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Coupled Impact of Points of Interest and Thermal Environment on Outdoor Human Behavior Using Visual Intelligence

Shiliang Wang [1,*], Qun Zhang [1], Peng Gao [2], Chenglin Wang [1], Jiang An [3] and Lan Wang [1]

[1] Faculty of Architecture, Xi'an University of Architecture and Technology, Xi'an 710064, China; zhangqun@xauat.edu.cn (Q.Z.); wcl@xauat.edu.cn (C.W.); wanglan@xauat.edu.cn (L.W.)
[2] Faculty of Engineering and Information Technology, University of Pécs, 7622 Pécs, Hungary; rfde6z@tr.pte.hu
[3] School of Resources and Civil Engineering, Northeastern University, Shenyang 110819, China; anjiang@stumail.neu.edu.cn
* Correspondence: shiliangwang@xauat.edu.cn

Abstract: Although it is well established that thermal environments significantly influence travel behavior, the synergistic effects of points of interest (POI) and thermal environments on behavior remain unclear. This study developed a vision-based outdoor evaluation model aimed at uncovering the driving factors behind human behavior in outdoor spaces. First, Yolo v5 and questionnaires were employed to obtain crowd activity intensity and preference levels. Subsequently, target detection and clustering algorithms were used to derive variables such as POI attractiveness and POI distance, while a validated environmental simulator was utilized to simulate outdoor thermal comfort distributions across different times. Finally, multiple classification models were compared to establish the mapping relationships between POI, thermal environment variables, and crowd preferences, with SHAP analysis used to examine the contribution of each variable. The results indicate that XGBoost achieved the best predictive performance (accuracy = 0.95), with shadow proportion (|SHAP| = 0.24) and POI distance (|SHAP| = 0.12) identified as the most significant factors influencing crowd preferences. By extrapolation, this classification model can provide valuable insights for optimizing community environments and enhancing vitality in areas with similar climatic and cultural contexts.

Keywords: outdoor human behavior; points of interest; thermal environment; visual intelligence; machine learning

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1. Introduction

1.1. Background

The layout of points of interest (POIs) [1] and the outdoor thermal environment [2] are key factors influencing residents' behavior patterns in open spaces. At the community scale, POIs include seating areas, fitness equipment, playgrounds, landscape sculptures, plazas, lawns, garbage dumps, and parking sheds [3]. The outdoor thermal environment encompasses natural factors such as sunlight, wind, temperature, and humidity, which directly affect residents' physical and psychological perceptions and their experience of thermal comfort. Various outdoor activity spaces in residential areas meet the needs for aesthetic appeal, safety, comfort, and convenience. The combination of attractive POIs and high-quality outdoor thermal environments can effectively encourage residents, especially the elderly and children, to engage more in outdoor activities, promoting physical and mental health and enhancing social interactions [4]. However, due to the complexity of urban spatial structures, the uncertainty of crowd preferences, and the lack of high spatiotemporal resolution data on activity intensity [5], revealing the multidimensional driving factors and nonlinear dynamics of outdoor human behavior presents significant challenges.

1.2. Literature Review

1.2.1. The Impact of Points of Interest on Human Behavior

POIs are locations marked on maps that are interesting or relevant, such as parks, bars, cafes, community centers, and bookstores [6]. These sites are widely used in geographic information science and computational urban science to study human behavior, representing destinations for work, travel, leisure, and navigation [7]. Scholars investigate how people utilize these POIs [8] and how they evolve with technological and cultural changes [9]. Studies also focus on the impact of POI activities on innovation [10], disease transmission [11], economic activity [12], and crime [13]. Additionally, the lack of amenities and its potential to worsen overall outcomes or exacerbate urban inequality is a key research focus [14]. These studies highlight the importance of POIs in urban life, providing valuable insights for urban planning and public policy, and helping to enhance residents' quality of life and promote sustainable development.

At the community scale, the layout of POIs significantly influences residents' behavior patterns. First, the reasonable layout of POIs can significantly increase residents' frequency of outdoor activities [15]. For example, seating areas and fitness equipment placed at the center of residential areas or at crossroads can attract more residents to rest and exercise. Second, the diversity and distribution of POIs attract different groups of people [16,17]. Elderly individuals tend to choose quiet, well-equipped resting areas, while younger people and children prefer active spaces like fitness equipment and playgrounds. Therefore, diverse configurations of POIs can meet the needs of different groups, promoting cross-generational interaction and communication [18]. Finally, the functionality and convenience of POIs are also crucial factors affecting residents' behavior.

Although there is a well-established research framework for POIs at the urban scale, there is still a lack of studies on the identification of POIs and their impact on human behavior at the community level. The main reason is the lack of methods that can detect POIs and human behavior at high spatiotemporal resolution. Currently, deep learning methods contribute to scene understanding and knowledge discovery at the urban and community levels [19–22]. The YOLO (You Only Look Once) model, a popular target detection algorithm in recent years, excels in recognizing and tracking human behavior, behavioral trajectories, and target detection [23–25]. YOLO efficiently identifies and locates objects in images, such as pedestrians, vehicles, animals, and items. In behavior trajectory analysis, the YOLO model can continuously track individuals in videos and record their movement paths. In this work, we use YOLO v5 to identify and cluster potential POIs and detect the number and intensity of pedestrian activities, providing a basis for identifying high-resolution pedestrian dynamics.

1.2.2. The Impact of the Thermal Environment on Human Behavior

The thermal environment of residential areas is a crucial indicator of urban livability [26], significantly influencing residents' willingness and frequency to engage in various outdoor activities. In recent years, public attention to outdoor thermal comfort has increased. Outdoor thermal comfort is affected not only by microclimatic conditions but also by subjective factors such as personal experience, expectations, and exposure duration, which can be assessed using indices like PET or UTCI [27,28]. Studies have shown that most residents prefer shaded areas to enhance comfort. A study in Sweden found that residents tend to choose cooler environments with lower solar radiation, moderate humidity, and higher wind speeds, i.e., shaded areas [29]. Human thermal comfort is influenced by various heat adaptation behaviors, such as seeking shade or wearing sun hats to cope with high temperatures, as commonly seen in Singapore [30].

The correlation between outdoor thermal comfort and space occupancy has been confirmed by numerous studies [31,32]. Under high-temperature conditions, people tend to choose shaded areas to avoid heat. Research further reveals the differences in thermal comfort between shaded and non-shaded areas, significantly impacting residents' attendance rates [33]. Rising temperatures and increased solar radiation led to a decrease in outdoor activity, directly correlating with attendance rates and thermal environment conditions. Studies have found that the elderly prefer to cool off in shaded areas with high canopy coverage [34]. This behavior pattern of seeking shade in high-temperature environments has been validated by multiple studies, emphasizing the importance of strategically placing shaded areas to enhance thermal comfort in outdoor space design.

Despite extensive research on thermal comfort and human behavior, current studies have not effectively classified and labeled the diversity of outdoor activities, including factors such as activity type, time, age, and gender. Additionally, existing research has not revealed the synergistic effect of POI spatial location and thermal environment, limiting the understanding and optimization of human behavior responses in complex environments. Previous studies have demonstrated the ability of deep learning and machine learning to capture nonlinear dynamics and interactions [35,36], showing potential in uncovering the mechanisms by which POIs and the thermal environment influence human behavior.

1.3. Research Objective

Although existing studies have extensively explored the impact of POI on human behavior at the urban scale, research at the community scale remains insufficient, particularly in identifying POIs with high spatiotemporal resolution and their specific effects on residents' behavior. Current studies have not adequately classified and annotated the diversity of outdoor activities, lacking detailed analysis of behavior across different activity types, times, age groups, and genders. Furthermore, the synergistic effects of POI spatial distribution and thermal environments on human behavior have not been thoroughly investigated, limiting our understanding of human behavior response mechanisms in complex environments. We assumed a synergy between POI distribution and thermal comfort, influencing behavior, and that these behaviors remain consistent despite short-term weather changes.

To address the gaps in current research, this study aims to develop a data-driven framework based on visual intelligence to comprehensively describe the impact of POI and thermal environment characteristics on crowd dynamics in outdoor open spaces at the community scale. (1) By employing high spatiotemporal resolution identification methods, the study accurately captures POIs and their specific effects on resident behavior. (2) The research utilizes a machine learning classification model to provide detailed categorization and annotation of the diversity of outdoor activities, including behavior characteristics across different activity types, times, age groups, and genders. (3) The study further explores the synergistic effects of POI spatial layout and thermal environment on human behavior using interpretable machine learning, revealing the response mechanisms of human behavior in complex environments. These findings offer empirical support and theoretical guidance for optimizing outdoor space design in communities, providing valuable insights for similar studies and practices in regions with comparable climates.

2. Methods

2.1. Research Workflow

This study integrates popular visual intelligence models, thermal comfort simulations, and machine learning methods to establish a technical framework that provides insights into the driving forces behind human behavior at a community-level high resolution. This study follows the steps outlined below: First, human behavior recognition and preference evaluation are conducted using Yolov5 and deep learning techniques to statistically analyze summer residential area crowd activities, constructing high-resolution spatiotemporal behavior models. By combining survey data and crowd statistics, we establish crowd preference grading labels through weighted processing. Second, we fine-tuned the Yolov5 model to precisely detect POIs like landscape nodes and vending points, enhancing detection accuracy in community settings. Third, thermal environment simulation and validation are performed using Ladybug to simulate the community microclimate, collecting key environmental parameters (e.g., SR, SVF, MRT). Thermal comfort simulations were validated with field measurements, ensuring accuracy and credibility. Finally, machine learning modeling involves training a classification model with POI and thermal environment characteristics as input variables and crowd preference grades as output. The trained model is then spatially extrapolated to predict the outdoor environmental quality of the entire community. The technical roadmap is illustrated in Figure 1.

