologies for self-reported comfort feedback from urban dwellers provides a promising opportunity for citizens to actively participate in the adaptation of urban areas to better support outdoor comfort and climate resilience.

In this work, subjective feedback data from 22 participants in a longitudinal test in Seoul, South Korea was collected through a smartwatch application. Participants were required to wear a smartwatch for 4–6 weeks, during which time their location as well as environmental and physiological data were collected. Participants were also requested to complete hourly micro-surveys, in which they were asked about their activities, location, thermal preference, clothing level, comfort adaptations, and mood. This information was complemented by an urban scale dataset comprising building geometries and data from 1000+ weather stations over the same period.

This cross-scale dataset was then used to investigate the relationship between urban form and environmental parameters with occupants' survey responses. The relationship between indoor comfort and environmental parameters in the case study is discussed, with recommendations for further research into this topic. The use of machine learning to leverage the combination of spatial, temporal, and subjective preference data to predict occupants' outdoor comfort as a function of their urban environment is also explored.

KEYWORDS

Urban microclimate, Thermal comfort, Occupant behavior

INTRODUCTION

The increasing availability of data in urban environments, from sources such as urban weather stations, smart meters, telecommunications providers, and remote sensing, can provide valuable information to decision makers in urban planning. These dynamic and complex information streams have not only digitized the planning profession but increased the intractability of urban modeling and participatory planning, making urban analytical methods indispensable (Yap et al. 2022). In particular, distributed weather

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stations combined with modeling techniques can provide insight into the effects of urban morphology on land surface temperatures and the urban heat island (Maiullari 2023, Jeon et al. 2023). Such insights can be valuable tools to planning urban interventions to ensure outdoor and indoor thermal comfort and support urban climate resilience (Mei and Yuan 2022).

At the same time, the use of wearable technologies in research to measure physiological and behavioral data to help understand the health and well-being of building occupants throughout their daily activities is gaining interest (Becerik-Gerber et al. 2022). Environmental data combined with occupant feedback and physiological information can be used to train personalized comfort models to support optimal building system controls, post-occupancy evaluation, and spatial recommendations in activity-based workspaces (Jayathissa et al. 2020). Similarly, outdoor climate information combined with sensing technologies can also be used to investigate outdoor thermal perception and walkability in urban environments (Peng et al. 2022). By deploying humans as sensors in urban areas, researchers have collected urban-scale datasets on humans' subjective perception and physiological and environmental measurements to investigate noise distraction and thermal preference across a diversity of spaces (Miller et al. 2023).

In this paper, we explore the use of urban-scale data from GIS and distributed weather sensors along with physiological data and subjective feedback from participants to investigate indoor and outdoor thermal comfort in a dense urban area. For this purpose, we recruited 22 study participants, who wore smartwatches that collected their physiological and location information and prompted them to complete hourly micro-surveys on their location, activities, and subjective comfort over a 4–6-week period. This information is complemented by an urban-scale dataset including building geometries and environmental data from 1000+ sensors in the city of Seoul, South Korea. This information is used to explore the use of this data to train personal comfort models in indoor and outdoor environments and present their limitations and suggestions for future research.

METHODOLOGY

This work entailed the collection of an urban-scale dataset about the city of Seoul, South Korea, along with a building occupant-scale dataset about participants' physiology, location and subjective feedback over a 4- to 6-week period. A general description of the data collection effort is presented in Mosteiro-Romero et al. (2024).

Study participants were recruited from the student population at Chung Ang University in Seoul. Before participation, they completed an onboarding survey in which demographic information was collected (gender, age, height, weight) as well as completing surveys to establish their sensitivity to their environment rated on a 7-point scale (Pluess et al. 2023), their satisfaction with life score on a 7-point scale (Diener et al. 1985) and their score on the big five personality traits, again on a 7-point scale (Gosling et al. 2003). Participants were required to wear a smartwatch on weekdays from 9 am to 7 pm for a minimum of four weeks, during which time they received hourly reminders to complete a micro-survey through the smartwatch application Cozie. As seen in Fig. 1, the micro-survey questions related to their location, activity, thermal preference, mood, and any adaptive comfort adaptations they might have undertaken in the previous hour. During this time, their location was also recorded, as well as physiological information from the smartwatches' health kit data. After selecting relevant health-related parameters and dropping parameters with insufficient information, the following health-related parameters were selected: heart rate, environmental audio exposure, stand time, and walking distance.

