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Counter-intuitive heat adaptation: How 360° behavioral tracking reveals unexpected park design solutions for urban climate resilience

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A B S T R A C T

Urban heat adaptation strategies rely on assumptions about how people use public spaces, yet actual behavioral responses remain largely unexplored. Using 360° video tracking and AI-powered object detection (YOLOv10) across 11 Beijing parks, we reveal counter-intuitive patterns that challenge conventional cooling design. While rising temperatures suppress overall park use, specific facilities exhibit unexpected effects: sports courts sustain and even increase youth activity under heat stress, suggesting functional needs override thermal discomfort. Conversely, sheltering elements prove essential for vulnerable populations, with pavilions and shaded seating promoting critical static rest behaviors. Our multi-scale analysis demonstrates that macro-environmental context (e.g., the greenery level of the park's surroundings) modulates these micro-scale effects (e.g., the influence of specific in-park facilities), with parks in less vegetated surroundings becoming vital cooling refuges. These behavioral insights enable a fundamental shift from reactive cooling strategies to proactive design that strategically leverages human adaptation patterns, providing empirical foundations for climate-resilient urban spaces.

1. Introduction

The intensification of extreme heat events in terms of frequency, intensity, and duration, driven by global climate change (IPCC, 2021, 2022; Raymond et al., 2020), poses an increasingly severe threat to urban environments and their inhabitants (Mora et al., 2017; Wu et al., 2013; Li et al., 2021). Projections indicate a continuation of global warming, with the potential to further intensify the urban heat island effect (Zhou et al., 2022), particularly under scenarios exceeding 1.5 °C of warming (Chen et al., 2022). This necessitates the urgent enhancement of urban resilience. Despite extensive research focusing on the severe health consequences of heat exposure, i.e. the "backend" impacts of failed heat adaptation (Gasparrini et al., 2015; Vicedo-Cabrera et al., 2021; Navas-Martín et al., 2022; Åström et al., 2013), critical knowledge gaps persist in understanding and promoting "frontend" behavioral heat adaptation strategies in daily urban life (Harlan & Ruddell, 2011; Heaviside et al., 2020). It is vital to acknowledge the significance of heat adaptation behaviors in mitigating heat stress and maintaining well-being. However, individual responses to heat are complex and varied. Urban residents often face conflicting pressures between mitigation (e.g., energy saving) and adaptation behaviors, suggesting that behavioral choices are heavily context-dependent and involve navigating trade-offs across various daily scenarios, from leisure to mobility (Kondo et al., 2021; Zhang et al., 2026) . While some users may simply avoid heat, others persist in outdoor activities due to social needs. This variability suggests that adaptation is not a linear process but involving multiple decision-making factors. Such behaviors include adjusting activity timing, type, location, and utilizing environmental resources (Kuras et al., 2015). The core of this study lies in understanding two levels of heat adaptation: first, what macro-level factors determine people's adaptive choice to enter a park on a hot day; and second, after making this choice, how the micro-environment within the park then shapes their specific behavioral patterns (e.g., choosing dynamic or static activities).

Urban outdoor public spaces, such as parks and green spaces, are of paramount importance for daily life and for the adoption of heat adaptation behaviors (Yang et al., 2013). Maintaining the "viability" of these public spaces under increasing heat requires a transdisciplinary

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approach that goes beyond physical measurements to include social and behavioral dimensions (Foshag et al., 2020). The potential for these green spaces and their specific spatial configurations to offer cooler microclimates (Feyisa et al., 2014; Li et al., 2023) and a variety of amenities (Hartig et al., 2014; Kenny et al., 2010) renders them of crucial importance for public health, particularly for vulnerable demographics (Hartig et al., 2014; Kenny et al., 2010). It is evident that individuals modify their park usage patterns in response to changing thermal environmental conditions, a fundamental behavior in climate adaptation (Guan et al., 2021; Roberts et al., 2017; Lai et al., 2019). This adaptation has the potential to reduce reliance on indoor air conditioning and to support physical and mental health (Hartig et al., 2014; Obradovich & Fowler, 2017). However, despite the benefits of these measures being well-recognised (see Hartig et al., 2014; Cohen et al., 2020), there remains a significant lack of understanding of how to proactively enhance their capacity to support heat adaptation behaviors through micro-scale built environment design.

The limitations of extant research can be summarized as follows:

Scalar Mismatch and Thermal Determinism: While the benefits of park usage are well-recognized, current research faces critical theoretical and practical limitations that hinder effective design. A significant "scale mismatch" exists in adaptation research. A plethora of studies concentrate either on macro-scale cooling effects (e.g., overall park cooling intensity) (Feyisa et al., 2014) or isolated technological interventions (Hong et al., 2020). This leaves a "missing middle" at the micro-scale—the human scale where actual behavioral decisions are made. We lack a comprehensive understanding of how specific design combinations (e.g., the spatial relationship between a bench and a tree) synergistically influence usage, creating a disconnect between high-level adaptation goals and on-the-ground design practice (Middel et al., 2014). Perhaps more critically, existing literature is largely dominated by "Thermal Determinism." Most traditional thermal comfort models (e.g., PMV/PET) assume that when physiological stress exceeds a certain threshold, users will inevitably vacate the space. However, this perspective ignores the complex "psychological adaptation" proposed by Nikolopoulou and Steemers (2003), where functional needs and social motivations may override thermal sensations. Current literature fails to quantify this trade-off, and we do not yet know the "tipping point" where the functional affordance of a facility (e.g., a basketball court) becomes strong enough to sustain activity despite heat stress. Addressing this theoretical gap is crucial for shifting the paradigm from merely "avoiding heat" to actively "facilitating life" under climate change.

Uncovering the Mechanisms of Behavioral Adaptation: The intrinsic pathways and quantitative relationships by which specific micro-environmental features (e.g., a pavilion, a patch of tree shade) influence individual thermal perception and subsequently guide or inhibit specific adaptive behaviors (e.g., choosing to sit and rest versus engaging in activity), especially the variations across different population groups, remain largely unclear (Guan et al., 2021; Potchter et al., 2018; Cheung & Jim, 2019; Helbich et al., 2019; Yin et al., 2024). In this study, 'micro-environmental features' refer to the specific, small-scale physical and spatial characteristics within a defined park area that directly shape a user's immediate sensory experience and behavioral choices. These are broadly categorized into: (1) Facility Elements, which are tangible, man-made or natural objects such as benches, pavilions, sports courts, and water features; and (2) Spatial Layout, which are quantifiable spatial qualities of the immediate surroundings, such as the Green View Index (GVI), Sky View Factor (SVF), and the overall size of the activity area (see Appendix, Figure S3 for visual examples). This research aims to illuminate these pathways by quantitatively assessing how specific micro-environmental features influence thermal perception and guide adaptive behaviors across diverse population groups.

Bottlenecks in Data Acquisition: Traditional methods struggle to capture, across multiple sites and with high precision, real-world adaptive behaviors that are closely linked to immediate micro-environmental conditions (Helbich et al., 2019; Yang et al., 2021; Li et al., 2025; Ma et al., 2025). This fundamentally constrains deep insights into complex adaptation mechanisms. Recent reviews on algorithmic green infrastructure optimization (e.g., Shaamala et al., 2024) have emphasized the transformative potential of artificial intelligence (AI) driven approaches in tackling climate change challenges. Aligning with this emerging trend, our study leverages AI-driven observational techniques for multi-site, high-precision capture of real-world adaptive behaviors and associated micro-environmental conditions.

Challenges in Adaptation Planning: Current climate adaptation planning practices often encounter challenges. Early plans tended to prioritise macro-level capacity building, with insufficient specific actions (Preston et al., 2011). Recent assessments also indicate that many urban plans still have shortcomings in quality and internal consistency, particularly in effectively linking risks, goals, and measures. This leads to an 'adaptation gap' between planning and actual needs (Reckien et al., 2023a, 2025). This study seeks to bridge this 'adaptation gap' by providing granular, evidence-based insights into how micro-scale design can effectively support heat adaptation behaviors, thereby informing more actionable and targeted adaptation planning.

Facing these challenges, this study aims to drive a fundamental paradigm shift: moving the focus of heat adaptation from assessing passive health impacts to exploring how proactive urban and landscape design can actively shape and enhance the built environment's adaptive capacity. For combating the issue of heatwaves, urban areas should consider a strategic approach involving the incorporation of adaptive 'genes' (i.e., specific design features fostering thermal comfort and adaptive behaviors) into their spatial design. Ensuring the effectiveness of such measures and the avoidance of "maladaptation" – interventions that inadvertently increase vulnerability or cause other negative side effects, especially for different demographic groups (Reckien et al., 2023b) – demands meticulous consideration of their multi-faceted impacts.

Therefore, this research distinctively integrates Artificial Intelligence (AI)-driven high-resolution environmental and behavioral sensing with a novel multi-scale analytical framework. It aims to systematically decode urban park users' complex heat adaptation responses under heat stress, precisely quantify how the micro-built environment (particularly facilities) guides these adaptive behaviors, and ultimately propose a new paradigm for fine-grained, heat-adaptive design. Building upon the identification of an 'adaptation gap' in current planning by scholars like Reckien et al. (2023a, 2025), this study seeks to provide critical empirical evidence—specifically by decoding micro-scale environment-behavior interactions—to bridge this gap and foster more consistent, effective adaptation strategies.

Therefore, this research aims to drive a fundamental paradigm shift from assessing passive health impacts to proactively shaping the built environment's adaptive capacity through targeted design. The primary objective is to systematically decode how urban park users' adaptive behaviors are shaped by multi-scale environmental factors under heat stress, in order to bridge the 'adaptation gap' and provide empirical evidence for climate-resilient design. To achieve this, we address three interconnected questions: First, we examine how heat stress differentially affects the adaptive behavior patterns of diverse user groups within defined park activity areas (DAAs). Second, we identify which macro-morphological and connectivity features of park surroundings interact with temperature to determine a park's overall attractiveness as an urban "heat adaptation space". Critically, we then analyze how micro-environmental elements within these parks moderate the pathways between perceived thermal conditions and behavioral choices, ultimately shaping final heat adaptation outcomes. These objectives are systematically addressed in the 'Results' chapter, which first describes park and DAA occupancy characteristics (Section 3.1), then examines the overall suppressive effect of heat on park user behavior (Section 3.2), and finally decodes the specific regulatory role of micro-environmental elements in shaping adaptive responses (Section 3.3).

