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Bridging objective and subjective heat stress: A human-centered multiscale review of urban thermal experience

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ABSTRACT

Urban heat stress research has rapidly advanced in measuring and modeling thermal exposure, yet a persistent gap remains between objective heat stress (OHS) and subjective heat stress (SHS). Existing reviews often examine these streams separately and lack a unified human-centered perspective for explaining their divergence. This study conducts a PRISMA-guided systematic review of 223 studies, including OHS-focused studies (n = 68), SHS-focused studies (n = 56), and conceptual or mechanistic studies that support the analysis of OHS–SHS relationships and underlying mismatch mechanisms (n = 99).

The results reveal clear structural differences between the OHS- and SHS-focused research streams. OHS studies generally rely on environmental variables and thermal indices, forming relatively consistent methodological pathways across city, street, and person-based exposure levels. In contrast, SHS studies are more heterogeneous and context-dependent, with data sources ranging from individual-level surveys and interviews to participatory sensing, thermal walks, and large-scale digital traces such as social media. The review further identifies three recurrent sources of OHS–SHS mismatch: (1) differences in observation units, (2) scale-dependent representations of heat processes, and (3) limited integration of physiological processes linking environmental conditions to perceived experience.

Building on these findings, we propose a human-centered integrated framework that conceptualizes heat experience as a process linking environmental exposure, physiological response, and perceptual–expressive outcomes, with behavior acting as a key modulator. This framework provides a conceptual basis for multi-source integration, cross-scale validation, and discrepancy-based heat-risk assessment, supporting a shift toward more experience-oriented urban heat governance.

1. Introduction

With global warming and more frequent extreme heat events, urban heat stress has become a critical issue for public health, livability, and social equity (Ebi et al., 2021). Prolonged or intense heat exposure increases cardiovascular and respiratory risks, with disproportionate impacts on older adults, outdoor workers, and socially vulnerable populations (Gabriel & Endlicher, 2011; Tuholske et al., 2021). Accordingly, accurately characterizing urban heat exposure and identifying areas with elevated heat-stress risk have become central concerns in urban climate research (Silveira et al., 2025).

Conceptually, urban heat stress is not a single-dimensional form of environmental exposure, but a composite phenomenon involving both Objective Heat Stress (OHS) and Subjective Heat Stress (SHS) (Rosso-Alvarez et al., 2025). OHS is generally understood as the thermal load imposed on the human body by environmental conditions, and its measurement and modeling can be classified into three levels. The first level consists of environmental thermal variables, including air temperature (Ta), mean radiant temperature (Tmrt), relative humidity, wind speed, and other meteorological variables (Forouzandeh, 2018). These variables are independent of person-specific physiological, behavioral, and demographic characteristics, and form the physical basis of urban heat exposure. The second level includes integrated biometeorological indices, such as the Universal Thermal Climate Index (UTCI), the Physiological Equivalent Temperature (PET), and the Wet Bulb Globe Temperature (WBGT), which combine multiple

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meteorological variables into a standardized measure of heat stress through physiological models (Zare et al., 2018). Although these indices are objective and reproducible, they remain model-based physiological estimates derived from the assumption of a "reference person," rather than actual physiological responses of specific individuals. The third level refers to individual physiological responses, including skin temperature, heart rate variability, and sweating rate, which directly reflect the body's thermal load status (Lin et al., 2025). In this review, physiological responses are classified within OHS because they are objectively measurable bodily states, and are also regarded as a mediating mechanism through which environmental exposure may be translated into subjective thermal perception. However, large-scale and long-term physiological measurements remain rare in urban-scale studies due to equipment cost, experimental conditions, and research ethics. Therefore, broader-scale urban heat stress research still primarily focuses on environmental variables and standardized biometeorological indices, while the actual individual physiological level is often absent (Nazarian et al., 2022). This structural gap introduces a potential mismatch between modeled physiology and actual physiological responses.

Even at the application level of environmental variables and biometeorological indices, high-precision meteorological observations and microclimate simulations remain costly and spatially constrained (Sakthivel & Sengupta, 2025). Reanalysis-based thermal products, such as ERA5-derived UTCI, can provide spatially continuous estimates of heat stress (Di Napoli et al., 2021), although their relatively coarse resolution limits direct interpretation at the pedestrian level. By contrast, pedestrian-level climate walks and mobile transect measurements can provide higher-granularity observations of microclimatic exposure along walking routes, but they are often limited in spatial coverage and sample size. Against this background, Land Surface Temperature (LST) has been widely used as a proxy for urban thermal conditions because of its broad coverage and relatively fine spatial resolution (Li et al., 2023). However, LST reflects surface energy states rather than the canopy-layer thermal environment in which people are directly exposed, leading to systematic differences from human heat load (Venter et al., 2021). This limitation does not mean that surface temperature measurements should be dismissed in urban heat-stress assessment. When obtained within urban canyons, they can provide useful information on pavements, façades, roofs, and shaded or sunlit ground surfaces, thereby helping to identify localized radiant conditions that may influence pedestrian-level exposure. These measurements should therefore be interpreted as complementary indicators rather than direct substitutes for canopy-layer thermal conditions or actual human heat exposure. The problem arises when surface-based measurements are treated as equivalent to human thermal exposure, because this extends environmental-level information to represent pedestrian-level conditions, an assumption whose limitations become increasingly evident when explaining actual thermal experiences and related health risks (Hu & Uejio, 2024). Overall, even within the OHS framework, multi-level uncertainties persist among environmental variables, modeled physiological responses, and actual physiological conditions.

In contrast to OHS, SHS refers to individuals' perceived experience of the thermal environment (Kunz-Plapp et al., 2016), including thermal sensation (e.g., cold, warm, hot), thermal comfort evaluation, emotional responses, and behavioral regulation strategies (Noelke et al., 2016; Sang et al., 2025; Wu et al., 2025; Xiao et al., 2022). SHS is not a simple subjective reading of physiological states. Existing studies suggest that under similar or even identical physiological heat load conditions, individuals may report different levels of thermal perception and discomfort due to differences in psychological state, cultural background, prior thermal experience, environmental expectations, emotional state, environmental aesthetics, and social context (Baecker et al., 2025). This irreducibility at the perceptual level implies that discrepancies between objective and subjective heat stress cannot be fully eliminated, even with more refined physiological measurements. In addition, individual factors such as age, gender, health status, thermal acclimatization, and socioeconomic background, as well as behavioral strategies such as seeking shade, reducing exposure, or using cooling devices, further mediate the relationship between actual exposure and subjective experience (Chen et al., 2024; Zendeli et al., 2025).

In terms of data acquisition, SHS has traditionally relied on questionnaire surveys or laboratory experiments, which are limited in temporal continuity and spatial coverage. However, with the development of emerging data sources such as mobile communication data and social media text, high-frequency and spatially explicit expressions of subjective thermal perception have become increasingly accessible (Tian et al., 2024; Xu et al., 2025). This provides a new data foundation for identifying perceptual differences, behavioral responses, and spatial mismatches at the urban scale.

Building on the multi-level structure outlined above, although OHS and SHS have each developed rich research traditions, their theoretical structures and analytical approaches remain partly divergent (Slesinski et al., 2025). Existing studies tend to focus either on the measurement and modeling of OHS based on environmental variables and integrated biometeorological indices, or on the spatial distribution and social differentiation of SHS based on individual perception and behavioral expression. However, limited attention has been paid to systematically linking the two through physiological responses, behavioral regulation, and environmental mechanisms (Lopes et al., 2025). This creates a cross-level asymmetry: studies based on standardized indices or single environmental indicators often do not directly observe actual individual physiological responses, whereas studies focused on subjective perception often insufficiently explain its structural relationship with objective heat load. Therefore, OHS–SHS divergence may arise not only from differences in measurement and modeling scales, but also from the combined effects of physiological and psychological regulatory mechanisms. A systematic synthesis of these two research pathways from an integrative perspective is therefore essential for clarifying their hierarchical structure and analytical boundaries, and for advancing the understanding of urban thermal experience.

Based on the theoretical background outlined above, this study is positioned as an integration-oriented review that adopts a human-centered perspective on urban heat stress. Its scope is broader than conventional pedestrian-level outdoor thermal comfort surveys, but it does not treat all available data sources as equivalent measures of human thermal experience. Instead, this review distinguishes different approaches according to whether they primarily represent environmental exposure, physiological response, behavioral adaptation, directly reported perception, or digitally expressed heat experience. The aim is therefore not to merge heterogeneous methods into a single measurement category, but to clarify their respective roles, applicable scales, and limitations in explaining OHS–SHS mismatch. Accordingly, this study synthesizes multi-scale research on OHS and SHS and develops a cross-level analytical framework for understanding how urban thermal experience is formed. The main objectives of this study are as follows:

(1) Conceptual level: to systematically define the multi-level structure of urban OHS and SHS, and to clarify the hierarchical relationships and analytical boundaries among environmental variables, modeled physiological estimates, actual physiological responses, and subjective experience.
(2) Methodological level: to review the major measurement and modeling approaches for urban OHS and SHS across different spatial scales and analytical levels, and to compare the structural differences in their indicator systems and data sources.
(3) Integrative level: to propose a cross-level analytical framework that links environmental conditions, physiological responses, and experiential expressions, and to clarify where OHS–SHS mismatch may arise and how it can be examined through cross-scale validation, multi-source integration, and discrepancy-based heat-risk assessment.

The remainder of this paper is organized as follows. Section 2 describes the review procedure. Section 3 summarizes the measurement approaches and scale-specific characteristics of OHS and SHS. Section 4 discusses OHS–SHS relationships and proposes an integrative framework. Section 5 outlines future research directions, followed by the conclusion.

2. Methods

The search and refinement process of this review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. This review aims to systematically evaluate measurement and modeling approaches, multi-scale characteristics, and underlying linkage mechanisms of OHS and SHS in urban contexts. Rather than quantifying the effects of individual interventions or specific indicators, the focus is on methodological synthesis and comparison to reveal the strengths, limitations, and structural differences of different research pathways in characterizing urban thermal experience.

2.1. Literature search strategy

The literature search was primarily conducted using the Web of Science Core Collection and Scopus databases, with Google Scholar used as a supplementary search tool. The supplementary search was intended to identify relevant studies not indexed in Web of Science Core Collection and Scopus, including journal articles and conference papers, thereby improving the completeness of the literature coverage. This step also helped address differences in database coverage and reduce the risk of potential omissions. The search was completed in March 2026, with no restriction on publication year, in order to ensure comprehensive inclusion of relevant studies and to capture the rapid development of data sources and methodological approaches in urban heat stress research.

Two groups of keywords were used to cover the main research streams of OHS and SHS. To improve transparency and reproducibility, the Boolean logic of the search strategy is specified as follows. Within each concept group, synonymous or related terms were connected using the OR operator, while different concept groups were combined using the AND operator. The search strings were adapted to the syntax requirements of each database.

The first group (Search A) focused on urban thermal environments and objective heat stress measurement and modeling. In general, Search A combined urban-context terms with heat-exposure, measurement, and thermal-index terms. Urban-context terms included “urban”, “city”, “outdoor”, “street”, and “urban microclimate”. Heat-exposure and measurement terms included “urban heat stress”, “heat exposure”, “thermal exposure”, “air temperature”, “mean radiant temperature”, “relative humidity”, “wind speed”, “physiological parameters”, and “wearable sensors”. To capture studies using integrated biometeorological and thermal stress indices, the search terms also covered “UTCI”, “PET”, “WBGT”, “SET”, “thermal comfort index”, and “heat stress index”. UTCI and PET were highlighted in the manuscript because they were the most frequently used outdoor urban thermal indices in the included studies, rather than because other indices such as WBGT or SET were excluded.

The second group (Search B) targeted subjective thermal experience and perception-related data sources. In general, Search B combined heat- or thermal-related terms with perception descriptors and data-source or method-related terms. Heat- or thermal-related terms included “heat”, “thermal”, “hot”, and “temperature”. Perception descriptors included “thermal perception”, “heat perception”, “thermal sensation”, “thermal comfort”, “thermal discomfort”, “thermal acceptability”, “thermal preference”, “heat discomfort”, “perceived heat”, “thermal experience”, “emotion”, and “subjective heat stress”. These terms were further combined with data-source and method-related terms, including “questionnaire”, “survey”, “interview”, “thermal walk”, “citizen sensing”, “participatory sensing”, “crowdsourcing”, “social media”, “GPS”, and “mobility”. The terms “GPS” and “mobility” were included because they are commonly used to identify activity spaces, movement trajectories, and behavioral adaptation to heat, which are relevant for linking subjective perception with exposure context, although they do not directly measure perception by themselves.

