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Impacts of the built environment features and comprehensive experience on adaptive behavior in the context of climate change: A partial least squares structural equation modeling approach

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A R T I C L E I N F O

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A B S T R A C T

Under the combined pressures of global climate change and high-density urbanization, public open spaces (POSs) are critical infrastructure for enhancing urban resilience. However, current "one-size-fits-all" design paradigms often fail to meet users' adaptive needs. To bridge this gap, this study proposes a replicable theoretical and analytical framework, which integrates spatial type, built environment, individual background, comprehensive experience, and adaptive behavior to quantify how environmental features drive differentiated adaptive behaviors. Validating this framework using Lhasa, China, as a test-bed site, the study identifies spatial types through multi-source data fusion and cluster analysis. Furthermore, it systematically verifies hypothesized pathways using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Multi-Group Analysis (PLS-MGA). Empirical results confirm the robustness and interpretability of the framework. While the core psychological cognitive process: "attitude to perception to willingness to adaptive behavior of spatial" remains universal, the framework sensitively captures the "context dependency" of the drivers behind adaptive behavior. Additionally, the study clarifies that the built environment exerts an indirect regulatory effect through psychological mediators, rather than acting as a direct physical determinant. Consequently, this study advocates a paradigm shift from "standardized supply" to "precision support." By providing a scalable research framework, this study empowers policymakers and urban planners to formulate context-aware and resilient spatial governance strategies. These strategies can adapt to diverse geographical and cultural contexts.

1. Introduction

Under the dual pressures of global climate change and high-density urbanization, the safety and environmental comfort of urban outdoor spaces are facing unprecedented challenges (Rückle et al., 2025). The increasing frequency and intensity of climate events, such as extreme heat, torrential rain, drought, and the urban heat island effect, not only make evident the limited response capacity of urban ecosystem but also significantly affect residents' activity patterns and space use (Goodwin et al., 2025) calling for a more systemic understanding of the influence on Public Open Spaces (POSs) (Han et al., 2022a). According to the definition of UN—Habitat (2018), POSs refer to all outdoor areas in cities that are freely accessible to the public and used for recreation, social interaction, and ecological regulation, including plazas, parks, streets, and community green spaces UN—Habitat (2022). In the field of urban sustainable development and climate adaptation, POSs are repeatedly emphasized as a key interface connecting natural and social systems, playing a crucial role in supporting urban resilience (Luo et al., 2025b) potentially contributing to alleviate the effects of climate-related stressors (Mahmoud & Elbardisy, 2023), and promote residents' health and social cohesion becoming core urban infrastructure for addressing climate change (Koohsari et al., 2015; Rückle et al., 2025).

In contrast to this ideal role, the design and renovation of POS systems often follow in many cities global-trend-driven homogenized design solutions (Senderos et al., 2025) that directly apply generic principles or mechanically replicate so-called "successful cases," repeatedly applying similar materials, facilities, and spatial layouts to different types of POS in different contexts and conditions (Abu-Rayash & Dincer, 2021; Huovila et al., 2019). While this approach improves construction efficiency in the short term, it tends to weaken the space's responsiveness to local climate characteristics, cultural contexts, and functional needs in the long term (Goodwin et al., 2024; Kang et al.,

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2024). On the other hand, with the intensification of climate change and the continuous transformation of population structure, the usage environment of many POSs has deviated significantly from their original design assumptions (Shi et al., 2025) that often are no longer able to meet the new requirements for comfort and safety (Carmona, 2021). Since the objective physical environment is difficult to adjust completely in the short term, space users are gradually becoming proactive "adaptive subjects" in response to environmental changes (Warrick et al., 2017).

"Adaptive behavior" is defined as a set of behavioral adjustment strategies that individuals actively adopt to maintain their intended activity goals and a comfortable experience. These strategies may include adjusting the timing of activities, moving to different locations, or substituting one activity with another (Bixler et al., 2021; Engle, 2011). This concept emphasizes an individual's proactive ability to adjust to environmental constraints rather than simply reacting passively (Lindell & Prater, 2003; Zaalberg et al., 2009). It is important to note that seemingly scattered individual actions at the microscale can produce clear aggregation effects at the scale of the whole city (Cruz et al., 2021). When many users face similar environmental pressures and adopt similar adaptive strategies, individual adjustments accumulate across space and time. These repeated actions gradually form collective behavior patterns with systematic characteristics over time (Kopp & Pérez del Pulgar Frowein, 2024). For example, under conditions of high temperature or strong solar radiation, users often adjust their activity times, reduce activity intensity, or move to areas with better shade, ventilation, or greenery to reduce environmental exposure (Engle, 2011; Sang et al., 2025). When many users adopt similar strategies, the spatial distribution of people and the density of activities within POSs may change. At the same time, areas with better microclimatic conditions may attract more use. As these individual adaptive behaviors continue to accumulate, relatively stable patterns of space use can gradually emerge (Borzino et al., 2026). Therefore, urban climate adaptation should not rely solely on large-scale planning and physical interventions. It is also important to understand how individuals adjust their behavior in daily activities. These micro-scale responses form an important foundation for the resilience of POSs and the wider urban system under climate pressure (Jiang et al., 2026).

However, current planning and renewal practices for POSs still rely to some extent on standardized or experience-based design approaches. This "one-size-fits-all" design and fixed-space supply logic are gradually becoming disconnected from users' dynamic, changing needs (Clemente, 2023; Han et al., 2024). This structural contradiction not only leads to problems such as low utilization efficiency, functional degradation, and even spatial idleness in many POSs, but also fundamentally weakens their resilience in responding to climate change (Kang et al., 2024). At the same time, urban research in recent years has made significant progress in areas such as thermal comfort, urban microclimate, and environmental exposure. These studies provide an important empirical basis for understanding how the built environment influences POS use. However, most of these studies still focus on identifying direct relationships between built environment attributes and behavioral outcomes. A growing body of recent studies suggests that objective environmental conditions do not directly determine user behavior, instead, behavior develops gradually through a series of psychological processes, including multiple stages such as attitudes, perceptions, and willingness (Giles-Corti et al., 2016; Hunter et al., 2019).

In this context, simply relying on large-scale reconstruction or comprehensive renovation is neither in line with the reality of resource constraints nor with the principles of sustainable development (United Nations DPI, 2017). Therefore, there is an urgent need to explore users' adaptive behavior within the existing physical spatial conditions by diagnosing and optimizing the built environment elements of POSs (Han et al., 2022b).

1.1. Literature overview

In the field of urban and environmental studies, the correlation between the built environment and behavior can usually be objectively measured (Han et al., 2022a; He et al., 2024). being the built environment defined as a physical spatial system constructed and organized by humans, including the overall human settlement environment composed of buildings, roads, open spaces, public facilities, and basic infrastructure (Frank & Engelke, 2001; Jackson & Kochtitzky, 2012), encompassing the conditions that influence human activities (Liu, 2023), travel, and experiences (Frank & Engelke, 2001). Within this consensus, numerous empirical studies have examined the correlation between specific built environment elements and general behavioral indicators (Luo et al., 2025b). For example, studies have confirmed that higher green view rates are positively correlated with longer dwell times and the incidence of positive social interactions (Hegetschweiler et al., 2017), while morphological indicators such as building density and street height-to-width ratio significantly affect pedestrian path selection and spatial distribution density (Elzeni et al., 2022; Yoshihara et al., 2021). However, such studies often adopt a static, cross-sectional analytical paradigm (Zhang et al., 2021), treating the environment as a stable, unchanging background condition and simplifying complex behaviors into single outcome variables. While this paradigm reveals correlations, it fails to capture how POSs, as a complex system, dynamically guide and shape users' adaptive behaviors in response to dynamic environmental pressures, such as extreme weather events or sudden crowd congestion (Wilson et al., 2020).

In recent years, research in environmental psychology has increasingly emphasized the key bridging role of comprehensive experience in the relationship between environment and behavior (Gu et al., 2022; Peng, 2022) that refers to the overall psychological experience that individuals form when interacting with environmental conditions (Yang et al., 2023b). Scholars in this field generally agree that human behavior is not a simple reaction to physical environmental stimuli, but it develops gradually through a series of psychological processing stages (Li et al., 2025). Within this theoretical context, the "stimulus-organism-response (S-O-R)" framework has been widely used to explain how environmental factors influence behavioral decisions through internal psychological states (Erul et al., 2024; Sultan et al., 2021). In urban and built environment research, the S-O-R framework is often used to describe the psychological process by which environmental stimuli elicit behavioral responses. (Grapas et al., 2025). Organism refers to the comprehensive experience formed when individuals receive and interpret environmental information (Bower et al., 2019; Yuan et al., 2023). To explain this comprehensive experience in more detail, recent studies have further divided the organism component into several sequential stages. One commonly used framework is the "attitude-perception-willingness" (Gao et al., 2022), where attitude refers to the initial evaluation or overall orientation that users form upon entering a space, including basic judgments about safety, cleanliness, or the overall environmental impression (Balai Kerishnan & Maruthaveeran, 2021). As users begin to use the space, they then develop more specific perceptions through direct interaction with the environment reflecting experiential cognition and emotional evaluation, such as feelings about spatial comfort, environmental quality, or functional support (Nian et al., 2025). Based on these experiences, users develop behavioral willingness, which refers to the intention or readiness to adopt specific behavioral strategies in a given context (Borzino et al., 2026). However, this mediating role is often oversimplified in practice with (Han et al., 2021). Most studies reducing this comprehensive experience to a single indicator, such as overall satisfaction, thermal sensation vote (TSV), or thermal comfort vote (TCV) (Yang et al., 2025). Although this approach makes quantitative analysis easier, it overlooks the complex process linking environmental stimuli, psychological processing, and behavioral decision-making. As a result, existing studies can often determine whether environmental variables influence behavior but struggle to explain why the same environment may lead to different perceptions and behavioral responses among users.

In this context, behavioral adaptation has been proposed as an important link between environmental change and the response of social systems (Jiang et al., 2026), and it has been introduced to explain how individuals regulate their actions in response to environmental stimuli such as heat stress (Niu et al., 2022), intense solar radiation (Yang et al., 2023a), or crowding (Peng, 2022). This lines of research effectively answers the question of "what people do under specific environmental stresses". However, its limitation is that these behaviors are often isolated from specific spatial contexts, which prevents a linkage between adaptive behaviors and the structural characteristics of the built environment across different types of POSs. In other words, although the academic community knows "how users adapt" (Motomura et al., 2022), it is still unclear "what built environment characteristics, under which POS types, promote or hinder specific adaptive behaviors".

Furthermore, some scholars have called for attention to the typological differences among POSs, noting that treating them as homogeneous spaces may lead to overconsider their distinct spatial forms, social functions, and cultural contexts (Yang et al., 2023a). For example, urban squares (Martinelli et al., 2015), community parks (Niu et al., 2022), and waterfront promenades (Ma, 2023) differ significantly in their purposes of use, behavioral rhythms, and degrees of environmental exposure. These differences suggest that environmental stimuli, users' comprehensive experience processes and patterns of space use, may vary across different types of POSs. Although the S-O-R framework provides an important theoretical basis for understanding the relationship between environment and behavior, comprehensive experience may not always appear stable or consistent in complex real-world situations. As a result, some relationships may vary across contexts or even become insignificant under certain conditions. This suggests that, in specific research, it is necessary to understand the relationship between environment, experience, and behavior from a more contextual perspective.

1.2. Research gaps and hypotheses

While existing research has made progress in its respective fields, it still looks fragmented in the perspectives, rarely considers the spatial context, and often oversights of the crucial moderating role of "space type" in this complex causal chain Hou et al. (2024). This not only makes the process of "how the environment triggers adaptive behavior" unclear but also makes it difficult to translate existing research findings into actionable adaptive design strategies effectively. Therefore, the need for a comprehensive framework systematically integrating the relationship between the built environment, users' comprehensive experience, and adaptive behavior, is emerging as a priority to reveal how POSs influence comprehensive experience and drive users' adaptive behavior in the context of climate change.

This theoretical gap suffers from the following issues:

– Research perspectives are mostly limited to correlational analyses of static environments and universal behaviors, making it difficult to capture users' adaptive behavior processes under dynamic pressures such as climate change (Bixler et al., 2021).
– Users' comprehensive experience is often simplified to a single psychological indicator, which fails to elucidate the intrinsic psychological process of "environmental stimulus - psychological processing - adaptive response" (Schreuder et al., 2016).
– The moderating effect of spatial type on environmental impact is rarely considered, making it difficult to explain why the same design intervention can have opposite effects across different POSs (Hou et al., 2024).
– A lack of an integrated "space - experience - behavior" evidence system that directly supports urban climate-adaptive design and transformation.

This study takes the following core scientific question as its starting point: "Do the built environment characteristics of different types of POSs ultimately guide differentiated adaptive behavior patterns by influencing users' comprehensive experience?" To answer this question, this study proposes a set of structured research hypotheses (H), which together constitute operational exploration and a potential answer to the core question:

H0. POSs can be identified and classified into several significantly distinct space types based on the systematic differences in their built environments.

H1. POS type significantly moderates the effects of the processes from the built environment to comprehensive experience and from comprehensive experience to adaptive behavior.

H2. Users' comprehensive experience plays a significant mediating role between the built environment and adaptive behavior.

H3. Individual background factors influence the performance of both comprehensive experience and adaptive behavior.

To address the above hypotheses, this study aims to construct and test a theoretical framework that integrates the processes of "built environment - comprehensive experience - adaptive behavior" and incorporates "space type" as a core moderating variable. The overall workflow is shown in Fig. 1. By identifying the core environmental elements and key psychological processes driving adaptive behavior under different space types, this study aims to provide a scientific basis for developing precise and efficient design intervention and spatial optimization strategies under limited resource supporting policymakers' and urban planners' decision-making (Hou et al., 2024).

2. Methodology

2.1. Conceptual model design

This study integrated the theoretical foundations of three major fields: environmental psychology (Kang et al., 2024), urban design (Koohsari et al., 2015), and behavioral geography (Guzman et al., 2026; Zhang et al., 2021). Its core framework was based on the "Stimulus - Organism - Response (S-O-R)" framework. This study developed the above framework, constructing a comprehensive conceptual model that includes mediating and moderating effects. In this model, the built environment characteristics of POSs served as external stimuli (S), the user's comprehensive experience represented the internal psychological processing (O), and the user's adaptive behavior reflected the final response outcome (R). The core process of this model is shown in Fig. 2 assuming the following definitions:

Stimulus (S): The built environment referred to the physical environment shaped by spatial form and functional attributes (Frank & Engelke, 2001). In this study, the Built Environment (BE) was operationalized through objective quantitative indicators (Koohsari et al., 2015). Details of indicator construction and calculation are provided in Section 2.2.

Organism (O): Comprehensive experience described the affective, cognitive, and intentional responses individuals exhibited when exposed to specific spatial stimuli (Schreuder et al., 2016). In this study, the Comprehensive Experience (CE) was defined as a higher-order variable composed of three subdimensions, all measured using a five-point Likert scale:

– Attitude (A): overall evaluation of the POSs' safety, cleanliness, and comfort.
– Perception (P): direct sensory cognition of the POS's atmosphere, order, and environmental features.

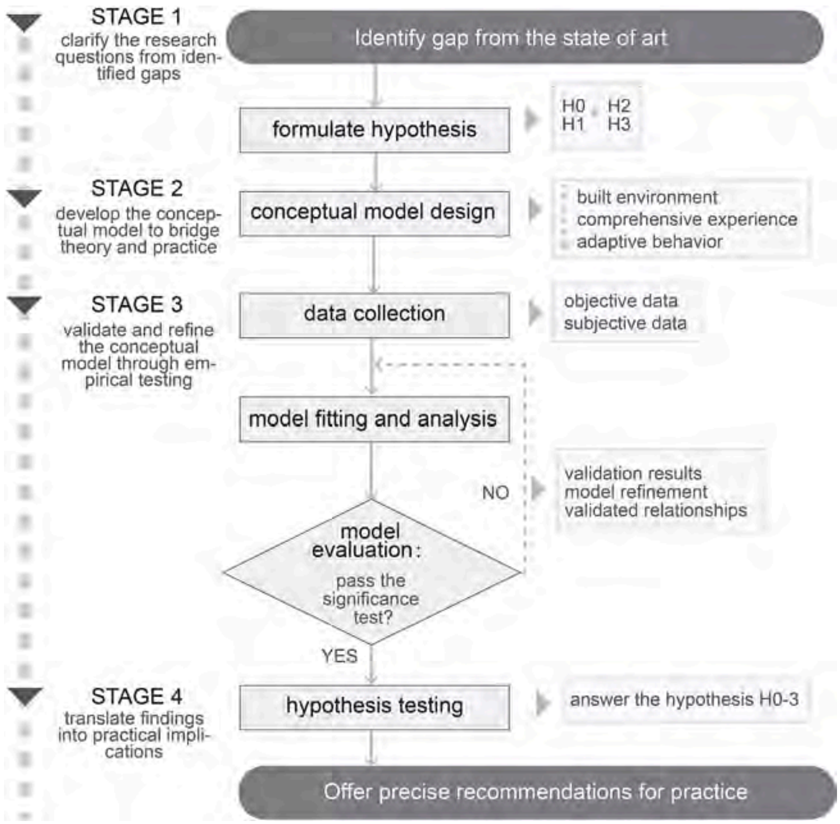


Fig. 1. Overall workflow of the study.

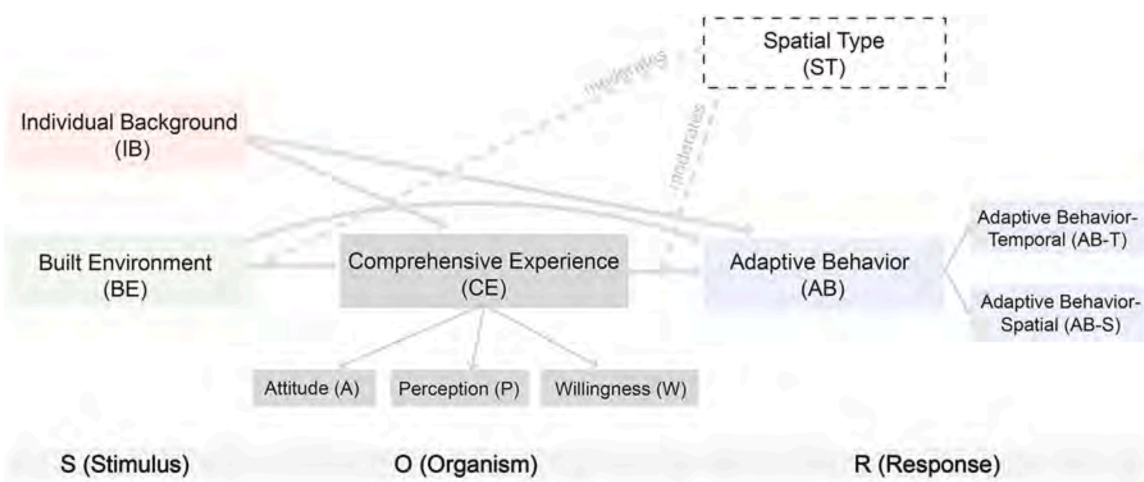


Fig. 2. Core structure of the conceptual model.