2. Data and methods

2.1. Research framework

The core framework of this study is based on a dual-scale analysis, which represents not merely a methodological design but a theoretical innovation in understanding heat adaptation. This framework integrates the environment-perception-behavior adaptation chain proposed by Nikolopoulou and Steemers (2003) with the social ecological model by Sallis et al. (2016), constructing a multi-scale model for understanding heat adaptation from micro environmental elements to macro urban morphology. This theoretical integration enables us to simultaneously examine: (1) individual-level heat adaptation behavior choices (e.g., seeking shade for rest); (2) environment-guided adaptive behavioral decisions (e.g., activities stimulated by specific facilities); and (3) regional-level interactions between heat environments and usage patterns (e.g., the relative value of parks versus surrounding urban fabric). This multi-scale, multi-pathway conceptualization of heat adaptation transcends the limitations of traditional research that simplifies heat adaptation to a single temperature-behavior relationship (Potchter et al., 2018; Cheung & Jim, 2019), providing a more comprehensive theoretical framework for understanding the complex human-environment interactions under high temperatures (Fig. 1).

For data collection, we selected 11 representative parks in the Shijingshan District of Beijing as samples, obtaining high-resolution geocoded behavioral and environmental data through on-site mobile panoramic video recording combined with GPS positioning. The original video data were processed using artificial intelligence (YOLOv10 model object recognition and tracking algorithms) to automatically identify pedestrian quantities, behaviors, attributes, and environmental elements, while matching GPS data to obtain spatial locations of pedestrians, behavioral occurrences and facilities.

At the park scale, we focus on the overall attractiveness of parks, using the total number of park users as the dependent variable, and exploring the influence of temperature and macro park characteristics (e.g., park area, accessibility indicators, surrounding environmental elements) as independent variables. Analysis at this scale employs the XGBoost model to identify key macro features affecting the total number

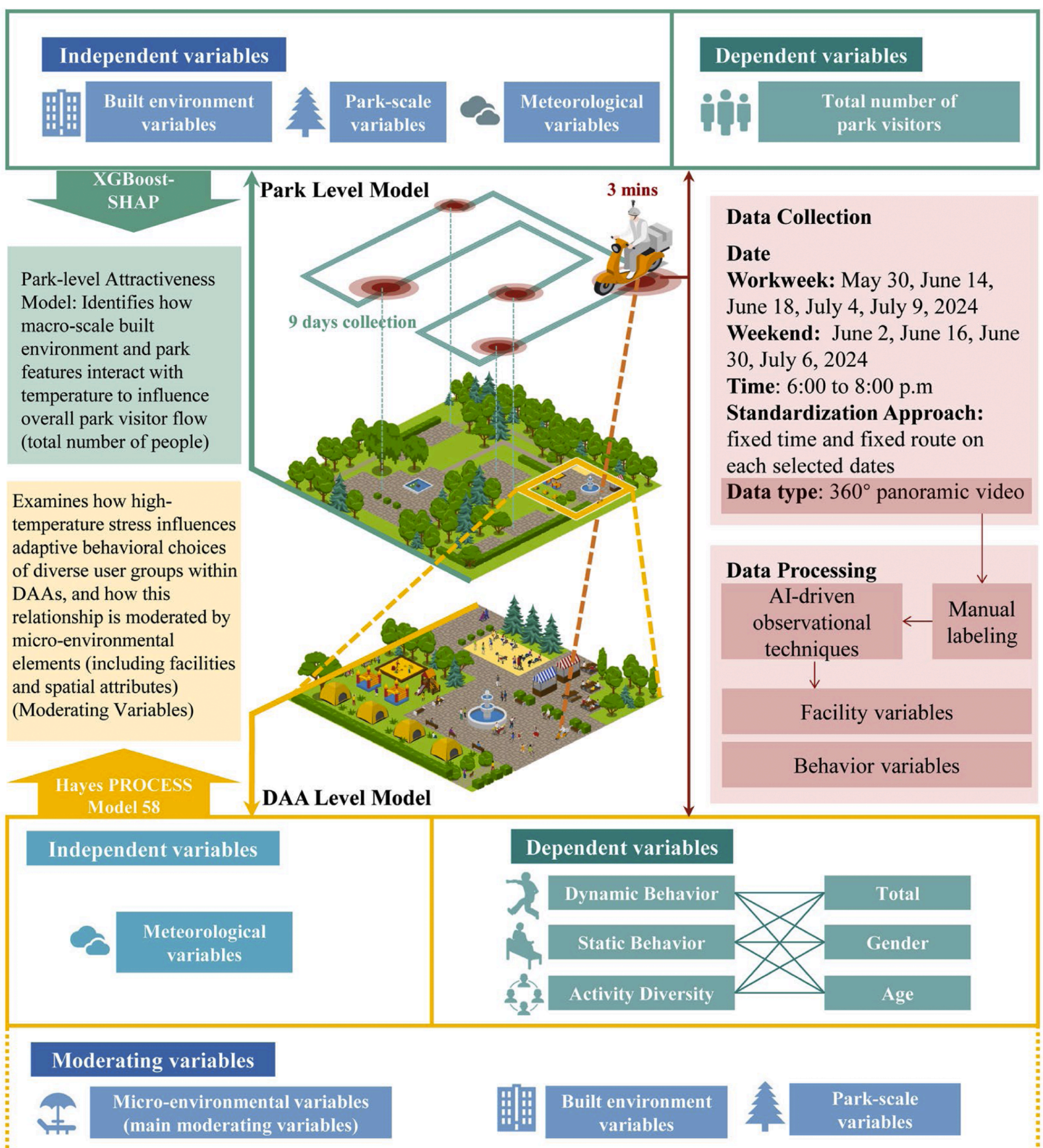

Fig. 1. Conceptual Framework.

of park users and their interactions with temperature, with interpretation provided through explainable machine learning methodology SHAP. At the DAA scale, we focus on user behaviors in specific activity spaces within parks, using adaptive behavior indicators of DAA users (e.g., dynamic/static behavior counts, behavioral diversity) as dependent variables and temperature as the independent variable. To account for its confounding effect, relative humidity (%) was included as a control variable in all analyses. We acknowledge in the limitations section that the absence of data on wind speed and solar radiation is a constraint of this study and a key direction for future research. On this basis, we introduce DAA attractiveness (cumulative total number of people within the DAA over 3 min) as a mediating variable, and examine the moderating effects of DAA micro-environmental characteristics (e.g., presence and quantity of various facilities, spatial attributes) and demographic attributes (gender, age group). Analysis at this scale employs a moderated mediation model Hayes PROCESS Model 58 (Hayes, 2022). This integrated framework, through multi-source data and targeted multi-level analysis methods, systematically aims to reveal the intrinsic mechanisms of heat adaptation behaviors in urban parks under high temperatures.

2.2. Research area and data collection

This study was conducted in Shijingshan District (39°53′–39°59′ N, 116°07′–116°14′ E), located in the western part of Beijing, China. A detailed map illustrating the geographic location of the district within Beijing's urban structure and the specific spatial distribution of the 11 sampled parks is provided in Supplementary Figure S1. Geographically, the district sits at the transition zone between the Western Hills and the Beijing plain, characterized by a distinct topography ranging from low-lying urban plains (approx. 40–60 m altitude) to mountainous terrain in the northwest. The area features a mix of high-density residential land use and extensive ecological reserves, making it an ideal "natural laboratory" for studying the heat adaptation functions of green spaces in complex urban built environments. Climatologically, the region experiences a hot-summer humid continental climate (Köppen classification: Dwa), characterized by hot, humid summers and cold, dry winters. The study focused on the early summer period (May-July), a critical window for outdoor activity, where daily maximum temperatures typically range from 24 °C to 35 °C with high relative humidity, imposing significant heat stress on the population.

This region was chosen based on the following considerations: First, as an important component of Beijing, Shijingshan District faces severe urban heat challenges. Second, Shijingshan District holds a prominent position among Beijing's districts due to its superior ecological environment. The area possesses abundant forest and mountain resources and is known as "half mountain, half water, half city, half market," with urban green coverage rate and per capita public green space area ranking among the highest in Beijing's central urban districts (Beijing Municipal Government). According to reports, its urban green coverage rate reaches 52.38%, and the per capita park green space area is approximately 20.51 square meters (Beijing Municipal Government), making it an important green conservation area and ecological barrier for Beijing. This excellent green foundation provides an ideal "natural laboratory" for studying the heat adaptation functions of green spaces in urban built environments. Third, the diversity and varying scales of parks within the region, ranging from large comprehensive parks to community-level small green spaces, provide rich samples for studying differences in heat adaptation behaviors across different types of green spaces. Ultimately, we selected 11 representative parks in the Shijingshan District for data collection based on park size, type, facility characteristics, and surrounding community features. Within each park, we predetermined several 'Defined Activity Areas' (DAAs). The selection criteria for DAAs were based on their function as primary gathering places with clear functional or spatial characteristics, such as plazas, main fitness equipment areas, pavilion surroundings, and children's playgrounds. Volunteers would stop for a three-minute, fixed-point video recording upon reaching these predetermined DAAs. Example photos of different DAA types are provided in Supplementary Figure S2.

Data collection strictly followed a unified protocol to ensure objectivity, accuracy, and comparability. Collection was conducted during the early to mid-summer period (May 30 - July 9, 2024), with observed environmental temperatures ranging between 24 °C and 35 °C. We selected a total of 9 days, including 6 weekdays and 3 weekends, conducting data collection from 5 PM to 8 PM. We strategically chose the 5 PM to 8 PM period for data collection because it represents a critical intersection of peak public leisure activity and the peak of daily accumulated heat. This timeframe captures the most diverse mix of population groups, making it the most critical window for studying heat adaptation behavior. All data collection was conducted under clear or partly cloudy weather conditions with no rain and low wind speed (≤ Beaufort scale 2, as determined by the Beaufort wind scale), to eliminate significant interference from other meteorological factors on data quality. Data collection tasks were divided among 5 trained volunteers, who were consistently assigned to the same specific parks throughout the study to ensure consistency. To ensure data comparability given that observations were not strictly simultaneous across all 11 parks, we established a rigorous, standardized protocol. On each data collection day, observations commenced at approximately 17:00. The collection route and sequence for each park was fixed, and on each collection day, volunteers followed identical sequence and path at a controlled walking speed. This procedural consistency ensures that although inter-park comparisons contain a fixed time lag, the data for any single park is temporally consistent across different observation days (e.g., Park A was always observed at the same relative time slot). This rigor effectively minimizes random temporal variations, providing a robust basis for our longitudinal analysis. Any remaining variation due to non-simultaneous observation is acknowledged as a limitation of the study.