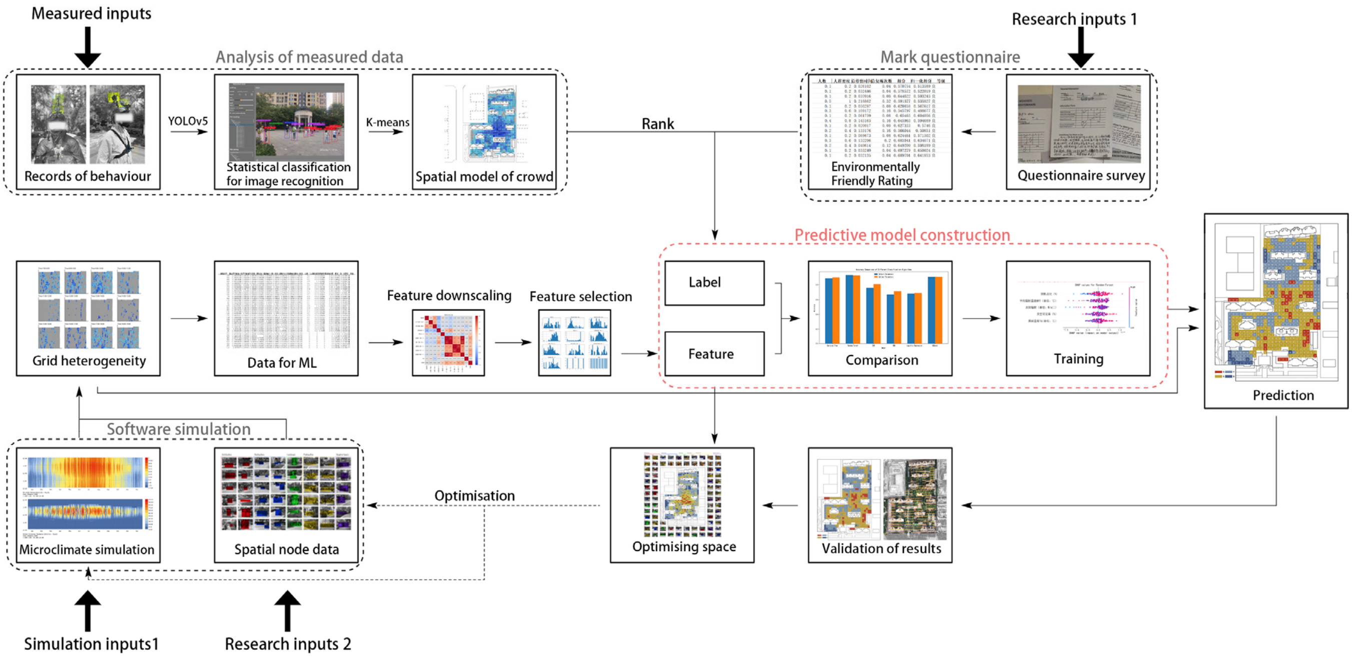

Figure 1. Overview of the research workflow and methodology.

2.2. Study Site

Xi'an, the capital of Shaanxi province, is the largest and most urbanized city in Western China (34°16′ N 108°54′ E/34.267° N 108.9° E). Xi'an has a warm temperate semi-humid continental monsoon climate. The community selected for this study is located in the Yanta District of Xi'an, bordered by the North Third Ring Road to the south and Yanxiang Road to the east (Figure 2). This community comprises 2463 households with a registered population of 5847 residents.

2.3. Human Behavior Recognition and Preference Evaluation

2.3.1. Data Collection of Human Behavior

In this study, our primary task was to obtain data on the distribution of community activities during weekdays and weekends and to analyze their behavioral characteristics and patterns.

To achieve this, the community was divided into six areas, with volunteers moving at a constant speed within these zones. Equipped with action cameras mounted on helmets, capturing a 270° field of view, the volunteers collected data from 7:00 a.m. to 8:00 p.m.. The cameras took one photo per second, recording coordinates and time. In total, 4694 valid images were collected, each annotated with location, time, and activity details.

2.3.2. Human Behavior Recognition

The objective of this section was to accurately detect individuals, sports equipment, faint segmentation lines, and leisure seating in images, and to classify the detected individuals by gender and age range.

We trained YOLOv5 on an annotated dataset to develop a model for detecting individuals and POIs in images (Figure 3). After training, the model was applied to unannotated photos for automatic detection and precise localization. For each detected individual, features such as color, texture, and deep features from CNNs were extracted from the bounding box. These features were then used to train classifiers that predicted the gender (male, female) and age range (child, young adult, middle-aged, elderly) of the individuals, ensuring diversity and balance through manually annotated data.

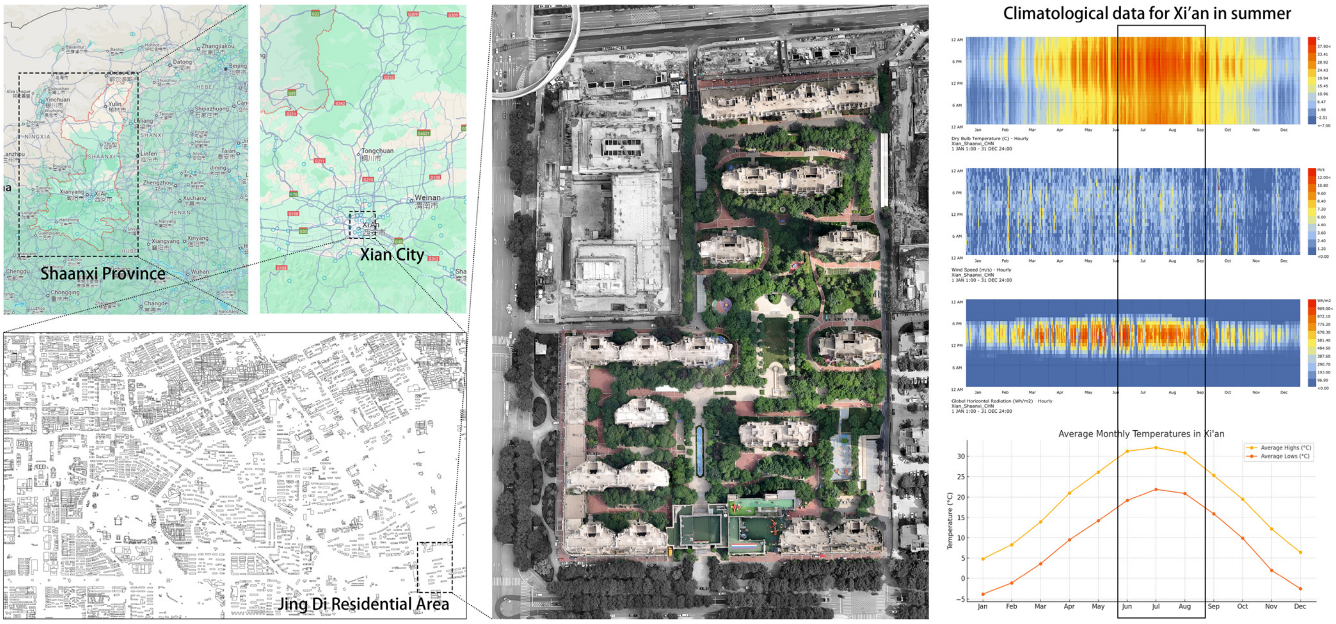

Figure 2. Study site location and characteristics in Xi'an, Shaanxi Province.

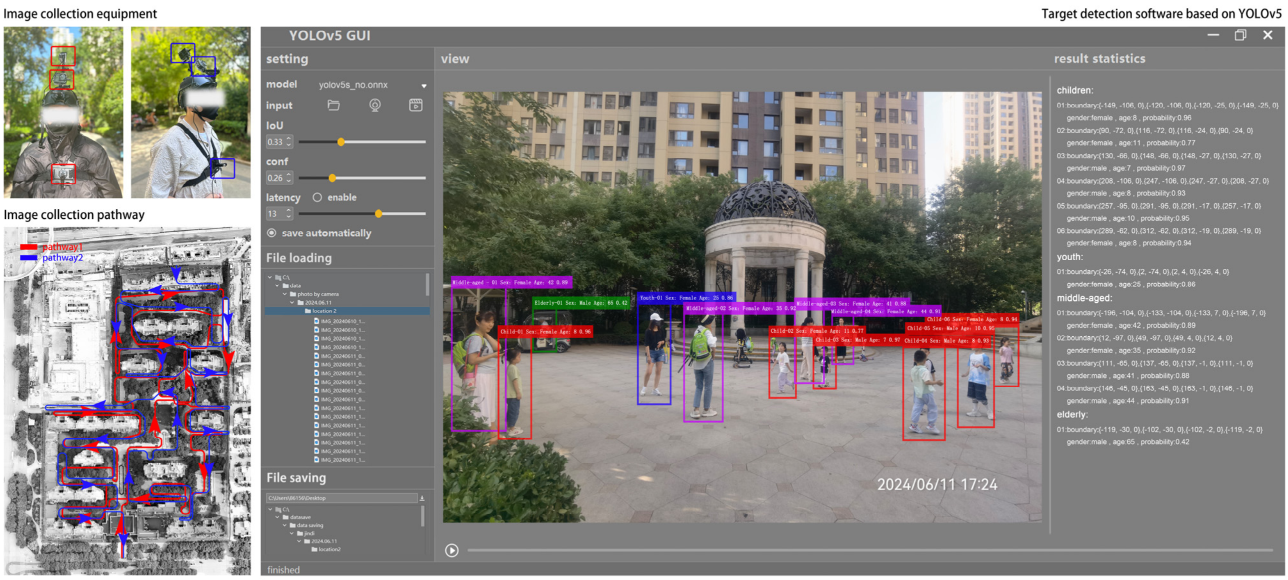

Figure 3. Data collection of human behavior and YOLOv5 target detection.

2.3.3. Preference Evaluation

To quantitatively assess and classify the environmental comfort of the measured grid areas, this study designed and implemented an evaluation system combining comprehensive questionnaire surveys and weighted crowd statistics.

This system covered 536 simulated grid points, with hourly random sampling of 60 points, collecting a total of 780 rating questionnaires over 13 daylight hours. The questionnaires focused on participants' subjective perceptions in three main dimensions: perceived temperature comfort, shadow coverage perception, and POI attractiveness. Simultaneously, the questionnaire evaluations were weighted with statistical data identified by YOLOv5, including the total number of active individuals, their dwell time, and frequency of appearance, to assess crowd preferences in the grid areas. The final scores were normalized to ensure consistency and comparability, and the grid areas were classified into four levels: "Excellent" (top 25%), "Good" (25–50%), "Average" (50–75%), and "Poor" (bottom 25%). These crowd preference levels will serve as the prediction target for the subsequent classification model.

2.4. POI Target Detection

The primary objective of this study was to achieve accurate identification and classification of POIs in residential environments by leveraging manual annotation and fine-tuning a deep learning model. We assume that the influence of POI attractiveness on crowd behavior is consistent across similar urban spaces. Additionally, the study aimed to analyze the distribution of these POIs and assess their impact on community dynamics, particularly by measuring their attractiveness to the crowd.

To accomplish this, we first collected 259 images featuring various POIs, such as playgrounds, fitness facilities, garbage dumps, landscape sculptures, and lawn squares, and manually annotated each image to clearly indicate the location and category of each POI. After annotation, we split the dataset into a training set and a test set in an 80/20 ratio. The data were assumed to follow the IID assumption, allowing reliable spatial extrapolation of the machine learning model across the community.

We fine-tuned the YOLOv5 model, an efficient object detection algorithm, by adjusting the input size, updating anchor values, and optimizing hyperparameters to enhance its accuracy in detecting specific POIs. This fine-tuning process leveraged the annotated images to improve detection precision.