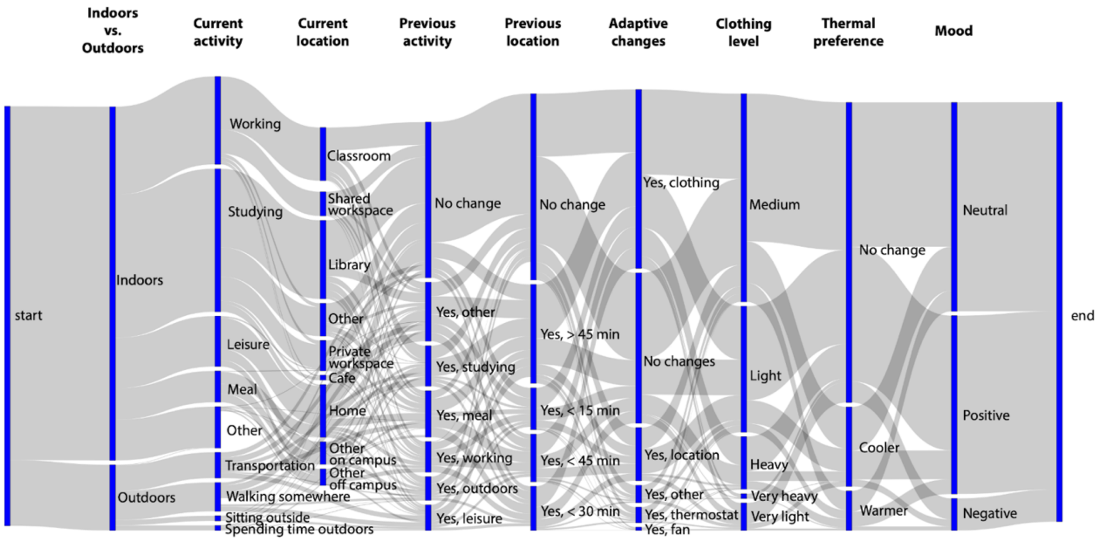

__Figure 1.__ Distribution of survey responses for all participants at the end of the study.

Participants who completed a minimum of 100 surveys in less than four weeks were invited to extend their participation for another two weeks, meaning that the duration of the study for all participants varied from 4 to 6 weeks, with a minimum of 100 surveys per participant. Participant data collection was carried out in October and November 2023. The goal was to capture participants' responses during the fall period, when Seoul's climate transitions from a hot and humid season to a cold, dry winter.

Urban scale data was collected in order to be used as potential explanatory variables to predict occupants' thermal preference responses during the period of analysis. The urban scale dataset comprised open-access data from geographic information systems (GIS) along with data from 1000+ weather sensors distributed throughout the city of Seoul.

The distributed urban weather sensors (Fig. 2) recorded the minimum, mean and maximum values of each 19 parameters at hourly resolution. The most interesting parameters were selected based on their relevance to comfort perception and after cleaning up the available data the following parameters were selected: air temperature, relative humidity, wind speed, fine particulate matter ($PM_{2.5}$) and coarse particulate matter (PM_{10}). The distribution of air temperatures during the period of study (Fig. 2) shows a high variability in maximum recorded temperatures during the two-month period of analysis.

Participants' physiological records and survey responses were then related to the weather data for the closest weather sensor at the time when the information was recorded. Given the high variability of wind speeds throughout an urban area, the wind speed at the closest weather station might not actually be close to the one experienced by the participant. Furthermore, the collected wind speed data had a particularly large number of missing records. Therefore, the average wind speed at urban scale was used for all records as an indicator of whether the record happened during a generally windy time.