To ensure high-precision data acquisition and study replicability, we employed a standardized set of on-site measurement equipment, the reliability and performance of which have been validated in our previous mobile sensing studies (Zhang et al., 2024a, 2025). Visual data were captured using a head-mounted Insta360 RS ONE panoramic camera equipped with the Dual-Lens 360 Mod, configured to 4 K resolution (3840 × 1920 pixels) at 60 frames per second (fps). This setup, consistent with the protocols detailed in Zhang et al. (2025), provided a complete spherical field of view to prevent data loss at the periphery. Spatial tracking was performed using a professional-grade handheld GPS recorder (BHCnav K20S) set to a 1-second sampling interval (1 Hz) with SBAS-enabled accuracy of 1–3 m (Zhang et al., 2024a). Data collection employed a rotated mobile sensing approach. Researchers first walked at a uniform speed (controlled at approximately 1.2–1.5 m/second) or, where permitted, rode electric bicycles (controlled at approximately 4–5 m/second) along all accessible roads in the park to ensure comprehensive coverage of all paths within the park. This process primarily captured instantaneous information about users on pathways and the configuration of park facilities. Second, during the traversal, when reaching predetermined activity DAAs in the park (referring to open spaces with certain activity capacity and crowd gathering characteristics, such as squares, main equipment areas, pavilion surroundings, etc.), volunteers would stay for three minutes to record behavioral patterns as they changed over time. This duration was determined based on our pilot studies and is consistent with common practices in public space behavioral observation research (e.g., Cohen et al., 2020; Sallis et al., 2016). Pilot tests indicated that three minutes is sufficient to capture the main behavioral patterns and minor shifts within a space (e.g., transitioning from walking to sitting) while avoiding observer effects that might arise from prolonged stays. This portion of data was primarily used for DAA-scale behavioral analysis.

Regarding meteorological parameters on the collection day, this study used historical weather data from the Weather application provided by Apple Inc. as the source for environmental temperature (°C) and relative humidity (%). For each data collection period at each park (e.g., from 5 PM to 8 PM on a certain day at a certain park), the environmental temperature and relative humidity were calculated as the average of the hourly values recorded between 5 PM and 8 PM. Importantly, the use of regional rather than in-situ microclimatic data represents a deliberate methodological choice grounded in four considerations. First, this standardized, public data source was chosen to enhance reproducibility and to align with the psychological aspect of visitor decision-making, as individuals typically decide whether to visit a park based on macro-level weather forecasts on their phones rather than unknown on-site microclimatic conditions (Nikolopoulou & Steemers, 2003). The regional temperature thus captures the perceived thermal context under which behavioral decisions are initiated. Second, while these city-wide readings do not capture heterogeneous microclimatic variations (e.g., local wind speed, radiant heat) within the parks, our analytical framework addresses this limitation structurally: the moderating variables in our model—including Sky View Factor (SVF), Green View Index (GVI), tree canopy coverage, and built shading structures—are well-established physical determinants of local thermal environments (Lindberg & Grimmond, 2011; Middel et al., 2014; Lee et al., 2016). By testing how these design features moderate the temperature–behavior relationship, our framework implicitly captures microclimatic variation through its physical proxies, providing the design-actionable information that planners require. Third, using a uniform regional thermal baseline across all 53 DAAs eliminates synchronization errors inherent in multi-site portable weather station deployment, ensuring that observed behavioral differences can be attributed to physical design characteristics rather than measurement artifacts. Fourth, the publicly accessible nature of the data source enables replication across cities without requiring dense on-site sensor networks, supporting the scalability of this monitoring approach.

Built environment data included multiple sources: micro-facilities within parks were recorded through on-site observation and panoramic image recording; macro characteristics of parks and surrounding built environment data (such as buildings, roads, POIs, etc.) were obtained from the AutoNavi open platform (URL: https://lbs.amap.com/api/webservice/guide/api-advanced/search, acessed on May 20, 2025).

2.3. Variable definition and measurement

This study defines and measures relevant variables at both park and DAA scales according to the dual-scale analytical framework (Table S1).

At the park scale, the dependent variable (Y_park) is the total number of park users, referring to the sum of users identified through AI statistics at all DAAs (3-minute cumulative count) and all path sampling points (instantaneous count) during a specific observation period. Independent variables (X_park) include temperature (°C) and a series of macro park characteristics. These macro characteristics encompass park attributes (i.e., total park area in square meters), park green coverage rate (the percentage of total green space area within the park relative to the total park area, obtained from Shi et al. (2022)), park accessibility (i.e., surrounding road density calculated by total road length within a 200-meter buffer zone outside the park boundary divided by the net buffer area with unit of km/km^2), surrounding transit stop density (i.e., number of transit stops within a 200-meter buffer zone outside the park boundary divided by the net buffer area with unit of number/km^2), distance to nearest metro station (i.e., walking network distance from the main park entrance to the nearest metro station entrance with unit of meters), as well as average building density in the 200-meter buffer zone around the park (i.e., total building footprint area within a 200-meter buffer zone outside the park boundary divided by the net buffer area, unit: %), average surrounding residential building floor area ratio (estimated based on POI and relevant planning parameters), and surrounding built area green coverage rate (the percentage of total vegetation coverage area within a 200-meter buffer zone outside the park boundary and excluding the park itself). The 200-meter buffer zone was selected based on the consideration of the area accessible within a 5-minute walk for urban residents, aiming to define the most potential user source for the park, with calculations excluding the park area itself.

At the DAA scale, dependent variables (Y_DAA) are DAA adaptive behavior indicators, specifically including dynamic and static behavior counts. The dynamic behavior count refers to the cumulative number of individuals identified as engaging in activities with higher physical exertion. Behaviors were classified as dynamic if they involved significant bodily movement and energy expenditure, with observed examples including running, jogging, playing sports (such as basketball, football, and tennis), using fitness equipment, vigorous children's play (e.g., climbing, sliding), and brisk walking. In contrast, the static behavior count refers to the cumulative number of individuals identified as engaging in activities with low physical exertion. These behaviors were classified as static if they were relatively stationary or involved minimal movement, and observed examples included sitting (on benches, chairs, or the ground), resting, standing, talking, observing others, reading, or slow-paced strolling. Finally, behavioral diversity was also included and measured using the Shannon Diversity Index to assess the richness and evenness of different behavior types recorded during the 3-minute observation period at the DAA. The calculation formula is:

$$H = -\sum_{i=1^s} p_i \ln(p_i)$$

where S is the total number of behavior types, and p_i is the proportion of individuals engaged in behavior type i relative to the total cumulative number of individuals at the DAA over 3 min.

The independent variable (X_DAA) is the temperature (°C). The mediating variable (M_DAA) is DAA attractiveness, operationalized as the DAA 3-minute cumulative total count, i.e., the total number of individuals identified through AI during the 3-minute observation period at a specific DAA, reflecting the actual usage intensity of that DAA at a specific temperature. Moderating variables (W_DAA) include DAA micro-environmental characteristics and demographic variables. DAA micro-environmental characteristics are divided into facility variables (such as types and numbers of seating, fitness equipment, children's play facilities, sports venues, pavilions, pergolas, etc.) and spatial attributes (such as DAA GVI, SVF). Among these, green view index (GVI) refers to the proportion of green vegetation within an individual's field of vision at the center position of the DAA, calculated by processing 360-degree panoramic images collected in this study, using DeepLabV3+ image segmentation method to identify green vegetation pixels, then calculate the percentage of green pixels relative to total field of vision pixels. Sky view factor (SVF) is similarly calculated by the proportion of sky element. Demographic variables are also classified through AI, including gender (male/female) and age groups (children [0–12 years], youth [13–18 years], middle-aged [19–59 years], elderly [60 years and above]), serving as classification or control variables for behavioral analysis.

2.4. Pedestrian and behavior recognition

Following the completion of raw data collection, a series of precise data preprocessing and information extraction steps were implemented. First, GPS data processing and sampling point generation involved cleaning the original GPS trajectory data (e.g., removing drift points) and coordinate system conversion (converted to WGS84). For path data, sampling point coordinates were extracted from GPS trajectories at approximately 20-meter intervals along all accessible roads within parks using GIS software (such as ArcMap 10.2); for DAAs, their predetermined center point coordinates were directly recorded. Second, frame extraction and geocoding were performed: for each path sampling point, image frames were extracted from the corresponding 360-degree video stream according to their GPS timestamps. For each DAA, the original panoramic video data from the continuous 3-minute recording between the start and end times of the stay were preserved for subsequent detailed behavioral analysis. Finally, the core AI technology—YOLOv10 model: Building upon the proven efficacy of the YOLO series in accurately assessing urban physical environments (Li et al., 2018; Li & Long, 2024; Li et al., 2024), this study employed the YOLOv10 deep learning object detection model (Wang et al., 2024) for automatic identification and quantification of crowds, behaviors, and facilities. To ensure model applicability and high precision for the specific scenes in this study, we constructed and annotated a specialized localized training dataset. This dataset contained approximately 1000 images extracted from videos collected in this study, covering complex scenes across different parks, lighting conditions, and crowd densities. Annotation content included: pedestrians (bounding boxes), pedestrian attributes (gender: male/female; age groups: children/youth/middle-aged/elderly), preliminary behavior classification (mainly distinguishing between dynamic and static activities, with preliminary annotations for typical behaviors such as walking, running, sitting, standing, playing ball, etc.), and facilities (bounding boxes and categories for facilities such as benches, fitness equipment, pavilions, etc., totaling 31 facility types). To ensure the quality of the annotations, we implemented a rigorous multi-person annotation and validation protocol. We calculated the Fleiss' Kappa coefficient to measure inter-annotator agreement among three trained annotators, achieving a score of 0.88, which indicates substantial agreement. Based on this, all final discrepancies in the full dataset were resolved through a consensus discussion to ensure the accuracy of the training labels. We used this high-quality dataset to fine-tune the pre-trained YOLOv10s model. The dataset was divided into training (80%), validation (10%), and testing (10%) sets using a stratified random split to ensure diverse representation. We applied transfer learning and fine-tuning to a pre-trained YOLOv10s model using this localized dataset. During the fine-tuning process, key training parameters, including learning rate 0.01, SGD (Stochastic Gradient Descent) optimizer, 100 epochs were employed. The model's performance was rigorously evaluated using common pedestrian detection evaluation metrics, achieving an mAP@0.5 (mean Average Precision at IoU threshold 0.5) of 98%, gender classification accuracy of 99%, and behavior classification accuracy of 89% on the validation set, indicating its ability to meet the data accuracy and reliability requirements of this study. Detailed performance metrics, including per-class precision, recall, and confusion matrices for age and behavior groups, are provided in the Supplementary Information (Tables S3-S5).