To further analyze the distribution of POIs, we employed clustering algorithms, specifically the K-means algorithm, to group the POIs into six categories: activity areas (red), resting areas (blue), landscape areas (green), commercial areas (orange), parking areas (yellow), and negative areas (purple). Features were extracted from each POI image to serve as inputs for the clustering algorithm. Based on survey results and actual conditions, we assigned weights to each POI category to reflect their attractiveness to the crowd. We then calculated the average distance from each POI to others, categorizing these distances as positive or negative. These calculated distances were subsequently used as input features for the following classification model.

2.5. Thermal Environment Simulation and Validation

2.5.1. Numerical Simulation of Thermal Environment

This study aimed to simulate the microclimate environment using the Grasshopper platform integrated with Ladybug Tools. The simulation was designed to capture the spatial heterogeneity and its impact on the microclimate within the study area.

Meteorological data were obtained from the open-source Xi'an Station (570360_CSWD). The simulation period was set from June 13 to June 30, with hourly data recorded and daily averages calculated for analysis. The study area was divided into 536 grid units, each measuring 8 m by 8 m, with the center point of each grid serving as the survey reference point. Data were collected daily from 7:00 a.m. to 8:00 p.m., over a span of 13 h. The simulated objects include sky view factor (SVF), shadow percentage (SP), mean radiant temperature (MRT), solar radiation (SR), Universal Thermal Climate Index (UTCI), etc.

2.5.2. Validation of Thermal Environment Simulation

To validate the accuracy of the numerical simulation data for the thermal environment, this study conducted on-site measurements at selected locations within the community.

Eight representative and diverse measurement points were chosen, covering various surface types and spatial usage attributes. High-precision equipment, including solar radiometers, WBGT heat index meters, dry bulb thermometers, black globe thermometers, and hygrometers, was used to collect data continuously from 7:00 a.m. to 8:00 p.m. daily from 13 June to 30 June 2024, recording hourly microclimate parameters. The collected data underwent cleaning and statistical analysis before being compared with the simulation results. Based on these comparisons, the model was calibrated and optimized as needed to improve simulation accuracy.

2.6. Machine Learning Modeling

The purpose of developing the machine learning classification model in this study was to understand the relationship between spatial heterogeneity and environmental behavior in residential areas. By using this model, the study aimed to identify how different environmental features, such as POIs and thermal conditions, influence crowd behavior and preferences. Additionally, the use of SHAP (SHapley Additive exPlanations) was intended to provide clear insights into the contributions of each feature to the model's predictions, helping to pinpoint the most influential factors.

Each survey point considered 11 characteristic indicators, including grid number (GN), average distance to POIs (PD), average distance to negative POIs (NPD), sky view factor (SVF), shadow percentage (SP), MRT, SR, UTCI, WBGT, black globe temperature (TG), and time period (t). These indicators collectively formed a dataset that described the spatial microclimate and spatiotemporal characteristics. The description of the indicators is shown in Table 1. We began by conducting a comprehensive statistical analysis of the 11 feature indicators across 536 grid units, with each unit recording hourly data over 13 h, resulting in 6968 records. The dataset was rigorously preprocessed to remove null and anomalous data, ensuring high data quality. For the classification labels, we adopted a sampling strategy, selecting 60 samples per hour from the 536 grids, totaling 780 samples. After this, we performed correlation analysis and feature selection to construct the initial dataset for analysis.

Table 1. Indicators definition.

Indicator	Abbreviation	Definition
Grid number	GN	Identifies the grid unit of each survey point for data location and classification.
Average distance to POIs	PD	Measures the average distance from the survey point to points of interest, reflecting accessibility.
Average distance to negative POIs	NPD	Measures the average distance to negative POIs, indicating potential environmental drawbacks.
Sky view factor	SVF	Represents the openness of the area, affecting sunlight exposure and heat dissipation.
Shadow percentage	SP	Indicates the proportion of shadow coverage, reflecting shading conditions.
Mean Radiant Temperature	MRT	Evaluates the combined effect of radiation and ambient temperature on thermal comfort.
Solar Radiation	SR	Measures the intensity of solar radiation, influencing surface temperature and comfort.
Universal Thermal Climate Index	UTCI	Assesses thermal comfort considering temperature, humidity, wind, and radiation.
Wet Bulb Globe Temperature	WBGT	Gauges heat stress by combining temperature, humidity, wind speed, and solar radiation.
Black globe temperature	TG	Measures combined radiative heat, indicating overall heat environment intensity.
Time period	t	Specifies the time frame of data collection for analyzing temporal variations in microclimate.

We compared various machine learning models, including decision trees, random forests, support vector machines, k-nearest neighbors, logistic regression, and XGBoost, to develop a robust classification model that explores the relationship between spatial heterogeneity and environmental behavior. The performance of each model was evaluated using an independent test set and 10-fold cross-validation to ensure reliability.

To further understand the model mechanism, we employed SHAP to assess the key feature contributions in the XGBoost model. SHAP values provided an interpretable method to understand each feature's impact on the model's predictions, helping us identify the most important features in the decision-making process. Finally, based on the optimal model, we conducted comprehensive classification predictions and assigned evaluation values to the remaining grid points.

3. Results

3.1. Human Behavior Analysis Results

The YOLOv5 model's output was analyzed hourly to reveal the spatiotemporal distribution of community activities, providing a basis for constructing behavior activity pattern models. After 150 iterations of training on a diverse dataset that includes various scenes and lighting conditions, the model achieved a mean average precision (mAP) of 82.3%, a precision of 87.1%, and a recall of 75.8%. Compared with the traditional YOLOv4 model, YOLOv5 showed a 4.5% improvement in gender recognition accuracy and a 3.8% increase in age recognition accuracy. Additionally, this study explores the challenges of maintaining high accuracy in large-scale crowds and proposes an improved non-maximum suppression (NMS) algorithm to reduce false positives. The analysis (Figure 4) indicates that community activity peaks between 17:00 and 19:00, when the sun's angle is lower, resulting in shaded spaces, reduced solar radiation, and lower temperatures. This time period sees a significant increase in activities, particularly among elderly individuals and children. The presence of children during this time is likely linked to the end of school hours and their proximity to playgrounds and recreational POIs, while elderly individuals may be drawn to shaded resting areas and fitness equipment.

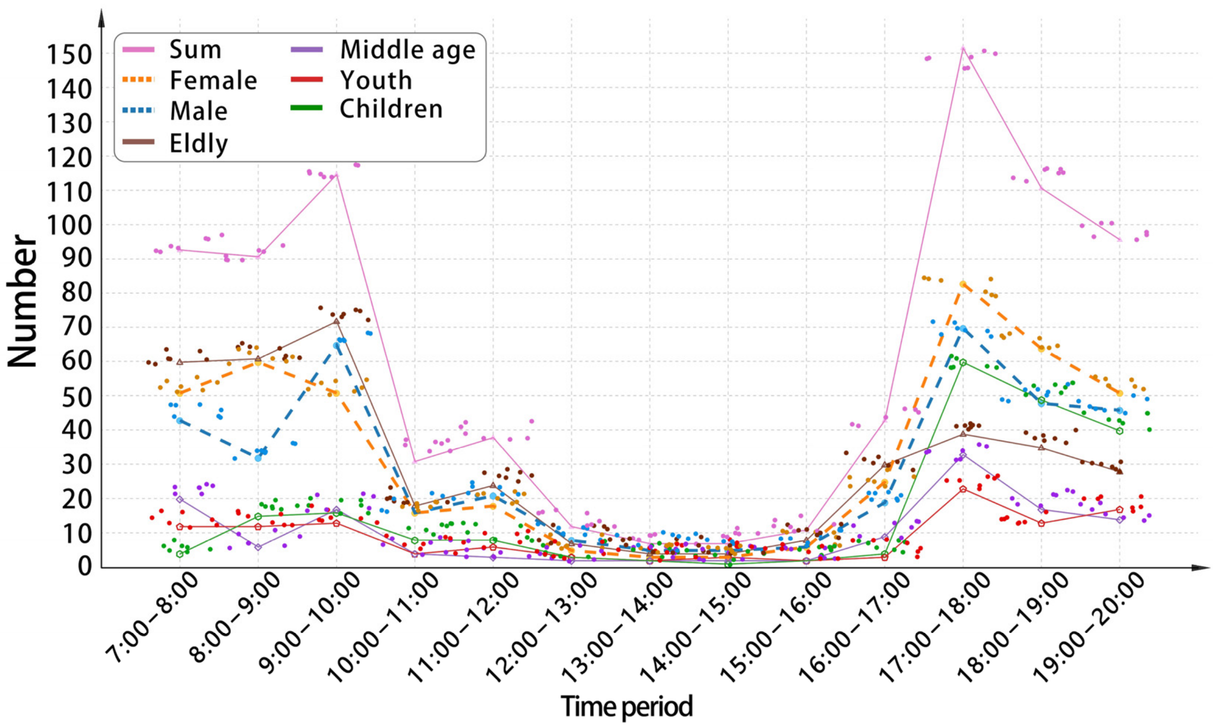

Figure 4. Hourly activity patterns of different types of people.

A second activity peak occurs before 9:00 a.m., primarily involving elderly residents engaging in morning exercises near fitness-related POIs. Children's activity is minimal during this time, reflecting school schedules and the lack of child-friendly POIs in use. From noon to 4:00 p.m., activities significantly decrease due to high temperatures and intense solar radiation, with fewer than 10 people typically active, including a small number of children. The lowest activity level occurs between 12:00 and 13:00, suggesting a need for shaded areas or other climate-sensitive POIs to encourage activity during hotter periods.

Overall, gender and age analysis show higher participation among females, with elderly individuals being the most active group, particularly in the early morning and late afternoon. These patterns highlight the importance of designing community spaces that cater to the specific needs of different demographic groups. For example, placing child-friendly POIs in shaded areas and providing accessible resting spots for the elderly can enhance activity levels and overall community engagement.

3.2. POI Clustering Results

By conducting K-means clustering analysis on the POIs detected by YOLOv5, we revealed the non-homogeneity and significant clustering characteristics of POIs' influence on crowd behavior. We identified 81 POIs and classified them into six categories (Figure 5). The real scenes of all POIs are shown in Figure A1. We conducted crowd behavior statistics for each category, with results presented in Figure 6. Specifically, landscape nodes and activity areas showed high crowd attraction, with longer average stay times and higher frequencies of occurrence, indicating that these spaces are well-designed or fully functional, effectively promoting crowd gathering and interaction. Landscape nodes and activity areas mainly include plazas and playgrounds, where the elderly tend to rest and chat in plazas with seating, while children prefer outdoor play spaces like slides.

In contrast, resting areas exhibited lower attractiveness, with shorter average stay times and lower frequencies of occurrence, suggesting that these areas' design and functionality need further optimization. Generally, areas near garbage dumps, parking sheds, and roadways are less attractive due to noise, pollution, or safety hazards.