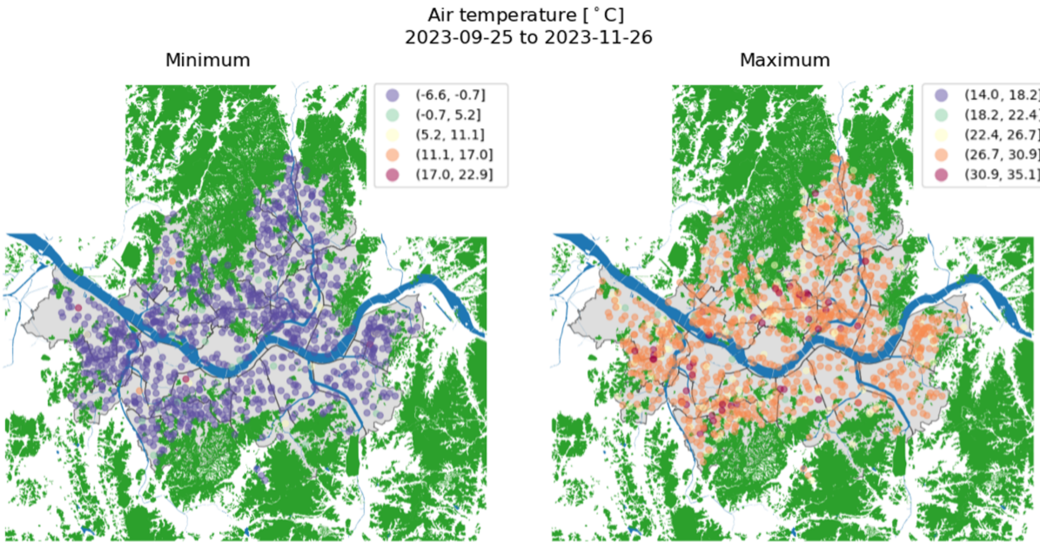

Figure 2. *Distribution of the weather sensors located throughout Seoul, showing each sensor's minimum (left) and maximum (right) recorded air temperature during the period of study. The boundaries of the districts of Seoul are shown in gray, whereas major green areas and water bodies are shown in green and blue, respectively.*

In addition to weather data, the potential role of urban form features on participants' comfort perception was also explored. First, shapefiles containing the footprints of all buildings in Seoul, major green spaces and major waterways were obtained from Seoul's open data portal. Three of the most important climate-related morphological variables (Maiullari 2023) were used as potential explanatory variables for participants' thermal comfort during the study, namely the Floor Space Index (FSI), Ground Space Index (GSI) and Open Space Ratio (OSR). For each weather sensor, a buffer *b* was first defined (100 m, 200 m and 300 m in radius), and the urban form parameters were calculated as follows:

$$FSI_b = \frac{GFA_b}{A_b} \quad \forall\, b \in [100, 200, 300] \tag{1}$$

$$GSI_b = \frac{A_{footprint}}{A_b} \quad \forall\, b \in [100, 200, 300] \tag{2}$$

$$OSR_b = \frac{A_b - A_{footprint}}{GFA} = \frac{1 - GSI_b}{FSI_b} \quad \forall\, b \in [100, 200, 300] \tag{3}$$

where *GFA* is the gross floor area for buildings within buffer *b*, $A_{footprint}$ is the building footprint within that buffer area, and A_b is the buffer area (i.e., $A_b = \pi \cdot b^2$).

Based on this information, the goal of this study was to rank the variables that most affected occupants' thermal preference responses and to train a machine learning model to predict occupants' perception in outdoor and indoor spaces. A random forest (RF) classifier was used for this purpose, as it has been widely used for comfort-related studies and shown to perform better than other algorithms (Jayathissa et al. 2020, Guerra-Santin and Upasani 2023), especially during fall (Bai et al. 2022).

RESULTS

As seen in Fig. 1, most responses (2500) were collected indoors, with only 265 collected outdoors, plus 156 collected on public transportation. Therefore, the indoor responses are analyzed first.