Further statistics was implemented based on the machine learning model. Regarding path sampling point image analysis, the trained YOLOv10 object detection model was used to batch process key frame images from all path sampling points, automatically completing pedestrian detection, crowd attribute (gender, age) estimation, and counting. Regarding DAA video analysis, first, the YOLOv10 object tracking model was used to track pedestrians and classify attributes in each video. Subsequently, DeepSORT (Wojke et al., 2017) was employed for tracking. This object detection method was also used to identify and quantify various facilities within DAAs. Instead of relying on a single key frame, we utilized the video prediction mode within the Ultralytics framework to process the continuous 3-minute video stream. This approach continuously detects and tracks facility elements across frames, ensuring that static facilities (e.g., benches, sports courts) are accurately recorded even if they are temporarily occluded by moving crowds or subject to dynamic lighting changes. Final counts were aggregated from these continuous detection results and underwent a final manual verification by researchers to ensure absolute accuracy.

Finally, all behavior data (such as the number of people engaged in various behavior types, behavior diversity index), crowd attribute data, and facility data extracted through AI recognition were integrated with the GPS coordinates of corresponding sampling points/DAAs, temperature data at that moment, and pre-calculated built environment characteristic data at various scales (such as park area, surrounding road density, DAA GVI, SVF, etc.) obtained through tools including ArcMap, Python and its Pandas library were used to construct structured databases for park-scale and DAA-scale analyses, respectively.

2.5. Environment-perception-behavior mechanism

This study employed multi-level statistical analysis methods to address scientific questions at different scales. All statistical analyses were completed using Python.

At park-scale, we employed the XGBoost (Extreme Gradient Boosting) regression model (Chen & Guestrin, 2016) to explore the comprehensive influence of temperature and the park characteristics on the total number of park users. To ensure model robustness and avoid overfitting, we implemented a 5-fold cross-validation strategy during model training. Model hyperparameters were optimized through a learning_rate of 0.01, max_depth of 10, n_estimators of 50, subsample of 0.5, and colsample_bytree of 0.5. We evaluated the model's generalization capability using out-of-sample performance metrics, achieving a satisfactory test-set $Rˆ2$ and Root Mean Square Error (RMSE), which confirms the stability of the derived predictors. To further interpret the model's predictions and quantify the contribution of each feature, we introduced the SHAP (SHapley Additive exPlanations) analysis method (Lundberg & Lee, 2017) to evaluate the relative importance of various macro characteristics using SHAP mean absolute values and to deeply explore the potential interaction effects between these characteristics and temperature on overall park attractiveness, generating SHAP interaction value maps.

At DAA scale, to precisely analyze the microscopic mechanisms at the level of DAAs, the study employed Hayes (Hayes, 2022) Model 58 for moderated mediation effect testing (Preacher et al., 2007). This model, a moderated mediation model, allows us to simultaneously test how the micro-environment moderates two key pathways: from temperature to the space's attractiveness, and from that attractiveness to adaptive behavior. This approach aligns perfectly with our theoretical framework, which examines how the environment influences the willingness to enter a space and the subsequent behaviors within it, making the model the most appropriate tool for our multi-pathway, multi-level hypotheses. This model aims to examine how temperature (X_DAA) affects various adaptive behavior indicators (Y_DAA: dynamic behavior count, static behavior count, behavior diversity) through its influence on the DAA 3-minute cumulative total count (M_DAA, as a mediating variable), with a focus on investigating the moderating effects of DAA micro-environmental characteristics (such as presence/number of facilities, GVI, SVF, etc.) and demographic attributes (gender, age group) as moderating variables (W_DAA) in these relationships. Specifically, we examined the moderating effects of W_DAA on path a (X_DAA→M_DAA) and path b (M_DAA→Y_DAA). Parameter estimation for the model employed the Bootstrap method with 5000 resamples to generate robust standard errors and 95% bias-corrected confidence intervals (CIs) for all path coefficients and conditional indirect effects; an effect is considered statistically significant if its 95% CI does not contain zero. To assess the explanatory power of the models, the R-squared (R^2) value was reported for each equation. All continuous variables introduced into the model were centered before analysis to reduce multicollinearity and provide clearer interpretation of interaction terms (Fig. 2). Prior to modeling, Variance Inflation Factor (VIF) diagnostics were conducted, confirming that no multicollinearity issues were present (all VIFs < 5). Full model results—including unstandardized coefficients (b), standard errors (SE), R^2 values for each equation, and 95% CIs for all paths—are detailed in the Supplementary Information (Tables S3-S6). Sensitivity analyses, including the visual inspection of bootstrap sampling distributions, were conducted and confirmed the stability of the key findings.

We selected these distinct analytical models to address specific challenges at each scale, though each bears limitations that readers should consider. At the park scale, the XGBoost model was chosen for its superior ability to capture non-linear interactions between temperature

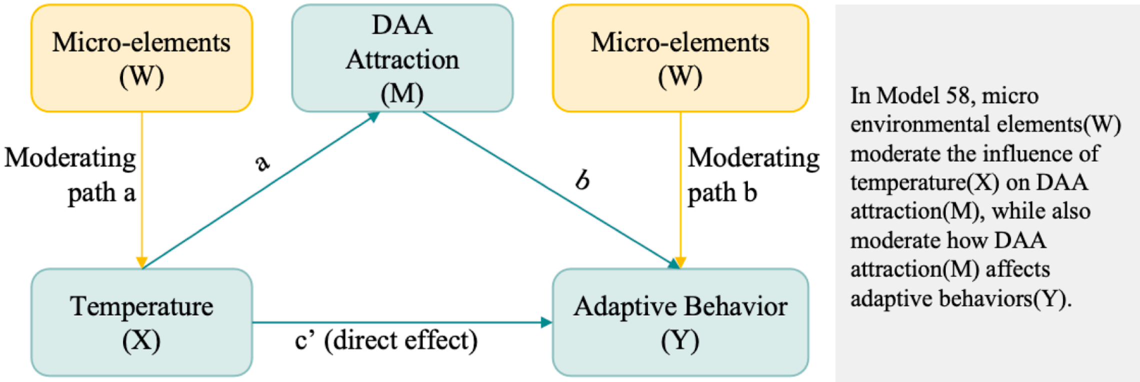

Fig. 2. Conceptual Diagram of the Moderated Mediation Model (Hayes PROCESS Model 58) for DAA-Level Heat Adaptation Analysis.

and complex urban morphology, which traditional linear regression often fails to detect. To mitigate its inherent "black-box" nature and potential for overfitting, we assessed the prediction error margin by reporting the Root Mean Square Error (RMSE) derived from 5-fold cross-validation (detailed in Section 4.5), while employing SHAP analysis to quantify individual feature contributions.

In parallel, at the DAA scale, the Hayes PROCESS Model 58 was utilized for its specific capacity to explicitly test conditional indirect pathways, allowing us to quantify how micro-environmental features alter the trajectory from heat stress to adaptive behavior. While this model relies on linear assumptions, we ensure transparency regarding statistical uncertainty by reporting full 95% bias-corrected Confidence Intervals (CIs) and Variance Inflation Factors (VIF) for all effects (see Table S6), where significance is determined by intervals strictly excluding zero. Additionally, to address potential error margins in the observational input data regarding user demographics and activity levels, validation metrics (confusion matrices) are provided in Tables S3–S5.

3. Results

3.1. Park and DAA occupancy characteristics

Fig. 3 provides a comparative overview of the 11 urban parks investigated. It presents park-level total visitor numbers for each observation day, illustrating overall park attractiveness. Complementing this, it displays key characteristics and daily total user counts for DAAs within these parks, including demographic breakdowns (e.g., age, gender) for DAA users. The complete results of this park-level analysis, including the SHAP summary plot visualizing the impact of all features, are provided in the Supplementary Information (see SI Section S1 and Supplementary Figure S4).

Across the 9-day observation period, our systematic tracking in the 11 parks captured a total of 23,832 behavioral instances. There was significant variation in overall park attractiveness, with average daily visitor counts ranging from approximately 51 persons per day in Dahuaishu Park to over 440 persons per day in Lugu Olympic Culture Park, indicating a clear gradient of use across the sites (Fig. 1).

At the micro-scale, we analyzed a total of 53 defined activity areas (DAAs). A demographic analysis of the DAA occupants revealed that middle-aged adults (19–59 years) were the most predominant user group, accounting for 44.1% of the total population observed in DAAs. They were followed by older adults (60+ years) at 24.3%, children (0–12 years) at 23.9%, and youth (13–18 years) at 7.7%. In terms of behavioral patterns, static activities (e.g., resting, talking) were dominant across all DAAs, comprising an average of 78.4% of all observed behaviors, while dynamic activities (e.g., sports, play) accounted for the remaining 21.6%. These baseline descriptive statistics provide a crucial foundation for understanding the subsequent analyses of how heat stress impacts these different population groups and behavioral patterns.

3.2. General suppression of park use by heat and adaptive behavior cues

Rising temperatures significantly suppressed park use, revealing complex heat adaptation patterns (Fig. 4).

Activity suppression, particularly static behaviors: High temperatures markedly suppressed static (total effect $c \approx -1.129$ persons/ °C, $p < .001$) and dynamic behaviors ($c \approx -0.287$ persons/ °C, $p < .05$). The decline in static behaviors was more pronounced, suggesting that maintaining even low-energy activities becomes challenging due to direct thermal discomfort and the physiological drive to minimize metabolic heat production (Parsons, 2014; Havenith, 2001).

Population-specific sensitivity: The analysis revealed notable differences in heat sensitivity between demographic subgroups. Specifically, males demonstrated greater behavioral sensitivity to heat compared to females, while the elderly and children showed more significant activity declines when compared to youth and middle-aged adults (especially in static behaviors). This aligns with known physiological vulnerabilities, such as reduced thermoregulatory capacity in older adults and children, and potentially different risk perceptions or social roles influencing exposure patterns (Kenny et al., 2010; WHO, 2021).