In addition, targeted searches were conducted to identify studies examining the relationship between OHS and SHS. These searches combined objective heat-stress terms, subjective heat-stress or perception terms, and relationship-related terms, such as “objective–subjective heat”, “objective heat stress”, “subjective heat stress”, “mismatch”, “difference”, “divergence”, “relationship”, “perceived heat”, “heat perception differences”, and “thermal experience”. All retrieved records were subsequently screened according to the criteria described in Section 2.2.

2.2. Literature screening and classification

The initial search yielded approximately 4943 records. After removing duplicates, 2844 records remained for title and abstract screening. During this stage, 2524 records were excluded because they focused exclusively on indoor thermal comfort, occupational heat stress, non-urban settings, or did not include explicit heat stress measurement, modeling, or perception-related methods. This resulted in 320 records for full-text eligibility assessment. A full-text review was then performed on these 320 studies, with particular attention to whether the research explicitly addressed outdoor urban heat exposure and employed identifiable OHS or SHS measurement and modeling approaches.

A total of 223 studies were ultimately included and categorized into three groups based on their research objectives as well as measurement and modeling approaches. The first group consists of OHS studies ($n = 68$), covering indicators such as Ta, Tmrt, UTCI, PET, and physiological parameters, along with their multi-scale modeling approaches. The second group includes SHS studies ($n = 56$), comprising questionnaire surveys, experimental studies, crowdsourcing approaches, and social media text analysis. The third group includes background, conceptual, and theoretical studies, as well as studies examining the relationship between OHS and SHS, including spatial mismatches, behavioral regulation, and integrative frameworks ($n = 99$). Studies were assigned to this conceptual/mechanistic group when their primary contribution was not the direct measurement or modeling of OHS or SHS alone, but the explanation of underlying mechanisms, cross-domain relationships, behavioral mediation, spatial mismatch, or integrative frameworks linking environmental exposure, physiological response, and subjective perception. This group provides a foundation for understanding heat stress and thermal experience and directly informs the structure of the subsequent sections of this review. Accordingly, the numbers reported for the OHS- and SHS-focused groups should be interpreted within the scope of this review and its classification criteria, rather than as a quantitative representation of the overall size of the broader OHS and SHS literatures.

2.3. Data extraction and synthesis

To support a systematic comparison of methodological heterogeneity, a unified data extraction framework was applied to selected studies. The following information was recorded: (1) study scale (individual, street, community, or city level); (2) types of heat stress indicators; (3) data sources as well as measurement and modeling approaches (e.g., in situ monitoring, model simulation, questionnaire surveys, or digital expressions); (4) spatial or temporal modeling and analytical methods; and (5) whether the study focuses on OHS or SHS.

Given the methodological heterogeneity across the included studies and the synthesis-oriented rather than effect-estimation focus of this review, formal quality assessment using standardized tools (e.g., risk of bias scales) was not applied. Instead, study quality was considered through the restriction to peer-reviewed publications and the evaluation of methodological transparency, data sources, and analytical approaches during the thematic synthesis, which prioritizes methodological comparison over quantitative aggregation. However, several potential biases should still be acknowledged. Because this review primarily relied on peer-reviewed studies indexed in Web of Science and Scopus, grey literature and local planning reports may be underrepresented. In addition, the reviewed studies may be affected by uneven data availability: OHS research is often shaped by access to meteorological observations, simulations, and remote sensing products, whereas SHS research may be influenced by survey sampling, platform participation, demographic representation, and language-expression biases. These limitations should be considered when interpreting the methodological patterns and research gaps identified in this review. The PRISMA flow diagram is shown in Fig. 1.

3. Results

3.1. Structural patterns of the literature

Based on the systematic coding of the included literature, this study extracts the structural characteristics of OHS research across four dimensions: indicator, data source, estimation approach, and scale. In SHS research, data sources and estimation approaches are treated as a unified data source dimension, reflecting their close coupling in perception-oriented measurements. For OHS, this review distinguishes three analytical levels according to the dominant unit of observation and exposure representation: the city scale (the background thermal conditions of the urban canopy layer), the street scale (street-canyon microclimate), and person-based exposure (dynamic exposure along individual trajectories and physiological responses). By contrast, scales in SHS research reflect the level at which thermal perception is measured or expressed, typically encompassing individual, community, and city scales.

This distinction implies that scale classification in OHS and SHS does not rely on the same criteria, but instead follows their respective conceptual foundations. Accordingly, the following sections summarize the structural patterns of the two research streams in terms of indicator systems, data sources and methodological pathways, scale-coupling relationships, and disciplinary and temporal evolution. Sections 3.2 and 3.3 then provide detailed discussions of the scale definitions and measurement paradigms specific to OHS and SHS, respectively.

3.1.1. Indicator systems and distributions

In terms of indicator distribution, OHS studies exhibit a clear pattern of concentration across scales. At the city scale, Ta/Ws/RH dominate

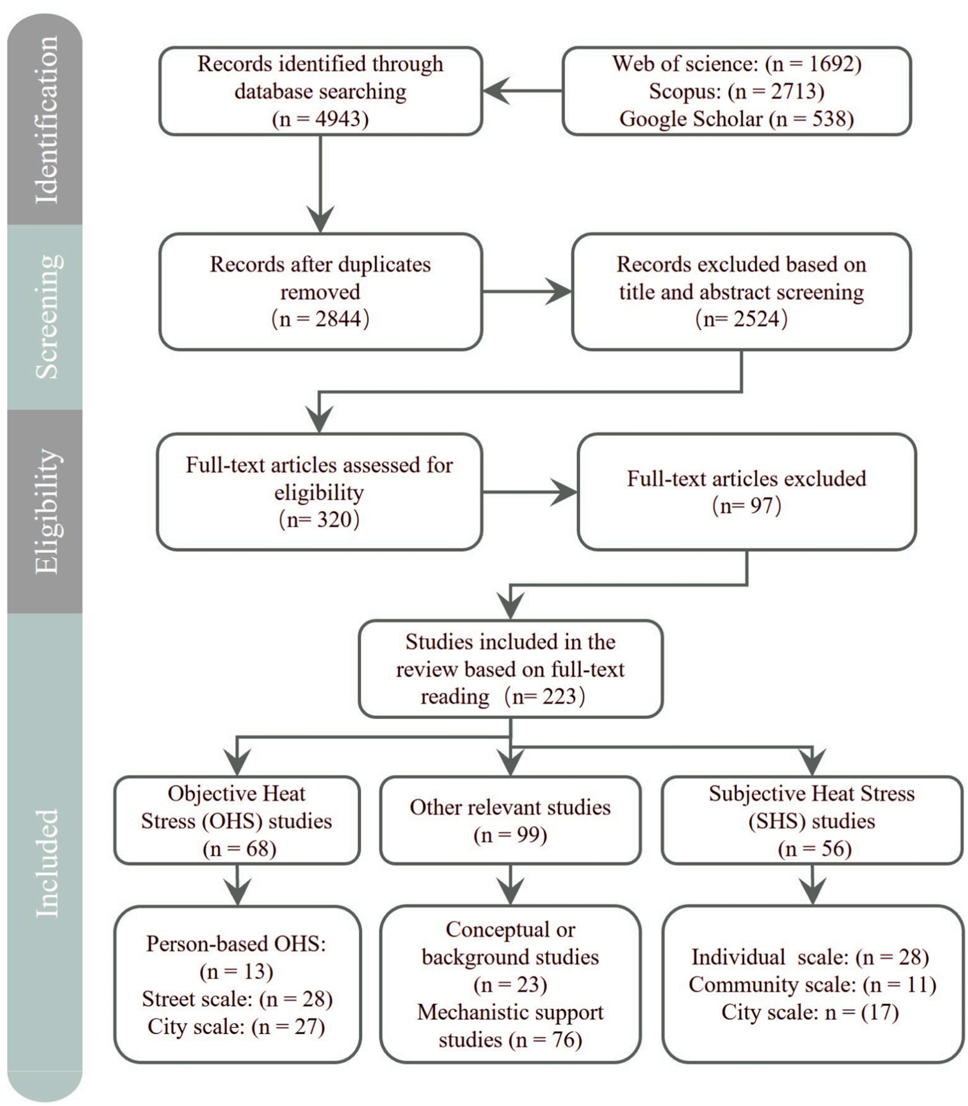

Fig. 1. PRISMA flow diagram of the literature search and selection process.

and are used far more frequently than other indicators, followed by UTCI and PET. At the street scale, PET and Tmrt are the most commonly used indicators, with Tmrt showing a particularly prominent share. At the person-based exposure level, the distribution of indicators expands from environmental variables toward physiological responses, mainly including physiological parameters (e.g., skin temperature and heart rate) as well as integrated biometeorological indices such as PET and UTCI (Fig. 2, left).

This pattern indicates that the OHS indicator system gradually shifts from environmental representation at city and street scales toward person-based exposure and physiological responses. Meanwhile, the dominant role of radiation-related variables (e.g., Tmrt) at the street scale highlights the importance of the radiative microclimate in characterizing spatial variability.

In contrast, the indicator system of SHS is more diverse and context-dependent. At the individual level, SHS is highly concentrated on questionnaire-based subjective measures, such as the Thermal Sensation Vote (TSV), Thermal Acceptability Vote (TAV), Thermal Comfort Vote (TCV), and Thermal Preference Vote (TPV), with TSV and TAV being the most frequently used. At the street scale, the number of subjective indicators is relatively limited, and the analysis is still largely supported by TSV, TCV, and TPV. At the city scale, however, SHS shifts toward expression-based indicators, including keyword frequency, heat-related emotions, perceived heat mapping, and heat perception intensity (Fig. 2, right).

This pattern suggests a structural transition of SHS across scales, from scale-based subjective ratings toward expression- or semantic-based representations of thermal perception.

3.1.2. Data sources and methodological pathways

In terms of data sources and estimation pathways, OHS research demonstrates a relatively strong degree of methodological convergence. At the city scale, studies primarily rely on meteorological station data, supplemented by in situ observations and citizen weather stations. At the street scale, greater emphasis is placed on in situ measurements and numerical simulations, with increasing adoption of UAV-based observations, mobile monitoring, and wearable devices. At the person-based exposure level, research is highly dependent on in situ observations and wearable data (Fig. 2, left). Correspondingly, methodological approaches vary systematically across scales: the city scale is dominated by statistical and machine-learning modeling as well as spatial interpolation; the street scale exhibits pronounced model-driven characteristics; and the person-based exposure level centers on point-based exposure assignment. This structure suggests that OHS research has developed a relatively coherent technical chain from place-based thermal fields to person-based exposure assessment. It includes heat-field reconstruction at the city scale, mechanism-oriented simulation at the street scale, and exposure assignment at the person-based level.

By contrast, methodological pathways in SHS research exhibit a pronounced branching structure. At the individual level, studies are almost entirely dominated by contextual questionnaires, with EMA and route-based evaluation serving as complementary approaches. At the community level, questionnaire-based methods are increasingly combined with participatory mapping, GPS, and social media data. At the city scale, social media data become the dominant source, jointly with participatory mapping and GPS, forming a measurement pathway characterized by collective expression and spatial aggregation (Fig. 2, right). Consequently, the methodological structure of SHS research reflects a clear contrast: the individual-level emphasizes measurement consistency, whereas the city scale prioritizes data availability and expressive intensity, resulting in a noticeable methodological discontinuity between scales.

3.1.3. Scale-Coupling relationships

The Sankey diagram further illustrates the dominant flows of OHS and SHS along the “indicator–data–method–scale” chain Fig. 3. In OHS studies, indicators such as Ta, Tmrt, PET, and UTCI are derived from data sources including in situ measurements, meteorological stations, and numerical simulations. These are primarily linked to climate models and exposure assignment approaches, forming the strongest flow concentrations at the city and street scales. Among these, the pathway from numerical simulation to climate modeling and then to the street scale is particularly prominent.

At the person-based exposure level, physiological parameters (e.g., skin temperature and heart rate) together with integrated biometeorological indices (e.g., PET and UTCI) constitute another important pathway. These indicators are typically obtained through wearable devices or in situ measurements and are mainly associated with point-based exposure assignment and individual trajectory reconstruction, forming a key link between environmental conditions and actual individual heat load.