– Willingness (W): behavioral intentions such as staying, socializing, or revisiting.

Response (R): Adaptive behavior was defined as strategies in which individuals actively adjusted their activity patterns to cope with environmental stress, thereby maintaining comfort or achieving behavioral goals (Engle, 2011; Warrick et al., 2017). In this study, the Adaptive Behavior (AB) was measured via two composite dimensions:

– Adaptive Behavior of Temporal (AB-T): flexibility in time-related decisions, such as changing the visiting period or adjusting the length of stay (Pintos-Toledo et al., 2024).

– Adaptive Behavior of Spatial (AB-S): adjustments in spatial use, including shifts in movement range, preferences for rest areas (e.g., shade or ventilation), and changes between dynamic and static activity types (Han et al., 2022a).

Moderating and Control Variables: to strengthen the model's explanatory power across different contexts, two auxiliary variables were included:

– Spatial Type (ST): a moderating variable used to classify POSs with similar form and function, enabling the detection of differences in process effects across spatial structures.

– Individual Background (IB): a control variable covering sociodemographic attributes such as gender, age group, ethnicity, and place of residence, included to reduce sampling bias and test heterogeneity.

Based on these definitions, this study proposed the following hypothesized causal pathways ('pathway' and 'path' herein refer to influencing processes involving direction and effect size (Chan et al., 2017), rather than physical routes), where BE drove AB through the mediation of CE. This process was moderated by ST and controlled by IB.

The overall methodology framework is shown in Fig. 3 and consists of three main stages: Data collection, Data processing, and Data analysis.

During the data collection stage, a multi-stage survey approach is adopted including pre-field work online, fieldwork, and post-field process (see Fig. 4). The research team worked in two groups allowing the collection of both objective environmental and users' subjective data simultaneously. During data processing, multi-source data were integrated and cleaned using image semantic segmentation and variable standardization. A database was constructed for subsequent statistical analysis. In the data analysis stage, Principal Component Analysis (PCA) and Exploratory Factor Analysis (EFA) were used to examine the structure of the variables. On this basis, a PLS-SEM model was applied to identify the key paths linking BE, CE, and AB, and to compare differences across POS types. It should be emphasized that the design and measurement of all indicators in this methodology were based on a human scale. The focus was on environmental elements that users can directly perceive and experience during their daily activities. Detailed descriptions of each individual step of the methodology are reported in the following sections.

2.2. Measurement, quantification, and typology identification of the built environment

To support the quantitative verification of the BE in the conceptual model, this study constructed a multi-dimensional BE indicator system. This system referenced the theoretical foundations and quantitative logic of urban morphology (Elzeni et al., 2022) and environmental psychology (Bower et al., 2019; Ito et al., 2024). Five thematic dimensions (spatial layout, culture and landscape, functional supply, potential social support, and management maintenance) and 17 indicators were determined to systematically characterize the physical environmental characteristics of POSs (Li et al., 2016; Shen et al., 2024).

To ensure data integrity and verifiability, this study employed a multi-source fusion approach using four types of data sources to collect BE indicators, including: ① Field survey records; ② OpenStreetMap-based data; ③ Street view images; ④ On-site photograph images. Different data sources complemented each other during data collection, thereby improving the reliability of the measurements. As shown in Fig. 4a, the BE data collection process consisted of three stages. First, during the pre-field work stage, basic spatial information of the study area was obtained from OpenStreetMap (https://www.openstreetmap.org/). This included the boundaries of POSs, road structures, building forms, and characteristics of the surrounding built environment. Based on this information, fieldwork sampling areas were identified. At the same time, street view images were collected through the Baidu Street View Image API. Images were extracted at 30-meter intervals along the street networks. Second, during the fieldwork stage, Group A conducted on-site environmental recording at each sampling point. This included recording precise coordinates and on-site environmental characteristics using a predesigned quick checklist (the details were provided in the Appendix Tables B1 and B2). On-site photograph images were also taken to capture the actual environmental conditions of the space. These photographs were used to verify and supplement the street view data and to correct possible errors caused by outdated images or visual obstructions.

In the data processing stage, the SegNet deep learning semantic segmentation algorithm (Badrinarayanan et al., 2017) was used to

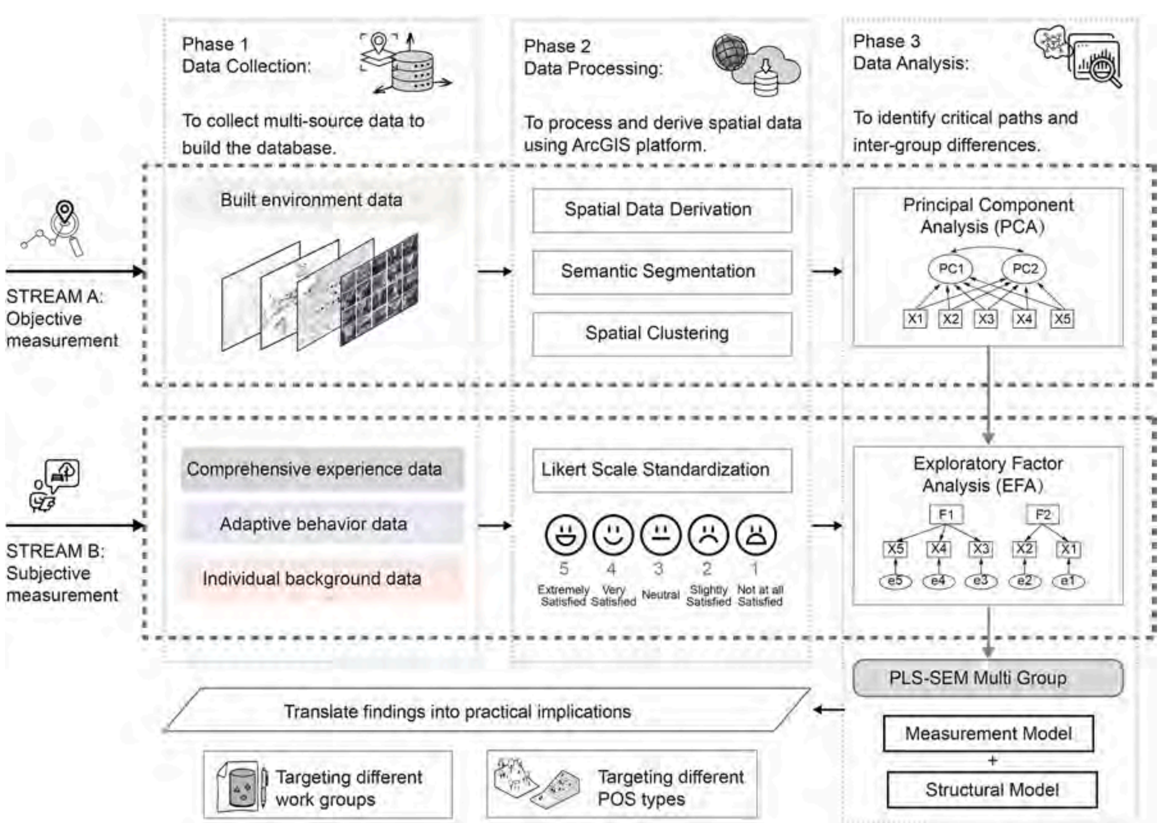


Fig. 3. Overall framework of the methodology.

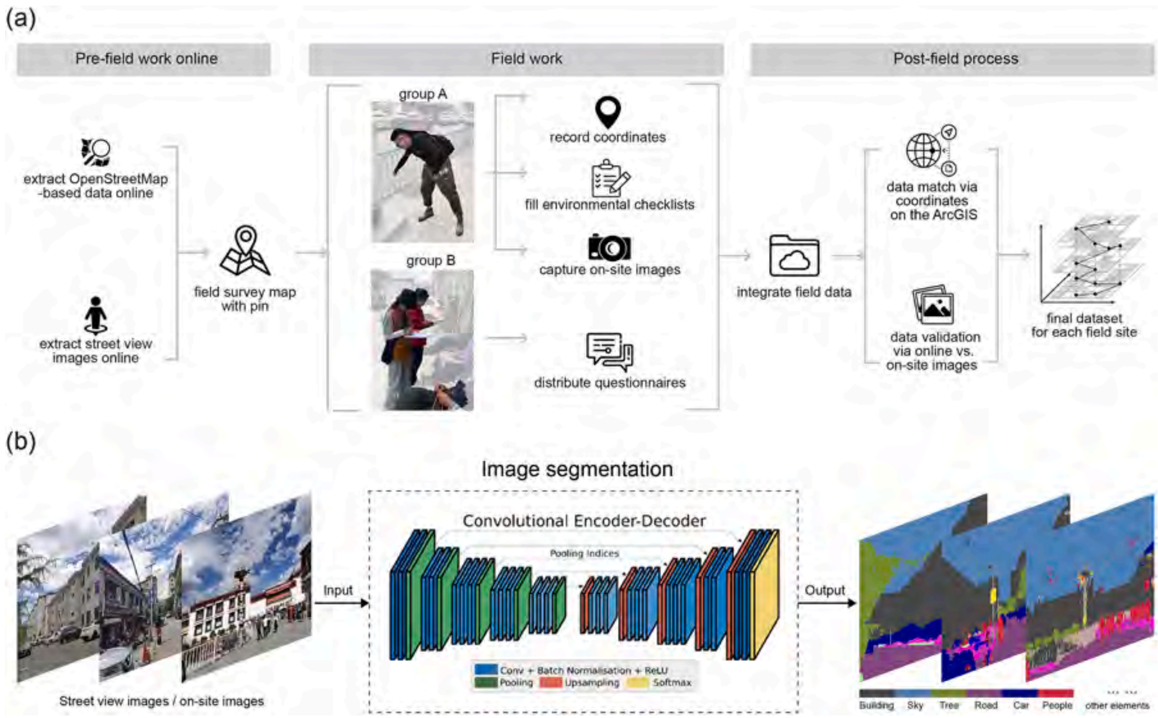


Fig. 4. Workflow of data collection and image segmentation process: (a) Multi-stage data collection and integration; (b) Image processing based on SegNet deep learning semantic segmentation.

classify and recognize the images, extracting the pixel proportions of elements including sky, greenery, roads, sidewalks, building facades, vehicles, and crowds. By calculating the pixel-area ratio for each category, key exposure indicators, such as the sky visibility factor, green view rate, and hard-paving rate, were further derived. This process was completed in batches in a Python environment, and the processing procedure was illustrated in Fig. 4b. The main objective of this phase was to extract environmental exposure indicators, such as the sky view factor and the green view index. Therefore, SegNet was selected due to its ability to reliably identify the broad environmental elements required for indicator extraction and to support batch processing of large image datasets. Then, all field measurement data and image recognition results were imported into the ArcGIS platform for spatial positioning and data cleaning (Li et al., 2016). Consistency of multi-source data was achieved through a unified projected coordinate system, resampling, and standardization (Z-score standardization). Subsequently, POSs were used as basic units for vectorization, integration, and mean aggregation to generate a database of BE indicators suitable for statistical analysis. Detailed definitions, measurement methods, and interpretations of all indicators were shown in Table 1. In this table, to ensure conciseness and consistency in variable citation, each BE indicator was assigned a unique and non-repeatable abbreviation code; this coding principle also was applied to the indicators in Section 2.3.

In addition, to examine the moderating effect of "space type" in the model, POSs were required to be objectively classified to identify systematic differences in environmental characteristics among them. This typological classification based on quantitative characteristics effectively avoids the bias of subjective classification. Therefore, this study conducted a cluster analysis based on the BE indicator system developed in this section to classify POSs into different STs. In terms of methodology, a combination of hierarchical clustering and K-means clustering was used to identify space types. First, Euclidean distance was used as the measure of similarity, and hierarchical clustering was performed using Ward's Minimum Variance method to identify potential cluster structures (Esfandi et al., 2022). Next, the optimal number of clusters was determined by considering both the silhouette coefficient and the interpretability of the ST. The classification results were then further refined using the K-means algorithm. The final space types were used as moderating variables in the subsequent model analysis.

2.3. Data collection and quantification methods for subjective users

To verify the roles of the CE and AB components in the conceptual model, this study designed and implemented an on-site questionnaire survey targeting POS users. Detailed definitions, measurement methods, and interpretations of all indicators were shown in Table 2. The questionnaire indicators were designed based on relevant literature in environmental psychology and were consistent with the S-O-R conceptual model proposed in this study (Sultan et al., 2021). This database comprised three modules, each corresponding to the pathway in the conceptual model.

– IB: Recorded the basic sociodemographic information of users and was included in the subsequent statistical analysis as categorical variables (Hasegawa & Lau, 2022).
– CE: Measurement items were designed around three dimensions: A, P, and W. These items captured users' experiences formed under environmental stimuli. The indicators were measured using a 5-point Likert scale and were treated as approximately continuous variables in the statistical analysis (Fatahi et al., 2025).
– AB: This focused on two dimensions: AB-T and AB-S, to quantify users' behavioral adjustment strategies under environmental pressure or changes in spatial conditions (Xu et al., 2026). The response categories reflected different forms of behavioral responses rather than a linear scale of higher or lower quality. To facilitate subsequent analysis, these behavioral categories were coded numerically from 1 to 5 and were treated as ordinal variables.

During the fieldwork stage, as shown in Fig. 4a, Group B was responsible for distributing questionnaires and conducting user interviews. Group B's researchers approached users who were actively using the selected POS sites and invited them to participate in the

Table 1
Names, data sources, and quantification methods of various indicators of the BE.

Dimension	Code	Indicator name	Data source	Mathematical formula and symbol definitions
Spatial layout	BEl1	Street Height-to-Width Ratio (Jim & Chen, 2010)	①,②	$BEl1 = \frac{1}{n}\sum_{i=1}^{n}\frac{H_i}{W_i}$ n: Total number of sampling points H_i: average building height at sampling point i *(m)* W_i: street width at sampling point i, measured between building facades *(m)*
	BEl2	Sky Openness Ratio (Nian et al., 2025; Yoshihara et al., 2021)	③,④	$BEl2 = \frac{P_{sky}}{P_{total}} \times 100\%$ P_{sky}: Total number of pixels identified as "sky." P_{total}: Total number of pixels in the image
	BEl3	Facade Continuity (Ito et al., 2024; Yoshihara et al., 2021)	③,④	$BEl3 = \sqrt{\frac{\sum_{i=1}^{n}\left(R_{b,i} - \overline{R}_b\right)^2}{n}}$ $R_{b,i}$: Ratio of building pixels in image i $\overline{R}_b$: Mean ratio of building pixels across all samples n: Total number of sampling points
Culture and landscape	BEc1	Green View Index (Han et al., 2024; Nian et al., 2025)	③,④	$BEc1 = \frac{P_{veg}}{P_{total}} \times 100\%$ P_{veg}: Total number of pixels identified as "vegetation."
	BEc2	Visual Element Diversity (Ito et al., 2024; Yoshihara et al., 2021)	②	$BEc2 = \frac{N_{elements}}{A_{total}}$ $N_{elements}$: Total number or types of visible landscape elements A_{total}: Total area of each spatial unit
	BEc3	Cultural Facility Density (Luo et al., 2025a)	①,②	$BEc3 = \frac{N_{cultural}}{A_{total}}$ $N_{cultural}$: Total number of cultural facilities (e.g., public sculptures, monuments, churches, temples, museums)
Functional supply	BEf1	Public Activity Facility Density (Song et al., 2025)	②	$BEf1 = \frac{N_{activity}}{A_{total}}$ $N_{activity}$: Total number of public activity facilities (e.g., benches)
	BEf2	Convenience Facility Density (Koohsari et al., 2015)	①,②	$BEf2 = \frac{N_{service}}{A_{total}}$ $N_{service}$: Total number of service facilities (e.g., nursing rooms, service stations, restrooms)
	BEf3	Waste Bin Density (Ito et al., 2024)	②	$BEf3 = \frac{N_{bin}}{A_{total}}$ N_{bin}: Total number of waste bins
	BEf4	Informal Social Node Density (Song et al., 2025; Xu et al., 2022)	①,②	$BEf4 = \frac{N_{social}}{A_{total}}$ N_{social}: Total number of informal social nodes (e.g., tea houses, cafes, bars)
Potential social support	BEs1	Presence of Mobile Vendors (Guzman et al., 2026; Xu et al., 2022)	②	$BEs1 = \begin{cases} n, & \text{if present} \\ 0, & \text{if absent} \end{cases}$ Measured as a dummy variable (*0*) or count variable (n); n indicates presence, *0* indicates absence
	BEs2	Pedestrian Density (Song et al., 2025)	③,④	$BEs2 = \frac{P_{human}}{P_{total}} \times 100\%$ P_{human}: Total number of pixels identified as "human"
	BEs3	Walkability (Zhang et al., 2019)	①,②	$BEs3 = \frac{1}{nr}\sum_{i=1}^{nr}\left(\frac{W_{sidewalk,i}}{W_{road,i}}\right)$ nr: Number of sampled road segments $W_{sidewalk,i}$: Width of the sidewalk at segment i $W_{road,i}$: Total width of the road at segment i
Management and maintenance	BEm1	Traffic Safety Facility Ratio (Yoshihara et al., 2021)	②	$BEm1 = \frac{L_{guardrail}}{L_{road}}$ $L_{guardrail}$: Total length of pedestrian/vehicle guardrails L_{road}: Total length of the road
	BEm2	Surveillance Facility Density (Ito et al., 2024)	②	$BEm2 = \frac{N_{camera}}{A_{total}}$ N_{camera}: Total number of surveillance cameras
	BEm3	Public Firefighting Facility Density (Xu et al., 2022)	②	$BEm3 = \frac{N_{fire}}{A_{total}}$ N_{fire}: Total number of firefighting facilities
	BEm4	Security Post Density (Ito et al., 2024)	①,②	$BEm4 = \frac{N_{post}}{A_{total}}$ N_{post}: Total number of security posts/checkpoints

Note: ① OpenStreetMap-based data; ② Field survey records; ③ Street view images; ④ On-site photograph images.

survey. The questionnaires were completed during on-site interviews, with researchers assisting respondents as needed. To ensure that the subjective questionnaire data could be spatially matched to the BE measurements, the precise coordinates of each questionnaire were recorded at the time of collection.

During the post-field work stage, all questionnaire data were coded and cleaned. This included removing questionnaires with substantial missing information or logical inconsistencies to ensure data quality. The cleaned questionnaire data were then imported into the ArcGIS platform for spatial positioning and integration. On this basis, the questionnaire variables were standardized, and an integrated database was constructed for subsequent statistical analysis.

Table 2
Indicator names and explanations for subjective user data.