Reduced behavioral diversity: Heat stress significantly reduced behavioral diversity (indirect effect $a*b \approx -0.012$ / °C, $p < .05$), notably for the elderly and children, thereby limiting activity choices. This likely reflects a shift towards essential or prioritized heat avoidance behaviors, narrowing the range of activities perceived as comfortable or safe under thermal duress (Nikolopoulou & Steemers, 2003; Lai et al., 2019).

"Heat deterrence" as a primary barrier: This overall suppression was primarily mediated by reduced DAA attractiveness (significant negative indirect effects a*b across groups), functioning as a "heat deterrence." This indicates that the initial decision to access or remain in a park space is strongly influenced by the perceived overall thermal stress, acting as an overarching filter before micro-environmental factors can further modulate behavior (Potchter et al., 2018).

3.3. Micro-environmental regulation of heat adaptation in DAAs

Moderated mediation analysis (Model 58) of DAAs showed that numerous micro-environmental elements critically regulated heat adaptation behaviors, influencing both DAA entry willingness ('a' path) and subsequent activity choices ('b' path) (Fig. 5).

Counter-intuitive role of specific sports facilities: Certain sports facilities unexpectedly maintained or increased dynamic activity under heat. For instance, Basketball Courts significantly boosted dynamic behavior in adolescents (+0.247 persons/ °C, $p < .001$), children (+0.179, $p < .01$), and the elderly (+0.170, $p < .001$). Football Pitches similarly promoted dynamic activity in middle-aged adults (+0.157 persons/ °C, $p < .05$) and children (+0.251, $p < .05$). Table Tennis

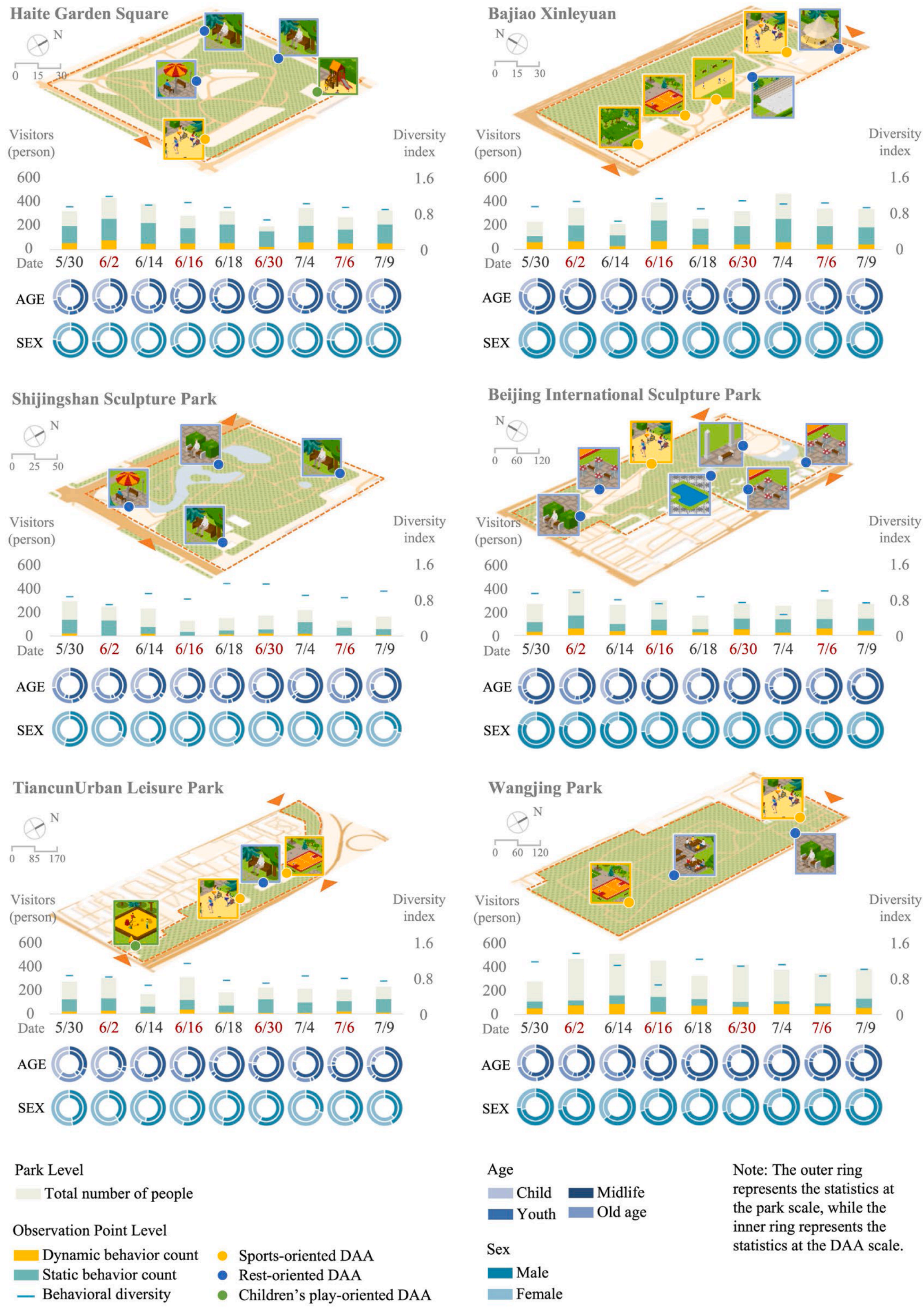

Fig. 3. Park-Level Visitor Occupancy and DAA Characteristics across the 11 Studied Parks.

Courts benefited the elderly (+0.026, $p < .01$) and middle-aged adults (+0.021, $p < 0.05$). Playgrounds attracted middle-aged adults and fostered adolescent dynamic behavior.

Sheltering and resting facilities enabling static adaptation: Sheltering elements were crucial for static rest. Pavilion Corridors strongly promoted static behavior across most groups (e.g., adolescents: +0.157

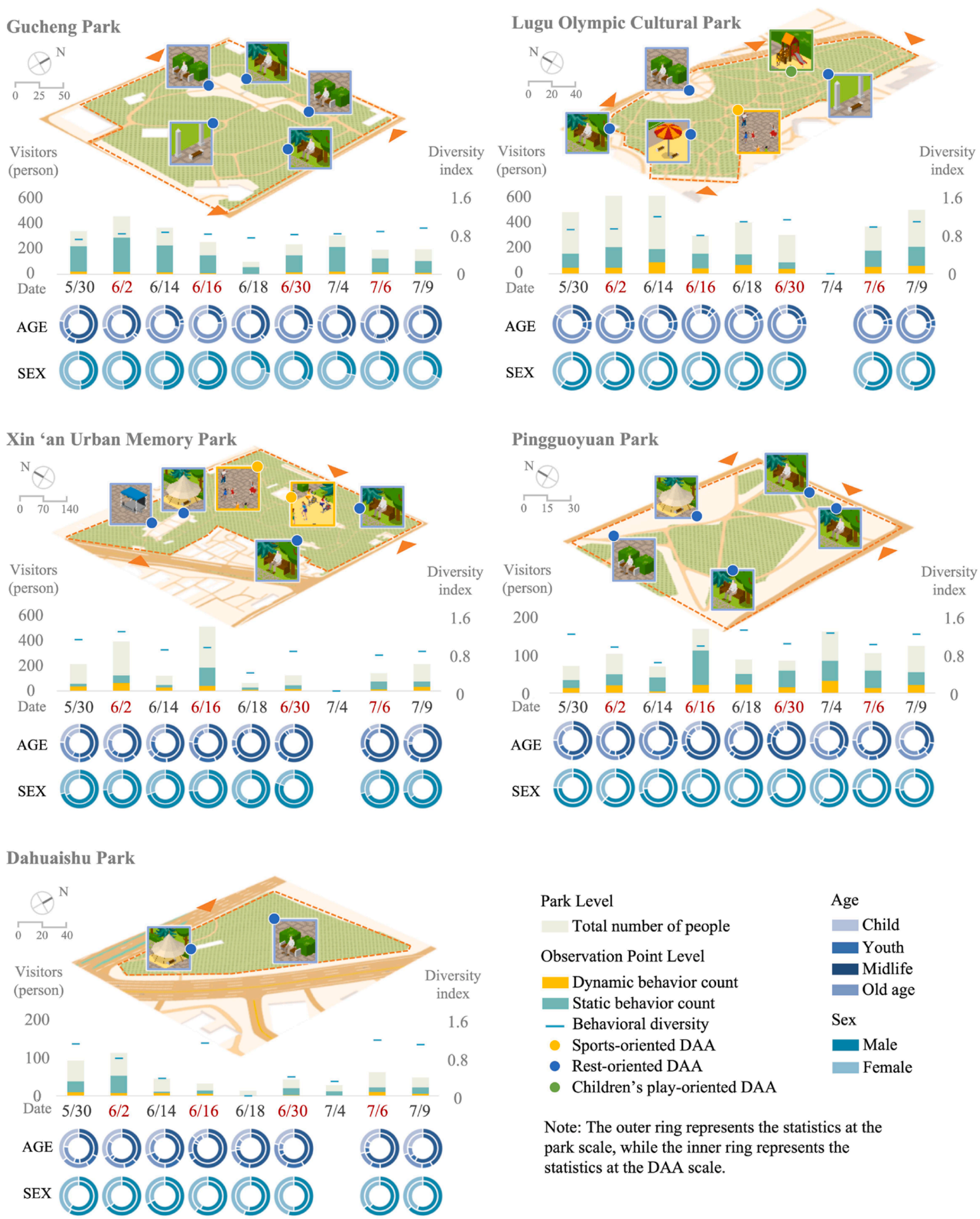

Fig. 3. (*continued*).

persons/ °C, p < .01). Stone Benches and Tree Planter Seats also significantly encouraged static rest, especially for younger individuals, while Pavilions and Sunshades benefited males and the elderly.

Complex effects of DAA spatial attributes: Higher DAA Green View Index (GVI) promoted dynamic behavior in males and the elderly but inhibited it in children, with varied effects on overall DAA attendance. Sky View Factor (SVF) generally reduced DAA attendance and strongly suppressed dynamic activity while promoting static rest (e.g., adolescent dynamic inhibition: −0.816 persons/ °C, $p < .001$). DAA Site Area also tended to reduce attendance for some groups and strongly favored static over dynamic activities.

Facility impacts on behavioral diversity: Certain features enhanced behavioral diversity. Wooden Seats markedly increased children's diversity (+4.960 index/ °C, $p < .05$). Circular Seating Arrangements and Lounge Chairs also showed positive effects. Conversely, elements like Sculptures negatively impacted diversity for some groups (e.g., females: −0.029 index/ °C, $p < 0.05$).