Indoor thermal preference

The importance of each of the explanatory variables in predicting occupants' thermal preference votes is shown in Fig. 3. These results show the outdoor temperature as the most important feature by far, which is expectable. Several other variables appear to have comparable feature importances, such as current mood, activity and clothing, and the three urban form parameters. Participants' demographics and personality traits, on the other hand, appear to have a more modest effect.

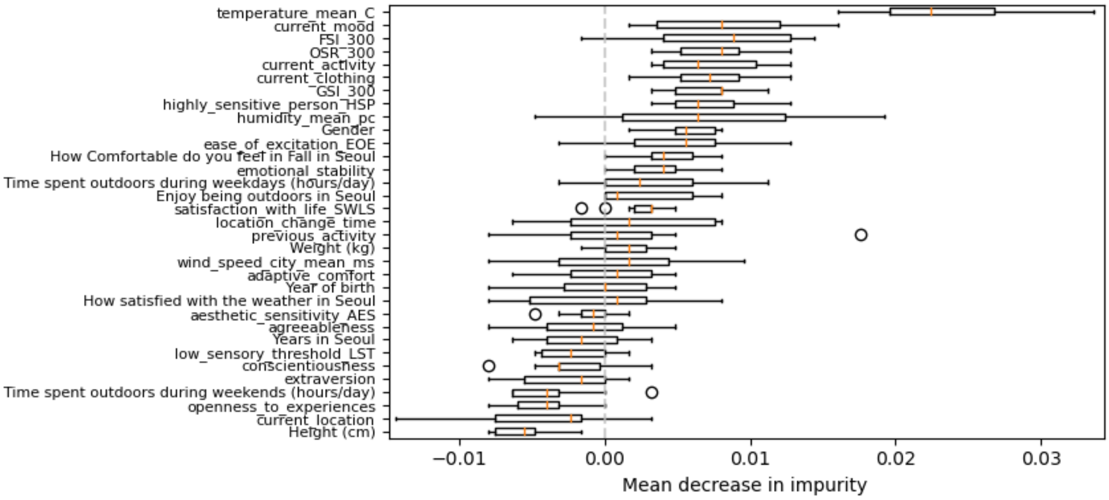

Figure 3. *Mean decrease in impurity of each of the explanatory variables as predictors for occupants' indoor thermal preference votes.*

An obvious limitation here is the lack of information on the indoor environment at the time of the surveys. While Fig. 4 shows that there is indeed some relationship between indoor comfort preference responses and outdoor temperatures, these vary by room type, as the indoor environmental quality of each space that occupants responded in might vary. This is somewhat of a limitation in deploying wearables in the wild, as done in this study. Nevertheless, the distributions in responses for different room types still show that participants were generally more satisfied and had more consistent responses when they occupied room types where they had control of their environment (home, private workspace) than when they occupied rooms in which they had less control, especially classrooms, libraries and public transportation. In planning smart building systems, therefore, it is important to not only include occupant behavior in the learning process, but also allow users to control their spaces to maintain their thermal comfort.

Outdoor thermal preference

In order to test the features in the outdoor environment that most affected occupants' thermal preference in the case study area, a random forest (RF) classifier was trained using the outdoor environment, urban form features, participant demographics and preferences, health kit data and survey responses as explanatory variables.