Dimension	Code	Indicator name	Explanation and measurement scale
Individual Background (IB)	IB1	Age	Represents the respondent's actual age, used to control for potential differences in spatial experience and behavioral responses across age groups. (1 ≤ 18; 2 = 18–30; 3 = 31–40; 4 = 41–50; 5 = 51–60; 6 ≥ 60)
	IB2	Gender	Records the respondent's gender to analyze differences in environmental perception and adaptive behaviors across gender groups. (1 = Male; 2 = Female)
	IB3	Ethnicity	Reflects the respondent's ethnic affiliation, used to explore how cultural background differences influence spatial perception and usage patterns. (1 = Majority ethnic group; 2 = Local ethnic minority group; 3 = Other ethnic groups / international visitors)
	IB4	Residential Location	Indicates the respondent's primary area of residence, used to control for the influence of geographic or urban context on experience and behavior. (1 = This neighborhood; 2 = This city; 3 = Other cities in this region; 4 = Other cities in this country; 5 = Other countries)
Attitude (A)	A1	Perceived Cleanliness	Reflects users' general perception of the cleanliness and maintenance of the space. (1 = Not at all satisfied; 2 = Slightly satisfied; 3 = Neutral; 4 = Very satisfied; 5 = Strongly satisfied)
	A2	Maintenance and Upkeep Quality	Measures users' subjective evaluation of the quality of daily maintenance and hygiene management. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
	A3	Perceived Safety	Indicates users' overall judgment of safety assurance and risk control within the space. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
	A4	Spatial Orientation Clarity	Reflects how easily users can orient themselves, recognize entrances, and navigate within the space. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
	A5	Perceived Crowdedness	Measures users' subjective perception of crowding and spatial density. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
Perception (P)	P1	Facility Completeness	Represents users' perception of the adequacy and completeness of facilities and public amenities in the space. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
	P2	Landscape Diversity	Reflects users' direct perception of the diversity of natural and artificial landscape elements. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
	P3	Functional Supportiveness	Measures the extent to which the space supports users' activities and social interactions. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
	P4	Spatial Attractiveness	Represents users' perception of the visual interest and aesthetic appeal of the space. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
	P5	Social Atmosphere	Reflects users' perception of the social interaction level, inclusiveness, and vitality within the space. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
Willingness (W)	W1	Willingness for Continued Use	Indicates users' tendency to continue using the space in the future. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
	W2	Spatial Form Attraction	Measures the extent to which spatial form and design features attract users to use the space. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
	W3	Behavioral Adaptation Intention	Reflects users' willingness to adjust their behavior to maintain comfort or achieve goals. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
	W4	Safety Acceptance Intention	Indicates users' willingness to stay or act within the space under acceptable safety conditions. (1 = Not at all satisfied ~ 5 = Strongly satisfied)
Adaptive Behavior of Temporal (AB-T)	AB-T1	Temporal Adjustment Frequency	Measures how frequently users maintain their activities despite changes in environmental conditions (Li et al., 2025). (1 = almost never; 2 = rarely; 3 = every month; 4 = every week; 5 = every day)
	AB-T2	Exposure Duration Management	Reflects users' ability to manage and regulate their exposure duration in open environments (Bower et al., 2019). (1 ≤ 1 h; 2 = 1–3 h; 3 = 3–5 h; 4 = 5–8 h; 5 ≥ 8 h)
	AB-T3	Behavioral Intensity Adjustment	Reflects the range of time periods during which users remain willing to engage in activities in the space despite changes in environmental conditions (Martinelli et al., 2015). (1 = Extremely narrow (only 1 time slot); 2 = Relatively narrow (2 time slots); 3 = Medium (3 time slots); 4 = Relatively wide (4 time slots); 5 = Extremely wide/All day (≥5 time slots or including long-term use))
Adaptive Behavior of Spatial (AB-S)	AB-S1	Spatial Adjustment Behavior	Refers to users' behavior of changing location or activity area to cope with environmental stressors (Pintos-Toledo et al., 2024). (1 = Static, low intensity physical activity; 2 = Low intensity but continuous activity / High frequency but not activity dominant; 3 = Moderate intensity, short duration but active / Long duration but intermittent; 4 = Continuous, high intensity activity; 5 = High intensity physical activity)

(continued on next page)

Table 2 (*continued*)

Dimension	Code	Indicator name	Explanation and measurement scale
	AB-S2	Spatial Preference Behavior	Reflects users' preference for specific spatial types (open, semi-open, or sheltered spaces) (Fatahi et al., 2025). (1 = Indoor/Strongly shaded; 2 = Semi-shaded/Fixed; 3 = Open/Slightly shaded; 4 = Almost unshaded; 5 = Fully open/Unshaded)
	AB-S3	Spatial Exposure Acceptance	Measures users' level of acceptance toward specific environmental exposures (e.g., sunlight, noise, crowding) (Yuan et al., 2023). (1 = Resistance and avoidance; 2 = Passive tolerance; 3 = Neutral adaptation; 4 = Active adjustment; 5 = Active utilization)

2.4. Validity analysis of model construction

Before constructing the structural model, it was essential to ensure that all variables exhibited adequate validity and reliability. Different types of variables required different strategies for dimensionality reduction and structural verification. All analyses were conducted in R (v4.3) (R Core Team, 2013).

The variables in this study came from two data types with different characteristics. One type consisted of objective BE indicators. The other type consisted of subjective psychological variables obtained from questionnaire scales, including CE and AB. Because these two types of variables differed in both data properties and theoretical meaning, different statistical methods were required to examine their structures. The BE indicators were objective continuous variables. They were mainly derived from spatial measurements and image recognition results and were used to describe the physical characteristics of the spatial environment. Since these indicators might be strongly correlated with each other, feature extraction methods were more suitable for reducing their dimensionality.

In contrast, the subjective psychological variables obtained from questionnaires (CE and AB) were used to capture users' psychological experiences and behavioral responses under environmental stimuli. Therefore, factor analysis was more appropriate for examining their latent structures. Based on these differences, this study applied Principal Component Analysis (PCA) and Exploratory Factor Analysis (EFA) to examine the structures of the two types of variables. In this way, the analysis improved the model's stability and explanatory power while preserving the theoretical meaning of the variables.

For the BE, Principal Component Analysis (PCA) was used to reduce dimensionality and to extract core features (Mohammadzadeh et al., 2023). First, parallel analysis was used to determine the number of principal components to retain. Only components with eigenvalues greater than the average eigenvalues from simulated random data were retained. Second, Promax oblique rotation was then applied to allow correlations among environmental dimensions, yielding a more realistic and interpretable component structure. The final components were used as composite proxy variables for the BE and were included in the subsequent structural model analysis.

For CE and AB, an Exploratory Factor Analysis (EFA) was used to validate the questionnaire scales' structure (Hasegawa & Lau, 2022; Mohammadzadeh et al., 2023). Before extraction, the Kaiser-Meyer-Olkin (KMO) statistic was used to test sampling adequacy, with an acceptable threshold of 0.50 or higher. Bartlett's test of sphericity was also conducted to examine whether the variables were sufficiently correlated, with a significance level of $p < 0.001$. Principal axis factoring was then used to extract factors, followed by Promax oblique rotation to obtain the latent factor structure. Only measurement items with factor loadings of 0.50 or higher and statistically significant values ($p < 0.05$) were retained. Items that did not meet these criteria were removed. The remaining indicators were used to construct the latent variables for CE and AB.

2.5. PLS-SEM analysis

This study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) as the core analytical method (Hair et al., 2017). Compared with covariance-based SEM (CB-SEM), PLS-SEM was more prediction-oriented and robust, making it suitable for studies with small sample sizes, non-normal data distributions, complex model structures, or formative constructs (Olanrewaju et al., 2022). These advantages made PLS-SEM particularly reliable in real-world urban fieldwork and have led to its widespread use in studies of thermal comfort (Yang et al., 2025), spatial experience (Fatahi et al., 2025), and environmental behavior process (Xu et al., 2026), demonstrating its methodological appropriateness in this domain.

Accordingly, this study applied PLS-SEM to assess path significance, explanatory power, and predictive validity, focusing on the relationships among the BE, CE, AB, and IB. Multi-group analysis was used to test the moderating effect of ST. All analyses were conducted in SmartPLS 4.0 (Hair et al., 2025; Mohammadzadeh et al., 2023) and R (v4.3) to ensure reproducibility and cross-validation.

A PLS-SEM consisted of a measurement model and a structural model, both of which were required to be evaluated to ensure reliability and validity. The measurement model addressed the question "How was this unobservable concept measured?" The measurement model was using convergent validity, reliability, and discriminant validity. Convergent validity was examined to determine whether indicators of the same latent variable were highly correlated, and it was evaluated through factor loadings and the Average Variance Extracted (AVE). Internal consistency was assessed using Cronbach's alpha, composite reliability (CR), and Rho_A. Discriminant validity was examined using the heterotrait-monotrait ratio (HTMT).

The structural model answered the question: "How did these concepts influence one another?" And the structural model was evaluated using bootstrapping with 2000 resamples to estimate the significance of path coefficients (β), their effect sizes (f^2), and the corresponding *t*-values and *p*-values.

Regarding sample size, PLS-SEM typically followed empirical minimum sample rules. One of the most commonly used guidelines was the "10-times rule", which suggests that the sample size should be at least ten times the maximum number of predictors in the model (Wagner & Grimm, 2023). In addition, to further assess the reliability of the model results, this study conducted a post hoc statistical power analysis. The analysis calculated statistical power based on the chosen significance level (α), the model effect sizes (f^2), and the maximum number of predictors. All post hoc power analyses were carried out using G*Power software (v3.1) (Faul, 2009). By combining the empirical sample size rule with statistical power analysis, the reliability of the model interpretation was further strengthened.

2.6. Test-bed site and field experiment process

To ensure the external validity of the model and the reproducibility of the results, this study conducted empirical research in a typical test-bed site. The selection of the test-bed site followed these principles:

– Spatial diversity principle, POSs that cover as many forms and functional characteristics as possible were selected, thereby reflecting the broad applicability of environmental factors to behavioral mechanisms.

– User heterogeneity principle, the test-bed site was designed to attract user groups with different socio-demographic backgrounds to improve sample representativeness.
– Sample size and representativeness principle, the test-bed site met the feasibility requirements and have a sufficient sample size.
– Spatiotemporal synchronization principle, synchronous objective measurement and subjective surveys were employed to ensure data consistency across temporal and spatial.

This study selected Lhasa, China, as the test-bed site, based on its unique climatic conditions and spatial evolution structure (Yao et al., 2022). Lhasa is located in the central Tibetan Plateau at an elevation of about 3650 m and is characterized by a typical high-altitude climate. As shown in Fig. 5a and b, the high elevation and thin atmosphere result in strong solar radiation and large day-night temperature differences throughout the year (WeatherSpark, 2026). In recent years, under the influence of climate change, climatic variability in plateau cities has further increased. This includes fluctuations in solar radiation, more frequent high-temperature events, and unstable precipitation patterns. The combined effects of these climatic changes create complex environmental pressures, requiring residents to continuously adjust their behavior, especially when using POSs (Jiang et al., 2026). At the same time, rapid urbanization in Lhasa has produced a spatial pattern where traditional Tibetan urban structures coexist with modern urban functions (Xiong et al., 2016). This spatial diversity provides an ideal setting for observing how users adapt their behavior under different conditions.

Based on the characteristics described above, this study adopted purposive sampling to select representative POSs. Previous studies have shown that POSs in Lhasa's main urban area exhibit relatively clear spatial form structures. They can generally be divided into three categories: the old city area, the mature development area, and the outskirt area (Luo et al., 2025a). Based on this classification, 12 POSs were selected from the three areas for investigation. These samples captured the main spatial types and their typical user contexts (Xiong et al.,

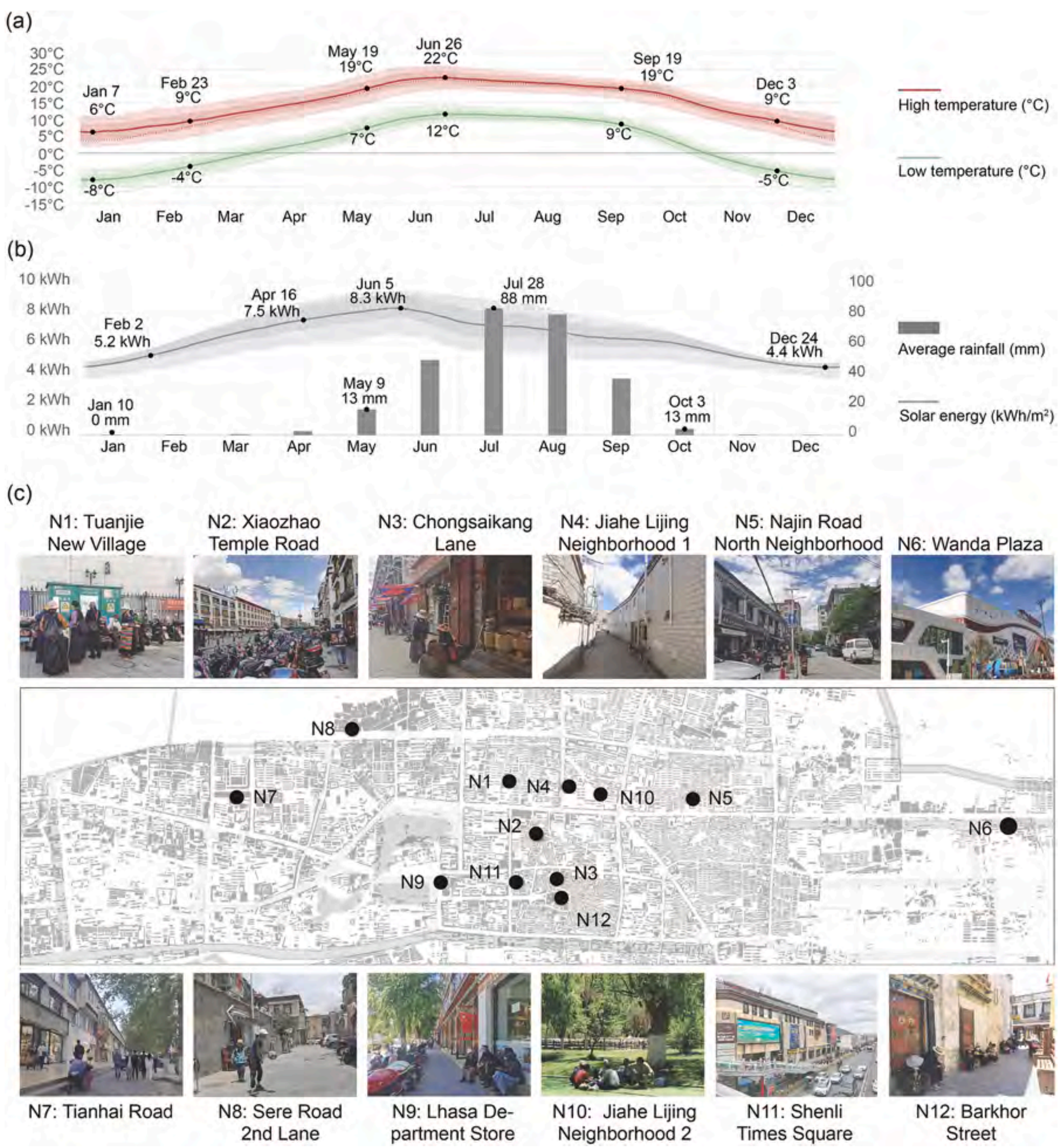


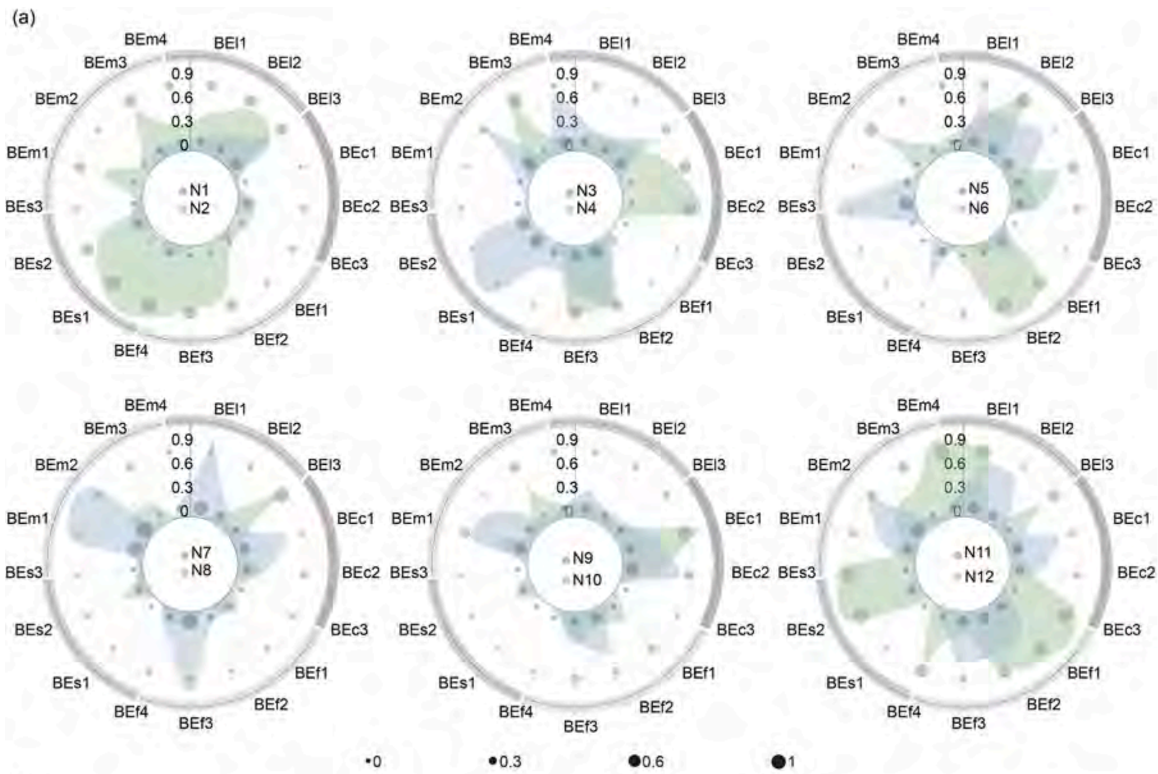
Fig. 5. Climatic characteristics and spatial distribution of the test-bed site: (a) Monthly average temperature variation; (b) Monthly average precipitation and solar radiation; (c) Geographical distribution and surrounding textural features of 12 typical POSs.

2016). Their geographical distribution and surrounding environmental characteristics are shown in Fig. 5c.

Following the procedure described above, data collection for this study was conducted in three stages in June 2021. The first stage was the pre-field work stage (June 3–9), during which open data for the study area were obtained. The second stage was the fieldwork stage (June 11–15), during which objective measurements and subjective surveys were conducted simultaneously, covering both weekdays and weekends. The third stage was the post-field work process stage (June 20–30), which mainly involved coordinate calibration and secondary data verification. The research group consisted of eight professionals, including master's students and local Tibetan undergraduate students in urban planning and architecture. This ensured the professionalism of environmental measurements and behavioral observations, and the participation of local researchers enhanced the accuracy of cultural understanding, effectively balancing the dual perspectives of professional assessment and local cognition (Sander van et al., 2015).