These findings quantify the distinct, often population-specific regulatory roles of micro-environments, providing a robust empirical basis for targeted adaptation design.

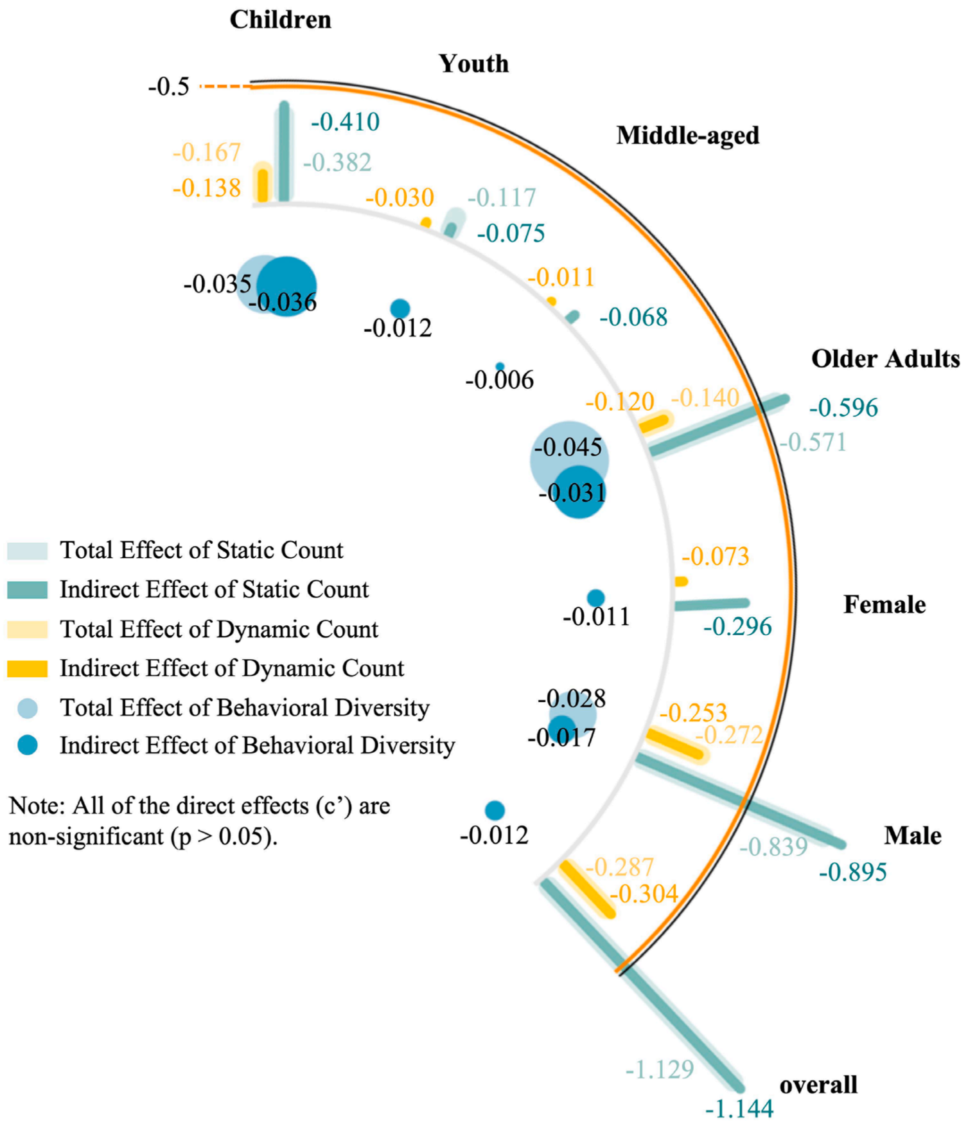

Fig. 4. Overall and Group-Specific Effects of Temperature on DAA Use Behaviors (Static, Dynamic, and Diversity).

4. Discussion

4.1. A paradigm shift towards proactive, evidence-based heat adaptation

This study fundamentally shifts the discourse on heat adaptation from a reactive focus on health outcomes to a proactive one centered on strategic urban and landscape design. By identifying specific environmental "leverage points" that modulate adaptive behaviors, we underscore the potential to embed intrinsic adaptability into the urban fabric. This transition towards proactive, fine-grained, evidence-based design directly addresses criticisms of earlier adaptation plans that often lacked specific actions and focused on broad capacity building (Preston et al., 2011). Our findings, by providing clear evidence on how micro-scale designs influence specific behaviors, can significantly enhance the quality and actionability of urban adaptation plans (cf. Reckien et al., 2023a).

4.2. Key scientific and methodological contributions

The key contributions are: Decoding Micro-Environmental Influences on Behavioral Heat Adaptation: This study moves beyond broad environmental categories to quantify how dozens of specific micro-built environmental elements (e.g., basketball courts, specific seating, pavilions) precisely modulate individuals' adaptive behavior choices (dynamic/static, activity type) under heat stress. This mechanistic understanding at a fine-grained level offers an unprecedented basis for targeted design interventions (Lin et al., 2023; Frühauf et al., 2020).

Developing a Multi-Scale Analytical Framework: Our novel analytical framework, combining XGBoost-SHAP (Chen & Guestrin, 2016; Lundberg & Lee, 2017) and PROCESS models (Hayes, 2022; Preacher et al., 2007), uniquely integrates macro-environmental influences (e.g., surrounding green coverage, road density) with micro-designs within parks. This addresses a critical gap (Middel et al., 2014; Li et al., 2023) by demonstrating how these scales interact to shape park use and adaptation behaviors.

Advancement in Behavioral Adaptation Research: By fusing mobile panoramic sensing with advanced deep learning, this study overcomes traditional data acquisition bottlenecks (Helbich et al., 2019; Yang et al., 2021). This AI-driven approach provides a powerful new methodology for investigating complex human-environment interactions, particularly adaptive behaviors in real-world settings (Bouteldja & Rounsevell, 2024; Ahmad et al., 2022; Zhang et al., 2024a, 2025).

Strengthening Evidence for Population-Specific Design: Our research reveals significant demographic variations (age, gender) in heat adaptation behaviors and their environmental drivers. This provides a quantitative basis for developing nuanced design principles that cater to

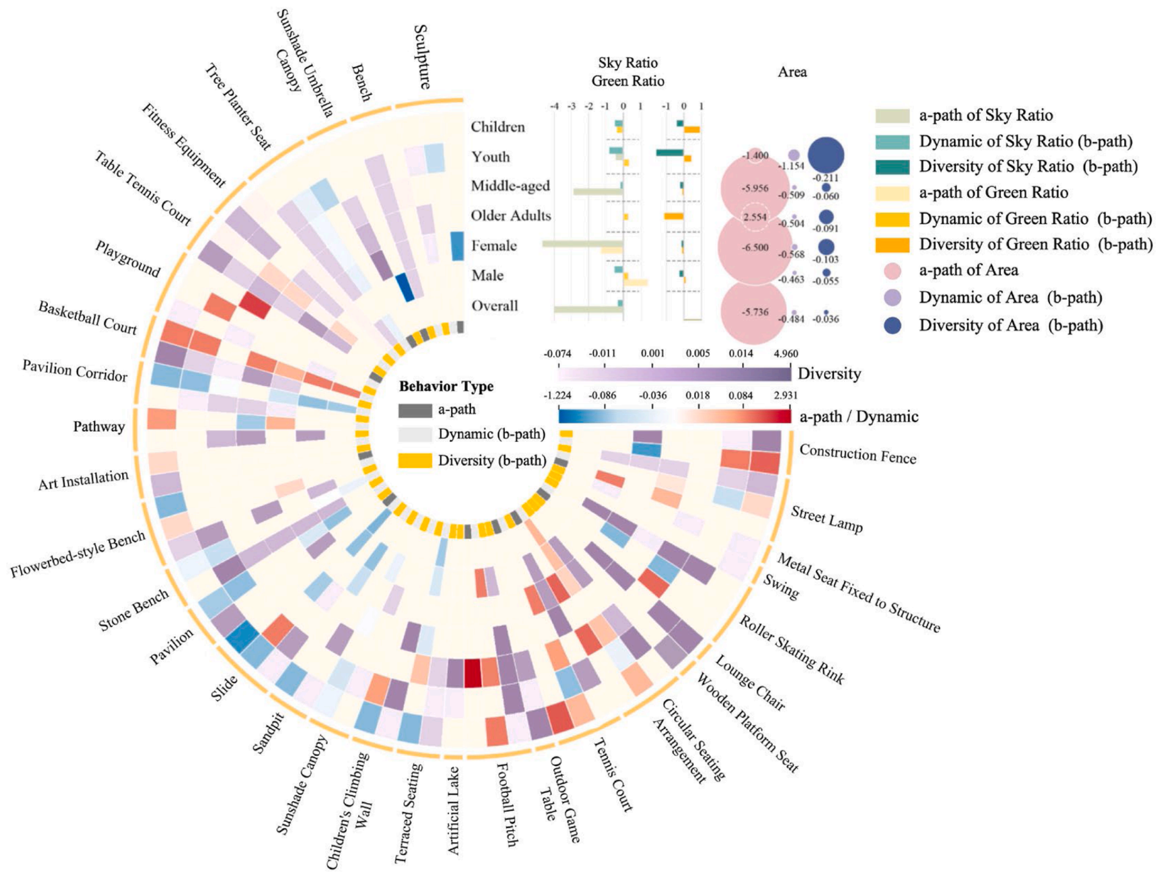

Fig. 5. Moderating Effects of Micro-Environmental Elements within DAAs on the Relationship between Temperature and Adaptive Behaviors across Different User Groups.

the specific needs of diverse populations, moving beyond generalized recommendations and supporting equitable adaptation outcomes (Giles-Corti et al., 2022).

Importantly, our analytical approach captures microclimatic variation through physical design proxies rather than direct thermal measurement. This 'design-feature-as-proxy' strategy is motivated by both practical and theoretical considerations. Practically, it produces recommendations expressed in terms of manipulable design features—the actionable units of urban planning—rather than abstract thermal indices. Theoretically, it recognizes that urban microclimate is not an exogenous force but an endogenous product of design decisions. The significant moderating effects of SVF, GVI, and built shading structures reported in Section 3.3 confirm that these proxies successfully capture behaviorally meaningful microclimatic variation. Nevertheless, we recognize that future integration with thermal simulation tools (e.g., ENVI-met, RayMan, or SOLWEIG) would enable precise quantification of the intermediate thermal pathway (design feature → local Tmrt → behavioral adaptation), complementing the direct design–behavior linkages established in this study (Middel et al., 2014; Matzarakis et al., 2007).