In contrast, the dominant pathways of SHS exhibit a polarized structure. On one end, questionnaire-based measures centered on TSV, TAV, TCV, and TPV are strongly linked to the individual level. On the

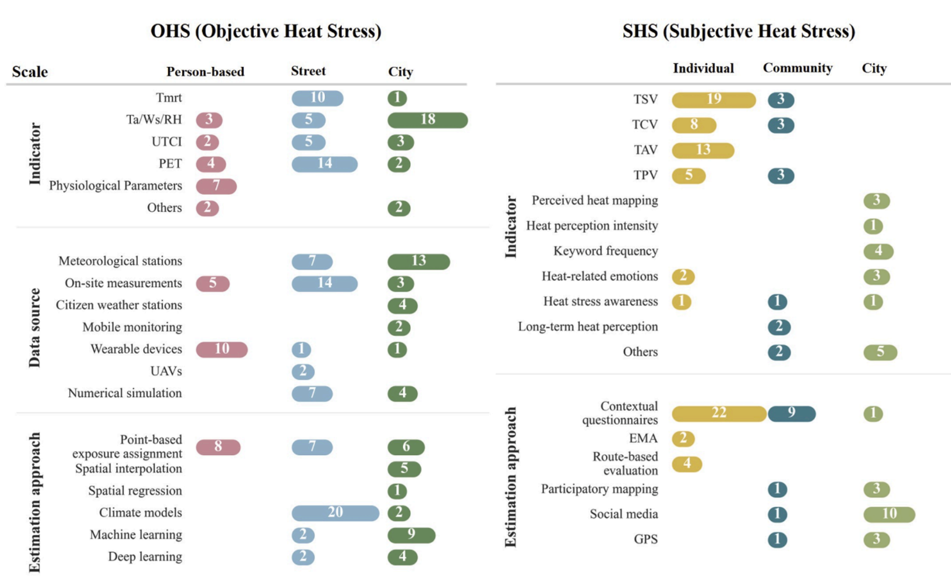

Fig. 2. Structural comparison of OHS and SHS research across key study dimensions.

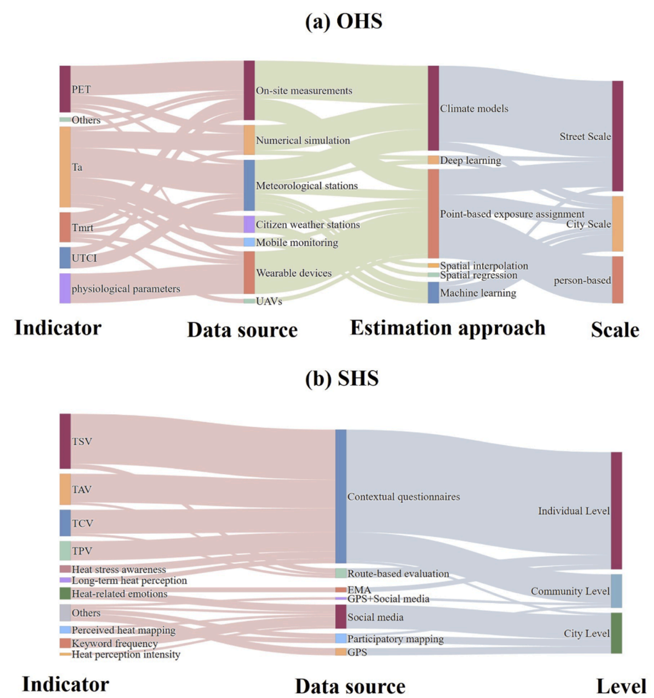

Fig. 3. Structural linkages across key study dimensions in OHS and SHS research.

other end, expression-based indicators, such as emotions, keyword frequency, and perceived heat mapping, are connected to the city scale through social media and participatory approaches. In comparison, the street or neighborhood scale remains relatively underrepresented.

3.1.4. Research domains and temporal evolution

Finally, in terms of research domains, OHS studies are predominantly concentrated in journals related to urban climate and the built environment, with additional representation in selected remote sensing and environmental data–oriented journals. By contrast, the journal distribution of SHS research is more interdisciplinary, extending notably into the fields of public health and social–environmental studies (Fig. 4). From a temporal perspective, both research streams have experienced rapid growth in recent years; however, their trajectories of expansion and disciplinary anchoring differ markedly.

Taken together, the distinctions between OHS and SHS extend beyond a simple "objective–subjective" conceptual dichotomy and instead reflect a systematic separation at the level of research structure. OHS research shows increasing convergence in indicators and methods, forming relatively stable technical chains at the city and street scales. In contrast, SHS measurement and modeling pathways are dominated by the individual and city scales, with methods and data sources that are more context-dependent and interdisciplinary in nature. These structural patterns provide an overarching framework and comparative basis for the subsequent in-depth discussion in Sections 3.2 and 3.3 on the multi-scale technical systems of OHS and SHS and their respective limitations.

3.2. Multiscale OHS measurement and modeling framework

In urban climatology, the formation of OHS involves the combined effects of thermal processes across multiple scales. The dominant mechanisms, available data, and modeling approaches vary substantially across spatial scales. From a human-centered perspective, this review focuses on three levels that are most directly related to the actual heat exposure experienced by urban residents: the city scale, the street scale, and person-based exposure (Wong et al., 2021).

At the city scale, the background thermal environment within the urban canopy layer is typically characterized at resolutions ranging from hundreds of meters to kilometers, reflecting the overall heat stress and its spatial gradients across the city (Y. Li, Ma et al., 2025). At the street scale, attention is given to the strong spatial heterogeneity within street canyons, shaped by radiative exchange and near-surface ventilation (Colaninno et al., 2025). Analyses at this scale, usually conducted at meter to tens-of-meters resolution, capture microclimatic variability through fixed-point measurements or spatially explicit simulations.

In person-based OHS assessment, analyses track the actual heat exposure experienced by specific individuals as they move through urban space, integrating microclimatic conditions with personal factors such as walking speed, route choice, and metabolic activity (Pioppi et al., 2022). Although street-scale and person-based analyses are conducted within similar physical environments, they differ fundamentally in their methodological perspectives: street-scale analysis is location-based and independent of individuals, whereas person-based analysis is centered on individuals and captures the role of behavior in modulating exposure. Person-based exposure does not represent a finer spatial resolution than the street scale, but rather a shift in the unit of analysis from place to person. It tracks the realization of heat exposure along individual trajectories by combining microclimatic conditions with walking speed, route choice, activity patterns, and physiological responses.

While larger atmospheric scales determine the background conditions of heat waves, they do not directly act on pedestrian-level exposure (Oh & Sushama, 2021). Similarly, neighborhood and regional scales (e.g., LCZ) primarily influence local thermal fields indirectly and are therefore incorporated into the city-scale discussion in this review (Kotharkar et al., 2024; Stewart & Oke, 2012).

Fig. 5 provides a human-centered synthesis of the dominant thermal mechanisms, typical indicators, data sources, and influencing factors of OHS across these three analytical levels. It also illustrates the hierarchical transition from the background urban thermal field at the city scale to street-level heterogeneity and further to instantaneous person-based exposure. Based on this multi-scale framework, the following sections examine the measurement and modeling approaches, technical developments, and limitations of OHS across different scales.

3.2.1. City-scale OHS: urban thermal background

From a human-centered perspective, the primary role of city-scale OHS measurement is to characterize the overall urban thermal field and its spatial gradients, thereby providing stable physical boundary conditions for street-scale radiation–ventilation differences and instantaneous person-based exposure. The focus is on the spatial distribution of environmental thermal variables (e.g., Ta and Tmrt) and their long-term structural differences across the city, rather than on actual exposure along individual trajectories. Once the city-scale thermal pattern is established, it becomes possible to explain why different neighborhoods experience varying levels of heat stress under similar meteorological conditions. In this sense, city-scale OHS should not be regarded as an independent analytical layer, but as the physical basis for subsequent microscale modeling and OHS–SHS bridging analysis.

In cities with relatively well-developed observation networks, the most direct approach to measuring city-scale OHS is to construct high-resolution temperature or heat index fields based on ground-based meteorological stations and extended observation networks (Cao et al., 2021). Using data from national or local meteorological stations, methods such as kriging interpolation, statistical regression models, and geographically weighted regression (GWR) are commonly applied (Colaninno & Morello, 2022; Eldrandaly, 2011; Shin & Yi, 2019). These approaches interpolate discrete observations onto urban grids and enable the estimation of indices such as UTCI or PET to characterize intra-urban OHS gradients during heatwave periods (Nath & Deka, 2025). However, in most cities, meteorological stations are sparse and often located in suburban or open areas, making it difficult to

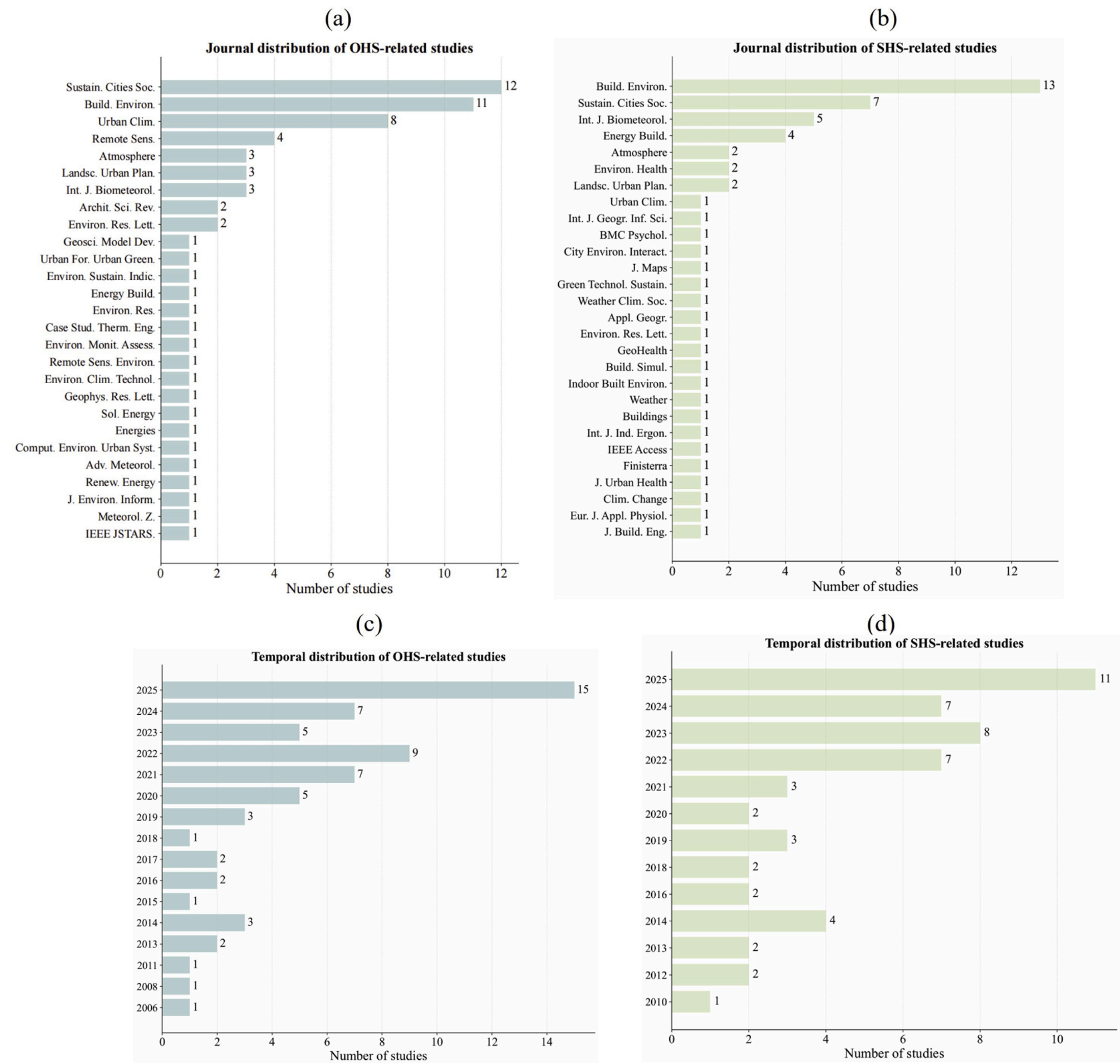

Fig. 4. Journal and temporal distribution of OHS- and SHS-related studies. Note: Since the literature search for 2026 only covered publications available up to March, studies published in 2026 were excluded from the temporal statistics but retained in the journal statistics.

capture spatial variations in heat stress across different urban environments.