3.3. Thermal Environment Simulation Results

Based on the site microclimate data simulation results, a heat map was generated (Figure 7), visually demonstrating the spatial distribution patterns of the microclimate. The time series simulation results are shown in Figures A2 and A3. These simulation data serve as the raw input for the machine learning model evaluation, laying the foundation for quantifying the relationship between the thermal environment and resident behavior and optimizing activity area layouts. The heat map clearly reveals the trends of key indicators such as temperature, radiation, and thermal comfort across different areas, providing an important basis for further analysis and optimization.

3.4. Thermal Environment Simulation Validation Results

Figure 8 shows the measured results. The measurements focused on five key microclimate indicators: solar radiation, WBGT heat index, dry bulb temperature, black globe temperature, and relative humidity. A comparison between the measured and simulated data revealed good agreement for most periods, although the measured values of solar radiation and relative humidity in the afternoon (after 15:00) were lower, possibly due to cloud cover, haze, and actual obstructions.

Solar radiation varied significantly between different survey points, with the greatest differences observed during the peak periods in the morning and early afternoon (9:00–10:00, 13:00–14:00), reaching up to 362 W/m^2. The black globe temperature also showed significant spatial differences in the morning. The microclimate indicators followed a typical diurnal pattern: solar radiation and temperature rose significantly from 9:00 a.m., peaked around 12:00 p.m., and then declined, with relative humidity reaching its lowest point at noon and gradually increasing until it dropped rapidly after 4:00 p.m.

Based on this, the period from 10:00 a.m. to 4:00 p.m. was defined as the high-temperature period with poor thermal comfort, aligning with previous spatiotemporal analysis of crowd activities.

In summary, the simulation results from Ladybug in this study demonstrated high reliability and closely matched the measured data, providing a solid foundation for subsequent machine learning modeling.

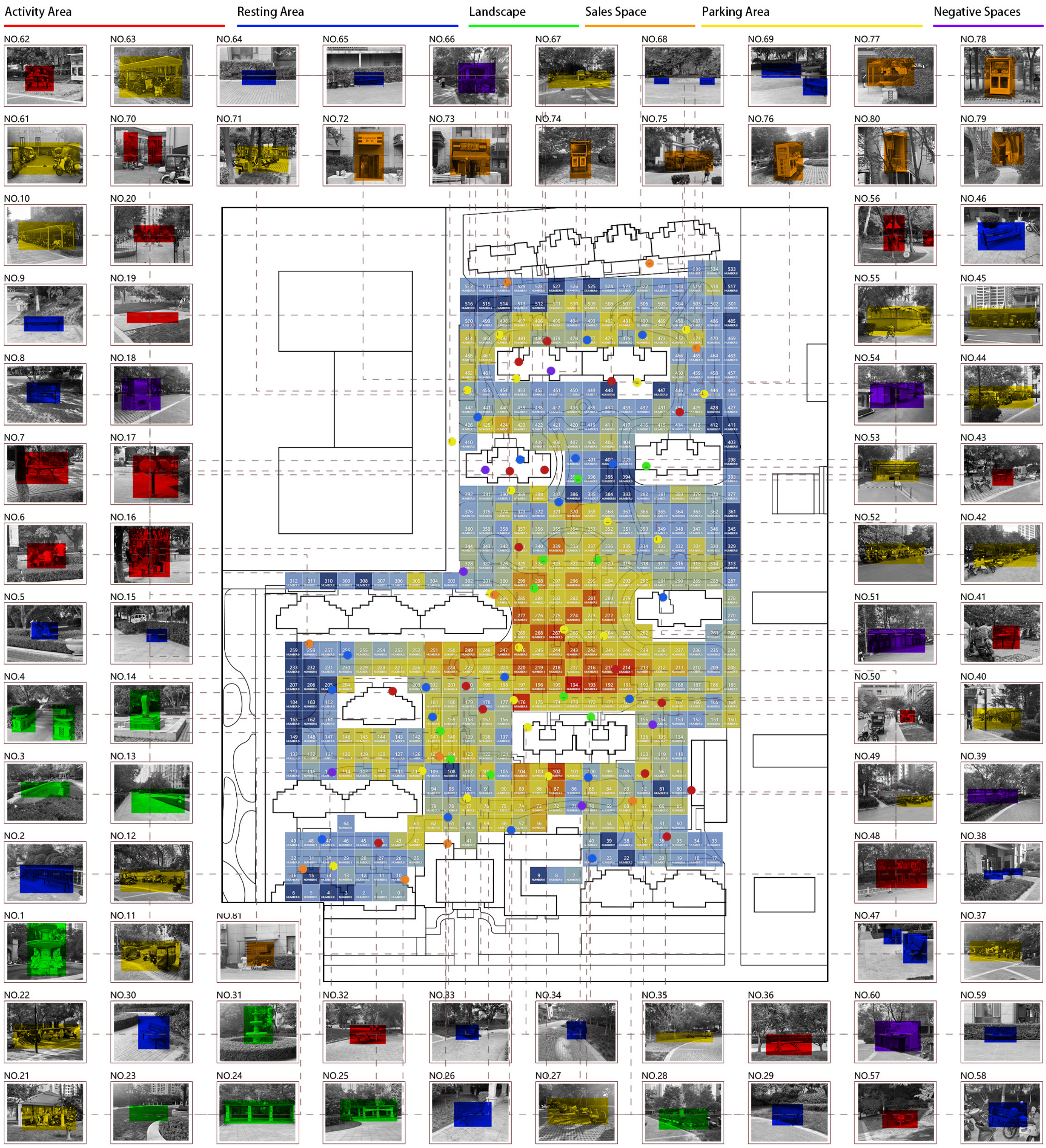

Figure 5. Spatial distribution and identification of POIs. The different colors of the mask represent: activity area (red), rest area (blue), landscape area (green), shops (orange), parking lot (yellow), and negative spots (purple).

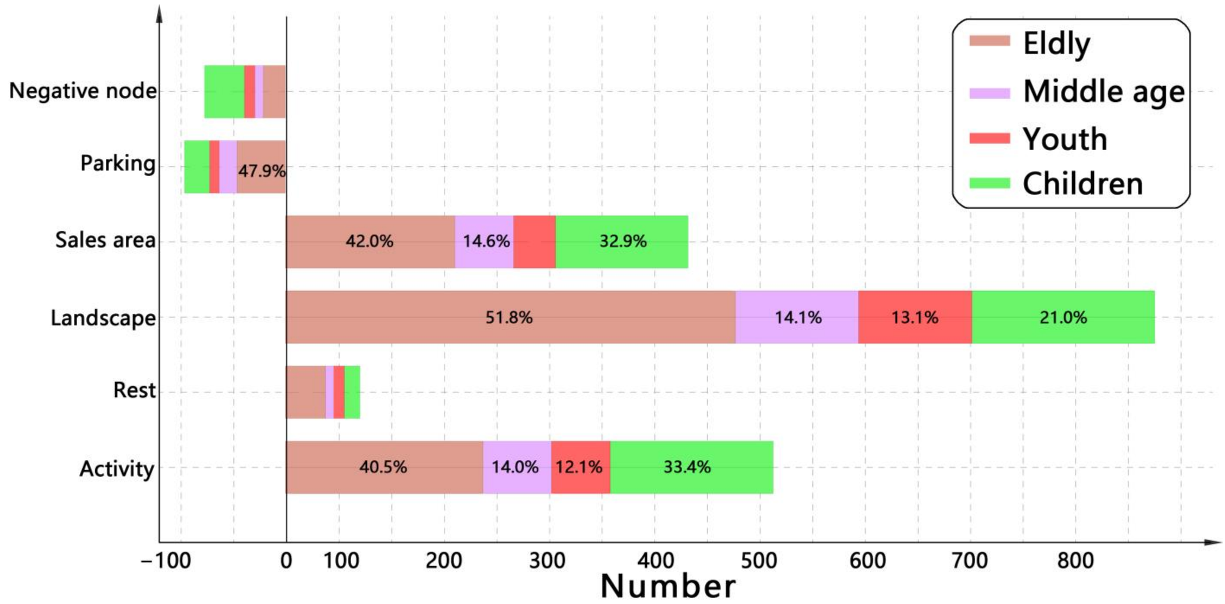

Figure 6. The attraction and repulsion effects of different clusters on various groups.

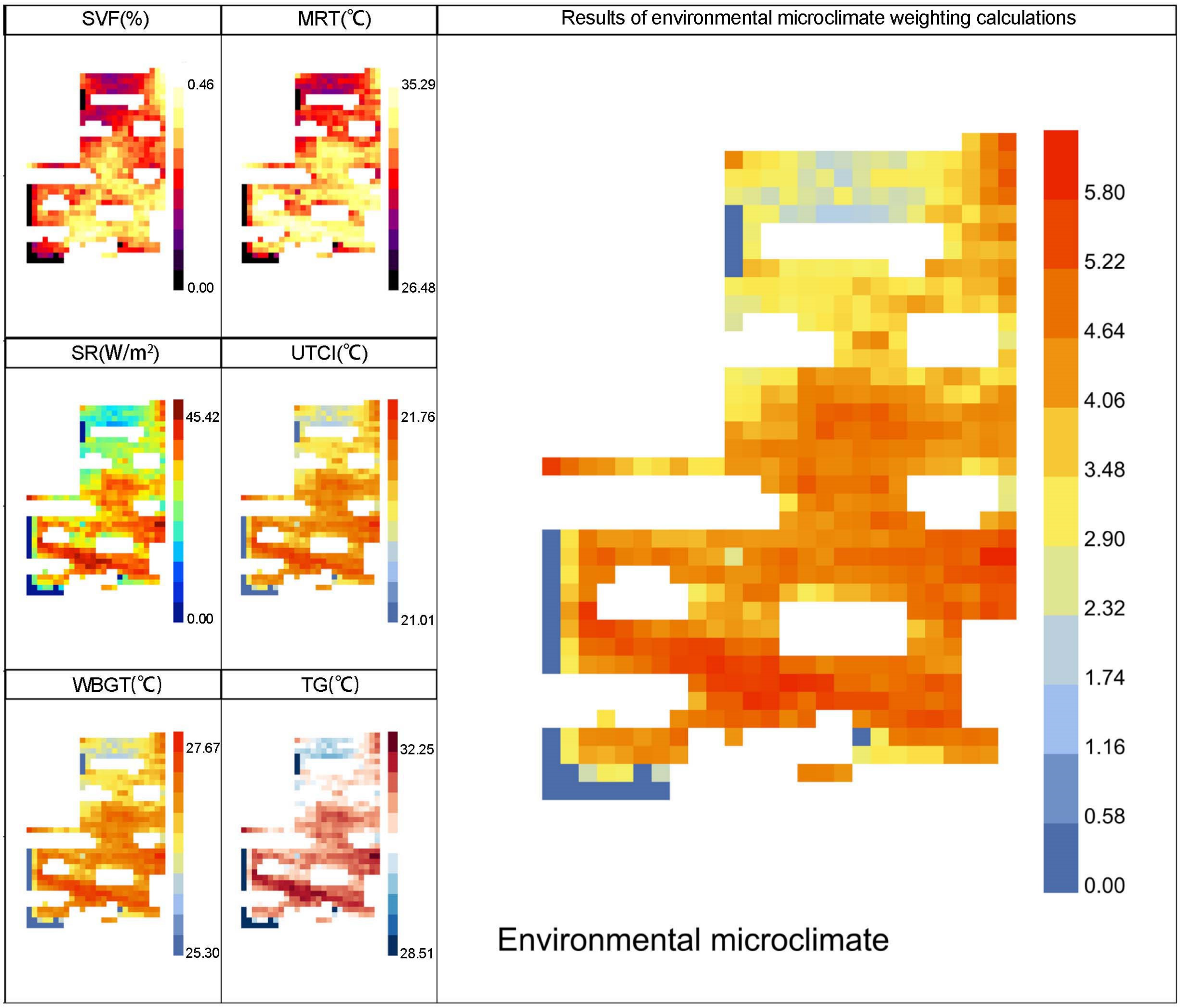

Figure 7. Simulation results of thermal environment indicators: SVF, MRT, SR, UTCI, WBGT, and TG.