Although the data were collected in the early post-pandemic period

(a)



(b)

		N8	N5	N1	N12	N3	N2	N6	N7	N11	N9	N4	N10
Street Height-to-Width Ratio	BEl1	0.36	1.04	0.60	1.36	0.72	0.89	0.81	1.46	1.14	0.75	0.65	0.59
Sky Openness Ratio	BEl2	7.79	15.18	11.10	5.10	10.53	18.25	23.40	10.21	16.80	8.77	9.83	7.68
Facade Continuity	BEl3	62.95	53.15	52.02	52.81	51.18	52.60	31.99	36.46	34.23	39.25	45.09	38.16
Green View Index	BEc1	3.47	7.45	2.30	5.10	1.29	1.90	16.53	16.66	16.59	11.65	18.20	24.40
Visual Element Diversity	BEc2	2.29	2.51	2.20	2.25	1.41	2.16	2.67	2.55	2.61	3.84	4.74	2.85
Cultural Facility Density	BEc3	0.38	0.00	0.00	4.67	0.00	0.86	0.00	0.00	0.00	0.00	0.00	0.00
Public Activity Facility Density	BEf1	1.91	2.76	0.94	8.65	0.94	1.51	7.17	1.28	4.22	0.24	0.00	2.85
Convenience Facility Density	BEf2	0.00	0.25	0.00	1.90	2.11	1.51	2.33	0.43	1.38	1.44	1.58	0.52
Waste Bin Density	BEf3	5.73	3.01	3.46	6.92	11.27	14.44	6.33	17.02	11.68	7.91	15.02	8.55
Informal Social Node Density	BEf4	3.00	9.00	4.00	13.00	6.00	16.00	1.00	5.00	3.00	1.00	1.00	2.00
Presence of Mobile Vendors	BEs1	0.00	0.00	0.00	0.00	5.00	5.00	0.00	0.00	0.00	0.00	0.00	0.00
Pedestrian Density	BEs2	1.24	1.35	2.55	8.67	7.36	6.30	0.90	3.41	2.16	2.53	0.56	0.76
Walkability	BEs3	0.60	5.00	0.63	5.00	0.38	0.60	0.50	0.30	0.40	0.30	0.30	0.20
Traffic Safety Facility Ratio	BEm1	0.01	0.04	0.00	0.04	0.02	0.09	0.00	0.17	0.08	0.13	0.00	0.07
Surveillance Facility Density	BEm2	20.23	5.26	7.23	28.03	49.30	13.15	44.83	55.11	49.97	31.65	16.60	6.99
Public Firefighting Facility Density	BEm3	0.38	0.25	0.31	0.52	0.23	0.65	0.33	0.21	0.27	0.24	0.79	0.52
Security Post Density	BEm4	0.00	0.25	0.31	3.11	2.35	1.08	0.67	0.43	0.55	0.48	0.40	0.52

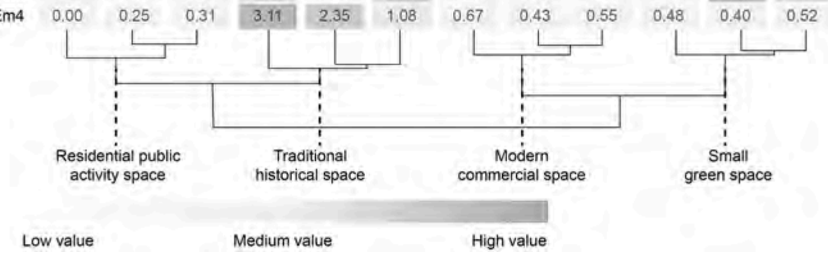


Fig. 6. Clustering identification results of POSs: (a) the mean results after quantification; (b) the clustering results.

(Hou et al., 2024), the adaptive behaviors studied mainly arise from human physiological and psychological responses to environmental stimuli such as sound, light, and heat. At the city scale, the basic patterns of activity and gathering in POSs tend to remain relatively stable over time (Han et al., 2022b). In addition, the survey was conducted in mid-June, which aligns with Lhasa's climatic characteristics. As shown in Fig. 5a and b, this period is marked by strong solar radiation and large diurnal temperature differences. Such conditions often prompt users to seek shade or adjust their activity time. By contrast, during the rainy season or snowy winter, environmental stress becomes more pronounced, and people often avoid outdoor activities. Therefore, conducting the survey during a period when environmental conditions are relatively stable yet sufficiently stimulating helps capture how users adjust their behavior in response to everyday environmental pressures.

3. Results

3.1. Quantification of the built environment and identification results of POS types

To address the spatial differences among POS types, this study conducted quantitative and cluster analysis on 12 POS types (N1-N12) based on the aforementioned quantitative index system for the BE.

To better reflect the actual characteristics of POSs in Lhasa, several BE indicators were moderately adjusted during the quantification stage to incorporate the local cultural context. These include BEc2, BEc3, BEf4, and BEs1. When applied to other cities, these indicators can also be calibrated according to local climatic conditions and cultural characteristics. For example, in Lhasa, BEc2 also identified locally distinctive visual elements such as prayer flags and murals; in Western urban contexts, comparable elements may include fountains or heritage markers. For BEc3, in addition to cultural facilities such as museums and art galleries, the indicator also included religious facilities such as temples, street incense burners, and prayer wheels; in European historic cities, similar elements may include sculptures, monuments, or churches. For BEf4, this study considered the Tibetan teahouse as an important daily social space; in other urban contexts, comparable places may include cafés or bars that function as third places.

To examine the robustness of the clustering results, this study conducted a simple sensitivity analysis by comparing classification results under different numbers of clusters (k = 3–5) and different distance metrics. The results showed that the ST structures remained highly consistent across parameter settings, and the optimal number of clusters was four. Therefore, four STs were adopted as the classification basis for subsequent analyses. Fig. 6 shows the mean results after quantification and the clustering results.

Residential public activity space (N8, N5, N1, n = 47): This type of space was mainly distributed around residential areas, and was characterized by high building enclosure (BEI3) and low open exposure (BEm2), with a moderate number of facilities and management level (BEf3, BEm1). The space functions primarily for community activities, neighborhood interaction, and daily rest, with high potential for social support (BEs1, BEs2). The overall environment of this type of space exhibits stable, low-disturbance, and life-oriented characteristics.

Traditional historical spaces (N12, N3, N2, n = 67) were represented by historical streets and traditional neighborhoods, and possesses high cultural and landscape indices (BEc1, BEc3) and relatively rich functional offerings (BEf4). These spaces are characterized by small street scale, winding roads, good walkability, and relatively limited public activity space, yet rich spatial perception. They often retain strong regional cultural characteristics and serve as shared experiential venues for residents and tourists.

Modern commercial spaces (N6, N7, N11, n = 57) were identified as exhibiting high facility density (BEf1, BEf3) and high exposure (BEm2), while also showing greater openness in building facades (lower BEI3), reflecting the openness and dynamic nature of modern commercial activities. They demonstrate high levels of management and maintenance (BEm1) and prominent spatial diversity (BEc1, BEc2), but relatively low green space. These spaces serve as core areas of high activity and high accessibility.

Small green spaces (N9, N4, N10, n = 50) were characterized by smaller but have higher green coverage and visual openness (BEm2, BEI3), and primarily function as ecological recreation areas and visual buffers. They have fewer facilities (BEf2, BEf4), but are generally quiet and visually comfortable, providing important environmental buffering and psychological recovery (Hou et al., 2024).

3.2. Individual background, comprehensive experience, and adaptive behavior patterns of users

A total of 221 valid questionnaires were collected. The distribution of respondents' IB characteristics is shown in Fig. 7. As shown in Fig. 7a, the age distribution reflected a structure dominated by young adults, with representation from middle-aged and older users. Fig. 7b shows a near-balanced gender distribution, with females at 50.7% and males at 49.3%, indicating good gender representation. In terms of ethnicity, Fig. 7c shows that Tibetan users accounted for the largest proportion (52.5%), followed by Han users (44.8%), while other ethnic groups and international users together account for 2.7%, this pattern reflects cultural diversity within the sample. Fig. 7d illustrates substantial geographic diversity in respondents' place of residence. Users living within Lhasa city accounted for the largest share (43.4%), and residents in this neighborhood accounted for 17.2%, indicating that the POSs served both local residents and users from across the city. Notably, 24.4% of users came from other Chinese cities, and 8.6% were international users, suggesting that these POSs function not only as daily-use spaces for locals but also as important recreational spaces for visitors.

Fig. 8 summarizes respondents' overall CE scores. The results show generally positive user experiences, but with notable variation across dimensions.

In the A dimension (Fig. 8a), users expressed strong approval of basic environmental quality. Perceived cleanliness (92.8% positive), Maintenance and upkeep quality (91.4%), and perceived safety (91.9%) all received over 90% positive ratings. Spatial orientation clarity also scored highly (92.7%). In contrast, perceived crowdedness showed substantial divergence: 36.2% of users reporting feeling crowded. Overall, good cleanliness, maintenance, and safety formed the basis of positive attitudes, while spatial density and flow management emerged as key issues shaping momentary impressions.

In the P dimension (Fig. 8b), users also responded positively to the aesthetic and functional qualities of the spaces. Spatial attractiveness received very high approval (93.6%), followed by landscape diversity (89.6%) and facility completeness (89.6%). The social atmosphere was viewed positively by 86% of respondents. However, functional supportiveness received comparatively lower evaluations, with 72.4% positive responses. This result suggests that although users appreciate the landscape quality and social atmosphere of these POSs, their capacity to support diverse activities remains limited. In other words, even when a POS is visually attractive, limited functional support may still restrict users' activity choices and reduce their flexibility to adjust behavior in response to changing environmental conditions.

In the W dimension (Fig. 8c), a more complex pattern of behavioral intentions emerged. Willingness for continued use was very strong (95.0%), and spatial form attraction was also high (83.7%), indicating a strong sense of attachment to these POSs. However, safety acceptance intention (60.7%) and behavioral adaptation intention (50.2%) were only moderate. This implies that although users wish to keep using the spaces, they tend to be conservative when deciding whether to adopt AB in response to environmental pressures.

The scoring results for AB are shown in Fig. 9.

For AB-T, the results exhibited a moderate distribution concentration overall. This suggests that while users adjust their schedules based on

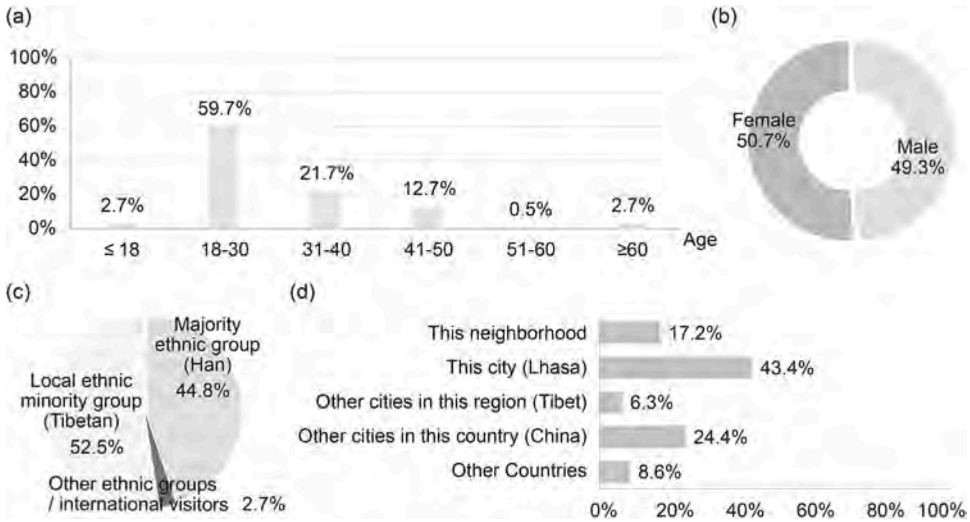


Fig. 7. Distribution of IB features: (a) Age; (b) Gender; (c) Ethnicity group; (d) Residential Location.

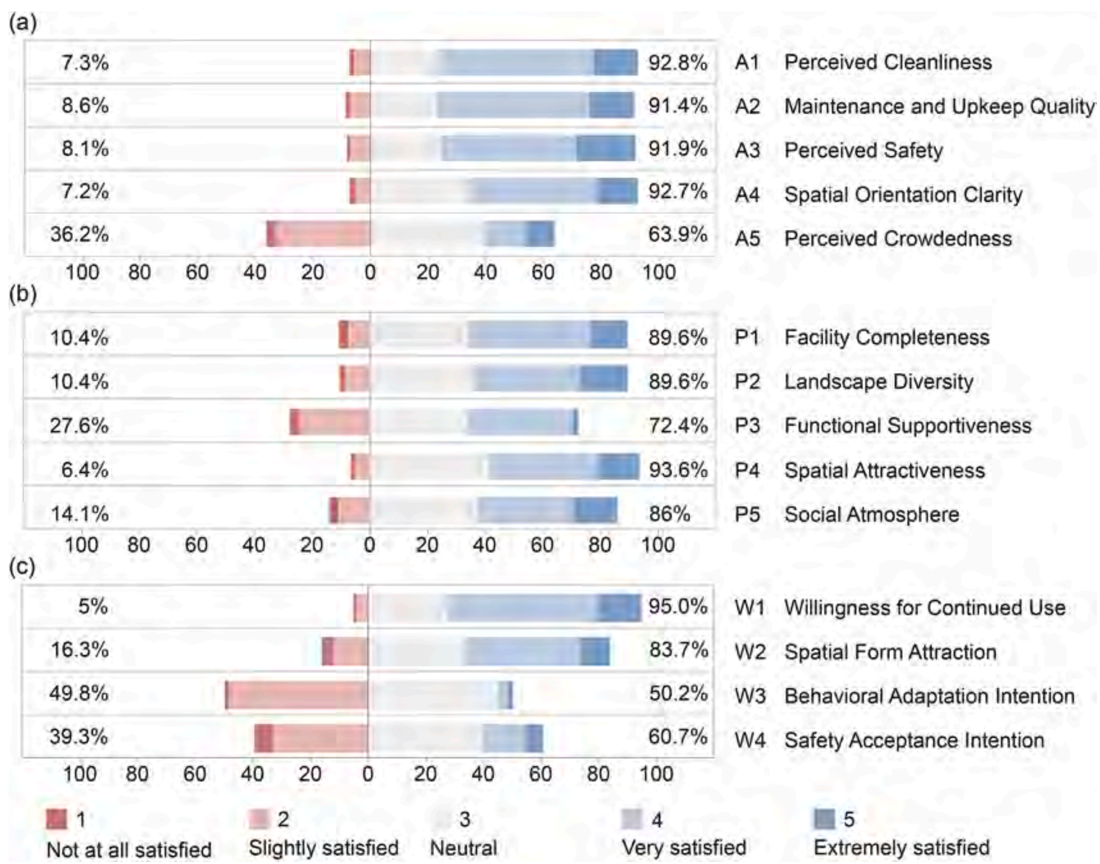


Fig. 8. User's overall experience scores. (a) A (Attitude), (b) P (Perception), (c) W (Willingness).

environmental conditions, these behaviors are generally neither high frequency nor extreme. The scoring results for temporal adjustment frequency indicate that the majority of users (63.2%) engaged in moderate-to-high frequency adjustments (at least once per month), reflecting proactive time-planning strategies. Exposure duration management showed a bimodal distribution: approximately 45% of users preferred short exposure (<3 h), while 38% preferred long exposure (>5 h). This divergence likely relates to the purpose of use, distinguishing between purposeful visits and leisure-oriented social activities. Behavioral intensity adjustment showed a balanced distribution, indicating that users flexibly modify their activity levels in response to real-time environmental conditions.

For AB-S, a more complex logic was observed. Spatial adjustment behavior results revealed a coexistence of high-mobility (levels 4–5) and static (levels 1–2) behaviors. This may reflect distinct user strategies; some prefer fixed locations, while others actively relocate to cope with environmental stress, demonstrating higher behavioral flexibility. The mean score for spatial preference behavior was significantly higher than other indicators, skewing toward the high range (preference for almost unshaded or semi-open spaces). This indicates a clear trend in user

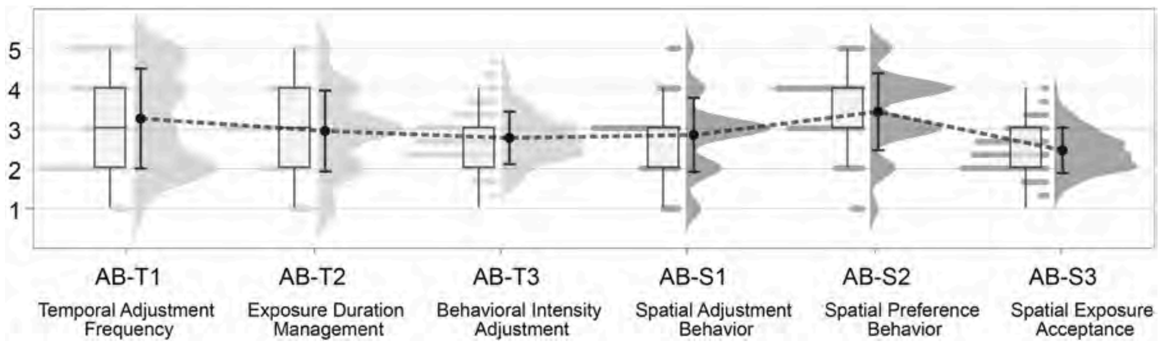


Fig. 9. Scoring results for AB of users.

preferences for spatial form, underscoring the built environment as a key driver of spatial behavior. Spatial exposure acceptance revealed significant psychological differences: the majority (58.3%) showed neutral-to-positive acceptance (levels 3–5), while a substantial proportion (41.7%) exhibited resistance or passive tolerance. This divergence may stem from individual differences in thermal comfort perception and cultural background (Yao et al., 2022; Yuan et al., 2023).

3.3. Validity and robustness of model construction

Principal Component Analysis (PCA) was employed to reduce the dimensionality of the 17 BE indicators, thereby mitigating multicollinearity and extracting core feature dimensions (Fig. 10, Table 3).

First, data suitability was assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. The KMO value was 0.519, which was slightly above the commonly accepted threshold

Table 3
Eigenvalues, variance explained, and parallel analysis results of Principal Component Analysis (PCA).