To address the limited spatial representativeness of conventional station networks, recent studies have incorporated observation sources that are more closely aligned with urban living environments, including citizen weather stations (CWS), mobile monitoring, and high-density urban sensor networks (Cureau et al., 2024; Fenner et al., 2019; Muller et al., 2015; Park et al., 2020). Evidence from multiple European cities shows that quality control and bias correction of large numbers of CWS can significantly improve the spatial resolution and reliability of canopy-layer temperature fields (Meier et al., 2017; Venter et al., 2020). Mobile sensing platforms, such as vehicle-mounted sensors or shared bicycles, can capture localized thermal variations that are not covered by fixed stations (Yin et al., 2020). Moreover, high-density fixed sensor networks can produce urban temperature fields at resolutions approaching 10 m, enabling a more detailed representation of the spatial structure of OHS (Zumwald et al., 2021).

Overall, recent city-scale OHS modeling shows a clear shift from observation-based interpolation toward multi-source environmental modeling. Instead of relying only on sparse meteorological stations, studies increasingly combine limited Ta or UTCI observations with remote sensing products, land-cover information, urban morphology, vegetation indicators, and topographic variables to reconstruct spatially continuous heat-stress fields. Machine-learning models, such as random forests, support vector machines, gradient boosting, and other ensemble approaches, have been widely used in this process because they can capture nonlinear relationships between urban form, land surface characteristics, and near-surface thermal conditions (Briegel et al., 2024; Chajaei & Bagheri, 2024; Sampaio et al., 2025; Wu et al., 2023; Zhou et al., 2025). These studies generally demonstrate that urban morphology and land-cover structure play a central role in shaping city-scale OHS patterns, while also highlighting the dependence of model performance on observation density, predictor quality, and transferability across cities.

In addition, regional climate models, particularly the Weather Research and Forecasting (WRF) model and its urban parameterization

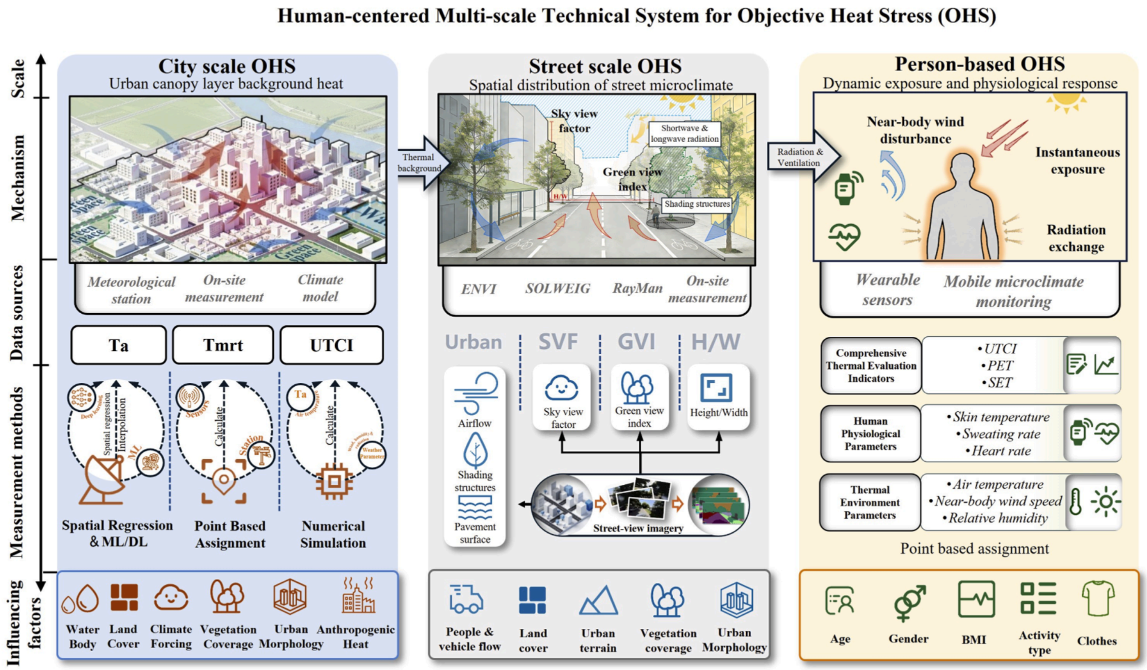

Fig. 5. Human-centered multi-scale technical system for OHS.

schemes (e.g., WRF–UCM), provide an important complementary approach for measuring city-scale OHS (Afshari et al., 2023; Bilang et al., 2022; Blizer et al., 2024). Unlike models that rely solely on observations or statistical relationships, WRF–UCM simulates canopy-layer Ta, Tmrt, and related thermal indices within a physically consistent framework of urban–atmosphere interactions. Even in regions with extremely limited ground observations, these models can be driven by reanalysis data (e.g., ERA5) to generate physically consistent urban-scale OHS fields (Aquino-Martínez et al., 2025). However, these models also have notable limitations, including high computational cost, sensitivity to urban parameterization, and relatively coarse spatial resolution, which limit their ability to efficiently capture fine-scale variations in the urban thermal background (Shen et al., 2019).

More recently, deep learning approaches have further advanced high-resolution downscaling and reconstruction of city-scale OHS. Rather than relying only on conventional statistical relationships, these approaches use models such as U-Net and generative adversarial networks (GANs) to refine coarse-resolution Ta or Tmrt fields derived from WRF, ERA5, or meteorological stations into finer urban-scale representations (He et al., 2024; Wu et al., 2021; Zhang et al., 2022). Their performance is often improved by incorporating remote sensing data, LST, LCZ, and urban morphology, which provide additional spatial information for reconstructing OHS patterns (Gong et al., 2025; Jia et al., 2025; Su et al., 2025). In parallel, physics-informed model distillation uses high-fidelity Tmrt or UTCI outputs from climate models as training targets, enabling faster reconstruction of computationally intensive thermal indicators (Ding et al., 2023; Kim et al., 2025; Song & Roh, 2021; Wang et al., 2019). Overall, these methods improve computational efficiency and spatial detail, but their outputs remain strongly dependent on training data quality, spatial representativeness, and the physical consistency of the target variables.

Despite these advances, city-scale OHS approaches still have limited capacity to represent microscale radiation–ventilation processes and instantaneous exposure variations within specific street environments. This limitation has driven a shift toward street-scale investigations, contributing to the development of a cross-scale, human-centered framework for understanding urban thermal environments.

3.2.2. Street-scale OHS: radiative and ventilation heterogeneity

From a human-centered perspective, street-scale OHS research focuses on the microclimatic environment within pedestrian activity spaces, such as street canyons and their adjacent areas. Unlike the city scale, which characterizes the background thermal environment of the urban canopy layer, this scale emphasizes the spatial distribution of microclimatic conditions within pedestrian space. Under similar city-scale climatic conditions, different street segments may exhibit substantial spatial heterogeneity in heat load due to variations in urban geometry and radiation–ventilation environments (Paolini et al., 2014).

Accordingly, the central question at this scale is “where is hotter or cooler within urban pedestrian space,” enabling the identification of localized heat exposure hotspots (Acero & Herranz-Pascual, 2015). In this sense, the street scale serves as a critical intermediary linking the background urban thermal environment and person-based exposure (Andreou, 2013).

At this scale, the thermal environment is primarily governed by street canyon geometry (e.g., height-to-width ratio, sky view factor, and building configuration), shading structures (e.g., trees and canopies), surface materials, and near-surface wind conditions (De & Mukherjee, 2017; Deng & Wong, 2020; Ma, Chau et al., 2025). The highly constrained radiative environment leads to pronounced spatiotemporal variability in indicators such as Tmrt (Xiong et al., 2022), while limited ventilation directly reduces sensible heat dissipation efficiency, resulting in localized “hot spot–cool spot” patterns of OHS (Aliabadi et al., 2019). Such fine-scale variations are often averaged out in city-scale background fields and therefore cannot be directly captured at coarser resolutions (Geletič et al., 2023).

Therefore, the measurement and modeling of street-scale OHS is not only fundamental for assessing heat exposure, but also provides direct support for urban design strategies, such as enhancing accessible shading and optimizing urban ventilation corridors.

Traditional measurement of street-scale OHS primarily relies on in situ observations and radiation–wind monitoring. Fixed and mobile micro-meteorological stations are commonly deployed in representative street canyons and key locations to record variables such as Ta, wind speed, shortwave and longwave radiation, and Tmrt (Cardenas-Jiron et al., 2023; Lee et al., 2013). These observations can capture the actual variability of street-scale thermal environments, for example, pronounced radiative contrasts between street canyons with different height-to-width ratios under daytime solar exposure (Dai & Schnabel, 2014), or the stronger cooling effects of vegetation on UTCI in shallow canyons compared to deeper ones (Coutts et al., 2016). However, due to the highly localized nature of street-scale microclimate variability, observation-based approaches alone are often insufficient to achieve comprehensive coverage across urban street networks.

To address these limitations, street-scale OHS research has increasingly incorporated microclimate numerical models, particularly radiation–energy balance simulation tools such as ENVI-met, SOLWEIG, and RayMan (Ketterer & Matzarakis, 2014; Lee et al., 2019; Thom et al., 2016). ENVI-met simulates radiative exchange, heat storage, and local airflow under high-resolution urban geometry, providing physically consistent estimates of Ta and Tmrt, and is widely used to evaluate the effects of street greening, surface materials, and morphological modifications on local heat stress (Liu et al., 2021). In contrast, SOLWEIG and RayMan focus more on rapid estimation of radiation budgets and shading effects, and are commonly applied in analyses of street orientation, surface albedo, and tree canopy shading (Meng et al., 2025; Vieira Zezzo et al., 2023). Although these models are computationally demanding, they provide an essential physical basis for understanding microclimatic structures within street environments.

With the development of street view imagery, LiDAR, unmanned aerial vehicles (UAVs), and 3D modeling techniques, the spatial measurement of street-scale OHS has increasingly shifted toward data-driven approaches (E.-S. Kim et al., 2022; X. Zhao et al., 2020). Recent studies have constructed pedestrian-level heat stress assessment frameworks by integrating UAV imagery with ground-based observations (Zhong et al., 2025), improved the accuracy of Tmrt simulation using LiDAR and thermal infrared imaging (Zhong et al., 2026), and applied image-driven machine learning models to efficiently approximate microclimate simulation outputs (Ma et al., 2025; Zhang et al., 2025). In addition, regression models of UTCI based on street view semantic segmentation combined with mobile micro-meteorological observations have been shown to effectively capture the spatial patterns of street-scale OHS (Qin et al., 2025). These studies indicate that three-dimensional visual features have significant potential for predicting street-scale OHS, enabling high-resolution estimation of thermal environments across urban street networks at relatively low cost, while achieving strong spatial agreement with in situ observations and microclimate simulation results.

Overall, street-scale OHS research reveals the rapid variability of radiation and ventilation conditions within pedestrian spaces. Its primary objective is to characterize the spatial distribution of microclimatic conditions in urban pedestrian environments, thereby providing a critical microclimatic context for subsequent analyses of individual heat exposure.

3.2.3. Person-based OHS: dynamic exposure and physiological response

Finally, person-based OHS research focuses on the actual heat exposure experienced by specific individuals as they move through urban space. Even within the same street segment, substantial differences in heat load may arise among pedestrians due to variations in walking speed, stopping behavior, route choice, and individual physiological characteristics (Goto et al., 2024; Li et al., 2023). Accordingly, the central objective of person-based OHS is to characterize “who experiences what level of heat exposure, where and when,” thereby revealing the role of behavioral patterns and individual characteristics in modulating heat exposure. Within the multi-level structure of OHS, person-based OHS involves both the measurement of individual exposure pathways and, in some cases, the observation of actual physiological responses, thus serving as a key link between the physical thermal environment and SHS.

In person-based OHS assessment, human heat load is typically determined by three coupled processes: (1) radiation reception from an individual perspective, including direct shortwave radiation, reflections from ground and building surfaces, and longwave radiative exchange that varies with position and orientation; (2) near-surface wind conditions and local ventilation, which are influenced not only by street geometry and obstacles but also by individual movement and posture; and (3) human energy balance processes, including metabolic rate, clothing insulation, thermoregulation of skin temperature, and evaporative heat loss (Choudhary & Udayraj, 2023; Kocik et al., 2025; Yang et al., 2025; Zhou, Yu et al., 2025). These factors are highly sensitive in both space and time, such that individuals may experience substantial variations in heat load over short distances. For example, rapid transitions of 10–20 °C in PET can occur across shaded–sunlit boundaries or high-albedo surfaces (Gulyás et al., 2006; Mayer et al., 2008), highlighting the highly dynamic nature of individual exposure.