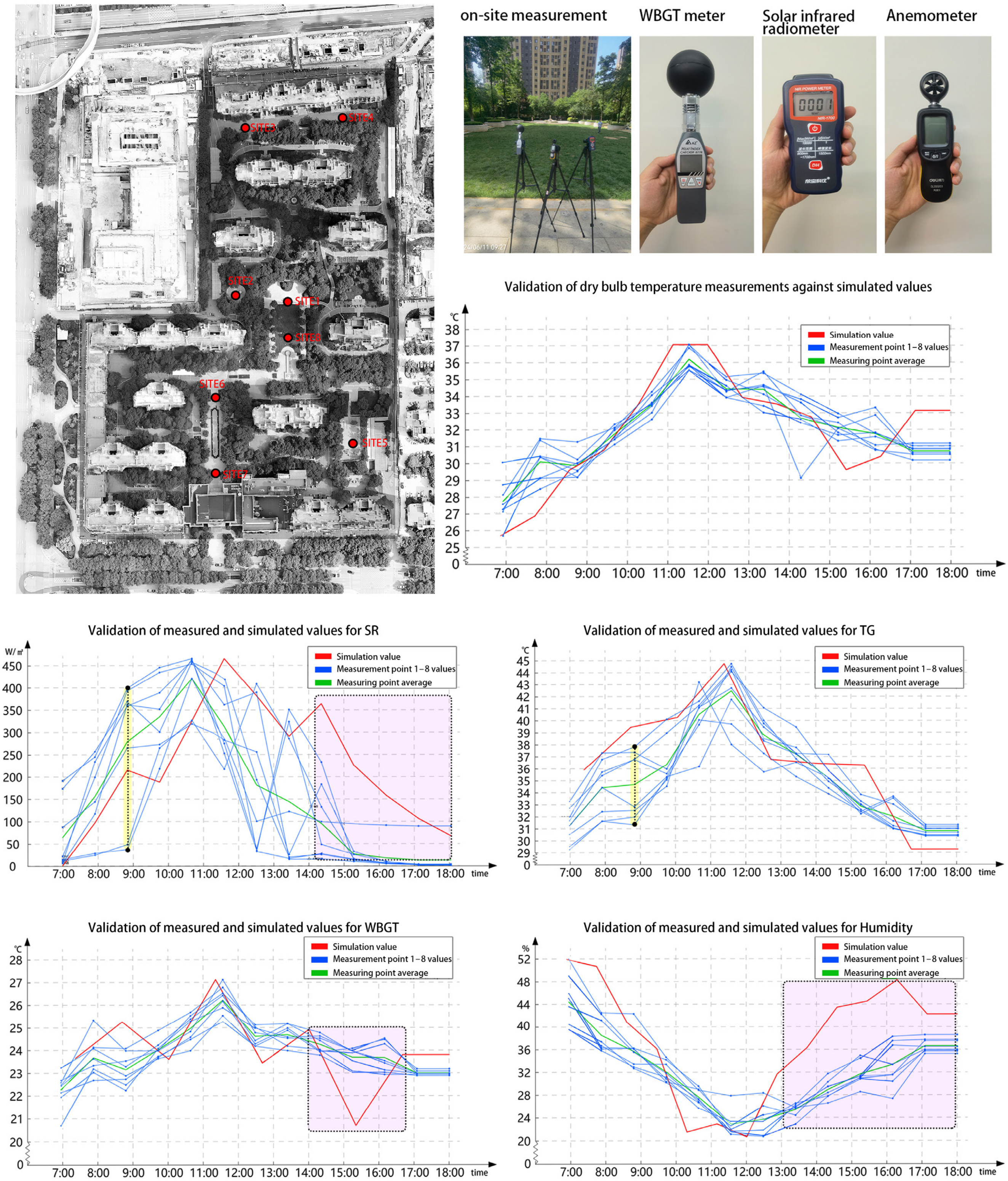

Figure 8. Comparison of measured and simulated thermal environment results. Black dotted line with yellow background: time points with significant regional measurement differences; the pink square: time periods with large discrepancies between simulated and measured values.

3.5. Machine Learning Model Performance

During the feature data preprocessing stage, the selection of key features is crucial for model performance. Through correlation assessment (Figure 9a), we identified strong correlations between SR, SP, and the rating levels, which were retained as core features. Although SVF showed a weak correlation with the rating levels, its significant impact on thermal comfort made it an important auxiliary feature. PD and NPD, despite having low independent correlation, might provide additional information in the comprehensive model. Given the computational dependencies and redundancies among TG, WBGT, and UTCI, MRT was selected as the representative thermal environment indicator. Ultimately, SP, SR, PD, SVF, and MRT were chosen as the key feature sets for the model.

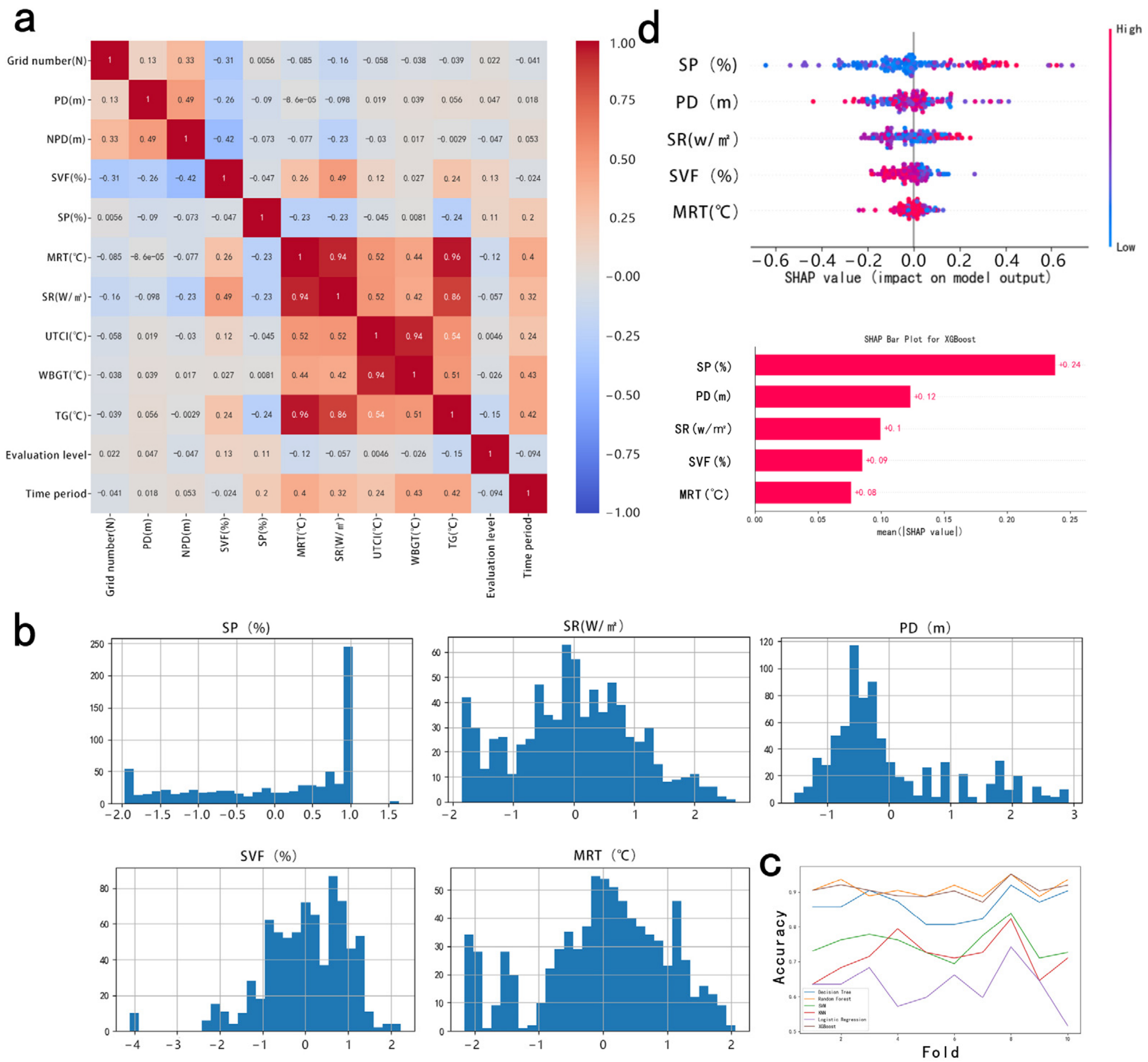

Figure 9. Correlation analysis and machine learning results: (**a**) Correlation analysis—red indicates positive and blue negative; (**b**) Key variable distributions; (**c**) Classification model performance comparison; (**d**) SHAP analysis—red indicates positive model contribution, blue negative.

We examined the distribution of machine learning variables to detect biases and outliers in the data, understand the numerical range, and determine appropriate data preprocessing strategies. The results are shown in Figure 9b, where outliers were removed based on the distribution. Secondly, due to significant differences in data values, normalization was necessary. We found that SP was the least normally distributed, while PD and

SVF were closer to a normal distribution. Additionally, SR and MRT exhibited a bimodal distribution. Ultimately, we chose an ensemble learning method to effectively handle these non-normal distribution scenarios.