Metric	PC1	PC2	PC3	PC4	PC5	PC6
Unrotated scheme						
Eigenvalues	5.42	2.87	2.64	1.96	1.57	1.09
Variance explained (%)	0.32	0.17	0.16	0.12	0.09	0.06
Cumulative variance (%)	0.32	0.49	0.64	0.76	0.85	0.92
Rotated Solution						
Sum of Sq. Loadings	3.73	3.56	2.71	2.14	1.92	1.50
Variance explained (%)	0.22	0.21	0.16	0.13	0.11	0.09
Cumulative variance (%)	0.22	0.43	0.59	0.71	0.83	0.92
Parallel analysis						
Actual data factor eigenvalues	4.99	2.05	1.84	1.10	0.69	0.46
Simulated data average eigenvalues	0.62	0.43	0.36	0.28	0.22	0.17

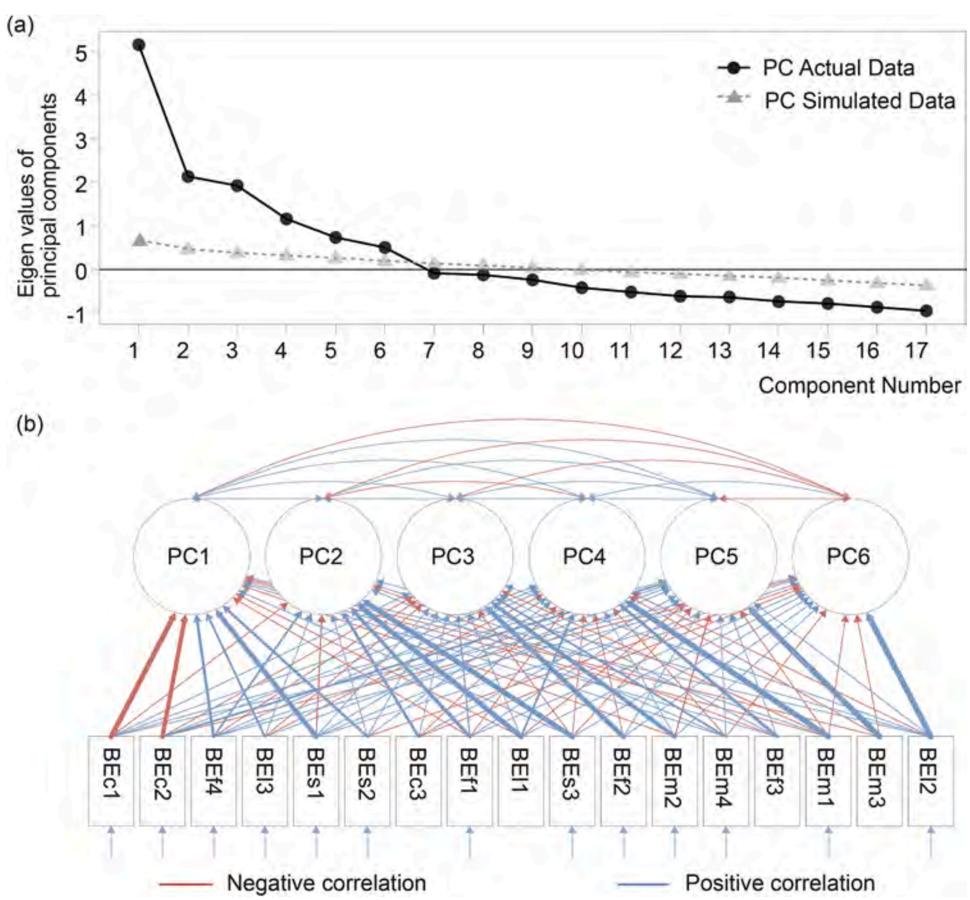


Fig. 10. Principal component analysis results of BE variables: (a) scree plot; (b) Component loading plot.

(0.50). Because objective environmental variables often show relatively strong structural independence, this result did not necessarily imply that the PCA results were unreliable. In such cases, the model structure should be evaluated by considering additional statistical tests together. Bartlett's test was significant (χ^2 = 15,145.07, df = 136, p < 0.001), confirming sufficient inter-variable correlation for factor analysis. Parallel Analysis (PA) was used to determine the optimal number of components (Fig. 10a); the first six eigenvalues of the actual data exceeded the mean eigenvalues of randomly simulated data, whereas the seventh fell below them. This aligned with the scree plot inflection point and supported the retention of six principal components to represent the latent structure of the BE. After Promax rotation, the six components explained approximately 91.5% of the cumulative variance (Table 3).

The component-loading matrix is shown in Fig. 10b. Based on the variables with the highest loadings, the components were conceptualized as follows: PC1: spatial enclosure and order (mainly BEc1, BEc2, BEs1, BEs2), reflecting physical maintenance, cleanliness, and order. PC2: facility and functional configuration (BEf2, BEf1, BEf4), representing amenities, accessibility, and convenience. PC3: landscape and aesthetic quality (BEl1, BEl3, BEs3), reflecting visual landscape, aesthetics, and morphological quality. PC4: comfort and safety regulation (BEc3, partial BEf), embodying environmental pressure, exposure conditions, and comfort regulation structures. PC5: social and cultural facilities, primarily associated with activity density and disturbance factors. PC6: commercial vitality and mobility, reflecting functional mix, commercial nature, and dynamic usage intensity. Inter-component correlation coefficients were all below 0.40 (ranging from −0.38 to 0.35), indicating satisfactory independence among the extracted components.

To explore the underlying stability of the CE and AB constructs, Exploratory Factor Analysis (EFA) was conducted on all scale items (Table 4). Before extraction, data suitability was assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. KMO values for all constructs ranged from 0.577 to 0.81, exceeding the acceptable threshold (> 0.50). Bartlett's tests were highly significant (p < 0.001), confirming sufficient inter-variable correlations for factor analysis. Items with loadings below the standard threshold (≥ 0.40) or lacking significance were excluded. Specifically, A5 (0.18), P5 (0.06), and W4 (0.08) were removed from the final measurement model due to low loadings and insignificance. The remaining items exhibited significant loadings ranging from 0.49 to 0.99 on their respective factors (p < 0.005), indicating robust convergence of the latent structure. Model fit indices further validated structural adequacy. Although the RMSEA for construct W (0.16) suggested a relatively weak fit for its single-factor model, it was retained as other indices remained acceptable (CFI = 0.94, SRMR = 0.05). For all other constructs, RMSEA values fell within the acceptable range (< 0.10). Additionally, all constructs demonstrated good fit, with CFI ≥ 0.90 and SRMR ≤ 0.08, indicating minimal residuals and high overall model fit.

3.4. PLS-SEM analysis results

Following variable screening, the final measurement models demonstrated acceptable statistical fit and explanatory power. The final PLS-SEM structure is presented in Fig. 11, clearly distinguishing between the measurement and structural components. The measurement Model, this component links observed variables (PC1–6, IB1–4, A1–4, P1–4, W1–3, AB-T1–3, AB-S1–3) to their corresponding latent variables (BE, IB, A, P, W, AB-T, AB-S), illustrating how each latent construct is operationalized by its indicators. The structural Model, this component defines the causal pathways between latent variables, revealing the internal process governing the core constructs. In the visualization, the thickness of the path lines represents the magnitude of the path coefficients, while the colors indicate the direction of the effects. Blue represents positive effects, and red represents negative effects. Fig. 11 presents the structural diagram of the model and includes all potential path relationships proposed in the research hypotheses. Whether each path reached statistical significance (p < 0.05) was determined using the bootstrapping test, and the detailed statistical results are reported in Tables 5 and 6.

The measurement model was evaluated for validity using the full dataset (n = 221). Overall, the measurement model demonstrated satisfactory overall validity, with core constructs exhibiting strong convergent validity, reliability, and discriminant validity. Table 5 presents the results.

For the BE, modeled as a formative construct, multicollinearity

Table 4
Results of Exploratory Factor Analysis (EFA) and model fit indices for latent constructs.

Code	KMO	Bartlett's test			Factor loading		Model fit indices		
		χ^2	df	p	Loading	Sig.	RMSEA	CFI	SRMR
(Acceptable threshold)	>0.50	-	-	<0.05	≥0.40	<0.05	<0.10	>0.90	<0.08
A		393.81	10	<0.001			0	1	0.02
A1	0.81				0.77	<0.00			
A2	0.77				0.77	0.00			
A3	0.87				0.63	0.00			
A4	0.81				0.73	0.01			
A5	0.88				0.18	-			
P	0.72	424.89	10	<0.001			0.1	1	0.01
P1	0.81				0.7	<0.00			
P2	0.68				0.85	0.00			
P3	0.81				0.49	0.00			
P4	0.67				0.78	0.04			
P5	0.32				0.06	-			
W	0.58	186.58	6	<0.001			0.16	0.94	0.05
W1	0.79				0.74	<0.00			
W2	0.55				0.52	0.00			
W3	0.56				0.57	0.03			
W4	0.35				0.08	-			
AB-T	0.58	282.64	3	<0.001			0.09	0.99	0
AB-T1	0.55				0.73	<0.00			
AB-T2	0.53				0.66	0.00			
AB-T3	0.52				0.99	0.00			
AB-S	0.58	142.1	3	<0.001			0.09	1	0
AB-S1	0.56				0.74	<0.00			
AB-S2	0.79				0.53	0.00			
AB-S3	0.55				0.84	0.00			

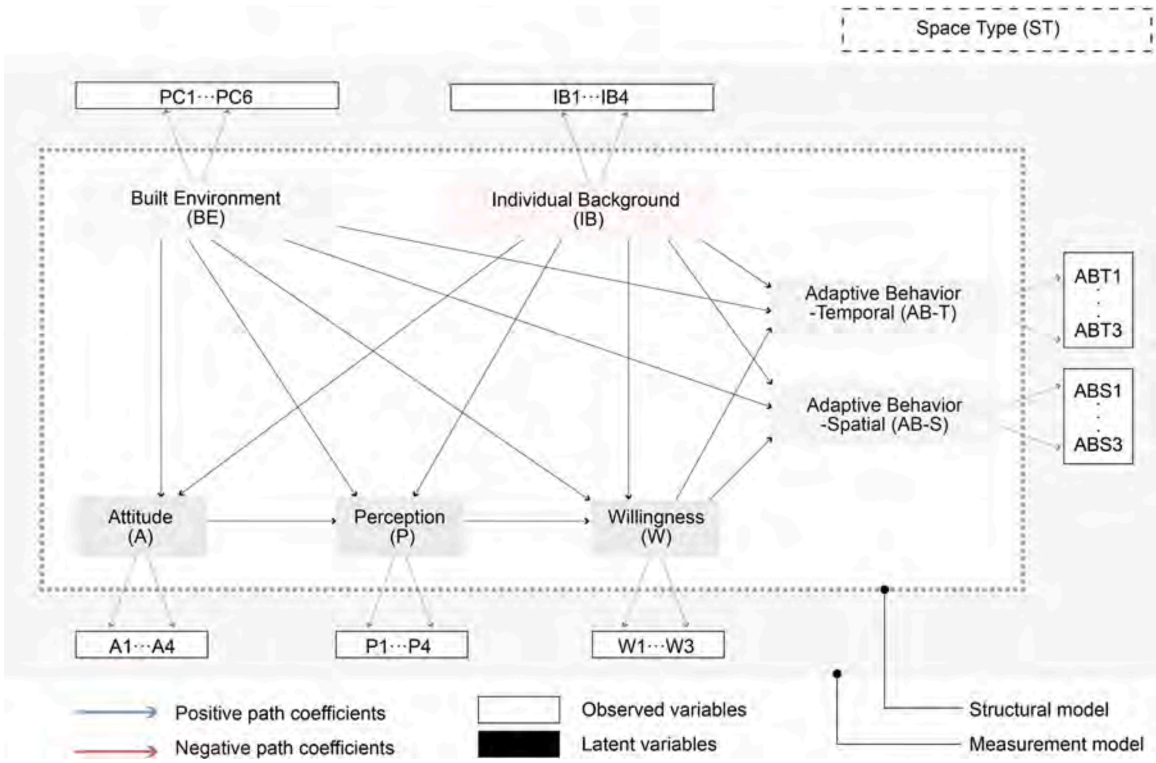


Fig. 11. Schematic diagram of the final PLS-SEM.

Table 5
Results of validity testing and evaluation of the measurement model.

Latent variable code	Convergent Validity		Internal Consistency Reliability			Discriminant validity
	Loadings	AVE	Cronbach's Alpha	Rho_A	Composite Reliability (CR)	HTMT Ratio Supported?
(Acceptable threshold)	>0.50	>0.50	>0.60	>0.60	>0.60	<0.90
A	0.80	0.64	0.81	0.82	0.88	Yes
P	0.78	0.62	0.79	0.82	0.86	Yes
W	0.79	0.59	0.65	0.72	0.81	Yes
AB-T	0.70	0.58	0.71	0.98	0.78	Yes
AB-S	0.69	0.50	0.63	0.95	0.74	Yes

among indicators was evaluated using the Variance Inflation Factor (VIF). All VIF values were below 5.0, indicating no severe collinearity. Traditional reliability and validity metrics did not apply to IB, which served as a set of categorical control variables.

For the reflective constructs A, P, W, AB-T, and AB-S, most demonstrated satisfactory convergent validity. Specifically, the mean factor loadings and AVE values for A, P, and W exceeded the 0.50 threshold, indicating that these constructs explained over 50% of the variance in their corresponding indicators. Subsequently, reliability test results showed that the core constructs exhibited excellent reliability, with Cronbach's Alpha, Rho_A, and Composite Reliability (CR) values significantly exceeding the recommended 0.60 threshold. The Rho_A values for AB-T (0.98) and AB-S (0.95) were relatively high; therefore, the results should be interpreted with some caution. Under the environmental conditions of high altitude and strong solar radiation in Lhasa, users often adopt coordinated behavioral responses to cope with climate stress. For example, when users reduced their visit frequency (AB-T1), they also tend to shorten their exposure duration (AB-T2) or adjust their activity location (AB-S2). Such highly co-occurring behavioral strategies under real environmental constraints may lead to stronger correlations among indicators, which can result in higher Rho_A values. Despite this, the indicators still represent different dimensions of AB at the conceptual level and maintain clear theoretical distinctions. At the same time, the CR values remained within acceptable ranges, and the HTMT was below the conservative threshold of 0.90, confirming sufficient statistical distinction among latent variables. Therefore, the indicators for AB-T and AB-S were retained at the current stage, and their stability and validity can be further examined.

The structural model was evaluated to test the proposed research hypotheses. Bootstrapping (2000 resamples) was performed to calculate the significance of path coefficients (direct effects) and total indirect effects. The results are detailed in Table 6.

Overall, the PLS-SEM results indicated that AB-S was primarily driven by A, P, and W. IB played a non-negligible role in both AB-T and AB-S. Conversely, the BE showed no statistically significant direct effects and only marginally significant indirect effects in this sample. This indicates that psychological cognitive factors, rather than direct physical environmental features, are the critical antecedents of AB.

First, in terms of direct effects, the paths revealed a clear causal chain: A → P → W → AB-S.

– This identifies the A, P, and W sequence as the dominant process driving AB-S. A → P: A exerted a significant positive effect on P ($\beta = 0.73$, $t = 19.86$, $p < 0.001$), indicating that a more positive A significantly enhanced positive P. P → W: P positively influenced W ($\beta = 0.49$, $p < 0.001$). W → AB-S: W demonstrated a very strong effect on AB-S ($\beta = 0.81$, $p < 0.001$), identifying it as the most critical driver of AB-S.

Table 6
Assessment of structural model path coefficients and indirect effects.

Path	β	t	p	Path-level effect size f^2	Hypothesis	Supported
Direct effect						
A → P	0.73	19.86	<0.001	1.03	H2	Yes
P → W	0.49	7.66	<0.001	0.33	H2	Yes
W → AB-T	−0.02	0.37	0.71	0.001	H2	No
W → AB-S	0.81	30.86	<0.001	1.48	H2	Yes
IB → A	−0.18	2.40	0.02	0.04	H3	Yes
IB → P	−0.13	2.37	0.02	0.02	H3	Yes
IB → W	−0.09	1.30	0.19	0.01	H3	No
IB → AB-T	−0.56	4.64	<0.001	0.45	H3	Yes
IB → AB-S	−0.16	2.43	0.02	0.02	H3	Yes
BE → A	0.14	0.82	0.41	0.02	H2	No
BE → P	−0.04	0.52	0.60	0.003	H2	No
BE → W	0.20	1.90	0.06	0.04	H2	No
BE → AB-T	0.01	0.12	0.90	0.001	H2	No
BE → AB-S	0.16	1.89	0.06	0.02	H2	No
Total indirect effect						
A → AB-T	−0.01	0.37	0.71	-	H2	No
A → AB-S	0.29	6.75	<0.001	-	H2	Yes
A → W	0.36	6.62	<0.001	-	H2	Yes
P → AB-T	−0.01	0.37	0.71	-	H2	No
P → AB-S	0.40	7.89	<0.001	-	H2	Yes
Significant specific indirect effects						
A → P → W → AB-S	0.29	6.75	<0.001	-	H2	Yes
P → W → AB-S	0.40	7.89	<0.001	-	H2	Yes
IB → A → P → W → AB-S	−0.05	2.20	0.03	-	H3	Yes
IB → A → P	−0.13	2.37	0.02	-	H3	Yes
A → P → W	0.36	6.62	<0.001	-	H2	Yes
IB → A → P → W	−0.07	2.20	0.03	-	H3	Yes

Note: - indicates that the path effect is not applicable or does not exist; significance level: $p < 0.05$; β represents standardized path coefficients; Larger f^2 values indicate stronger predictive contributions of the predictor constructs; Only statistically significant specific indirect effects ($p < 0.05$) are reported.

– IB Effects: IB showed significant negative effects. Specifically, the paths IB → AB-T ($\beta = -0.56$, $p < 0.001$), IB → A ($\beta = -0.18$, $p < 0.05$), and IB → P ($\beta = -0.13$, $p < 0.05$) were significant, suggesting that individual background played a key regulatory role in adaptation.
– BE Effects: In contrast, most paths related to the BE were not statistically significant. This implies that the BE did not directly drive AB but influenced it through psychological mediators such as A and P.
– Total indirect effects of several mediation paths were significant:
– A → AB-S: A had a significant indirect effect on AB-S ($\beta = 0.29$, $p < 0.001$), acting primarily through the mediators of P and W.
– P → AB-S: P also exerted a significant indirect effect ($\beta = 0.40$, $p < 0.001$), confirming its role as a key mediating process.
– IB Effects: Beyond its direct impact on AB-T, IB had a significant negative indirect effect on AB-S ($\beta = -0.16$, $p < 0.05$) and on P ($\beta = -0.13$, $p < 0.05$), suggesting that it constrained adaptation by influencing psychological variables.
– BE Effects: Notably, while the direct effect of the BE was insignificant, its indirect effect on AB-S ($\beta = 0.16$) was marginally significant ($p < 0.1$). However, this suggests that potential threshold effects or nonlinear relationships may exist.

3.5. Results of partial least squares multi-group analysis (PLS-MGA)

To evaluate the robustness and context-dependence of the structural model across different POS types, a Partial Least Squares Multi-Group Analysis (PLS-MGA) was conducted (Hasegawa & Lau, 2022).

Before conducting the PLS-MGA, the adequacy of the subsample size for each ST was examined. A total of 221 valid questionnaires were obtained in this study and were divided into four subsamples based on the clustering results (n = 47–67). According to the commonly used "10-times rule" (Wagner & Grimm, 2023), the most complex endogenous variable in this study included three predictors, implying a minimum sample size of 30. All subsamples exceeded this threshold. In addition, a post hoc statistical power analysis was conducted (Appendix Table A1). The effect size (f^2) was derived from the model's coefficient of determination (R^2). At a significance level of $\alpha = 0.05$, the statistical power of the full sample ($n = 221$) exceeded 0.99. Although the statistical power of some subsamples (0.75, 0.77, and 0.79) was slightly below the commonly recommended threshold of 0.80, PLS-SEM is generally robust with relatively small samples. Combined with parameter estimation based on bootstrapping (2000 resamples), the sample size in this study still supports an exploratory PLS-MGA. Figs. 12 and 13 present the structural path coefficients for each type of POS (displaying only paths with $|\beta| \geq 0.30$).