Based on these mechanisms, measurement and modeling of person-based OHS can be further categorized into three hierarchically related pathways. The first involves direct recording of the exposure environment, using wearable or portable sensors to capture local meteorological conditions at the individual’s location, combined with trajectory data to reconstruct actual heat exposure in urban space (Parchami et al., 2025). This approach focuses on characterizing “what environmental conditions the individual experiences.” The second pathway is based on integrated biometeorological indices, such as UTCI and PET. These approaches apply heat balance models to integrate environmental variables, including air temperature, wind speed, humidity, and radiation, into standardized representations of heat stress for a reference individual, thereby linking environmental exposure to physiological response (Cureau et al., 2025). Compared with single meteorological variables, such indices partially account for thermophysiological processes, including skin temperature regulation, evaporative cooling efficiency, and convective heat exchange (Ioannou et al., 2022), and can therefore serve as a proxy in the absence of direct physiological measurements.

The third pathway involves direct observation of individual physiological responses, including indicators such as skin temperature, heart rate variability, and sweating rate. These physiological signals reflect the body’s actual response to thermal load and can be regarded as a key mediator linking environmental conditions and subjective perception (Cramer et al., 2022; Laouadi, 2024). For example, some studies have employed wearable devices to continuously monitor physiological indicators in real-world environments, capturing heat stress responses under high-temperature conditions (Zhao & Bergmann, 2026). However, due to constraints related to device cost, experimental conditions, and data management, large-scale and long-term physiological monitoring in real urban settings remains limited.

In terms of measurement and modeling approaches, person-based OHS is no longer based on fixed spatial locations, but instead centers on individuals’ actual activity processes within urban environments, emphasizing the reconstruction of continuous exposure trajectories. Such studies typically rely on wearable or portable environmental sensors (Johansson et al., 2014), including lightweight temperature–humidity sensors, six-directional radiation sensors, smartwatches, and skin temperature patches. During movement, these devices record local air temperature, humidity, and radiation conditions in real time, while GPS trajectories are used to quantify walking speed, dwelling time, and route choice, enabling the reconstruction of dynamic heat exposure pathways in urban space (Friedrich et al., 2025; Kantor et al., 2018; Kuras et al., 2017; Xia et al., 2024). These data allow researchers to directly characterize variations in heat load across different activity contexts and provide critical evidence for explaining inter-individual differences in SHS, for example, rapid changes in thermal conditions when moving between shaded and sunlit areas (Requena-Ruiz et al., 2025).

Overall, person-based OHS research integrates behavioral trajectories, environmental exposure, and physiological regulation processes to reveal the dynamic formation mechanisms of urban heat stress at the person-based level. Compared with city-scale analyses that describe background thermal conditions and street-scale studies that characterize spatial heterogeneity, person-based approaches focus on actual exposure in real activity contexts, providing a critical physical and physiological basis for understanding the formation of SHS.

3.3. Multi-level SHS measurement and modeling framework

Unlike OHS, which is structured around spatial scales defined by physical exposure conditions, SHS fundamentally reflects individuals' perceived experience of the thermal environment, including thermal sensation, thermal comfort, and related emotional responses. It is important to emphasize that the basic unit of observation in SHS is always individual perception. Differences across "scales" do not arise from distinct physical processes, but from different modes of spatial aggregation of individual perceptions.

In this sense, the individual, community, and city levels do not represent different types of SHS phenomena, but rather correspond to individual observations, localized spatial aggregation, and city-wide statistical representations, respectively. Specifically, the individual level focuses on immediate thermal experiences and perceptual differences (Martins Gnecco et al., 2023); the community level reflects the spatial clustering of individual perceptions within neighborhood units (Sha & Cheng, 2024); and the city level captures the overall distribution and collective expression of perceived heat across the urban area (Chen et al., 2024). This hierarchical framing aims to link individual-level perceptions with their spatial distribution patterns, thereby providing an operational framework for analyzing spatial mismatches between OHS and SHS.

Fig. 6 presents a human-centered synthesis of the main dimensions, typical data sources, and spatial representations of SHS across different aggregation levels, illustrating how individual thermal experiences are aggregated into collective spatial patterns. Based on this framework, the following sections examine the formation mechanisms of SHS and its measurement and modeling approaches across different levels of aggregation.

3.3.1. Individual-level SHS: perceptual and behavioral processes

Unlike person-based OHS, which describes the actual heat exposure experienced by individuals at the street level, individual-level SHS directly reflects subjective experiences of the thermal environment. Studies have shown that even under similar objective heat exposure conditions, substantial differences may exist in individuals' subjective evaluations. Such differences constitute an important source of structural divergence between OHS and SHS (Karjalainen, 2012; Potchter et al., 2018).

The formation of individual-level SHS is primarily shaped by cognitive and emotional processes that interpret environmental information. Factors such as emotional state, fatigue, prior experience, and environmental expectations can significantly modulate thermal perception (C. Lin & Zhang, 2025; Schweiker et al., 2020). For example, when actual experience deviates from expectations, perceived thermal discomfort may be amplified even under relatively stable objective conditions (Rissetto et al., 2022). Individuals experiencing anxiety or high cognitive load also tend to report stronger thermal discomfort (Özbey et al., 2025). In addition, populations accustomed to hot climates often exhibit higher thermal acceptability under similar conditions (X. Huang et al., 2023; Y. Lin et al., 2021). These findings suggest that SHS is not a direct response to physical heat exposure, but a subjective experience shaped by cognitive processing and emotional states.

It is important to note that, within this process, individual physiological responses (e.g., skin temperature, heart rate, and sweating rate), although closely related to thermal perception, are inherently measurable objective states and should be classified within the person-based exposure level of OHS. In this study, they are treated as mediating mechanisms linking environmental exposure and subjective perception, rather than components of SHS.

Similarly, individual behaviors (e.g., route adjustment, seeking shade, or modifying activity intensity) primarily reflect responses and adaptations to thermal discomfort, rather than direct measures of perception. They can instead be considered as indirect proxies for explaining perceptual differences. Individuals continuously modify their exposure through behavioral adjustments in real urban environments, such as entering shaded areas, changing walking speed, or temporarily staying in cooler locations (Levenson et al., 2025; Wen et al., 2025). Empirical evidence shows that even small changes in position or movement (e.g., transitions into shaded areas or changes in sky view factor) can lead to significant differences in heat stress, which may be

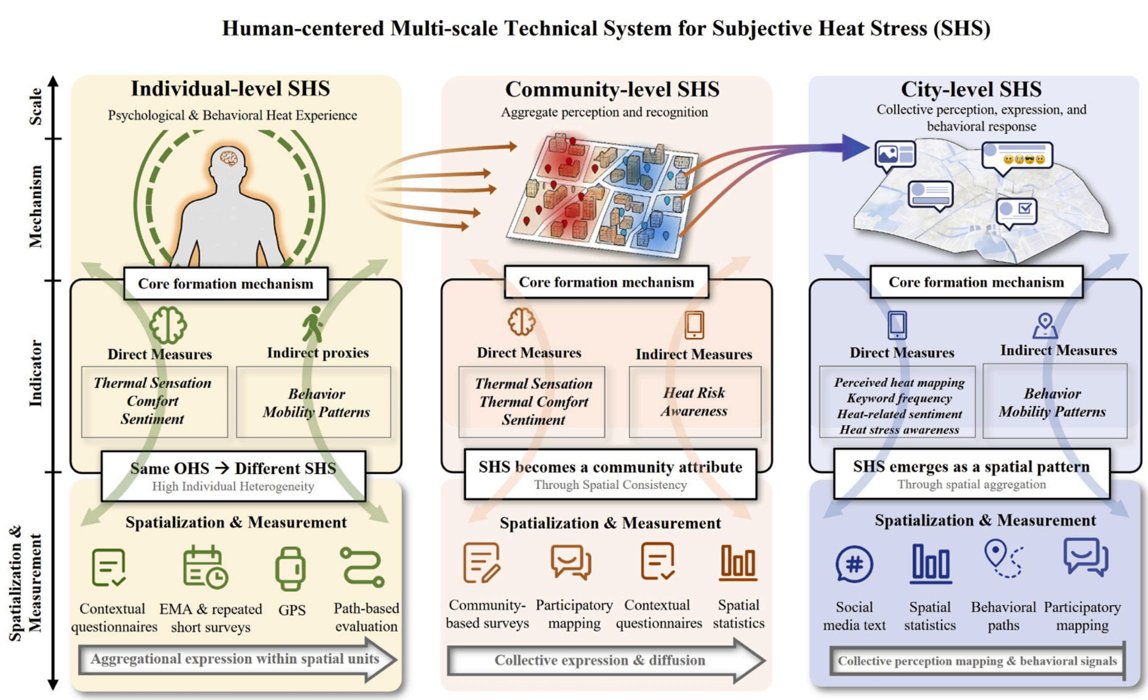

Fig. 6. Human-centered multi-scale technical system for SHS.

further amplified or mitigated by behavioral choices (Speak & Salbitano, 2022). For instance, areas with higher tree canopy coverage have been found to increase pedestrians' willingness to walk and improve thermal perception (Melnikov et al., 2022), while increased walking speed can elevate metabolic load and significantly intensify perceived thermal discomfort (Y. Zhang et al., 2024).

Taken together, individual-level SHS is not a direct projection of environmental exposure, but rather the outcome of continuous interactions between behavior and environment.

In terms of measurement and modeling approaches, individual-level SHS is primarily obtained through direct subjective reporting, which can be broadly categorized into three types. The first type involves standardized questionnaire-based scales (e.g., thermal sensation vote, comfort/discomfort, acceptability, and preference), typically collected through on-site intercept surveys or fixed-point investigations. These methods are cost-effective and allow for strong comparability across locations and populations (Broday et al., 2019; Cheung & Jim, 2019; W. Yang et al., 2013). However, they generally capture momentary perceptions at a single time point and are limited in their ability to represent dynamic changes during continuous exposure. They are also susceptible to non-thermal influences and therefore often require control for contextual variables such as activity type (Cohen et al., 2023; X. Li et al., 2022).

The second type is based on mobile device–enabled repeated sampling, commonly referred to as Ecological Momentary Assessment (EMA). By recording individuals' perceptions multiple times during daily activities, this approach captures temporal trajectories of perception for the same individual under varying conditions (Gallacher & Boehnke, 2025; Peng et al., 2022; Rodrigues & Cruz, 2025). Compared with single-time surveys, EMA is better suited for analyzing the cumulative effects of heat discomfort during prolonged exposure and its interaction with behavioral adjustments (Vellei et al., 2021). More broadly, SHS should not be interpreted only as an instantaneous response to current thermal conditions. Recent exposure history, acclimatization, prior heat experiences, and expectations may shape current perception through a form of thermal memory, in which previous heat exposure continues to influence perceived discomfort but gradually weakens over time. This suggests that future OHS–SHS linkage studies should incorporate repeated measurements, exposure histories, or time-lagged indicators, rather than relying solely on single-time thermal votes.

The third type is route-based segmental evaluation, in which participants are asked to move along predefined routes and repeatedly report their thermal sensation or discomfort at different spatial points. This approach directly links subjective perception to specific spatial environments and enables spatially explicit representation of individual-level SHS (Peng et al., 2022; Vasilikou & Nikolopoulou, 2020). It is particularly effective for examining the influence of micro-scale factors, such as street geometry and shading structures, on thermal experience (T. Zhao & Ma, 2025).

Overall, individual-level SHS represents a subjective experience centered on cognitive and emotional processes. Its measurement and modeling should be grounded in direct reporting, while its interpretation requires consideration of contextual factors and behavioral responses. Consequently, even under similar objective heat exposure conditions, substantial differences may exist between individuals, or within the same individual across different time periods. This variability constitutes a key source of inconsistency between OHS and SHS.

3.3.2. Community-level SHS: collective perception and socio-spatial differentiation

Compared with the individual level, which focuses on immediate subjective experience, community-level SHS emphasizes the aggregated expression of individual thermal perceptions within specific spatial units (Du et al., 2025). By aggregating dispersed individual perceptions at the neighborhood or community level, studies can identify spatially meaningful patterns of perception, thereby transforming individual-level experiences into spatial information relevant for planning and analysis (K. Li et al., 2016).

Existing studies show that when individual thermal perceptions exhibit stable spatial clustering, perceptual "hotspots" with planning relevance can be identified (Sha & Cheng, 2024). These hotspots do not simply correspond to areas of highest objective heat exposure, but are shaped and reconfigured by socio-spatial contexts (Lim et al., 2022). For example, communities with higher social vulnerability, stronger dependence on outdoor activities, or limited access to cooling resources may consistently report higher levels of heat discomfort, even when their objective heat exposure is not the highest (Ji et al., 2024). In contrast, areas with better shading conditions or higher-quality public spaces may exhibit lower SHS under similar or even less favorable meteorological conditions (Lai et al., 2014; Oliveira et al., 2014).