The 10-fold cross-validation process was employed to ensure that the models (Figure 9c) were evaluated for their consistency and generalizability across different subsets of the data. This process helps to minimize overfitting and ensures that the model's performance is robust when applied to new, unseen data. Model evaluation results demonstrated that Random Forest and XGBoost models performed excellently in terms of data processing and prediction accuracy. Most models reached their peak performance at the 8th iteration, followed by a slight decline, possibly due to data characteristics or model overfitting/underfitting. Considering all factors, XGBoost was selected as the final model (accuracy = 0.95) and further optimized to ensure the accuracy of environmental friendliness predictions.

The SHAP analysis was used to evaluate the key feature contributions of the XGBoost model. Figure 9d shows that SP (|SHAP| = 0.24) and PD (|SHAP| = 0.12) are the most critical features. The SHAP plot for SP illustrates its bidirectional regulatory effect on resident activity behavior, while the SHAP plot for PD reveals the varying impacts of distance on behavior preferences. Through model predictions, each grid point was assigned a crowd preference level label. The aggregated results formed a community crowd preference distribution map (Figure 10), providing scientific evidence for site optimization design and community planning. Optimizing spatial structures, especially with designs targeting the needs of the elderly and children, can significantly enhance space utilization and resident activity participation, thereby improving the overall quality of life and vitality of the community.

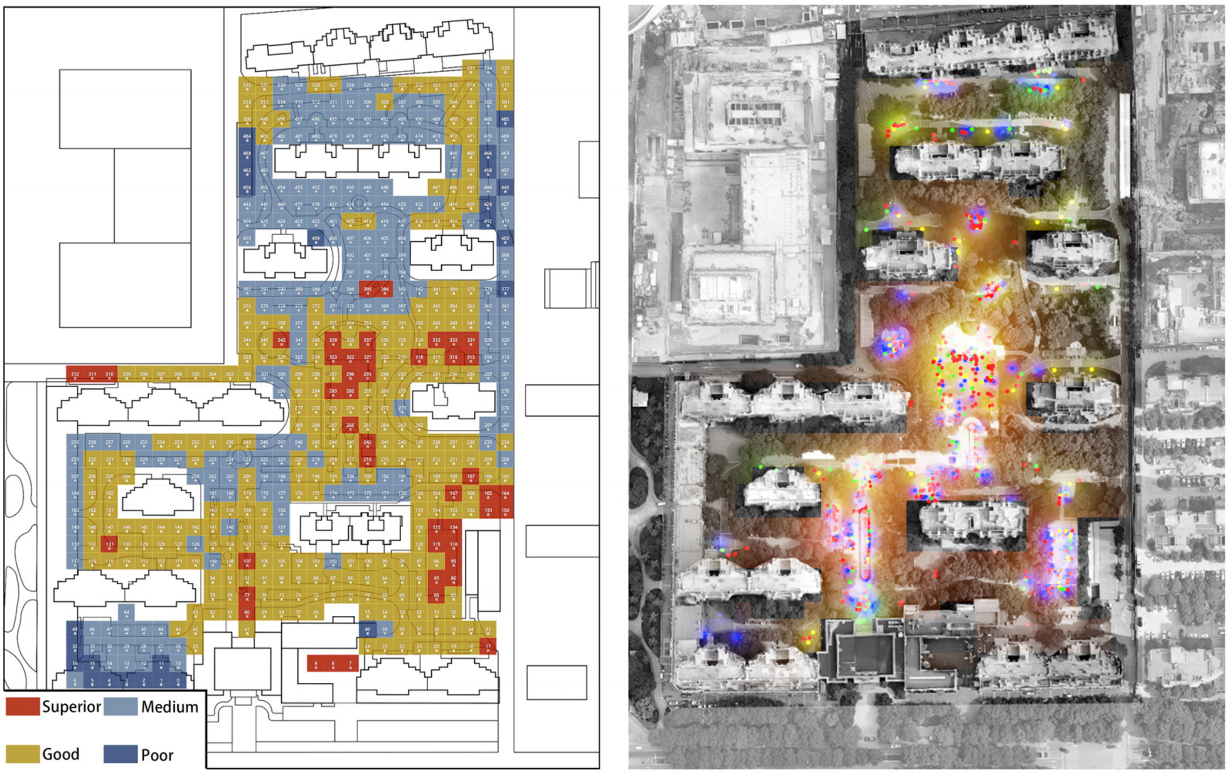

Figure 10. Machine learning predicted crowd preference distribution vs. real scene comparison. Colored dots: elderly (red dots), youth (green dots), middle-aged (blue dots), children (yellow dots).

4. Discussion

4.1. Crowd Behavior Analysis

Residents' activities in community open spaces exhibit significant spontaneity, driven by their own needs and external conditions rather than occurring randomly. Residents show preferential selection for locations that meet their activity requirements (Figure 11). Specifically, temperature and POIs significantly influence residents' activity decisions. During high temperature periods, residents avoid sun-exposed areas, while in cooler early mornings and late afternoons, the frequency and duration of activities increase significantly. Landscape nodes and activity areas (such as playgrounds and plazas) attract more residents, especially the elderly and children.

Figure 11. Residents choose shaded areas with low radiation for activities such as square dancing.

Using machine learning techniques to deeply explore the relationship between residents' behavior and environmental performance and to predict outdoor comfort zones holds substantial research value and practical significance. While previous research typically applied the Yolo model for facial detection [37] or indoor people counting [38], we extended its use to detect both people and POIs in outdoor residential environments. This extension allowed us to integrate POI detection with high-resolution thermal comfort analysis, providing a more comprehensive understanding of how spatial factors and human activity influence thermal comfort in outdoor spaces. This innovative use of the Yolo model bridges the gap between traditional indoor-focused analyses and the complexities of outdoor environments.

Machine learning can extract patterns of association between residents' activities and environmental factors (including temperature and POIs) from large datasets, leading to more accurate predictions and assessments of the environmental performance of different outdoor spaces at various times. Previous studies have reported prediction accuracies for outdoor thermal comfort in similar climate zones using ensemble learning algorithms ranging from 0.5325 to 0.9313 [39]. In this study, by incorporating POI indicators, we achieved a prediction accuracy of 0.95, representing an improvement of approximately 2.0% to 43.9%. This accuracy is comparable to the R^2 = 0.960 reported by previous studies using the best deep learning models [40], which require significantly more computational resources. Additionally, our findings confirmed that shading is the most critical factor influencing crowd preferences, aligning with conclusions from prior research [41]. The discrepancies may arise from differences in data collection timing and frequency, feature selection and processing, algorithm hyperparameter settings, and model training and validation methods. This provides scientific evidence for urban planners and designers to optimize the design of community open spaces, offering residents a more comfortable and convenient outdoor activity environment. Therefore, this study aims to reveal the link between residents' behavior and environmental performance through machine learning, providing new perspectives and approaches for optimizing outdoor spaces.

4.2. Community Environment Optimization

Based on the environmental friendliness levels and feature importance analysis predicted by the XGBoost model, this study formulated targeted spatial optimization strategies aimed at enhancing the utilization efficiency of community spaces and improving residents' quality of life, with particular attention to the special needs of vulnerable groups such as the elderly and children.

The optimization measures include increasing the number of trees and installing shade structures, such as canopies, in areas with high solar radiation (SR) to mitigate the negative impact on residents' activities. Solar radiation is a major factor affecting the thermal environment, and shade structures can effectively reduce surface and air temperature, thereby lowering the radiative heat load in the area. Trees not only absorb and reflect a portion of solar radiation through their leaves but also release moisture through transpiration, further cooling the air and improving the local microclimate's comfort.

In areas with low Sky View Factor (SVF), the study suggests adjusting the spatial layout to improve ventilation conditions. Low SVF indicates that longwave radiation from the ground is blocked by buildings or vegetation, making it difficult for heat to dissipate, which increases the Mean Radiant Temperature (MRT). By redesigning the spatial layout in these areas, such as increasing open spaces or introducing ventilation corridors, airflow can be enhanced, promoting effective heat dissipation and reducing MRT, thus improving thermal comfort.

Regarding the optimization of Points of Interest (POI), the study recommends placing children's play areas and fitness facilities in shaded zones while designating areas with poor climatic conditions as negative functional nodes, such as parking lots and garbage dumps. Children and high-intensity activity participants are more sensitive to thermal environments, so placing these functions in areas with lower heat loads can significantly improve their thermal comfort experience. Functions with lower thermal environment requirements, such as parking lots, can be located in areas with poorer thermal conditions, thereby minimizing the negative impact on the overall thermal environment.

Particularly in the optimization of the average distance (PD), the study explored the coupling effect between residents' needs and the thermal environment. PD represents the distance from residents' living areas to public functional nodes, which is closely related to residents' activity frequency and behavior patterns. In hot climates, long exposure to high-temperature environments significantly increases the human body's heat load, potentially leading to heat stress and discomfort, especially among vulnerable groups. Therefore, by designating areas with favorable climatic conditions (e.g., moderately temperate and well-shaded areas) as positive space nodes, optimizing path design and node layout, and reducing the PD between these nodes and residential areas, the time residents spend exposed to unfavorable thermal environments can be minimized. This reduces the risk of heat stress, enhances the efficiency of community space use, and improves residents' quality of life. Through this approach, the spatial layout not only meets functional needs but also fully considers the combined impact of the thermal environment on human health and behavior, achieving effective coupling between human needs and the thermal environment.

4.3. Research Contributions and Limitations

The theoretical contributions of this study include the following points: Firstly, by introducing the concept of spatial heterogeneity, it deepens the understanding of the complexity of environmental behavior and constructs a theoretical framework for space-behavior interaction. Secondly, by utilizing machine learning methods, it quantifies the relationship between spatial features (including POIs and thermal environments) and behavior patterns, providing new quantitative analysis tools for environmental behavior research. Lastly, by integrating climate models and community conditions, it reveals the important role of microclimate factors in regulating resident behavior, filling a gap in the field.

On a practical level, the outdoor environmental comfort map created in this study can visually identify areas needing improvement to optimize outdoor spaces and meet individual needs for diverse urban activities. For example, adjusting building layouts to increase summer shade coverage, optimizing walking paths to improve space accessibility, and reasonably planning open spaces to reduce the negative impact of the sky view factor on crowd activities. These strategies not only enhance residents' activity experience but also promote the sustainable development of the community. Additionally, the technical methods used in this study provide a reference path for similar research, applicable to urban renewal, humanistic care, safety, and commercial value aspects.

We further analyzed the environmental benefits and potential risks associated with this study. On one hand, optimizing outdoor space layout can promote residents' health, enhance community vitality, and achieve energy savings and emissions reduction. Rational space layout and shading design can reduce the use of air conditioning and other cooling devices, thereby lowering energy consumption and greenhouse gas emissions, while also attracting more residents to participate in outdoor activities and strengthening community cohesion.