4.3. *Theoretical implications: beyond heat avoidance to functional adaptation*

Theoretically, this research challenges the deterministic view inherent in many thermal comfort models, which predict that users will simply withdraw when physiological stress becomes acute. Instead, our findings support a model of "Functional Adaptation," where adaptation is not merely a reactive flight from heat, but a proactive negotiation between thermal discomfort and "place dependence" (e.g., the need for social interaction or exercise). This extends the "psychological adaptation" framework proposed by Nikolopoulou and Steemers (2003) by quantifying the specific threshold where functional needs override thermal sensations.

A critical question for this framework is whether the observed behavioral persistence under heat reflects localized thermal amelioration (i.e., design features create cooler microclimates that passively sustain activity) or genuine social-functional drivers (i.e., the utility value of the space actively overrides thermal discomfort). Our data provide several lines of evidence supporting the latter interpretation. Most compellingly, adolescents significantly increase dynamic activity on basketball courts under rising temperatures (+0.247 persons/ °C, $p < .001$). Basketball courts are typically open, hard-surfaced, high-SVF environments with minimal shade—among the hottest microenvironments in a park. If behavior were driven purely by thermal comfort, these areas should exhibit the strongest activity suppression, not enhancement. Furthermore, while our moderation analysis shows that higher SVF generally suppresses dynamic activity under heat (−0.816 persons/ °C for adolescents, $p < .001$), the facility-specific effect of basketball courts operates in the opposite direction for this demographic group. This divergence strongly suggests that the social-recreational utility of the facility functions as an independent behavioral driver alongside—not merely through—microclimatic conditions.

Additional evidence for the social-functional interpretation comes from the population specificity of these effects. Basketball courts promote dynamic activity specifically among adolescents and children—demographics for whom peer-group recreation and physical play hold particular social importance—but not uniformly across all age groups. If microclimatic amelioration were the sole mechanism, we would expect a more demographically uniform response pattern. Similarly, the differential effect of shading on behavior types—promoting static rest-seeking behavior (thermal comfort adaptation) rather than dynamic activity persistence (functional adaptation)—is consistent with a dual-mechanism model in which thermal amelioration and social function operate through distinct behavioral pathways.

We therefore propose a refined dual-mechanism framework for understanding heat adaptation in urban spaces: (i) thermal adaptation, in which behavior is modulated by localized microclimatic conditions created by design features (shade, vegetation, sky obstruction), primarily manifesting as increased static/rest behavior in thermally ameliorated areas; and (ii) functional adaptation, in which behavior is sustained by the social utility, recreational value, or place dependence afforded by specific facilities, potentially overriding thermal discomfort, primarily manifesting as persistent or increased dynamic activity despite thermally unfavorable conditions. These mechanisms are not mutually exclusive but co-occurring, and our moderation analysis provides initial evidence for their differential operation across behavior types (static vs. dynamic) and demographic groups.

In this model, adaptation is viewed not as a passive reaction but as a proactive value negotiation. Our findings demonstrate that the "social value and utility" of a specific amenity (e.g., a basketball court for adolescents) can effectively "outweigh" physical heat discomfort. This challenges the hierarchy of needs assumed in traditional thermal comfort models. For certain demographic groups, particularly adolescents, the powerful socio-psychological drivers of peer-group interaction, skill development, and recreation—functions uniquely afforded by a basketball court—can override purely physiological motivations.

The perceived social benefits temporarily outweigh the physical cost of thermal discomfort. This suggests that adaptation theories must evolve to incorporate a more nuanced 'behavioral calculus,' recognizing that human responses to climate stress are mediated by a diverse array of social values and psychological needs, moving beyond a singular focus on heat avoidance. Definitive decomposition of the relative contributions of thermal amelioration and social function to observed adaptation patterns will require coupling the behavioral monitoring framework developed here with on-site thermal simulation (e.g., ENVI-met or RayMan) or direct measurement of Tmrt at DAA locations—a priority direction for future research.

A critical methodological consideration underpinning our 'Functional Adaptation' framework concerns the relationship between regional thermal data and local microclimatic conditions. We acknowledge that regional air temperature, as recorded by weather applications, does not capture the full spectrum of microclimatic variation—particularly differences in mean radiant temperature (Tmrt), wind speed, and humidity—that users experience across different DAAs (Mayer & Höppe, 1987; Thorsson et al., 2007). However, our analytical approach is specifically designed to account for this: rather than quantifying the precise thermal microclimate at each DAA, we model the physical design features that produce microclimatic variation—SVF, GVI, tree canopy, built shading—as moderating variables. This 'design-feature-as-proxy' approach offers a distinct advantage for urban planning applications: it directly identifies which manipulable design elements buffer the impact of heat on behavior, without requiring the intermediate step of thermal simulation. The significant moderating effects we observe (e.g., SVF suppressing dynamic activity at -0.816 persons/ °C for adolescents, $p < .001$; Pavilion Corridors promoting static adaptation at $+0.157$ persons/ °C, $p < .01$) confirm that our physical proxies successfully capture meaningful microclimatic variation as it manifests in behavioral outcomes. Nevertheless, future research integrating on-site thermal simulation (e.g., ENVI-met or RayMan) with the behavioral monitoring approach developed here would enable precise decomposition of the relative contributions of social function versus thermal amelioration to observed adaptation patterns.

4.4. Practical implications for climate-resilient urban design

Practically, our emphasis on frontend behavioral interventions highlights the substantial potential of optimizing everyday built environments to enhance population-wide heat adaptation capacity. This proactive design approach is often more cost-effective, sustainable, and equitable than solely relying on reactive, resource-intensive cooling measures (Heaviside et al., 2020; Peng et al., 2021; Zhang et al., 2024b).

A critical implication for practice is the imperative to design for diverse populations to avoid "maladaptation". However, our findings suggest the solution is not merely to provide separate facilities for different groups, but to consider their spatial integration. For instance, strategically co-locating shaded seating and pavilions—essential for the static rest of older adults —in close proximity to playgrounds or sports courts allows for multi-generational use. This design approach creates a more inclusive and socially resilient park, enabling grandparents to comfortably supervise their grandchildren at play. It ensures the park can simultaneously satisfy the critical need for thermal relief for vulnerable users and the functional need for active recreation for younger groups, transforming the park into a functional social hub even under heat stress. This highlights that effective climate adaptation design is as much about thoughtful spatial arrangement as it is about providing specific amenities. Our AI-driven, disaggregated analysis, by revealing these differential responses, provides the empirical basis for nuanced designs that cater to diverse needs, thereby minimizing the risk of such maladaptive outcomes.

4.5. Bridging the adaptation gap with design guidelines

Furthermore, our findings underscore that a park's utility for heat adaptation is co-determined by multi-scale interactions with its wider urban surroundings. Factors such as the "relative value" conferred by lower surrounding green coverage, and accessibility moderated by road density, significantly influence park attractiveness under heat stress, echoing critiques about the insufficient integration of non-climatic factors in early adaptation planning (cf. Preston et al., 2011). As heatwaves intensify globally (Raymond et al., 2020), the creation of public spaces that actively support a spectrum of adaptive behaviors—as detailed in our results (Section 2.4) and synthesized into actionable design guidelines (Fig. 6)—will transition from being merely "beneficial" to "essential" for maintaining urban health, equity, and vitality, especially for vulnerable populations (Kenny et al., 2010).

Ultimately, this research addresses the "So-What" for policy by directly bridging the "Adaptation Gap" highlighted by Reckien et al. (2025; 2023a). A critical reason for this gap is the disconnect between high-level ambition and local implementation: while city-level climate action plans set broad resilience goals, they often lack the evidence-based mechanisms to implement them at the neighborhood scale. By precisely linking specific heat risks to demonstrably effective micro-environmental design solutions, we provide the "missing middle" evidence that translates abstract policy goals into tangible, on-the-ground reality. Practically, this study redefines park facilities—such as shaded pavilions and strategically placed benches—not merely as recreational amenities, but as critical "climate health infrastructure." Our findings empower practitioners to justify landscape investments not just on aesthetic grounds, but as essential public health interventions that determine whether vulnerable populations can maintain an active and healthy lifestyle in a warming world.

By precisely linking specific heat risks in parks to demonstrably effective micro-environmental design solutions that support diverse adaptive behaviors for varied demographic groups, we offer a clear pathway to translate adaptation goals and investments into tangible, on-the-ground outcomes. The visually presented design guidelines (Fig. 6), derived from our AI-driven behavioral analytics, serve as a novel and actionable tool for practitioners. It is crucial to emphasize that the design parameters presented in Fig. 6 are not subjectively determined universal standards but are common spatial characteristics derived from an inductive analysis of the best-performing DAA samples in our study (i.e., those that maintained higher usage or effectively supported