These findings indicate that community-level SHS reflects a redistribution of individual perceptions shaped by both social structure and spatial conditions, rather than representing a distinct heat stress mechanism independent of individual experience.

In terms of measurement and modeling, community-level SHS is primarily derived through the spatial aggregation of individual subjective data. Two main approaches are commonly used. The first involves questionnaire-based and context-specific surveys conducted within defined spatial units (e.g., neighborhoods or districts), embedding indicators such as thermal sensation, discomfort, and risk perception into structured spatial sampling frameworks to obtain spatially representative perception data (Haque et al., 2012; L. Li et al., 2025; W. Wang et al., 2023). The second approach involves participatory mapping and spatial annotation, where residents identify locations perceived as "hotter" or "cooler," enabling the detection of experiential differences that may not be directly captured by physical heat metrics (Delina et al., 2025).

At the analytical level, studies typically apply spatial statistics, hotspot analysis, and spatial autocorrelation tests to aggregated perception data, while distinguishing between individual-level and community-level variation to avoid misinterpreting sample composition effects as spatial patterns. Overall, the key contribution of community-level SHS lies in revealing how individual perceptions are amplified or moderated within socio-spatial structures, thereby providing a basis for identifying thermal inequities and informing targeted interventions.

3.3.3. City-level SHS: collective expression and representation

At the city level, SHS does not constitute a phenomenon independent of individual perception, but represents the spatial aggregation and expression of subjective thermal experiences at a large scale. Existing studies indicate that individual thermal perceptions vary significantly across urban space, and their distribution does not always align with objective heat exposure, but is jointly shaped by daily activity patterns, spatial contexts, and social cognition (Lane et al., 2014; Ruddell et al., 2012). Therefore, city-level SHS should be understood as the aggregated outcome of individual perceptions under socio-spatial processes, rather than a direct mapping of the physical thermal environment.

Unlike individual- and community-level studies, which can rely more directly on subjective reports, city-level studies often lack continuous and spatially comprehensive perception data. As a result, SHS at this scale is typically inferred through multi-source data, shifting the key question from "how to measure perception itself" to "how to reconstruct its spatial distribution using heterogeneous data sources." Early studies primarily relied on large-scale questionnaires or online surveys to derive city-wide perception patterns, but these approaches were limited in temporal continuity and spatial coverage (Cheung & Jim, 2018; Pantavou et al., 2013). With the development of digital platforms, social media text, participatory sensing data, and mobility trajectories have been introduced to address these limitations (Cecinati et al., 2019; Lehnert et al., 2023; Murakami et al., 2016).

However, these data sources do not represent the same type of "perception." Questionnaire and participatory sensing data can directly capture subjective experiences within specific spatiotemporal contexts and are therefore closer to spatial extensions of individual-level SHS (Potchter et al., 2018). In contrast, social media text reflects expressive behavior related to thermal environments and is influenced by communication intent and contextual framing (Soomro et al., 2025), while mobility or GPS-based data primarily capture adaptive behavioral responses to heat rather than perception itself (Kumakura et al., 2023). Therefore, city-level SHS is not directly observed from a single data source, but reconstructed indirectly through multiple types of information.

These data sources play complementary roles in representing city-level SHS. Participatory sensing can reveal perceived thermal differences by allowing residents to identify locations perceived as "hotter" or "more comfortable" (Bano et al., 2025). Areas identified as highly uncomfortable often correspond to public spaces where exposure is difficult to mitigate, while shaded or resting facilities are perceived as important buffers against heat discomfort (Delina et al., 2025; Lehnert et al., 2023). Social media, by contrast, is widely used to characterize the temporal dynamics and spatial distribution of heat perception because of its large volume, high update frequency, and explicit emotional expression (R. Xu et al., 2025). During heatwave periods, online discussions related to high temperatures often increase and exhibit temporal patterns aligned with urban activity rhythms (Young et al., 2021), with texts containing direct or implicit expressions of heat-related experiences, such as feelings of heat, fatigue, and restrictions on outdoor activities (P. Zhang et al., 2026).

The "perceptual hotspots" identified from such data are often concentrated in areas with high human activity, rather than strictly corresponding to locations with the highest objective heat exposure (Q. Liu & Hang, 2025), revealing the socially embedded and context-dependent nature of thermal experience. In recent years, Transformer-based language models have further improved the detection of implicit expressions of heat perception, enabling SHS to be represented in a more continuous manner at the city level (Che et al., 2025; He et al., 2026). Despite these advantages, social media data more closely reflect "expressed perception" rather than complete individual experience. Their spatial distribution is influenced not only by actual thermal perception, but also by user demographics, expression tendencies, and platform usage patterns (Q. Liu & Hang, 2025). In addition, some highly exposed or vulnerable populations may not participate in online expression, and natural language processing methods still face uncertainties in semantic interpretation and contextual understanding (He et al., 2026). The former limitation reflects a broader digital divide in SHS assessment. Older adults, low-income groups, outdoor workers, migrants, and people with limited digital access may be less visible in social media data, even though they may experience higher thermal vulnerability. Consequently, social media–based SHS maps should not be interpreted as representative maps of the entire urban population, but rather as spatial patterns of digitally expressed heat perception that require validation or calibration with surveys, participatory mapping, demographic data, or field observations. At present, systematic validation of social media–based SHS against concurrent survey data remains limited, indicating that its reliability in representing SHS requires further examination.

Similarly, behavioral data provide valuable city-level insights, but primarily reflect adaptive responses to thermal environments rather than perception itself. Under high-temperature conditions, individuals may reduce travel, adjust activity timing, or modify route choices to mitigate heat exposure (Ly et al., 2023; Tian et al., 2024). Although such patterns reveal how heat affects activity structures, they do not directly correspond to the intensity of subjective thermal perception (Zou et al., 2025). Therefore, at the city level, behavioral data are better suited for interpreting perception patterns than for directly representing SHS.

Overall, the measurement and modeling of city-level SHS relies on the indirect reconstruction of individual perceptions through multi-source data. The key challenge lies in the fact that different data sources capture different dimensions of perception. By distinguishing between direct perception, expressive behavior, and adaptive responses, and by integrating multiple data sources, it is possible to improve the interpretability of SHS at the city level and provide a more robust basis for understanding spatial mismatches between OHS and SHS.

3.3.4. Ethical constraints and data bias in SHS measurement

The use of emerging SHS data sources also raises ethical and governance concerns. Social media, mobility traces, participatory platforms, and wearable sensing can improve the spatial and temporal granularity of thermal perception research, but they also involve issues of consent, privacy, representativeness, and unequal participation (boyd & Crawford, 2012; Zook et al., 2017). Social media data are often publicly accessible, yet they are not necessarily produced for research purposes and should therefore be anonymized, aggregated, and interpreted cautiously (Williams et al., 2017). Mobility and GPS traces are more sensitive because they may reveal daily routines, home and workplace locations, and activity spaces. Wearable sensing and physiological monitoring require stronger safeguards, as they involve bodily responses and potentially sensitive personal characteristics.

These data sources may also underrepresent vulnerable groups. Social media users are often younger, more digitally active, and socioeconomically selective, while older adults, low-income groups, outdoor workers, migrants, and people with limited digital access may be less visible (Blank, 2017; Hargittai, 2020). Similarly, participatory and wearable sensing studies often rely on small volunteer samples. Therefore, SHS indicators derived from digital or sensor-based data should be treated as partial and context-dependent expressions rather than direct representations of the whole urban population. Responsible use requires anonymization, aggregation, clear consent where needed, validation with complementary data, and explicit reporting of uncertainty and population bias.

3.4. Comparative methodological robustness and trade-offs

Across OHS and SHS studies, methodological robustness depends on the alignment among observation unit, spatial scale, temporal resolution, and inferential purpose, rather than on the indicator or data source alone. For OHS, city-scale mapping is useful for identifying background thermal-risk patterns but remains limited in representing pedestrian-level exposure. Street-scale measurements and simulations better capture radiation–ventilation heterogeneity and design-relevant mechanisms, although their transferability across urban contexts is limited. Person-based sensing and physiological monitoring provide closer approximations of actual exposure and heat strain, but are constrained by small samples, high cost, participant burden, and limited generalizability.

For SHS, direct perception-based methods, including in-situ questionnaires, EMA/ESM, and thermal walks, provide stronger validity for individual-level thermal experience because they record subjective responses close to the time and location of exposure, but their spatial coverage and scalability are limited. Participatory mapping and social media data are more suitable for identifying collective or spatially aggregated patterns of perceived heat, while remaining vulnerable to recall bias, demographic bias, expression bias, and semantic uncertainty. Mobility and GPS data should be interpreted cautiously because they primarily reflect behavioral adaptation rather than SHS itself. Therefore, no single method is universally superior; each supports different inferential targets. Detailed comparisons of OHS and SHS approaches are provided in Supplementary Tables S1 and S2.

4. Bridging OHS and SHS across scales: toward an integrated heat experience framework

The preceding sections demonstrate that OHS and SHS differ systematically in both their formation mechanisms and modes of observation, yet together they constitute the actual thermal experience of urban residents. Reliance on either physical exposure or subjective perception alone may therefore lead to a partial understanding of urban heat risk. In particular, current research often lacks the critical intermediate layer of individual physiological response, resulting in a structural disconnect between environmental conditions and perceived experience.

Against this background, this section provides a cross-scale synthesis of the divergence between OHS and SHS, summarizing their spatial mismatches and underlying mediating processes, and further discusses potential pathways for multi-source integration and urban heat governance.

4.1. Why objective and subjective heat stress diverge

Understanding the divergence between OHS and SHS requires recognizing that they are not different measurements of the same thermal process, but distinct components within a hierarchical system. Based on the definitions established in previous sections, urban thermal experience can be conceptualized as a three-stage process: environmental conditions – physiological response – perceptual experience. Within this framework, OHS primarily corresponds to the objective representation of the first two components, whereas SHS reflects the final perceptual experience. Therefore, OHS–SHS mismatch should not be interpreted simply as a measurement or modeling error, but as a consequence of incomplete observation and modeling of this multi-layered system (Liu & Hang, 2025).

At the environmental level, OHS is typically represented by thermal variables or integrated indices, such as UTCI, which describe thermal conditions at a given location and time. These indicators effectively characterize the spatial structure of urban thermal environments, but they represent external environmental states or model-based estimates for a standardized individual, rather than the actual heat load experienced by specific individuals (Fiala et al., 2012). Moreover, OHS often captures thermal conditions at specific points in space and time, whereas SHS is more closely related to the integrated experience of a continuous exposure episode, incorporating duration, attention, and contextual factors (Lam et al., 2018). Thus, OHS describes “how hot the environment is at a given place and time,” whereas SHS reflects “how hot it feels during the experience.” Differences in spatiotemporal sampling and exposure units make a one-to-one correspondence between the two difficult at the observational level (Květoňová et al., 2024).

Between environmental conditions and perception, individual physiological response constitutes a critical but often underrepresented mediating layer. Individuals may respond differently to the same environmental conditions due to variations in age, health status, acclimatization, and metabolic rate. Although physiological variables such as skin temperature, heart rate, and sweating rate can directly reflect actual heat load, they are rarely systematically observed in urban-scale studies. Instead, most studies rely on integrated indices based on a “standard individual,” such as UTCI or PET, to approximate physiological responses, leaving a critical gap between environmental conditions and subjective perception (Kacker et al., 2024; Yang et al., 2026). This under-observed physiological layer therefore constitutes a central mechanism underlying OHS–SHS mismatch.

Individual behavior further modulates thermal experience by altering actual exposure pathways. People may adjust travel time, route choice, or dwelling locations in response to high temperatures, leading to deviations between experienced environmental conditions and their static spatial distributions (Batur et al., 2024). Behavior does not constitute perception itself, but indirectly influences subsequent physiological and perceptual processes by modifying exposure conditions.

Finally, the perceptual layer is shaped by psychological and contextual factors. Thermal discomfort depends not only on physiological load, but also on emotional state, expectations, and environmental context. Even under similar physiological conditions, individuals may report different thermal perceptions due to variations in psychological state or environmental appraisal (Lin & Zhang, 2025). This “irreducibility of perception” implies that divergence between OHS and SHS would still persist to some extent even with complete physiological observation.