On the other hand, we examined the potential risks of space optimization, including the balance between financial investment and cost-effectiveness, as well as the impact on the existing ecological environment. We emphasize that any spatial modifications require comprehensive environmental impact assessments to ensure sustainability. Additionally, the acceptance of the modification plans by residents is crucial; without broad support, the implementation may face challenges or even lead to social conflicts. Therefore, evaluating public acceptance is also a key aspect of this study.

Despite achieving certain results, this study has limitations. Firstly, the research data are primarily based on summer activity behavior; future studies could incorporate data from different seasons to comprehensively assess the impact of seasonal changes on resident behavior. In addition, we chose sunny days as the typical weather condition to ensure consistency with the meteorological data simulation. Discussing the impact of POIs under cloudy conditions in future work could help in isolating the effects of different variables. Secondly, we plan to validate these assumptions through multi-case comparative studies. This will involve observing POI attractiveness levels across multiple urban spaces in different geographic locations, cultural contexts, and climatic conditions. A local calibration mechanism will be implemented to adjust POI attractiveness rankings based on region-specific data. For example, a café that is highly attractive in a busy downtown area may not have the same level of attractiveness in a suburban neighborhood. By incorporating local social, cultural, and environmental factors, the model will better reflect the unique dynamics of different urban spaces, ensuring more accurate and context-specific predictions. Furthermore, we will explore ways to refine and adjust our model to accommodate varying factors in different urban spaces. Specifically, we will focus on how to more accurately quantify and assess the positive or negative value of POIs based on local social and environmental factors. This will help improve the applicability and accuracy of our model in different urban contexts.

5. Conclusions

This study integrated visual intelligence technology, thermal comfort simulation, and machine learning methods to construct a high-precision predictive framework based on the XGBoost model for analyzing the driving factors of crowd preferences in community environments. The results show that the XGBoost model performed exceptionally well in predicting crowd preferences, achieving an accuracy of 0.95, significantly outperforming other common machine learning algorithms. This finding not only validates the superiority of the XGBoost model in handling complex environmental data but also demonstrates the feasibility of combining multi-source data for environmental analysis at the community scale.

Through SHAP value analysis, the study identified shadow proportion and Points of Interest (POI) distance as the two most significant factors influencing crowd preferences, with SHAP values of 0.24 and 0.12, respectively. This indicates that in high-temperature environments, shading design significantly affects people's activity choices, and well-distributed shaded areas can effectively enhance residents' thermal comfort and willingness to engage in outdoor activities. Additionally, appropriately shortening the distance between residential areas and POIs not only increases the frequency of residents' use of these functional nodes but also promotes social interaction and community vitality.

By extrapolating this classification model to regions with similar climate and cultural contexts, this study provides strong support for the optimized design of community environments. The model's predictive results can offer empirical evidence for urban planning and public space design, particularly in effectively utilizing shade, strategically placing POIs, and optimizing residents' activity paths.

This study contributes to the theoretical understanding of the relationship between spatial heterogeneity and resident behavior by demonstrating the effectiveness of machine learning in predicting crowd preferences. However, there are limitations: the data are summer-specific, limiting seasonal generalizability, and the findings are based on a single community, necessitating further validation across diverse contexts. Future research should explore multi-seasonal data, conduct comparative studies across different regions, and apply more advanced machine learning algorithms to enhance the accuracy of behavioral predictions.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

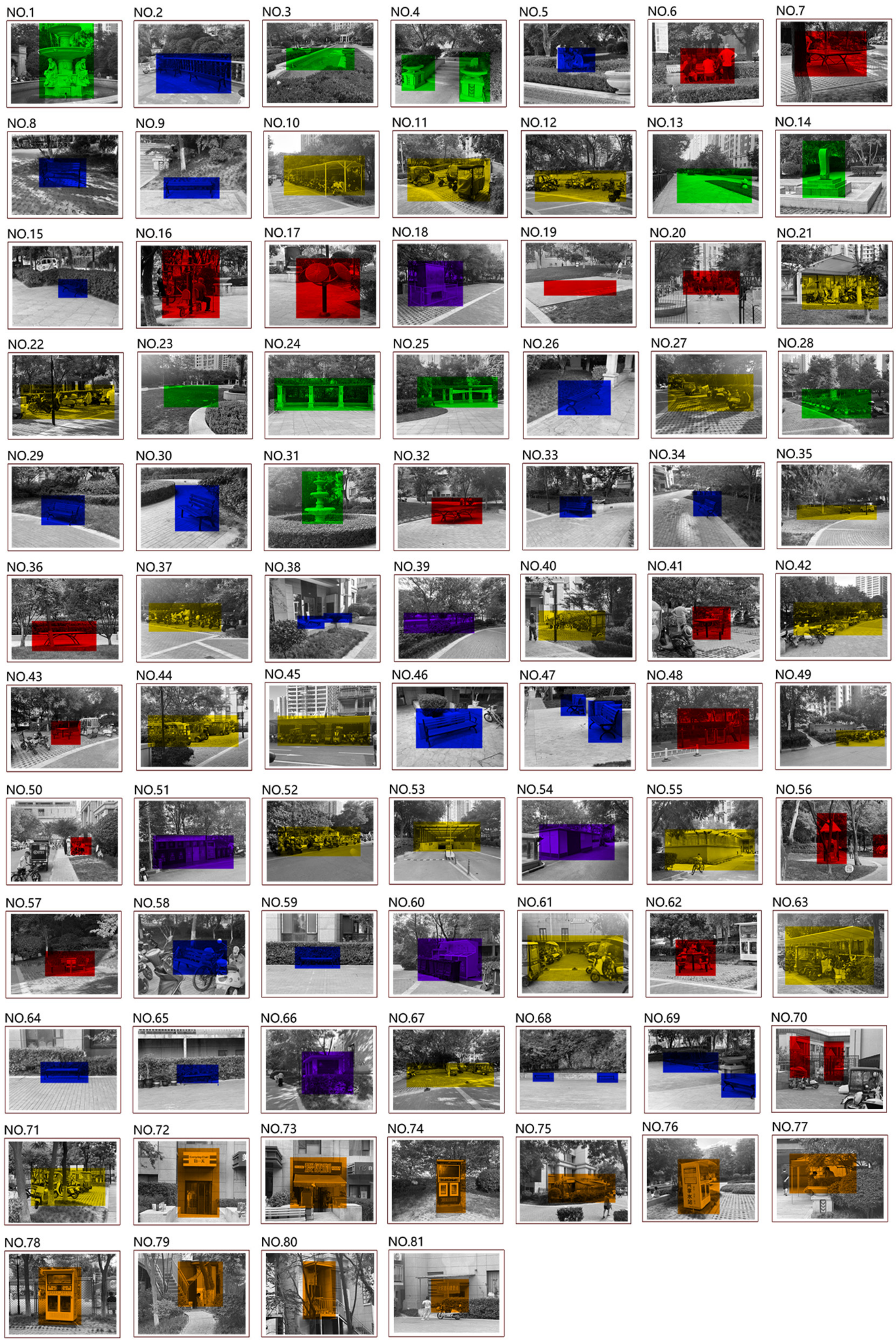

Figure A1. Real scenes of 81 points of interest within the site. The different colors of the mask represent: activity area (red), rest area (blue), landscape area (green), shops (orange), parking lot (yellow), and negative spots (purple).

Figure A2. Thermal environment time series simulation results 1.

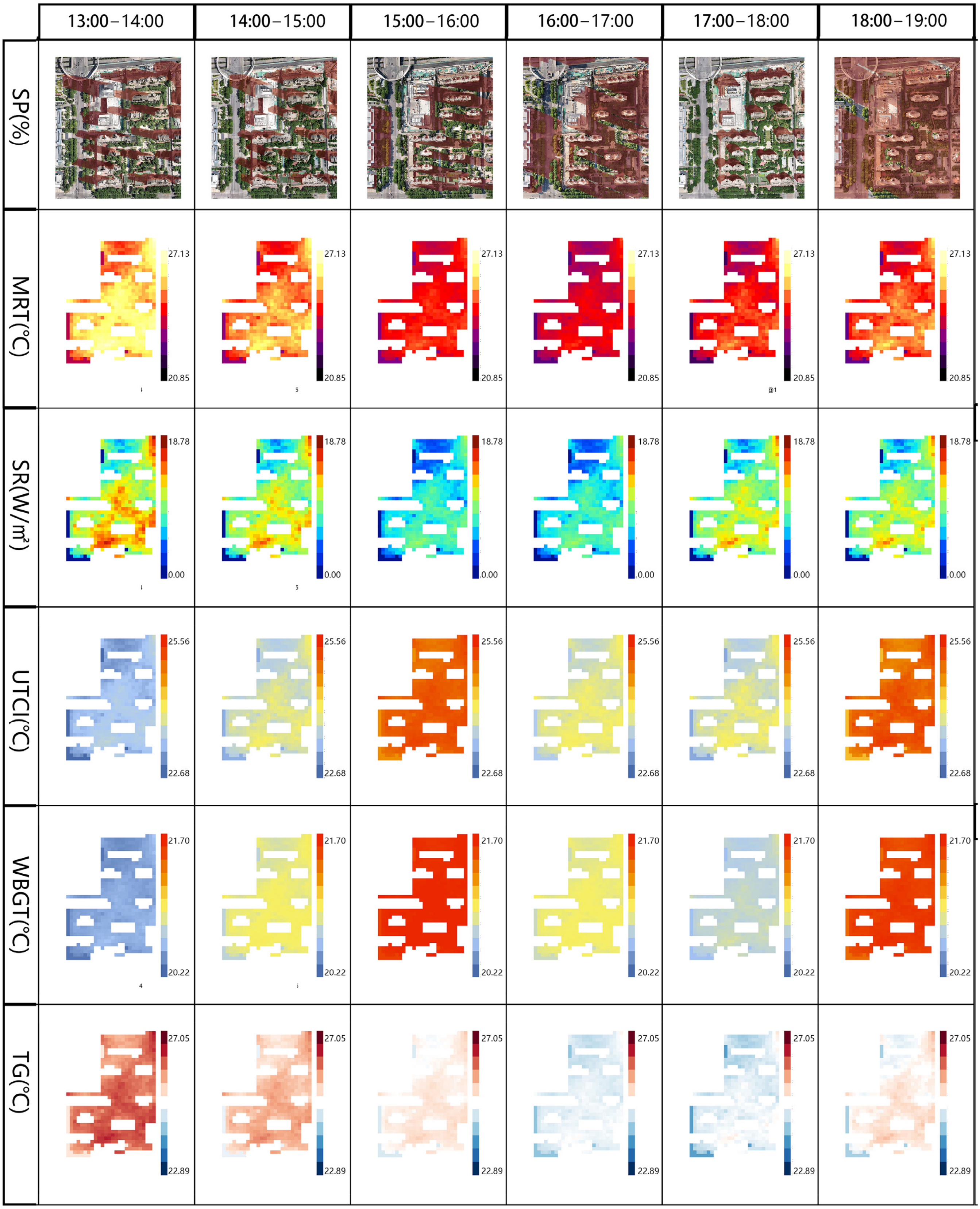

Figure A3. Thermal environment time series simulation results 2.