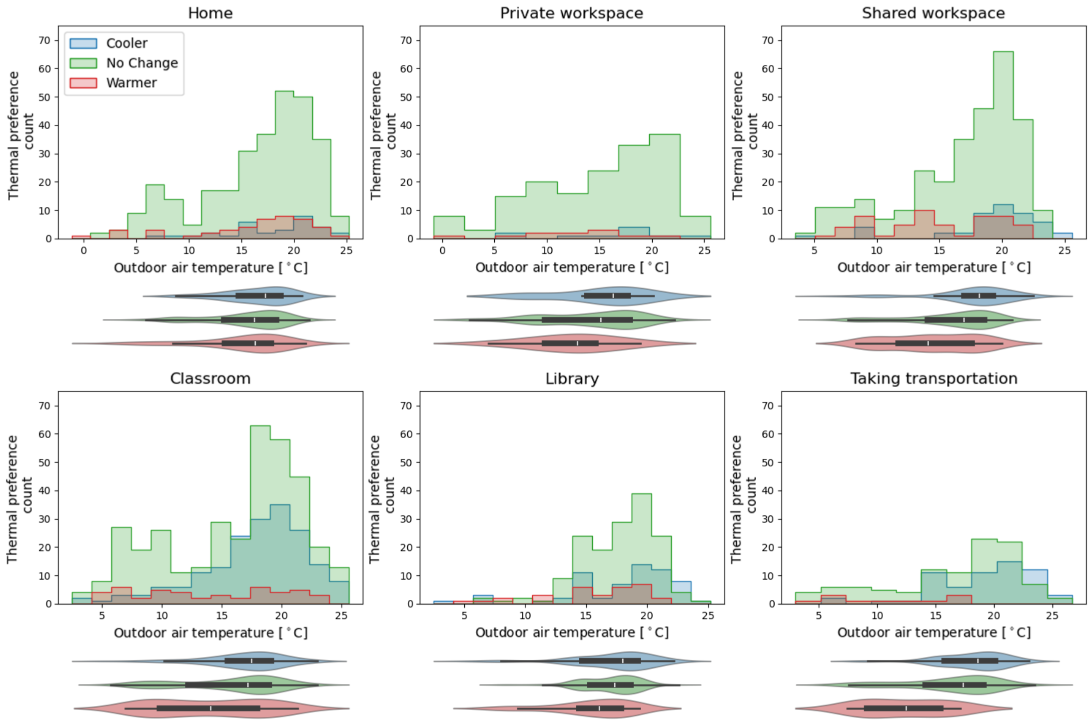

Figure 4*. Distribution of occupants' thermal preference responses as a function of outdoor air temperature for different locations.*

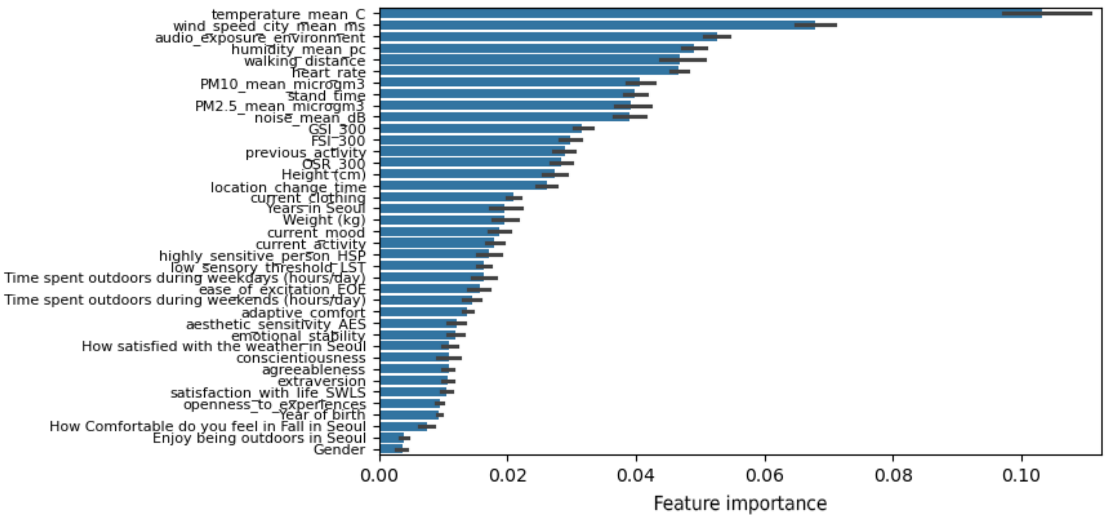

Figure 5*. Feature importance with 10-fold cross-validation showing the influence of different explanatory variables on the results of the RF classifier model.*