Overall, the core pathway "A → P → W → AB-S" remained significant and directionally consistent across all four POS types. This confirms the high cross-context universality of the user's cognitive-behavioral process, while the drivers for AB-T showed significant heterogeneity.

– A → P: This path was significant across all four types ($\beta = 0.67$–0.78). The effect was strongest in modern commercial space ($\beta = 0.78$), suggesting that in goal-oriented functional spaces, users' initial attitudes are more readily translated into distinct environmental perceptions.
– P → W: This influence was robust across types ($\beta = 0.32$–0.66). It was most prominent in residential public activity spaces ($\beta = 0.66$), indicating that subjective perceptions in familiar daily living environments more easily trigger behavioral intentions.
– W → AB-S: This path showed strong and stable effects across all types ($\beta = 0.76$–0.90). The highest conversion efficiency was observed in traditional historical space ($\beta = 0.902$) and modern commercial space ($\beta = 0.896$). This suggests that in spaces with distinct functional or cultural targets, users' adaptive behavior is highly deterministic and strongly driven by users' willingness. Whereas in small green spaces ($\beta = 0.760$), the effect was relatively weaker, indicating that natural environments with high behavioral freedom allow more flexible translation of willingness into actual spatial behavior.

While core psychological pathways were found to be universal, PLS-MGA results revealed significant spatial heterogeneity in key specific paths, highlighting the moderating role of spatial attributes in behavioral processes.

– IB → AB-T: This path exhibited the strongest context dependency and revealed a distinct dichotomy between "Habit-driven spaces" and "Choice-driven spaces." In modern commercial space ($\beta = 0.36$), this was the only POS type that exhibited a positive effect. This suggests that in consumption-oriented environments, AB-T is driven by active choice, with users with specific backgrounds proactively adjusting their visit times to maximize utility, reflecting a flexible usage pattern. In contrast, traditional historical space ($\beta = -0.84$), residential public activity space ($\beta = -0.50$), and small green space ($\beta = -0.40$) all showed significant negative effects. The traditional historical space showed the strongest negative coefficient; this implies

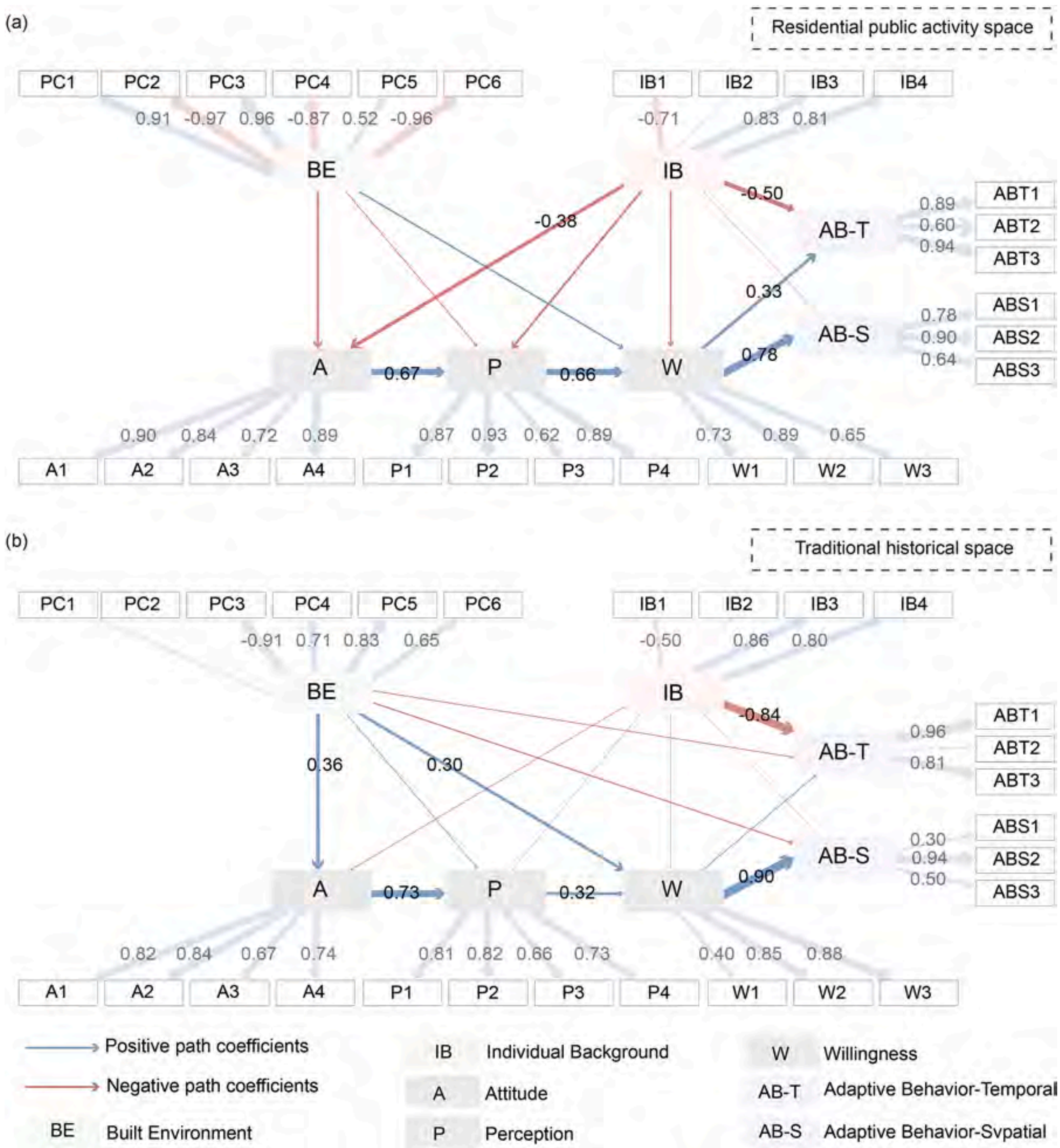


Fig. 12. Results of multiple group analyses: (a) residential public activity space; (b) traditional historical space.

that in the context of the test-bed site, Lhasa, usage is strongly governed by cultural rituals and fixed routines (e.g., daily circumambulation or prayer), users with stronger local ties or specific demographic traits tend to adhere to rigid schedules, resulting in lower temporal flexibility. Similarly, the negative effects of residential public activity and small green space suggest that usage is integrated into daily life rhythms; for local residents, visiting these POSs is a habitual activity with fixed time slots, leaving little room or need for active temporal adjustment.

- BE Effects: The impact of the BE on mediating variables and behavior also varied. While the BE primarily exerted indirect effects overall, significant deviations were observed in specific settings. In small green space, the BE played a dual role. It exerted a negative impact on A ($\beta = -0.32$), while simultaneously having a positive effect on P ($\beta = 0.33$). This suggests a mismatch where users may perceive deficiencies in physical facilities (e.g., maintenance or seating), lowering their evaluative attitude, while natural elements still enhance positive sensory perception. Notably, the BE showed a strong negative direct effect on AB-T ($\beta = -0.43$). This implies that a higher-quality environment in green spaces significantly reduces the need for users to make temporal adjustments, acting as a stabilizing factor. In traditional historical space, the BE demonstrated a positive driving role, significantly enhancing both A ($\beta = 0.36$) and W ($\beta = 0.30$). This indicates that the unique architectural fabric and rich cultural atmosphere effectively foster positive user evaluations and retention intentions. In modern commercial space, the BE had a significant negative effect on W ($\beta = -0.30$). This may result from efficient flow planning, fixed operating hours, or uniform environmental controls, which limit users' autonomy to adjust their duration of stay.
- P → W → AB-S: The efficiency of the internal psychological to behavioral pathway revealed a distinct trade-off between "sensory sensitivity" and "behavioral determinism" across POS types. In residential public activity and small green spaces, the pathway was characterized by "high sensitivity, relaxed execution". The conversion from P to W was robust ($\beta_{P \to W} = 0.66, 0.54$), indicating that

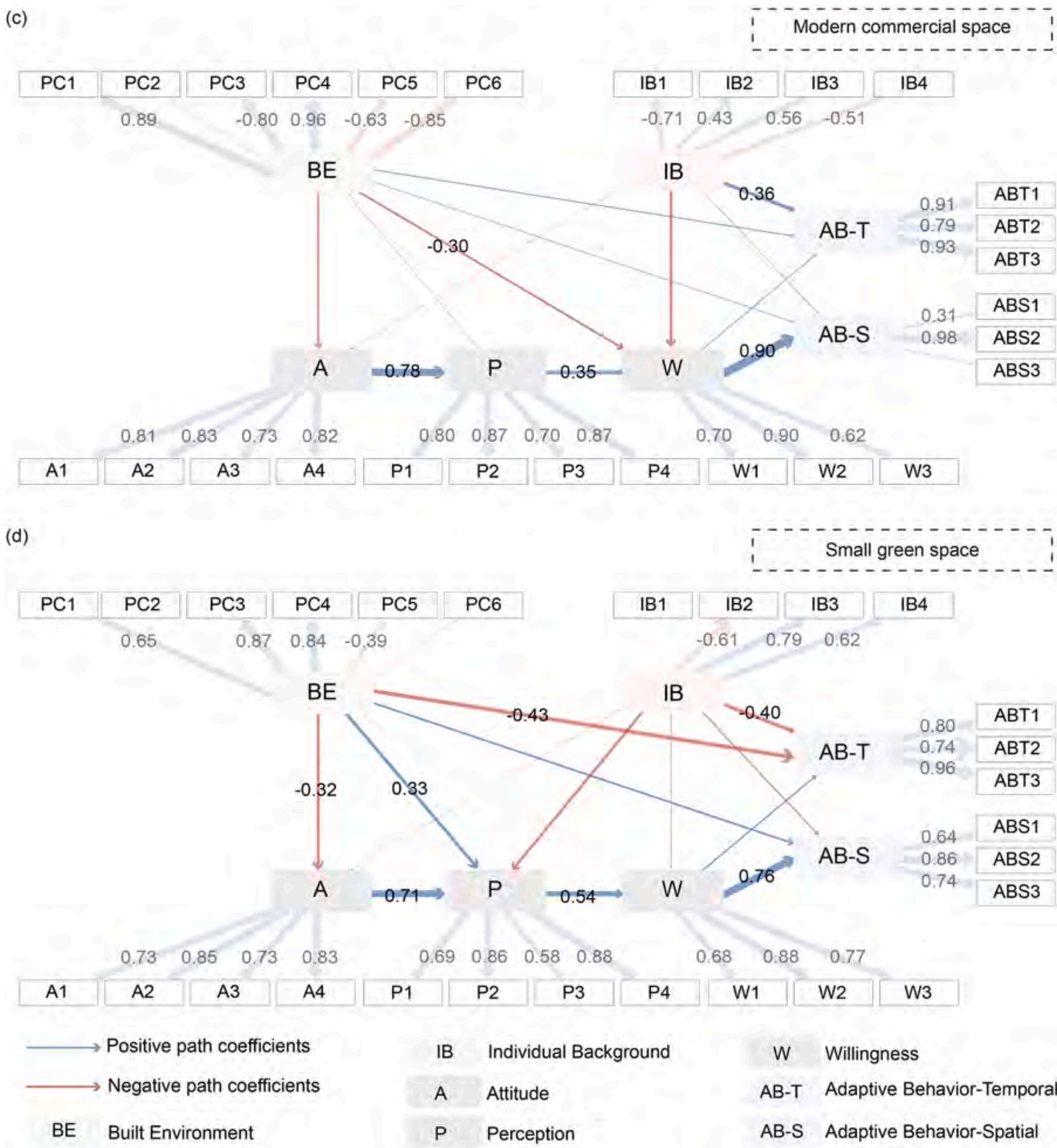


Fig. 13. Results of multiple group analyses: (c) modern commercial space; (d) small green space.

users' willingness on immediate sensory comfort. However, the subsequent translation into action was relatively moderate ($\beta_{W\rightarrow AB\text{-}S}$ = 0.78, 0.76). This suggests that in these familiar, leisure-oriented environments, users are easily influenced by the atmosphere yet maintain a sense of spontaneity, in which willingness does not necessarily compel rigid behavioral adjustments. In contrast, traditional historical and modern commercial spaces exhibited a "low sensitivity, decisive execution" pattern. The influence of P on W was notably weaker ($\beta_{P\rightarrow W}$ = 0.32, 0.35), suggesting that willingness is driven more by external goals than by immediate environmental feedback; yet, once willingness is formed, its translation into behavior is highly efficient ($\beta_{W\rightarrow AB\text{-}S}$ = 0.90 for both). This implies that in high functional or density spaces, adaptive behaviors such as seeking rest areas or adjusting the activity intensity are highly deterministic and purposeful, executed decisively to cope with environmental pressures.

4. Discussion

This section addresses and elaborates on the four core hypotheses proposed at the outset of the study, based on empirical results, and discuss their theoretical and practical implications for enhancing the climate resilience of urban POSs.

4.1. Response and elucidation of research hypotheses

H0. POSs can be identified and classified into several significantly distinct space types based on the systematic differences in their built environments.

The hypothesis was well supported. Hierarchical cluster analysis clearly identifieed four types of POS with significant differences in environmental characteristics: residential public activity space, traditional historical space, modern commercial space, and small green space.

These characteristics are highly consistent with the social functions and cultural contexts of each type (Elzeni et al., 2022). Traditional historical space exhibits a high density of cultural facilities and organic street patterns. In contrast, modern commercial space is characterized by high openness and facility density, and small green spaces demonstrate advantages in visual openness and ecological comfort. This finding, from a methodological perspective, confirms that systematic quantification based on objective BE indicators can effectively capture the essential differences in form and function among POSs. This provids an empirical basis for transcending subjective classification and establishing a reproducible spatial typology (Elzeni et al., 2022; Tian et al., 2022). Against the backdrop of climate change, which is intensifying spatial heterogeneity, this type of differentiated research based on spatial typology lays the necessary taxonomic foundation for transforming "standardized" to "contextualized" climate adaptation design.

H1. POS type significantly moderates the effects of the processes from the built environment to comprehensive experience and from comprehensive experience to adaptive behavior.

The hypothesis was fully supported. PLS-MGA results reveal that while the core pathway (A → P → W → AB-S) remained stable across all POS types, demonstrating cross-context universality, specific paths were significantly moderated by POS type. The most distinct contrast was observed in the impact of IB → AB-T, which exhibited a strong negative effect in traditional historical space but shifted to a significant positive effect in modern commercial space.

This finding suggests that different ST may influence users' adaptive strategies under different contextual conditions. In traditional historical spaces, religious and cultural activities often serve as the primary motivations for space use, such as pilgrimage or sightseeing. In such contexts, even when users experience physical or psychological discomfort, they may delay or weaken behavioral adjustments due to collective habits or cultural participation motives. As a result, relatively stable and consistent patterns of space use may emerge. Similar patterns have also been observed in studies on user behavior and place attachment, where cultural identity shapes how individuals perceive environmental stimuli and respond through behavior (Han et al., 2021). In contrast, behavior in modern commercial spaces is more strongly driven by individual purposes. Activities such as shopping, dining, or leisure are usually guided by clear personal plans (Hou et al., 2024). Users are more likely to adjust their behavior according to their schedule and environmental conditions. These findings indicate that in cities with strong religious traditions or cultural tourism, climate adaptation in POSs is not only an environmental issue but also linked to cultural practices and social behavior patterns.

H2. Users' comprehensive experience plays a significant mediating role between the built environment and adaptive behavior.

The hypothesis was partially supported. The model identifies a robust and powerful mediation pathway. However, the BE showed weak or insignificant direct effects on AB-T and AB-S in most POS types, confirming that its influence was primarily indirect, acting through mediating variables (A, P, and W). This reveals a stable cognitive framework governing behavioral adjustments to environmental stress. For urban managers, this stability is crucial, regardless of spatial form. Enhancing positive A, P, and W is the foundational strategy for driving AB.

This process varies across different types of POSs. These differences may be shaped not only by BE but also by spatial functions and the socioeconomic structure of user groups. For example, residential public activity spaces mainly serve the daily lives of nearby residents. Users in these spaces usually share relatively stable social backgrounds and life rhythms. As a result, IB variables often reflect long-term community structures. In contrast, small green spaces often serve as places for brief rest or as landscape buffers. Their users tend to be more diverse, including nearby residents, tourists, and temporary visitors. People from different backgrounds may have different motivations for using the space and different patterns of stay (Guzman et al., 2026).

In addition, the lack of a significant direct effect of the BE on AB does not mean that physical spatial factors are unimportant in behavioral regulation. Previous studies have shown that environmental factors in real urban environments often exhibit threshold effects or nonlinear relationships (He et al., 2024). In other words, users tend to adjust their behavior only when environmental conditions reach a certain critical level. This finding suggests that the relationship between the built environment and behavior may be nonlinear. From a climate adaptation perspective, relying solely on physical spatial parameters to directly change user behavior may have a limited effect. Strengthening positive attitude, perception, and willingness to use the space may be more effective in encouraging adaptive behavior.

H3. Individual background factors influence the performance of both comprehensive experience and adaptive behavior.

The hypothesis was supported. IB not only directly affects AB-T, but also indirectly influences AB-S through CE variables.

Based on the demographic variables collected in this study, differences among social groups can be understood from two aspects: social structure and environmental adaptive capacity. First, different age groups show clear differences in physiological tolerance and activity patterns. For example, older adults and children are generally more sensitive to extreme climate conditions. As a result, their activity time in POSs is more likely to be constrained by environmental conditions (Fatahi et al., 2025; Yang et al., 2023). In addition, ethnicity and residential location influence how individuals use space and how familiar they are with local environmental conditions (Guzman et al., 2026; Yao et al., 2022). Residents usually have richer knowledge and experience of the environment, while tourists or temporary visitors may find it more difficult to adjust their behavior in response to environmental stress (Tian et al., 2022). These findings suggest that environmental pressure from climate change is unlikely to be evenly distributed across social groups. Instead, it may reinforce existing social differences. From a spatial justice perspective, climate adaptation strategies for POSs should therefore pay closer attention to the needs of different user groups. This can help reduce the unequal impacts of environmental stress on vulnerable populations.

4.2. Practical implications and targeted recommendations

Based on empirical findings, this study proposes differentiated climate adaptation strategies, as detailed in Fig. 14.

As shown in Fig. 14, this study proposes a climate adaptation strategy framework for different POS types based on the empirical findings. The framework translates the key influence pathways identified in the model into concrete spatial interventions, thereby linking quantitative analysis results with planning practice.

The framework first takes different POS types as the starting point. Based on clustering and PLS-MGA results, the main optimization directions for each POS type are identified. On this basis, community workers, urban planners, and policymakers are defined as the target work group responsible for implementing the strategies.