Together, these mechanisms produce structured spatial patterns of OHS–SHS mismatch. The spatial distribution of SHS does not simply follow the physical gradients of OHS, but is shaped by human activity, space use, exposure pathways, and perceptual context. As a result, areas that are physically the hottest do not necessarily correspond to those perceived as most thermally uncomfortable at the urban scale.

4.2. A human-centered framework for interpreting ohs–shs mismatch

Building on the above analysis, urban thermal experience should not be understood as a linear mapping from OHS to SHS, but rather as a hierarchical process shaped by multiple interacting mechanisms. As shown in Fig. 7, the proposed framework integrates three analytically distinct but connected layers: environmental conditions, physiological responses, and perceptual experience. Rather than replacing existing thermal comfort, exposure science, or urban climate models, this framework reorganizes these established perspectives around the specific problem of OHS–SHS mismatch. Its added value lies in clarifying where divergence may emerge when objective thermal environments are transformed into subjective thermal experience.

The first component is the environmental conditions layer, grounded in multi-scale microclimatic processes. It characterizes the potential heat load imposed by urban environments across different scales and corresponds to environmental variables and standardized representations commonly used in OHS studies. The second component is the physiological response layer, which acts as a critical but often under-observed mediator. This layer reflects individuals’ actual heat strain under specific environmental conditions, including thermoregulation, metabolic load, and other bodily responses, and represents the transformation process linking environmental exposure to subjective perception. Notably, this layer does not require all urban-scale studies to collect direct physiological data at the population level; rather, it can be implemented according to research scale and data availability. In large-scale studies, biometeorological indices such as PET, UTCI, and WBGT can provide model-based approximations of potential physiological heat strain, whereas smaller field studies can use wearable sensing, physiological monitoring, thermal walks, or controlled field experiments for targeted validation. When individual-level data are available, physiological indicators such as skin temperature, heart rate variability, and sweating rate can be linked with GPS trajectories and subjective reports. Therefore, the physiological response layer is intended to guide how the otherwise unobserved body-level mediation can be approximated, validated, or directly measured, rather than to prescribe a universal data-collection requirement. The third component is the perceptual experience layer, shaped by cognitive processing, emotional state, prior experience, and contextual factors. This layer translates physiological and environmental inputs into perceivable thermal sensations, comfort evaluations, emotional reactions, and expressive outcomes, corresponding to the core of SHS.

Within this framework, individual behavior dynamically regulates exposure pathways through movement patterns, dwelling behavior, route choice, and avoidance strategies. In this sense, behavior resamples continuous environmental heat fields into differentiated exposure experiences across individuals, thereby modulating the relationship between environmental conditions and physiological responses. Meanwhile, social and psychological factors influence the transformation from physiological states to perceptual experience, such that similar levels of heat load may generate different subjective evaluations or expressions. Therefore, OHS–SHS mismatch may arise not only from measurement uncertainty, but also from differences in observation

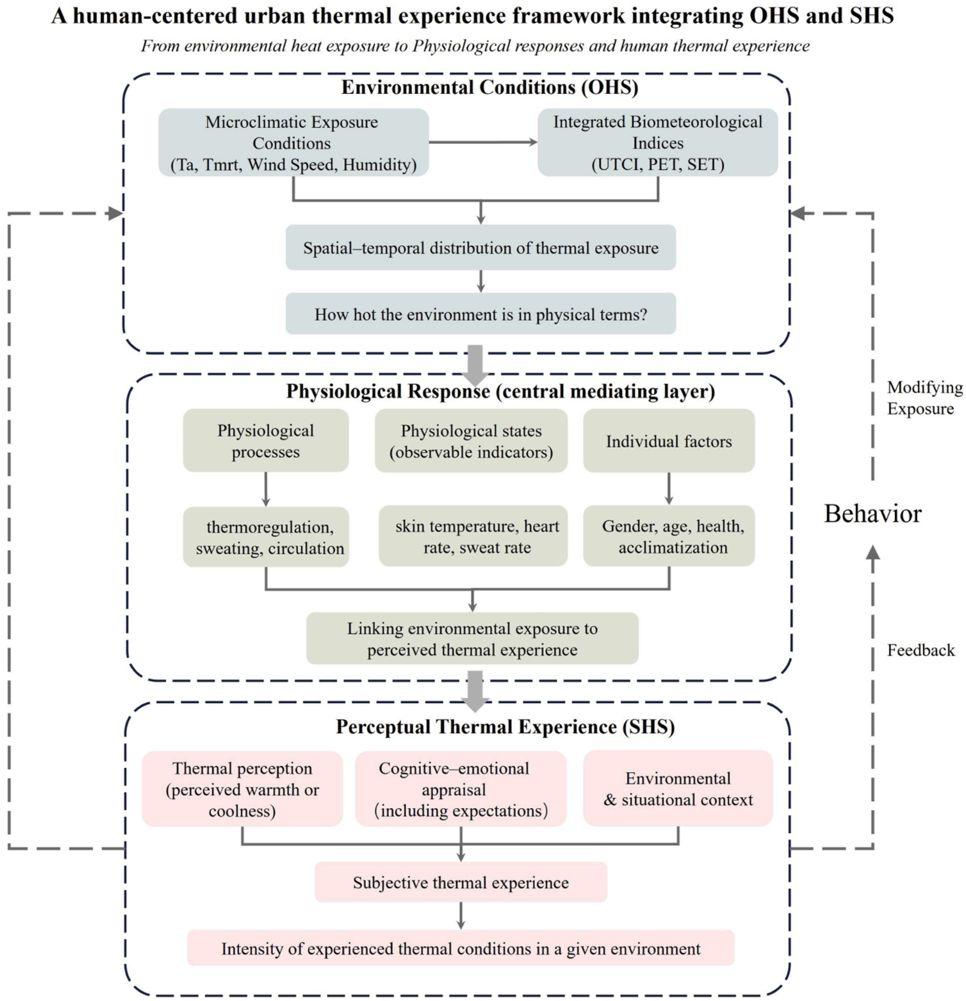

Fig. 7. A human-centered framework linking Objective and Subjective Heat Stress.

units, scale-dependent representations of heat processes, insufficient observation of physiological mediation, and contextual variation in perception and expression.

This layered structure provides a basis for more explicit analytical linkages between OHS and SHS. First, it supports cross-scale validation by comparing city- or street-scale OHS estimates with person-based physiological observations and individual-level perceptual reports. Second, it enables mismatch-oriented metrics, such as areas with high modeled OHS but low reported discomfort, or areas with strong perceived heat expression but moderate modeled OHS. Third, it supports the integration of conventional measurements with emerging data sources, including wearable sensors, GPS trajectories, participatory mapping, and social media text. Importantly, this framework should not be understood as a simple juxtaposition of scale-specific studies, nor as a single model that directly converts micro-scale physical simulations into city-scale social perception. Its cross-scale logic lies in person-based exposure pathways: spatially explicit OHS fields can be assigned to individuals through their locations, trajectories, activity timing, and behavioral choices; these estimates can then be linked with physiological proxies, thermal votes, EMA records, or social media expressions, and further aggregated to community or city scales. Thus, cross-scale coupling is achieved through exposure assignment, person-based validation, and spatial aggregation, rather than through direct causal equivalence between physical heat-exchange models and macro-scale social indicators.

From a governance perspective, distinguishing physical heat hotspots from perceived heat hotspots is important because they may require different adaptation strategies, ranging from microclimate-oriented interventions to behavioral guidance, risk communication, and socially targeted adaptation. In this sense, OHS and SHS are not separate domains, but different components within the same hierarchical process: OHS represents environmental conditions, standardized indices, and objectively measurable physiological responses, whereas SHS represents perceptual and expressive outcomes. Integrating them within a unified framework can therefore provide a clearer explanation of OHS–SHS mismatch and support more human-centered urban heat governance.

4.3. *From framework to practice: multi-source integration and governance implications*

Within the human-centered thermal experience framework outlined above, an operational OHS–SHS integrated assessment system does not require eliminating the differences between objective and subjective dimensions. Instead, it should integrate diverse types of information within a unified hierarchical structure. Environmental data characterize the spatial background and intensity of urban heat exposure; physiological data help operationalize the mediating layer between environmental exposure and subjective experience; and perceptual data reflect individuals' subjective experience of heat and its social expression. Wearable indicators, such as skin temperature, heart rate, heart-rate variability, and sweating-related responses, can be linked with GPS trajectories, microclimate measurements, and subjective reports to examine whether similar environmental exposures generate different bodily responses and whether these responses correspond to reported thermal sensation, discomfort, or behavioral adaptation. Recent work on urban chronotypes, for example, illustrates how climatic conditions, physiological and behavioral responses, and adaptive behavior can be jointly examined to identify differentiated patterns of climate vulnerability across diurnal urban contexts (Grapas et al., 2026). Therefore, the core of multi-source integration lies in capturing complementary observations of this layered process, rather than relying on a single indicator to represent complex human responses (Gallacher & Boehnke, 2025).

Methodologically, this integration can follow two broad pathways. The first is a physics-informed approach, in which behavioral and perceptual information is incorporated to refine and calibrate OHS representations (Lai et al., 2020). The second is a data-driven approach, which reconstructs urban-scale thermal experience patterns by jointly leveraging environmental and perceptual signals (C. Wu et al., 2023). In both pathways, it is essential to distinguish the roles and meanings of different data types, avoid directly substituting behavior or expression for perception, and reduce structural bias introduced by single data sources.

At the planning and governance level, this framework shifts heat adaptation from identifying "where it is hottest" toward understanding "who experiences greater thermal stress, and under what conditions." Integrating environmental conditions with subjective feedback in early warning systems, spatial interventions, and public health measures can help address uneven heat risks across populations and urban spaces. With the rapid development of sensors, mobility data, and participatory platforms, joint observation of environmental conditions and perception is becoming increasingly feasible, supporting more context-sensitive and equity-oriented heat governance.

To make this governance pathway more operational, Fig. 8 illustrates a workflow for translating SHS into planning-relevant metrics. At the city scale, SHS maps derived from surveys, participatory mapping, or heat-related social media expressions can be overlaid with modeled OHS maps to identify mismatch patterns, including high OHS–high SHS hotspots, high OHS–low SHS under-perceived risk areas, low OHS–high SHS perceived-discomfort areas, and low OHS–low SHS low-priority areas. These patterns can guide the selection of priority neighborhoods and be converted into indicators such as the OHS–SHS mismatch index, hotspot overlap ratio, perceived-discomfort intensity, activity density, and population-weighted risk. Within these neighborhoods, street-level diagnosis can examine physical causes of mismatch using microclimate simulation, street-view indicators, sky view factor, shading, greenness, ventilation, and PET/UTCI, while individual-level data such as GPS trajectories, activity timing, thermal votes, EMA records, and wearable sensing can validate whether street-level OHS is translated into actual exposure and perceived discomfort. The resulting evidence can then refine neighborhood priorities, city-wide mismatch maps, and design-scenario assessments involving shading, greening, cool materials, or ventilation improvements. In this sense, SHS can serve not only as a descriptive perception layer, but also as a planning-relevant metric for prioritizing interventions, identifying overlooked risk areas, comparing design scenarios, and evaluating whether cooling strategies improve both physical exposure and perceived thermal experience.

Overall, integrating OHS and SHS within a unified framework extends urban heat research from environmental measurement toward a more comprehensive understanding of human thermal experience, providing a theoretical and methodological basis for explaining OHS–SHS mismatch and informing urban heat governance.

5. Future directions

This review integrates OHS and SHS within a human-centered thermal experience framework, highlighting the layered relationships among environmental conditions, physiological responses, and perceptual experience. However, the current research landscape remains fragmented, limiting a systematic understanding of how thermal experience is formed and how urban heat governance can move from environmental measurement toward an experience-oriented perspective. Future research should further develop this layered system through advances in data, methods, cross-scale mechanisms, and applications.

First, the incompleteness of the layered observation system remains a key bottleneck. While environmental thermal data are relatively well established, individual physiological responses are rarely observed directly at the urban scale and are often approximated by standardized indices, creating a critical gap between environmental conditions and subjective perception (Elnabawi & Hamza, 2024). Meanwhile, SHS data are diverse but lack a unified structure, limiting cross-city comparability (Y. Li, Fei et al., 2025; Silva et al., 2024). Future work should develop integrated, cross-platform, and cross-city thermal experience databases with clearly defined correspondences among data types.