The resulting feature importances with 10-fold cross validation are shown in Fig. 5. Again, unsurprisingly, the main explanatory variable is outdoor air temperature, with other environmental features (wind speed, relative humidity) also showing a significant contribution. Information from the smartwatch health kit data also appear to have a significant influence, especially audio exposure, walking distance and heart rate. Participant demographics and personality traits again appear to have a lower influence. Given the observed importances, a simplified model using those six top features was also created and the performance of each was tested using the micro F1-scores with 10-fold cross validation. Given that the number of instances of each thermal preference label was unbalanced (i.e., there were many more “No Change” votes, and more “Prefer Cooler” votes than “Prefer Warmer”), the weighted F1-score was also explored.

The F1-scores and confusion matrices for each case are shown in Fig. 6. The model using all features has a mean micro F1-score of 0.65, which is comparable to studies on thermal comfort using the Cozie application in Singapore (Jayathissa et al. 2020) and a similar smartwatch application in the Netherlands (Guerra-Santin and Upasani 2023). The weighted F1-score of 0.62 is lower than the mean score for Bai et al. (2022)’s RF model for fall (0.7227), though somewhat comparable to the performance of the other ML models they considered. The model can be seen to overpredict “No Change” votes, which might again be related to the unbalanced nature of the dataset. The model using the top six features, on the other hand, performs worse in terms of both scores, especially the weighted F1, and shows an even higher overprediction of “No Change” votes.

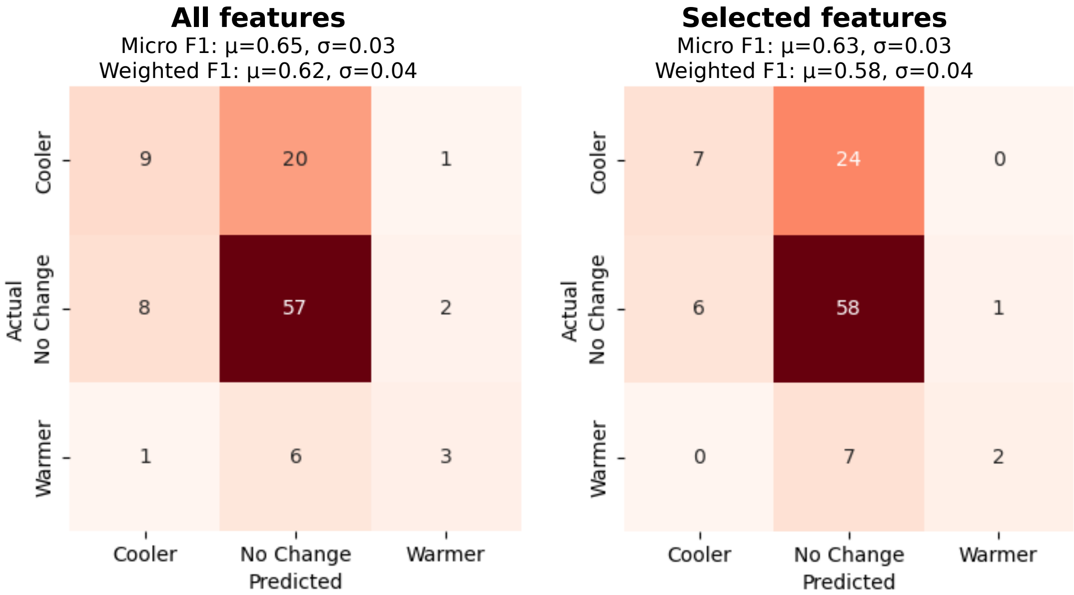

***Figure 6**. Confusion matrix for the RF classification model using all features (left) compared to the model using only the top six most important features.*