The box plots in the “Actionable strategies with priority levels” section of Fig. 14 show the distribution of path coefficients across different POS types. Paths with relatively high and stable coefficients are identified as priority intervention pathways. At the implementation level, these pathways are further translated into adjustable parameters (Tian et al., 2022). For example, the pathway W → AB-S can be addressed by increasing the shaded activity nodes or by promoting community knowledge of climate adaptation, which may strengthen users' adaptive capacity. The pathway A → P can be improved by increasing seating density and enhancing lighting and safety management, thereby improving users' perception of space. Based on their intervention attributes, the proposed measures are grouped into three

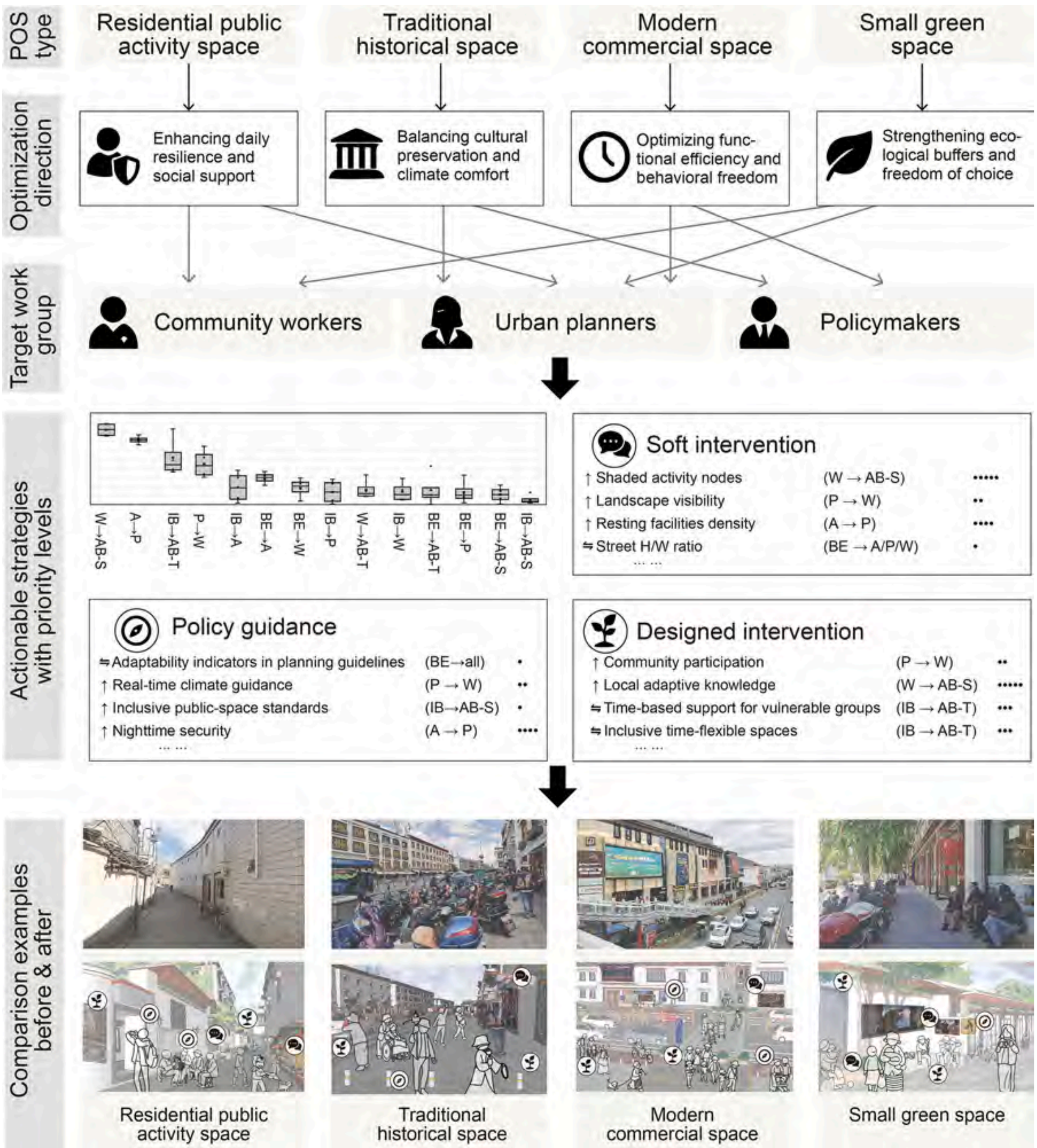


Fig. 14. Differentiated climate adaptation strategies across varying POS types.

categories: designed interventions, soft interventions, and policy guidance.

The bottom part of Fig. 14 presents before and after scenarios from the test-bed site to illustrate how these strategies may operate in real urban settings. The behavioral scenes are inspired by typical patterns of space use in Lhasa POSs (Xiong et al., 2016), such as daily social interaction in traditional clothing, sitting and resting directly on the ground, and street gatherings around teahouses. These activities reflect culturally specific patterns of space use and correspond to the AB identified in the model. They also help illustrate the practical potential of climate adaptation strategies in real urban contexts.

4.3. Limitations and future research

Despite establishing a comprehensive theoretical framework and providing robust empirical evidence, this study has several limitations that highlight directions for future research.

First, the analysis relied on cross-sectional data. While the model revealed associations between variables, it could not strictly infer causality or long-term stability. Future studies are encouraged to employ long-term longitudinal designs to track behavioral and psychological changes across seasons and extreme weather events, thereby capturing the dynamic evolution of adaptive behaviors.

Second, user experience was measured primarily through subjective questionnaires, although subjective perception directly drives behavioral willingness, the study lacked physiological validation. Future research may integrate multi-source data, comparing physiological responses monitored via wearable devices with subjective perceptions to quantify the actual effects of adaptive behavior more precisely. Such physiological data can also help identify how different social groups respond differently under climate stress, thereby providing more objective evidence for addressing issues of spatial justice.

Third, this study focused on four typical categories of POSs. Given the diversity of urban environments, future work may expand the range of spatial samples. Examining the complex impacts of spatial boundaries and mixed spatial attributes may help construct a more universal cross-spatial theory.

Finally, the test-bed site of this study is in Lhasa, a city with a highly distinctive urban context. As a result, behavior in POSs is shaped by both climate pressure and cultural practices. For example, religious activities and tourism may delay or weaken users' immediate behavioral responses to environmental discomfort. However, these findings offer useful insights for cities influenced by extreme climates and strong religious cultures, such as Dubai, Bangkok, and Penang. While caution is needed when applying the conclusions to other urban contexts, local cultural backgrounds and climatic conditions should be carefully considered. Future studies may also conduct comparative research across cities with different cultural and climatic settings to further test the applicability of the framework proposed in this study.

5. Conclusion

This study systematically explores how the built environment characteristics of Public Open Spaces (POSs) drive differentiated adaptive behavior patterns by influencing user comprehensive experience, against the backdrop of climate change and high-density urbanization. The study innovatively constructs and tests an integrated "Built Environment (BE) - Comprehensive Experience (CE) - Adaptive Behavior (AB)" structural equation model (PLS-SEM) and uses Multi-Group Analysis (PLS-MGA) to reveal the critical moderating role of Spatial Type (ST).

Based on empirical analysis, the main findings of this study are summarized as follows:

(1) The significant moderating effect of spatial types. PLS-MGA results confirm that ST significantly modulates the intensity and direction of behavioral drivers, revealing a distinct "context dependency." Consequently, AB is a context-specific adjustment rather than a uniform reaction. This indicates that standardized design approaches are insufficient, as they fail to address the distinct psychological and cultural mechanisms governing user responses.
(2) The core psychological processes of adaptive behavior have cross-spatial universality. "The pathway A (Attitude) → P (Perception) → W (Willingness) → AB-S (Adaptive Behavior of Spatial)" remains significant and directionally consistent across all four POS types. This suggests that despite physical variations, users rely on a stable, predictable cognitive framework when coping with environmental stress. W is identified as the most direct and potent antecedent of spatial adaptation.
(3) The built environment primarily exerts indirect and mediated effects. The BE does not drive AB directly but generates significant indirect effects through CE (A, P, and W). This implies that merely optimizing physical facilities (e.g., increasing seating or greenery) without enhancing positive subjective perceptions, is unlikely to trigger adaptive behavior effectively.

This study advances theoretical understanding of urban climate adaptation in two keyways. First, it validates the S-O-R (Stimulus-Organism-Response) Framework in the context of climate adaptation by clarifying the complete causal process from physical stimuli to psychological processing and behavioral response. Second, it establishes an evidence-based spatial typology perspective and quantifies the essential differences in behavioral regulation processes across STs.

To enhance urban resilience, this study proposes a shift from "standardized supply" to "precision support." For traditional historical space, a low intervention, micro-adjustment strategy should be adopted to respect autonomous adaptation shaped by cultural habits. Then, greater emphasis should be placed on soft psychological guidance. Since the built environment primarily functions through mediating variables, planners and managers should focus on enhancing users' environmental attitudes and perception. This can lead to more effectively encourage adaptive behavior through flexible and contextsensitive approaches.

In summary, this study provides a solid empirical basis for understanding dynamic human-environment interactions and offers scientific decision support for developing resilient POSs. Integrating physical space optimization with the enhancement of user cognition represents a critical pathway toward urban sustainability.

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CRediT authorship contribution statement

Zhengzheng Luo: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fangyu Chen:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lia Marchi:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization. **Jacopo Gaspari:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, 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.

Appendix

Table A1
Post-hoc statistical power of the PLS-SEM model across POS types.

Group	Dependent variable	Predictors	Number of predictors	Sample size	R^2	Adjusted R^2	Model-level Effect size f^2	Statistical power
Full sample	A	BE, IB	2	221	0.05	0.04	0.05	>0.99
	P	A, BE, IB	3	221	0.55	0.55	1.22	>0.99
	W	P, BE, IB	3	221	0.3	0.29	0.43	>0.99
	AB-T	W, BE, IB	3	221	0.32	0.31	0.47	>0.99
	AB-S	W, BE, IB	3	221	0.67	0.67	2.03	>0.99
Traditional historical space	A	BE, IB	2	67	0.15	0.12	0.18	0.87

(continued on next page)

Table A1 (*continued*)

Group	Dependent variable	Predictors	Number of predictors	Sample size	R^2	Adjusted R^2	Model-level Effect size f^2	Statistical power
	P	A, BE, IB	3	67	0.57	0.55	1.33	>0.99
	W	P, BE, IB	3	67	0.25	0.22	0.33	0.97
	AB-T	W, BE, IB	3	67	0.71	0.7	2.45	>0.99
	AB-S	W, BE, IB	3	67	0.73	0.71	2.70	>0.99
Residential public activity space	A	BE, IB	2	47	0.26	0.22	0.35	0.95
	P	A, BE, IB	3	47	0.71	0.69	2.45	>0.99
	W	P, BE, IB	3	47	0.51	0.48	1.04	0.98
	AB-T	W, BE, IB	3	47	0.52	0.48	1.08	0.98
	AB-S	W, BE, IB	3	47	0.63	0.61	1.70	>0.99
Modern commercial space	A	BE, IB	2	57	0.12	0.09	0.14	0.75
	P	A, BE, IB	3	57	0.61	0.59	1.56	>0.99
	W	P, BE, IB	3	57	0.32	0.28	0.47	0.98
	AB-T	W, BE, IB	3	57	0.12	0.06	0.14	0.77
	AB-S	W, BE, IB	3	57	0.79	0.77	3.76	>0.99
Small green space	A	BE, IB	2	50	0.1	0.07	0.11	0.79
	P	A, BE, IB	3	50	0.53	0.5	1.13	0.98
	W	P, BE, IB	3	50	0.31	0.26	0.45	0.96
	AB-T	W, BE, IB	3	50	0.41	0.37	0.69	0.98
	AB-S	W, BE, IB	3	50	0.67	0.65	2.03	>0.99

Note: Effect sizes (f^2) used for post-hoc statistical power analysis were derived from the coefficient of determination (R^2) using the formula: $f^2 = R^2/(1-R^2)$; Statistical power was calculated using G*Power assuming $\alpha = 0.05$; R^2 values were used for power estimation, while adjusted R^2 values are reported for reference.

Table B1
Explanation of codes used in the built environment field work survey checklist.

Meaning	Code / Symbol
Neighborhood type	I: Old City Area II: Mature Development Area III: Outskirt Area
Neighborhood formation period	Very early: * * * * Early: * * * Relatively early: * * Late: *
Topography	Flat: - Gentle slope: \\ Steep slope: |
Dominant functions within the neighborhood	Daily life: ① Commercial activities: ② Leisure and recreation: ③ Religious activities: ④ Tourist activities: ⑤
Description of the order of the surrounding road network	East - West - South - North
Lane type	One-way: | Two-way: || No clearly defined motor vehicle lane: ˆ (e.g., a two-way two-lane road is coded as ||2)
Quantity/count	Many: ■■■ Moderate: ■■ Few: ■ None: /
Binary indication	Yes: ✔ No: ×
Architectural style	Traditional style: ■ Historic style: ◆ Modern style: ▲
Building structure	Multi-storey slab type: □ Brick-concrete structure: ◯ Frame structure: △
Building orientation	South-North: S-N Random orientation: ## Slightly irregular orientation: #
Measurement unit	Unless otherwise specified, all measurements are in meters *(m)*

Table B2
Example of built environment characteristics and field survey records (Barkhor Street case).

Item	Description
Number of the field work site	N12–1
Neighborhood name	Barkhor Street
Area (*ha*)	4.59
Coordinates	29.64896° N, 91.13547° E
Perimeter (*m*)	901.21
Topography	-
Neighborhood formation period	****
Neighborhood type	I
Dominant functions (in order of importance)	④ ⑤ ② ① ③
Indicator	**Description**
Street continuity and width (*m*)	220,10 - 200,15 - 220,5 - 260,30
Motor vehicle lane type	||2 - ||2 - ^ - ||4
Pavement condition	■■■ - ■■■ - ■■ - ■■■
Average sidewalk width (*m*)	5 - 5 - / - 2
Lane separation facilities/markings	/ - ■■ - / - ■■■
Regularity of street pattern	×
Pavement condition	■■■
Average road width (*m*)	5
Sidewalk width (*m*)	3
Traffic separation facilities	/
Motor vehicle access allowed	✔
On-street parking spaces	■
Bicycle / non-motor vehicle parking points	✔
Parking lot	/
Bus stop	×
Pedestrian overpass	×
Architectural style	■ ◆
Average number of storey buildings	4
Average building height (*m*)	12
Structural type	□
Diversity of construction periods	■■■
Building orientation	S-N
Presence of mobile/temporary businesses	✔
Facility	**Quantity**
Waste bins	■■■
Public activity facilities	■
Public toilets	■
Convenience service station	■
Leisure seating	/
Nursing room	/
Street trees	■■
Planting flowerbeds	■■■
Sculpture	/
Fountain/water feature	/
Advertising boards	/
Security booth	■
Surveillance cameras	■■
Pedestrian guardrails	■■■
Fire hydrant/fire station	■■■
Temple	■
Incense-burning furnace	■■
Prayer-flag pole	■■
Prayer wheel	■■

Data availability

Data will be made available on request.

References

Abu-Rayash, A., & Dincer, I. (2021). Development of integrated sustainability performance indicators for better management of smart cities. *Sustainable Cities and Society, 67*, Article 102704. https://10.1016/j.scs.2020.102704.

Badrinarayanan, V., Kendall, A., & Cipolla, R. (2017). SegNet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 39*(12), 2481–2495. https://10.1109/TPAMI.2016.2644615.

Balai Kerishnan, P., & Maruthaveeran, S. (2021). Factors contributing to the usage of pocket parks–A review of the evidence. *Urban Forestry and Urban Greening, 58*. https://10.1016/j.ufug.2021.126985.

Bixler, R. P., Paul, S., Jones, J., Preisser, M., & Passalacqua, P. (2021). Unpacking adaptive capacity to flooding in urban environments: Social capital, social vulnerability, and risk perception. *Frontiers in Water, 3*. https://10.3389/frwa.2021.728730.

Borzino, N., Chng, S., & Schubert, R. (2026). Public support for urban heat resilience: Preferences and willingness to pay for mitigation strategies in Singapore. *Sustainable Cities and Society, 136*, Article 107110. https://10.1016/j.scs.2025.107110.

Bower, I., Tucker, R., & Enticott, P. G. (2019). Impact of built environment design on emotion measured via neurophysiological correlates and subjective indicators: A systematic review. *Journal of Environmental Psychology, 66*, Article 101344. https://10.1016/j.jenvp.2019.101344.

Carmona, M. (2021). *Public places urban spaces* (3rd ed.). Routledge https://10.4324/9781315158457.

Chan, S. Y., Chau, C. K., & Leung, T. M. (2017). On the study of thermal comfort and perceptions of environmental features in urban parks: A structural equation modeling approach. *Building and Environment, 122*, 171–183. https://10.1016/j.buildenv.2017.06.014.

Clemente, M. (2023). Setting–up the public space: From the temporary use of the city to user–centered design for resilient communities. *Resilient landscapes* (pp. 181–204). CRC Press.

Cruz, C., Palomar, E., Bravo, I., & Aleixandre, M. (2021). Behavioural patterns in aggregated demand response developments for communities targeting renewables. *Sustainable Cities and Society, 72*, Article 103001. https://10.1016/j.scs.2021.103001.

Elzeni, M. M., ELMokadem, A. A., & Badawy, N. M. (2022). Impact of urban morphology on pedestrians: A review of urban approaches. *Cities (London, England), 129*, Article 103840. https://10.1016/j.cities.2022.103840.

Engle, N. L. (2011). Adaptive capacity and its assessment. *Global Environmental Change. Part A, Human and Policy Dimensions, 21*(2), 647–656. *21*(2), 647–656 https://10.1016/j.gloenvcha.2011.01.019.

Erul, E., Karacabey, F. A., Woosnam, K. M., & Koc, E. (2024). Rethinking stimulus-organism-response theory for residents' behaviour in tourism. *Current Issues in Tourism*, 1–17. https://10.1080/13683500.2024.2417709.

Esfandi, S., Rahmdel, L., Nourian, F., & Sharifi, A. (2022). The role of urban spatial structure in energy resilience: An integrated assessment framework using a hybrid factor analysis and analytic network process model. *Sustainable Cities and Society, 76*, Article 103458. https://10.1016/j.scs.2021.103458.

Fatahi, N., Bahrami, B., & Aminpour, F. (2025). From the perspective of children and parents: What makes communal open spaces in multi-story residential neighborhoods child-friendly? *Cities (London, England), 158*, Article 105605. https://10.1016/j.cities.2024.105605.

Faul, F. (2009). Statistical power analyses using GˆPower 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*, 1149–1160.

Frank, L. D., & Engelke, P. O. (2001). The built environment and human activity patterns: Exploring the impacts of urban form on public health. *Journal of Planning Literature, 16*(2), 202–218. https://10.1177/08854120122093339.

Gao, W., Qian, Y., Chen, H., Zhong, Z., Zhou, M., & Aminpour, F. (2022). Assessment of sidewalk walkability: Integrating objective and subjective measures of identical context-based sidewalk features. *Sustainable Cities and Society, 87*, Article 104142. https://10.1016/j.scs.2022.104142.

Giles-Corti, B., Vernez-Moudon, A., Reis, R., Turrell, G., Dannenberg, A. L., Badland, H., Foster, S., Lowe, M., Sallis, J. F., Stevenson, M., & Owen, N. (2016). City planning and population health: A global challenge. *The Lancet, 388*(10062), 2912–2924. https://10.1016/S0140-6736(16)30066-6.