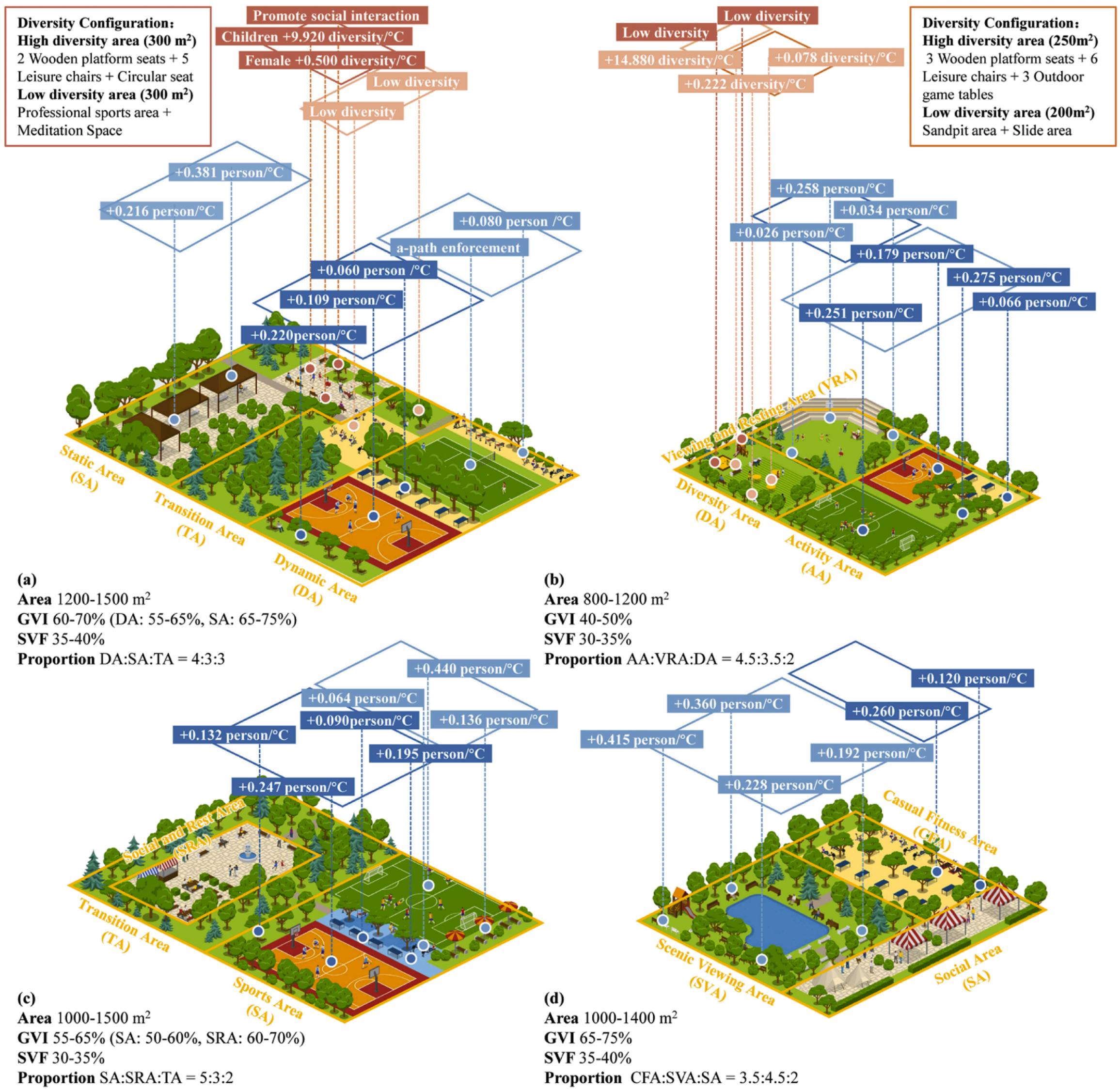

Fig. 6. Evidence-Based Design Guidelines for Heat-Adaptive DAAs in Urban Parks DAAs for (a) total population; (b)children (c)youth (d)elder adults.

adaptive behaviors under heat). For example, our model results (Fig. 5) show that 'wooden platform seats' significantly increase children's behavioral diversity (+4.960 index/ °C, $p < .05$); therefore, our design guidelines for children explicitly recommend the inclusion of 'wooden platform seats' and 'lounge chairs'. Similarly, the recommended GVI range (e.g., 55–65%) is based on a statistical analysis of the central tendency of GVI values from the most attractive DAAs. Thus, these guidelines should be considered a set of data-supported design recommendations or hypotheses based on this empirical study, providing a verifiable reference for future park design rather than a one-size-fits-all truth.

4.6. Limitations

Although this study provides important new insights, several limitations need to be acknowledged to guide future research. First, our study was conducted solely in the Shijingshan District of Beijing. Although the district offers a diverse range of high-quality parks, the findings may not be directly generalizable to other areas with different socio-demographic characteristics or urban morphologies, such as historic city centers or outer suburbs. Future research should validate these findings in a broader range of geographical and urban contexts. Second, limiting observations to 17:00–20:00 captured peak heat but missed full-day patterns, particularly morning activity among older adults. Additionally, the non-simultaneous observation across parks may have introduced temporal biases, making it difficult to distinguish time-of-day effects from thermal factors. Consequently, results are specific to the evening transition. Future studies should employ simultaneous, full-day monitoring (e.g., via cameras) to mitigate these limitations. Third, limitations regarding AI classification accuracy must be noted. While the model achieved high aggregate performance (mAP@0.5 = 0.98) and utilized continuous video tracking to mitigate occlusion errors for facility detection, granular misclassifications may still occur in complex dynamic scenarios, specifically in distinguishing specific age groups (e.g., older youth vs. young adults) or detailed behavior types. We have provided detailed performance metrics in the Supplementary Information (Tables S3-S5) to transparently quantify these potential biases. Fourth, our analysis relies on regional air temperature from the Apple Weather application rather than on-site microclimate measurements (e.g., mean radiant temperature, Tmrt). While this choice is justified by behavioral realism (users base park-visit decisions on regional forecasts), cross-site consistency (a uniform baseline across 53 DAAs), and the structural incorporation of microclimate proxies (SVF, GVI) as moderating variables (see Section 2.2 and 4.3), it means that we cannot fully disentangle whether the observed 'Functional Adaptation'—particularly the persistence of activity under heat—reflects the social utility of the space, the localized thermal amelioration provided by design features, or a combination of both. Future studies should integrate on-site thermal simulation tools (e.g., ENVI-met, RayMan, or SOLWEIG) with our behavioral monitoring framework. By processing the SVF and GVI data already collected in this study, these tools could estimate local Tmrt and thereby enable a precise decomposition of social-functional drivers versus microclimatic drivers of adaptive behavior (Middel et al., 2014; Lindberg & Grimmond, 2011). This integration would represent a powerful extension of the present framework. Finally, we must acknowledge the inherent limitations regarding causal inference imposed by the cross-sectional design of this study. While our analysis reveals robust associations between micro-environmental features and adaptive behaviors, the lack of longitudinal tracking or experimental manipulation means we cannot definitively claim that specific facilities cause changes in park use. Other unmeasured variables, such as individual physiological adaptation status, clothing, and air quality, could also influence adaptive behavior (Zhang et al., 2023). Therefore, the relationships identified in this study should be interpreted as identifying promising associations that generate "design hypotheses," rather than definitive causal mechanisms. Future research employing longitudinal or pre-post intervention designs is recommended to further validate these findings.

Building on these limitations, we identify the integration of thermal simulation with behavioral monitoring as a particularly promising direction for future research. The SVF and GVI data collected in this study can serve as direct inputs for tools such as RayMan (Matzarakis et al., 2007, 2010), SOLWEIG (Lindberg et al., 2008), or ENVI-met (Bruse & Fleer, 1998), enabling estimation of Mean Radiant Temperature (Tmrt) and other outdoor thermal comfort indices (e.g., PET, UTCI) at the DAA level. By coupling these thermal estimates with our AI-derived behavioral data within the moderated mediation framework, future studies could precisely decompose the relative contributions of localized thermal amelioration and social-functional attractiveness to observed adaptation patterns. This would provide the ultimate validation of the 'Functional Adaptation' hypothesis and offer a complete mechanistic pathway from design intervention to microclimatic modification to behavioral outcome.

5. Conclusion

This study demonstrates that urban heat adaptation is not a merely passive physiological reaction to thermal stress but a complex behavioral negotiation actively modulated by the micro-built environment. By leveraging AI-driven behavioral tracking across diverse urban parks, we revealed that specific design interventions—such as the strategic placement of shaded seating for the elderly or the provision of high-utility sports facilities for youth—can significantly extend the usability of public spaces during heatwaves. These findings challenge the traditional "thermal determinism" view, proposing instead a model of "Functional Adaptation" where social and recreational needs can override thermal discomfort when the environment provides sufficient functional affordances.

Crucially, this research bridges the persistent "adaptation gap" between high-level climate planning and on-the-ground reality. We argue that for high-density cities facing intensifying heat risks, "passive cooling" strategies alone are insufficient. Instead, urban resilience requires a proactive design paradigm that treats park facilities not just as amenities, but as essential public health infrastructure. By embedding these evidence-based, micro-scale adaptive "genes" into the urban fabric, planners can effectively minimize maladaptation risks and ensure that public spaces remain vital sanctuaries for health and social interaction in a warming world. Future research should extend this work through longitudinal studies to further validate these design hypotheses across different climatic and cultural contexts.

Data and code availability

The primary dataset generated and analyzed during the current study, consisting of 360° panoramic video recordings and the derived AI-processed behavioral and environmental data, is not publicly deposited in a repository but may be available from the corresponding author upon reasonable request. Third-party data used in this study are available from their original sources. Macro-level built environment data, including buildings, roads, and POIs, were obtained from the AutoNavi open platform. Data for park green coverage rates were sourced from the publicly available UGS-1 m dataset by Shi et al. (2022).

The analyses in this study were conducted using custom scripts written in Python. The study utilized several open-source models and methods, including the YOLOv10 object detection model, the DeepSORT tracking algorithm, the DeepLabV3+ image segmentation method, and the XGBoost machine learning model. The specific custom code used to implement the analysis is not publicly available but can be obtained from the corresponding author upon reasonable request.

Ethics approval and consent

This study was conducted by observing human participants in public parks in the Shijingshan District of Beijing, China. The study population included all individuals present in the 11 selected parks during the data collection periods, regardless of age or gender. Demographic data, specifically age (classified as children, youth, middle-aged, and elderly) and gender (classified as male or female), were estimated using a fine-tuned YOLOv10 artificial intelligence model from panoramic video recordings. This observational method was chosen to capture natural, unprompted behavioral responses to the thermal environment. The study protocol was approved by the Research Ethics Committee of University of Science and Technology Beijing (Approval No. 2024–3-109).

Due to the observational nature of this study in public spaces, informed consent to participate was not obtained from the individuals observed. However, to strictly protect participant privacy, we executed the study in full compliance with a rigorous "Data Management Protocol" (detailed in Supplementary Note S1). Briefly, this protocol mandated the use of automated algorithms to blur all faces immediately upon video ingestion, followed by a strict "process-then-discard" policy where raw footage was permanently deleted after the extraction of anonymized behavioral features. The research involved recording general public activity, and individuals were not personally approached or identified. All data was processed by an artificial intelligence model to extract anonymized, aggregated behavioral metrics for analysis. The data presented in this manuscript, including all figures, are aggregated and contain no images or information that could be used to identify individual participants.

CRediT authorship contribution statement

Yuyang Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yan Li:** Writing – review & editing, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Chunyu Zou:** Visualization, Data curation. **Wenke Ma:** Methodology, Formal analysis, Data curation. **Yanxiang Wang:** Methodology, Formal analysis, Data curation. **Yazhou Hua:** Methodology, Formal analysis, Data curation. **Ying Long:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2026.107401.

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