CONCLUSION AND IMPLICATIONS

This paper explored the use of wearable technologies and urban-scale datasets to assess building occupants’ indoor and outdoor thermal comfort preferences over a 4- to 6-week period in Seoul, South Korea. The preliminary results shown here show some insights into the main features affecting occupants’ thermal comfort, as well as some promising directions for future research. In terms of indoor comfort, given that no information about indoor environmental quality in the buildings that users occupied, no predictive model was trained. Nevertheless, the outdoor environment was still found to be of primary importance in the resulting thermal preferences reported by building occupants. Analyzing the results by room type showed that occupants were generally more comfortable in rooms where they had control over their environment, however future work could be conducted in order to combine the results from wearable technologies with sensor data in specific case study buildings. Furthermore, the main features affecting outdoor comfort were also explored, and found to be mainly related not only to outdoor environment features (air temperature, wind speed, relative humidity), but also occupants' noise exposure, walking distance and heart rate. It is worth investigating further the urban specific features in which occupants gave those responses that might have affected their reported thermal preferences. In the specific case presented here, other features such as urban form parameters and participant demographics were found to have relatively minor impacts on their perceived comfort. However, while the results of the RF classifier model to predict participants' thermal preference were in line with values observed in the literature, they still present room for improvement, and future work to include larger cohorts of participants and different seasonal characteristics should be considered.

REFERENCES

Ban Y, Liu K, and Wang Y. 2022. Comparative analysis of thermal preference prediction performance in different conditions using ensemble learning models based on ASHRAE Comfort Database II, *Building and Environment* 223: 109462.

Becerik-Gerber B. et al. 2022. The field of human building interaction for convergent research and innovation for intelligent built environments, *Scientific Reports* 12: 22092.

Diener E, Emmons RA, Larsen RJ, and Griffin S. 1985. The Satisfaction with Life Scale, *Journal of Personality Assessment*, 49: 71-75.

Gosling SD, Rentfrow PJ, and Swann WBJ. 2003. A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, 37: 504–528.

Guerra-Santin O and Upasani N. 2023. Comfort and occupancy data for FDD system, Brains 4 Buildings Deliverable 3.5 Report, TU Eindhoven (Netherlands).

Jayathissa P, Quintana M, Abdelrahman M, and Miller C. 2020. Humans-as-a-Sensor for Building—Intensive Longitudinal Indoor Comfort Models, *Buildings* 10: 174.

Jeon G, Park Y, and Guldmann JM. 2023. Impacts of Urban Morphology on Seasonal Land Surface Temperatures: Comparing Grid- and Block-Based Approaches, *International Journal of Geo-Information*, 12(12): 482.

Maiullari D. 2023. Urban form influence on microclimate and building cooling demand An analytical framework and its application on the Rotterdam case, *Ph.D. Thesis*, Delft University of Technology (Netherlands).

Mei SJ and Yuan C. 2022. Urban buoyancy-driven air flow and modelling method: A critical review, *Building and Environment* 210: 108708.

Miller C, Quintana M, Frei M, Chua YX, Fu C, Pichetti B, Yap W, Chong A, and Biljecki F. 2023. Introducing the Cool, Quiet City Competition: Predicting Smartwatch-Reported Heat and Noise with Digital Twin Metrics, *Proceedings of BuildSys '23: The 10th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*, p. 298-299.

Mosteiro-Romero M, Park Y, and Miller C. 2024. Converging Smartwatch and Urban Datasets for Sustainable City Planning: A Case Study in Seoul, South Korea. *E3S Web of Conferences* 562: 03004.

Peng Z, Bardhan R, Ellard C, and Steemers K. 2022. Urban climate walk: A stop-and-go assessment of the dynamic thermal sensation and perception in two waterfront districts in Rome, Italy, *Building and Environment* 221: 109267.

Pluess M, Lionetti F, Aron EN, and Aron A. 2023. People differ in their sensitivity to the environment: An integrated theory, measurement and empirical evidence, *Journal of Research in Personality*, 104, 104377.

Yap W, Janssen P, and Biljecki F. 2022. Free and open source urbanism: Software for urban planning practice, *Computers, Environment and Urban Systems* 96: 101825.