Goodwin, S., Olazabal, M., Castro, A. J., & Pascual, U. (2024). Measuring the contribution of nature-based solutions beyond climate adaptation in cities. *Global Environmental Change, 89*, Article 102939. https://10.1016/j.gloenvcha.2024.102939.

Goodwin, S., Olazabal, M., Castro, A. J., & Pascual, U. (2025). A relational turn in climate change adaptation: Evidence from nature-based solutions. *Ambio, 54*(3), 520–535. https://10.1007/s13280-024-02090-9.

Grapas, C., Pisello, A. L., Pigliautile, I., Guattari, C., & De Cristo, E. (2025). Multisensory urban climate zones (MUCZ): A framework for mapping dynamic multidomain Human comfort in complex urban fabrics beyond urban morphology. *Sustainable Cities and Society, 131*, Article 106673. https://10.1016/j.scs.2025.106673.

Gu, H., Hu, Q., Zhu, D., Diao, J., Liu, Y., & Fang, M. (2022). Research on outdoor thermal comfort of children's activity space in high-density urban residential areas of Chongqing in summer. *Atmosphere, 13*(12), 2016. https://10.3390/atmos13122016.

Guzman, L. A., Cantillo-Garcia, V. A., Criado, A., Sarmiento, O. L., & Moncada, C. (2026). What street do you like? Exploring the subjective perception of public spaces in unequal and segregated cities. *Cities (London, England), 168*, Article 106460. https://10.1016/j.cities.2025.106460.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *Aα primer on partial least squares structural equation modeling (PLS-SEM)* (2nd edition ed). SAGE.

Hair, J. F., Babin, B. J., Ringle, C. M., Sarstedt, M., & Becker, J. (2025). Covariance-based structural equation modeling (CB-SEM): A SmartPLS 4 software tutorial. *Journal of Marketing Analytics, 13*(3), 709–724. https://10.1057/s41270-025-00414-6.

Han, B., Li, D., & Chang, P. (2021). The effect of place attachment and greenway attributes on well-being among older adults in Taiwan. *Urban Forestry and Urban Greening, 65*, Article 127306. https://10.1016/j.ufug.2021.127306.

Han, S., Song, D., Xu, L., Ye, Y., Yan, S., Shi, F., Zhang, Y., Liu, X., & Du, H. (2022a). Behaviour in public open spaces: A systematic review of studies with quantitative research methods. *Building and Environment, 223*, Article 109444. https://10.1016/j.buildenv.2022.109444.

Han, S., Ye, Y., Song, Y., Yan, S., Shi, F., Zhang, Y., Liu, X., Du, H., & Song, D. (2022b). A systematic review of objective factors influencing behavior in public open spaces. *Frontiers in Public Health, 10*. https://10.3389/fpubh.2022.898136.

Han, S., Song, D., Shi, F., Du, H., Zhang, Y., & Yang, M. (2024). Assessing neighbourhood preference: An evaluation of environmental features within small-scale open spaces. *Land, 13*(4), 531. https://10.3390/land13040531.

Hasegawa, Y., & Lau, S. (2022). Comprehensive audio-visual environmental effects on residential soundscapes and satisfaction: Partial least square structural equation modeling approach. *Landscape and Urban Planning, 220*, Article 104351. https://10.1016/j.landurbplan.2021.104351.

He, P., Yu, B., Ma, J., Luo, K., Chen, S., & Shen, Z. (2024). Exploring the non-linear relationship and synergistic effect between urban built environment and public sentiment integrating macro- and micro-level perspective: A case study in San Francisco. *Frontiers in Psychology, 15*, Article 1276923. https://10.3389/fpsyg.2024.1276923.

Hegetschweiler, K. T., de Vries, S., Arnberger, A., Bell, S., Brennan, M., Siter, N., Olafsson, A. S., Voigt, A., & Hunziker, M. (2017). Linking demand and supply factors in identifying cultural ecosystem services of urban green infrastructures: A review of European studies. *Urban Forestry and Urban Greening, 21*, 48–59. https://10.1016/j.ufug.2016.11.002.

Hou, Y., Chen, C., Lin, X., Zhang, Z., Liu, X., Xie, J., & Guan, S. (2024). Do different types of urban streets lead to varying COVID-19 risk perceptions? An empirical study from a spatial heterogeneity perspective. *Environmental Impact Assessment Review, 104*, Article 107336. https://10.1016/j.eiar.2023.107336.

Hunter, R. F., Cleland, C., Cleary, A., Droomers, M., Wheeler, B. W., Sinnett, D., Nieuwenhuijsen, M. J., & Braubach, M. (2019). Environmental, health, wellbeing, social and equity effects of urban green space interventions: A meta-narrative evidence synthesis. *Environment International, 130*, Article 104923. https://10.1016/j.envint.2019.104923.

Huovila, A., Bosch, P., & Airaksinen, M. (2019). Comparative analysis of standardized indicators for smart sustainable cities: What indicators and standards to use and when? *Cities (London, England), 89*, 141–153. https://10.1016/j.cities.2019.01.029.

Ito, K., Kang, Y., Zhang, Y., Zhang, F., & Biljecki, F. (2024). Understanding urban perception with visual data: A systematic review. *Cities (London, England), 152*, Article 105169. https://10.1016/j.cities.2024.105169.

Jackson, R.J., & Kochtitzky, C. (2012). Creating a healthy environment: The impact of the built environment on public health.

Jiang, R., Dong, W., Bai, L., Qu, A., & Dong, Y. (2026). Which built environment factors promote urban residents' climate change adaptive behaviors? Multi-group application of an exploratory framework via adaptive motivations' mediation. *Sustainable Cities and Society, 139*, Article 107214. https://10.1016/j.scs.2026.107214.

Jim, C. Y., & Chen, W. Y. (2010). External effects of neighbourhood parks and landscape elements on high-rise residential value. *Land Use Policy, 27*(2), 662–670. https://10.1016/j.landusepol.2009.08.027.

Kang, S., Lee, M., & Jung, J. (2024). Analysis of sustainable urban forms for climate change adaptation and mitigation. *Environmental and Sustainability Indicators, 22*, Article 100337. https://10.1016/j.indic.2024.100337.

Koohsari, M. J., Mavoa, S., Villanueva, K., Sugiyama, T., Badland, H., Kaczynski, A. T., Owen, N., & Giles-Corti, B. (2015). Public open space, physical activity, urban design and public health: Concepts, methods and research agenda. *Health & Place, 33*, 75–82. https://10.1016/j.healthplace.2015.02.009.

Kopp, M., & Pérez del Pulgar Frowein, C. (2024). Overestimated environmental benefits of short-term changes in mobility behaviour: The case of Berlin during COVID-19. *Sustainable Cities and Society, 101*, Article 105137. https://10.1016/j.scs.2023.105137.

Li, S., Dragicevic, S., Castro, F. A., Sester, M., Winter, S., Coltekin, A., Pettit, C., Jiang, B., Haworth, J., Stein, A., & Cheng, T. (2016). Geospatial big data handling theory and methods: A review and research challenges. *ISPRS Journal of Photogrammetry and Remote Sensing, 115*, 119–133. https://10.1016/j.isprsjprs.2015.10.012.

Li, J., Niu, J., & Mak, C. M. (2025). Applicability of thermoregulation-sensation models and machine learning modelling to simulate dynamic physio-psychological thermal responses during walking in urban continuum. *Sustainable Cities and Society, 133*, Article 106829. https://10.1016/j.scs.2025.106829.

Lindell, M. K., & Prater, C. S. (2003). Assessing community impacts of natural disasters. *Natural Hazards Review, 4*(4), 176–185. https://10.1061/(ASCE)1527-6988(2003)4:4(176).

Liu, B. (2023). Human settlement, inhabitation, and travel environment construction theory and technology. *The trialism and application of human settlement, inhabitation and travel environment studies* (pp. 185–267). Springer. https://10.1007/978-981-19-9143-1_6.

Luo, Z., Marchi, L., Chen, F., Zhang, Y., & Gaspari, J. (2025a). Correlating urban spatial form and crowd spatiotemporal behavior: A case study of Lhasa, China. *Cities (London, England), 160*, Article 105812. https://10.1016/j.cities.2025.105812.

Luo, Z., Marchi, L., & Gaspari, J. (2025b). A systematic review of factors affecting user behavior in public open spaces under a changing climate. *Sustainability, 17*(6), 2724. https://10.3390/su17062724.

Ma, F. (2023). Seasonal effects on blue-green space preferences: Examining spatial configuration and residents' perspectives. *Environmental Research Communications, 5*(6), Article 065009. https://10.1088/2515-7620/acde39.

Mahmoud, R. A., & Elbardisy, W. M. (2023). Climate comfort due to spatial organization: A major factor of urban resilience in complex gentrification nodes in new urban communities. *Sustainability (Switzerland), 15*(4). https://10.3390/su15043563.

Martinelli, L., Lin, T., & Matzarakis, A. (2015). Assessment of the influence of daily shadings pattern on human thermal comfort and attendance in Rome during summer period. *Building and Environment, 92*, 30–38. https://10.1016/j.buildenv.2015.04.013.

Mohammadzadeh, N., Karimi, A., & Brown, R. D. (2023). The influence of outdoor thermal comfort on acoustic comfort of urban parks based on plant communities. *Building and Environment, 228*, Article 109884. https://10.1016/j.buildenv.2022.109884.

Motomura, M., Koohsari, M. J., Lin, C., Ishii, K., Shibata, A., Nakaya, T., Kaczynski, A. T., Veitch, J., & Oka, K. (2022). Associations of public open space attributes with active and sedentary behaviors in dense urban areas: A systematic review of observational studies. *Health and Place, 75*, Article 102816. https://10.1016/j.healthplace.2022.102816.

Nian, X., Cao, Y., Li, Y., Zhang, Y., & Hong, B. (2025). Effects of environmental factors on multisensory perceptions of comfort, safety, and pleasure in autumnal urban riverfront spaces. *Sustainable Cities and Society, 131*, Article 106710. https://10.1016/j.scs.2025.106710.

Niu, J., Xiong, J., Qin, H., Hu, J., Deng, J., Han, G., & Yan, J. (2022). Influence of thermal comfort of green spaces on physical activity: Empirical study in an urban park in Chongqing, China. *Building and Environment, 219*, Article 109168. https://10.1016/j.buildenv.2022.109168.

Olanrewaju, O. I., Kineber, F. A., Chileshe, N., & Edwards, D. J. (2022). Modelling the relationship between building information Modelling (BIM) implementation barriers, usage and awareness on building project lifecycle. *Building and Environment, 207*, Article 108556. https://10.1016/j.buildenv.2021.108556.

Peng, Z. (2022). *Enriching urban thermal experience: Thermal pleasure around urban public places*. https://www.repository.cam.ac.uk/handle/1810/353534.

A., F. H., A. Pintos-Toledo, E., Fernandez-Gimenez, S., Olivares, P. R., & Brazo-Sayavera, J. (2024). Analysis of the use of public open spaces and physical activity levels in children and adolescents from Rivera (Uruguay) *Health and Place, 88*, Article 103278 https://10.1016/j.healthplace.2024.103278

R Core Team, R. (2013). R: A language and environment for statistical computing.

Rückle, K., Rohrer, M., Mihók, B., Johansson, M., Andersson, H., Pomee, M. S., Vergadi, E., Rouva, G., Agrawal, A., Balázs, B., Brattich, E., Carelli, M., De Luca, C., Di Sabatino, S., Krishnan, V. S., Molter, A., Pilla, F., Ruggieri, P., Scolobig, A., & Hertig, E. (2025). Determinants and relationships of climate change, climate change hazards, mental health, and well-being: A systematic review. *Frontiers in Psychiatry, 16*, Article 1601871. https://10.3389/fpsyt.2025.1601871.

Sander van, d. L., Maibach, E., & Leiserowitz, A. (2015). Improving public engagement with climate change. *Perspectives on Psychological Science : A Journal of the Association for Psychological Science, 10*(6), 758–763. https://10.1177/1745691615598516.

Sang, Y., Qin, X., Yan, H., Wu, R., Yang, F., Middel, A., Nan, X., Zhu, L., & Shi, J. (2025). Dynamic changes of urban street thermal environment from the pedestrian perspective and their impacts on pedestrians' walking behaviors. *Sustainable Cities and Society, 135*, Article 106971. https://10.1016/j.scs.2025.106971.

Schreuder, E., Jan, v. E., Toet, A., & Kallen, V. L. (2016). Emotional responses to multisensory environmental stimuli. *Sage Open, 6*(1), Article 2158244016630591. https://10.1177/2158244016630591.

Senderos, M., Sagarna, M., Otaduy, J. P., & Mora, F. (2025). Globalization and architecture: Urban homogenization and challenges for unprotected heritage: The case of postmodern buildings with complex geometric shapes in the ensanche of San Sebastián. *Buildings (Basel), 15*(3), 497. https://10.3390/buildings15030497.

Shen, T., Zhou, W., Yuan, S., & Huo, L. (2024). Spatiotemporal characterization of the three-dimensional morphology of urban buildings based on Moran's I. *Sustainability, 16*(15), 6540. https://10.3390/su16156540.

Shi, X., Ling, G. H. T., & Leng, P. C. (2025). Demographic change and Commons governance: Examining the impacts of rural out-migration on public open spaces in China through a social–Ecological systems framework. *Land, 14*(7), 1444. https://10.3390/land14071444.

Song, H., Chen, J., & Li, P. (2025). Decoding the cultural heritage tourism landscape and visitor crowding behavior from the multidimensional embodied perspective: Insights from Chinese classical gardens. *Tourism Management (1982), 110*, 105180–17 https://10.1016/j.tourman.2025.105180.

Sultan, P., Wong, H. Y., & Azam, M. S. (2021). How perceived communication source and food value stimulate purchase intention of organic food: An examination of the stimulus-organism-response (SOR) model. *Journal of Cleaner Production, 312*, Article 127807. https://10.1016/j.jclepro.2021.127807.

Tian, Y., Hong, B., Zhang, Z., Wu, S., & Yuan, T. (2022). Factors influencing resident and tourist outdoor thermal comfort: A comparative study in China's cold region. *Science of the Total Environment, 808*, Article 152079. https://10.1016/j.scitotenv.2021.152079.

UN-Habitat. (2022). *Global public space programme annual report 2021*. UN Habitat. Retrieved from Informit Analysis and Policy Observatory (APO) https://unhabitat.org/global-public-space-programme-annual-report-2021.

United Nations DPI. (2017). *The sustainable development goals*. Stylus Publishing, LLC.

Wagner, R., & Grimm, M. S. (2023). Empirical validation of the 10-times rule for SEM. *State of the art in partial least squares structural equation modeling (PLS-SEM)* (pp. 3–7). Springer International Publishing. https://10.1007/978-3-031-34589-0_1.

Warrick, O., Aalbersberg, W., Dumaru, P., McNaught, R., & Teperman, K. (2017). The 'Pacific Adaptive Capacity Analysis Framework': Guiding the assessment of adaptive capacity in Pacific island communities. *Regional Environmental Change, 17*(4), 1039–1051. https://10.1007/s10113-016-1036-x.

WeatherSpark. (2026). *Average weather in lhasa, china*. n.d. WeatherSpark. Retrieved Retrieved March 27from https://weatherspark.com/y/112019/Average-Weather-in-Lhasa-China-Year-Round#Sections-Sources

Wilson, R. S., Herziger, A., Hamilton, M., & Brooks, J. S. (2020). From incremental to transformative adaptation in individual responses to climate-exacerbated hazards. *Nature Climate Change, 10*(3), 200–208. https://10.1038/s41558-020-0691-6.

Xiong, W., Zhang, Y., Liang, Y., & Jiang, C. (2016). When walking becomes praying: Walking environment survey and improvement for circumambulation paths in Lhasa, Tibet, China. *Transportation Research Record, 2581*(1), 134–144. https://10.3141/2581-16.

Xu, G., Zhong, L., Wu, F., Zhang, Y., & Zhang, Z. (2022). Impacts of micro-scale built environment features on tourists' walking behaviors in historic streets: Insights from Wudaoying Hutong, China. *Buildings, 12*(12), 2248. https://10.3390/buildings12122248.

Xu, S., Liu, S., Zhang, C., Shao, S., Li, H., Chen, X., & Wang, M. (2026). Synergistic effects of spatial morphology and thermal comfort on pedestrian activities in residential areas: A field-based study in Wuhan, China. *Building and Environment, 287*, Article 113782. https://10.1016/j.buildenv.2025.113782.

Yang, X., Fan, Y., Xia, D., Zou, Y., & Deng, Y. (2023a). Elderly residents' uses of and preferences for community outdoor spaces during heat periods. *Sustainability (Switzerland), 15*(14). https://10.3390/su151411264.

Yang, Z., Cui, M., Xiao, H., Sun, H., Wang, B., Lin, B., & Shi, W. (2023b). Analysis of thermal comfort experience using peak-end rule with air conditioner in heating season. *Building and Environment, 229*, Article 109965. https://10.1016/j.buildenv.2022.109965.

Yang, W., Yu, K., Xu, J., & Kang, X. (2025). Climate-responsive thermal comfort in rural mountain settlements: A dual-pathway adaptation model and A three-stage perception mechanism. *Building and Environment, 282*, Article 113232. https://10.1016/j.buildenv.2025.113232.

Yao, F., Fang, H., Han, J., & Zhang, Y. (2022). Study on the outdoor thermal comfort evaluation of the elderly in the Tibetan plateau. *Sustainable Cities and Society, 77*, Article 103582. https://10.1016/j.scs.2021.103582.

Yoshihara, T., Tanaka, T., Inachi, S., & Saito, H. (2021). Factors influencing street use frequency and evaluation of street image in densely built-up areas: A case study in Shinyo neighborhood, Nagata Ward, Kobe. *Journal of Asian Architecture and Building Engineering, 20*(5), 596–614. https://10.1080/13467581.2020.1800475.

Yuan, T., Hong, B., Qu, H., Liu, A., & Zheng, Y. (2023). Outdoor thermal comfort in urban and rural open spaces: A comparative study in China's cold region. *Urban Climate, 49*, Article 101501. https://10.1016/j.uclim.2023.101501.

Zaalberg, R., Midden, C., Meijnders, A., & McCalley, T. (2009). Prevention, adaptation, and threat denial: Flooding experiences in the Netherlands. *Risk Analysis, 29*(12), 1759–1778. https://10.1111/j.1539-6924.2009.01316.x.

Zhang, F., Wu, L., Zhu, D., & Liu, Y. (2019). Social sensing from street-level imagery: A case study in learning spatio-temporal urban mobility patterns. *ISPRS Journal of Photogrammetry and Remote Sensing, 153*, 48–58. https://10.1016/j.isprsjprs.2019.04.017.

Zhang, W., Ji, C., Yu, H., Zhao, Y., & Chai, Y. (2021). Interpersonal and intrapersonal variabilities in daily activity-travel patterns: A networked spatiotemporal analysis. *ISPRS International Journal of Geo-Information, 10*(3), 148. https://10.3390/ijgi10030148.