References

1. Gao, S.; Janowicz, K.; Couclelis, H. Extracting urban functional regions from points of interest and human activities on location-based social networks. *Trans. GIS* **2017**, *21*, 446–467. [CrossRef]
2. Silva, T.J.V.; Hirashima, S.Q.S. Predicting urban thermal comfort from calibrated UTCI assessment scale—A case study in Belo Horizonte city, southeastern Brazil. *Urban Clim.* **2020**, *36*, 100652. [CrossRef]
3. Li, S.; Ye, Y.; Chen, H.; Yang, Y.; Huang, Y.; Wu, Z. Vitality Analysis and Improvement of Micro Urban Spaces in Cold Regions Evidence from Harbin, China. *Int. Rev. Spat. Plan. Sustain. Dev.* **2024**, *12*, 95–117.
4. Sun, J.; Harris, K.; Vazire, S. Is well-being associated with the quantity and quality of social interactions? *J. Pers. Soc. Psychol.* **2020**, *119*, 1478–1496. [CrossRef] [PubMed]
5. Ali, A.; Zhu, Y.; Zakarya, M. A data aggregation based approach to exploit dynamic spatio-temporal correlations for citywide crowd flows prediction in fog computing. *Multimed. Tools Appl.* **2021**, *80*, 31401–31433. [CrossRef]
6. Psyllidis, A.; Gao, S.; Hu, Y.; Kim, E.-K.; McKenzie, G.; Purves, R.; Yuan, M.; Andris, C. Points of Interest (POI): A commentary on the state of the art, challenges, and prospects for the future. *Comput. Urban Sci.* **2022**, *2*, 20. [CrossRef]
7. Yeow, L.W.; Low, R.; Tan, Y.X.; Cheah, L. Point-of-Interest (POI) Data Validation Methods: An Urban Case Study. *ISPRS Int. J. Geo. Inf.* **2021**, *10*, 735. [CrossRef]
8. Zheng, M.; Wang, H.; Shang, Y.; Zheng, X. Identification and prediction of mixed-use functional areas supported by POI data in Jinan City of China. *Sci. Rep.* **2023**, *13*, 2913. [CrossRef]
9. Pan, C.; Wu, S.; Li, E.; Li, H.; Liu, X. Identification of urban functional zones in Macau Peninsula based on POI data and remote information sensors technology for sustainable development. *Phys. Chem. Earth Parts A/B/C* **2023**, *131*, 103447. [CrossRef]
10. Wang, Z.; Ma, D.; Sun, D.; Zhang, J. Identification and analysis of urban functional area in Hangzhou based on OSM and POI data. *PLoS ONE* **2021**, *16*, e0251988. [CrossRef]
11. Li, Y.; Xu, L. The Impact of COVID-19 on Pedestrian Flow Patterns in Urban POIs—An Example from Beijing. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 479. [CrossRef]
12. Lu, C.; Pang, M.; Zhang, Y.; Li, H.; Lu, C.; Tang, X.; Cheng, W. Mapping Urban Spatial Structure Based on POI (Point of Interest) Data: A Case Study of the Central City of Lanzhou, China. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 92. [CrossRef]
13. Cichosz, P. Urban Crime Risk Prediction Using Point of Interest Data. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 459. [CrossRef]
14. Zhang, J.; Xu, E. Investigating the spatial distribution of urban parks from the perspective of equity-efficiency: Evidence from Chengdu, China. *Urban For. Urban Green.* **2023**, *86*, 128019. [CrossRef]
15. Zeng, W.; Zhong, Y.; Li, D.; Deng, J. Classification of Recreation Opportunity Spectrum Using Night Lights for Evidence of Humans and POI Data for Social Setting. *Sustainability* **2021**, *13*, 7782. [CrossRef]
16. Xu, C.; Liu, D.; Mei, X. Exploring an efficient POI recommendation model based on user characteristics and spatial-temporal factors. *Mathematics* **2021**, *9*, 2673. [CrossRef]
17. Chen, Y.; Jia, B.; Wu, J.; Liu, X.; Luo, T. Temporal and Spatial Attractiveness Characteristics of Wuhan Urban Riverside from the Perspective of Traveling. *Land* **2022**, *11*, 1434. [CrossRef]
18. Werneck, H.; Santos, R.; Silva, N.; Pereira, A.C.M.; Mourão, F.; Rocha, L. Effective and diverse POI recommendations through complementary diversification models. *Expert Syst. Appl.* **2021**, *175*, 114775. [CrossRef]
19. Lin, H.; Wang, J.B.; Zhang, X.; Hu, F.; Liu, J.; Hong, X.C. Historical sensing: The spatial pattern of soundscape occurrences recorded in poems between the Tang and the Qing Dynasties amid urbanization. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 730. [CrossRef]
20. Jin, S.; Wang, X.; Meng, Q. Spatial memory-augmented visual navigation based on hierarchical deep reinforcement learning in unknown environments. *Knowl. Based Syst.* **2024**, *285*, 111358. [CrossRef]
21. He, S.; Chen, W.; Wang, K.; Luo, H.; Wang, F.; Jiang, W.; Ding, H. Region Generation and Assessment Network for Occluded Person Re-Identification. *IEEE Trans. Inf. Forensics Secur.* **2023**, *19*, 120–132. [CrossRef]
22. Mi, C.; Liu, Y.; Zhang, Y.; Wang, J.; Feng, Y.; Zhang, Z. A vision-based displacement measurement system for foundation pit. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 2525715. [CrossRef]
23. Zhang, H.; Zhou, X.; Li, H.; Zhu, G.; Li, H. Machine Recognition of Map Point Symbols Based on YOLOv3 and Automatic Configuration Associated with POI. *ISPRS Int. J. Geo. Inf.* **2022**, *11*, 540. [CrossRef]
24. Charitidis, P.; Moschos, S.; Pipertzis, A.; Theologou, I.J.; Michailidis, M.; Doropoulos, S.; Diou, C.; Vologiannidis, S. StreetScouting: A Deep Learning Platform for Automatic Detection and Geotagging of Urban Features from Street-Level Images. *Appl. Sci.* **2022**, *13*, 266. [CrossRef]
25. Qian, Z.; Liu, X.; Tao, F.; Zhou, T. Identification of urban functional areas by coupling satellite images and taxi GPS trajectories. *Remote Sens.* **2020**, *12*, 2449. [CrossRef]
26. Lai, D.; Lian, Z.; Liu, W.; Guo, C.; Liu, K.; Chen, Q. A comprehensive review of thermal comfort studies in urban open spaces. *Sci. Total Environ.* **2020**, *742*, 140092. [CrossRef]
27. Ma, X.; Tian, Y.; Du, M.; Hong, B.; Lin, B. How to design comfortable open spaces for the elderly? Implications of their thermal perceptions in an urban park. *Sci. Total Environ.* **2021**, *768*, 144985. [CrossRef]
28. Huang, C.; Zhang, G.; Yao, J.; Wang, X.; Calautit, J.K.; Zhao, C.; An, N.; Peng, X. Accelerated environmental performance-driven urban design with generative adversarial network. *Build. Environ.* **2022**, *224*, 109575. [CrossRef]

29. Yang, B.; Olofsson, T.; Nair, G.; Kabanshi, A. Outdoor thermal comfort under subarctic climate of north Sweden–A pilot study in Umeå. *Sustain. Cities Soc.* **2017**, *28*, 387–397. [CrossRef]
30. Gupta, S.; Anand, P. Improvement of outdoor thermal comfort for a residential development in Singapore. *Int. J. Energy Environ.* **2015**, *6*, 567.
31. Shawesh, R.; Mohamed, M. Post-occupancy evaluation of outdoor thermal comfort in hot arid zone. *Int. J. Low-Carbon Technol.* **2021**, *16*, 50–60. [CrossRef]
32. Nakano, J.; Tanabe, S.I. Thermal adaptation and comfort zones in urban semi-outdoor environments. *Front. Built Environ.* **2020**, *6*, 34. [CrossRef]
33. Cheela, V.R.S.; John, M.; Biswas, W.; Sarker, P. Combating Urban Heat Island Effect—A Review of Reflective Pavements and Tree Shading Strategies. *Buildings* **2021**, *11*, 93. [CrossRef]
34. Deilami, K.; Rudner, J.; Butt, A.; MacLeod, T.; Williams, G.; Romeijn, H.; Amati, M. Allowing Users to Benefit from Tree Shading: Using a Smartphone App to Allow Adaptive Route Planning during Extreme Heat. *Forests* **2020**, *11*, 998. [CrossRef]
35. Shen, Y.; Kong, W.; Fei, F.; Chen, X.; Xu, Y.; Huang, C.; Yao, J. Stereoscopic urban morphology metrics enhance the nonlinear scale heterogeneity modeling of UHI with explainable AI. *Urban Clim.* **2024**, *56*, 102006. [CrossRef]
36. Ni, H.; Wang, D.; Zhao, W.; Jiang, W.; Mingze, E.; Huang, C.; Yao, J. Enhancing rooftop solar energy potential evaluation in high-density cities: A Deep Learning and GIS based approach. *Energy Build.* **2024**, *309*, 113743. [CrossRef]
37. Jeoung, J.; Jung, S.; Hong, T.; Lee, M.; Koo, C. Thermal comfort prediction based on automated extraction of skin temperature of face component on thermal image. *Energy Build.* **2023**, *298*, 113495. [CrossRef]
38. Choi, H.; Um, C.Y.; Kang, K.; Kim, H.; Kim, T. Application of vision-based occupancy counting method using deep learning and performance analysis. *Energy Build.* **2021**, *252*, 111389. [CrossRef]
39. Xi, T.; Wang, M.; Cao, E.; Li, J.; Wang, Y.; Sa'ad, S.U. Preliminary Research on Outdoor Thermal Comfort Evaluation in Severe Cold Regions by Machine Learning. *Buildings* **2024**, *14*, 284. [CrossRef]
40. Zhong, G. Convolutional Neural Network Model to Predict Outdoor Comfort UTCI Microclimate Map. *Atmosphere* **2022**, *13*, 1860. [CrossRef]
41. Guo, R.; Yang, B.; Guo, Y.; Li, H.; Li, Z.; Zhou, B.; Hong, B.; Wang, F. Machine learning-based prediction of outdoor thermal comfort: Combining Bayesian optimization and the SHAP model. *Build. Environ.* **2024**, *254*, 111301. [CrossRef]