Second, modeling frameworks that bridge environmental,

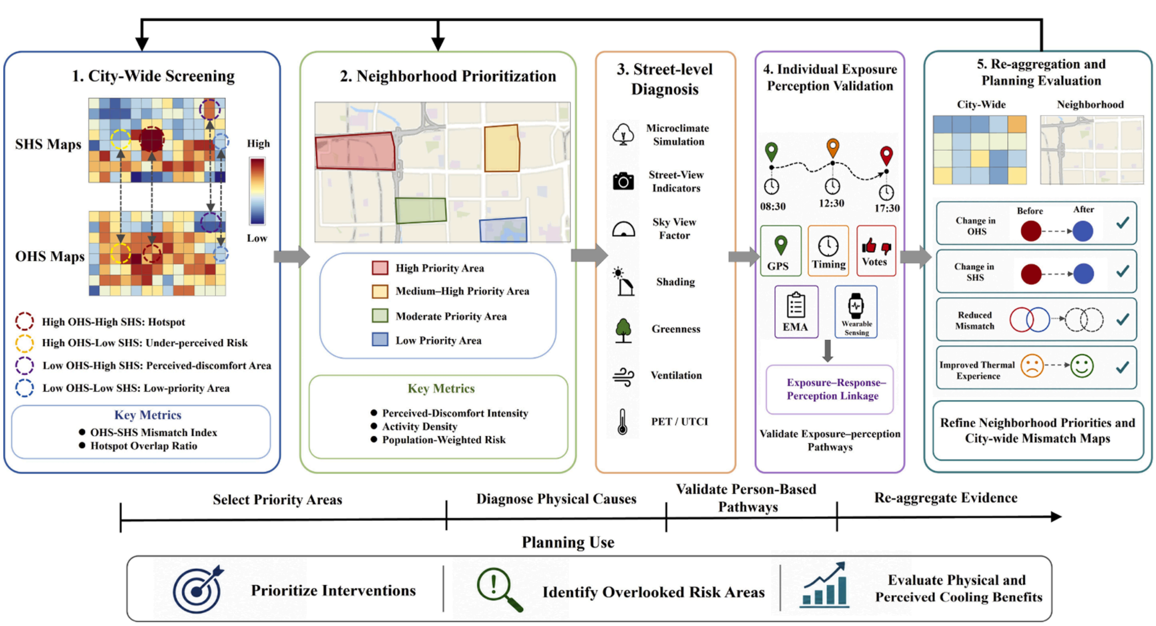

Fig. 8. Illustrative workflow for translating SHS into planning-relevant metrics.

physiological, and perceptual processes remain insufficient (Younes & Khovalyg, 2025; Zendeli et al., 2026). Existing approaches often focus either on physical processes or perceptual expression, making it difficult to capture the transformation mechanisms between them. Future research should develop multi-modal and multi-scale models that preserve physical consistency, explicitly represent the physiological layer as a mediator, and incorporate behavioral regulation of exposure pathways.

Third, cross-scale transformation mechanisms in urban thermal environments require further investigation. Although this study explains OHS–SHS divergence from a layered perspective, how street-scale microclimatic differences translate into perception through individual exposure and physiological response, and how city-scale thermal patterns are aggregated into SHS distributions, remain open questions. These issues could be addressed through experimental designs, quasi-experimental approaches, and cross-city comparative studies.

Finally, experience-oriented urban heat governance still lacks a systematic evaluation framework. Current policies are largely based on OHS indicators and have not sufficiently incorporated individual perception and contextual variation (Y. Zhang et al., 2025). Future efforts should integrate SHS into early warning systems and spatial-intervention evaluation, quantify combined environmental and perceptual effects, and account for differences in exposure and adaptive capacity across population groups to support more equitable and targeted heat adaptation.

Overall, the unified OHS–SHS framework provides an analytical basis for understanding urban thermal experience. With advances in observation technologies, modeling approaches, and interdisciplinary research, urban heat studies can move beyond single-indicator assessments toward a more integrated and human-centered system.

6. Conclusion

Urban heat stress has become a critical challenge for urban sustainability and public health. Existing research has largely been grounded in an environment-centered paradigm, representing heat risk through spatial distributions of thermal conditions across points or grids. While this approach provides a fundamental basis for characterizing urban thermal environments, it remains limited in explaining actual human thermal experience, which emerges from the interaction of environmental exposure, individual response, behavioral regulation, and cognitive processing.

This review systematically examined multi-scale measurement and modeling approaches for OHS and SHS and revealed a fundamental disconnect within the current research framework. OHS studies have extensively characterized physical heat processes across scales, from street-level radiation–ventilation heterogeneity to city-scale thermal patterns and broader meteorological conditions. However, they primarily describe environmental conditions and standardized representations of heat stress, with limited capacity to capture individual-level responses. In contrast, SHS reflects subjective experience, including thermal sensation, comfort, and emotional responses, and varies substantially across individuals, spaces, and contexts. Existing evidence therefore suggests that SHS cannot be directly inferred from OHS.

Based on this synthesis, this review emphasizes that OHS–SHS divergence should not be interpreted simply as measurement error, but as a structural property of a layered system. The transformation from environmental conditions to physiological responses and perceptual experience, together with behavioral and socio-contextual factors, produces systematic mismatches across space and time. Consequently, physically hottest areas do not necessarily correspond to the locations perceived as most thermally uncomfortable.

To address this issue, the review proposes a human-centered thermal experience framework based on the sequence of Environmental Conditions – Physiological Response – Perceptual Experience. By positioning physiological response as a key mediating layer, the framework clarifies the roles of objective representations and subjective experience within a unified system, and provides a basis for integrating OHS models, SHS data, and multi-source observations.

Methodologically, the increasing availability of wearable sensors, mobility data, participatory mapping, social media text, and environmental observations creates new opportunities for joint OHS–SHS analysis. The value of such integration lies not only in technical advancement, but also in improving the completeness and interpretability of thermal experience assessment. From an application perspective, the proposed framework supports a shift in urban heat governance from identifying “where heat load is highest” toward understanding “which populations experience greater thermal stress, and under what conditions.” Incorporating subjective experience alongside environmental indicators can improve early warning systems, intervention assessment, and the identification of vulnerable populations and critical spaces.

Overall, by unifying the conceptual frameworks of OHS and SHS, clarifying the mechanisms underlying their divergence, and proposing a layered integration pathway, this review advances urban heat research from environmental measurement toward a more comprehensive understanding of human thermal experience. This perspective can support healthier, more equitable, and more resilient cities.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to improve English grammar and language clarity. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Data availability

Data will be made available on request.

CRediT authorship contribution statement

Pingge He: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Bingjie Yu:** Validation, Software. **Lei Han:** Validation, Software, Investigation. **Chuanwang Hua:** Formal analysis, Validation. **Nicola Colaninno:** Writing – review & editing, Methodology, Investigation, Conceptualization, Supervision.

Declaration of competing interest

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

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2026.107668.

Appendix

(Table A1)(Table A2)

Table A1
OHS-related literature statistics.

Cite	Location	Journal	Year	Indicator	Data source	Estimation approach	Scale
(Gulyás et al., 2006)	Hungary	Building and Environment	2006	PET	Field observation	RayMan	Street
(Mayer et al., 2008)	Germany	Meteorologische Zeitschrift	2008	PET	Field observation	RayMan	Street
(Eldrandaly, 2011)	Saudi Arabia	Journal of Environmental Informatics	2011	Ta	Meteorological station	Spatial interpolation	City
(Andreou, 2013)	Not specified	Renewable Energy	2013	PET	Field observation	RayMan	Street
(Lee et al., 2013)	Germany	Advances in Meteorology	2013	Tmrt/PET	Field observation	Point-based exposure assignment + RayMan	Street
(Dai & Schnabel, 2014)	Netherlands	Architectural Science Review	2014	Tmrt	Field observation	SOLWEIG	Street
(Ketterer & Matzarakis, 2014)	Germany	Landscape and Urban Planning	2014	PET/UTCI	Meteorological station	RayMan and ENVI-met	Street
(Paolini et al., 2014)	Italy	In A. Haberle (Ed.)	2014	UTCI	Meteorological station data + field observation	UCP + HMT + CFD + RayMan	Street
(Acero & Herranz-Pascual, 2015)	Spain	Building and Environment	2015	PET	Field observation	ENVI	Street
(Coutts et al., 2016)	Australia	Theoretical and Applied Climatology	2016	UTCI	Meteorological station	Point-based exposure assignment	Street
(Thom et al., 2016)	Australia	Urban Forestry & Urban Greening	2016	Tmrt	Meteorological station data + field observation	SOLWEIG	Street
(De & Mukherjee, 2017)	India	Environmental and Climate Technologies	2017	PET	Field observation	ENVI	Street
(Meier et al., 2017)	Germany	Urban Climate	2017	Ta	Citizen weather station	Point-based exposure assignment	City
(Kantor et al., 2018)	Hungary	Landscape and Urban Planning	2018	PET	Wearable sensors	Point-based exposure assignment	Street
(Fenner et al., 2019)	Germany	Environmental Research Letters	2019	Ta	Citizen weather station	Point-based exposure assignment	City
(Lee et al., 2019)	Not specified	International Journal of Biometeorology	2019	Ta/Tmrt/PET	Numerical simulation	ENVI	Street
(Shin & Yi, 2019)	South Korea	Atmosphere	2019	Ta	Meteorological station	Machine learning	City
(Deng & Wong, 2020)	China	Sustainable Cities and Society	2020	PET	Numerical simulation	ENVI + RayMan	Street
(Park et al., 2020)	South Korea	Atmosphere	2020	Ta	Field observation	Point-based exposure assignment	Street
(Venter et al., 2020)	Norway	Remote Sensing of Environment	2020	Ta	Citizen weather station	Machine learning	City
(Yin et al., 2020)	United States	Computers Environment and Urban Systems	2020	Ta	Mobile monitoring	Machine learning	City
(X. Zhao et al., 2020)	China	Energies	2020	Tmrt	UAV	Point-based exposure assignment	Street
(Cao et al., 2021)	China	Landscape and Urban Planning	2021	Ta	Meteorological station	Point-based exposure assignment	City
(Wong et al., 2021)	Singapore	Urban Climate	2021	Ta	Numerical simulation	WRF	Street
(Y. Wu et al., 2021)	Canada	Geophysical Research Letters	2021	Ta	Numerical simulation	Numerical simulation + deep learning	City
(Nazarian et al., 2021)	Singapore	Environmental Research Letters	2021	heart rate/skin temperature	Wearable sensors	Point-based exposure assignment	Person-based
(Zumwald et al., 2021)	Switzerland	Urban Climate	2021	Ta	Citizen weather station	Machine learning	City
(Yeom, 2021)	South Korea	Environmental Monitoring and Assessment	2021	Ta	Mobile monitoring	Point-based exposure assignment	City
(Lam et al., 2021)	China	Building and Environment	2021	Skin temperature/ heart rate	Wearable sensors	Point-based exposure assignment	Individual
(Li et al., 2022)	China	Sustainable Cities and Society	2022	UTCI/ Skin temperature	Field measurement	Point-based exposure assignment	Person-based
(Bilang et al., 2022)	Philippines	Atmosphere	2022	Ta	Meteorological station	WRF	City
(Colaninno & Morello, 2022)	Italy	Urban Climate	2022	Ta	Meteorological station	Spatial regression model	City
(Kim et al., 2022)	South Korea	Remote Sensing	2022	Ta	Meteorological station	Machine learning + deep learning	Street
(Pioppi et al., 2022)	United States	Solar Energy	2022	Ta/Tmrt	Wearable sensors	Point-based exposure assignment	Person-based

(continued on next page)

Table A1 (*continued*)

Cite	Location	Journal	Year	Indicator	Data source	Estimation approach	Scale
(Xu et al., 2022)	China	Building and Environment	2022	skin temperatures/ tympanic temperature	Wearable sensors	Point-based exposure assignment	Person-based
(Xiong et al., 2022)	China	Urban Climate	2022	Ta/Tmrt/PET/UTCI	Field observation	Point-based exposure assignment	Street
(Zhang et al., 2022)	China / United States	Remote Sensing	2022	Ta	Meteorological station	Deep learning	City
(Zhu et al., 2022)	China	Case Studies in Thermal Engineering	2022	skin temperature/ oxygen saturation/ heart rate	Wearable sensors	Point-based exposure assignment	Person-based
(Afshari et al., 2023)	Germany	Remote Sensing	2023	Ta	Numerical simulation	Deep rest	City
(Cardenas-Jiron et al., 2023)	Chile	Urban Climate	2023	PET	Meteorological station	RyMan	Street
(Ding et al., 2023)	China	Building and Environment	2023	Ta	Meteorological station	Spatial interpolation	City
(Geletič et al., 2023)	Czech Republic	Building and Environment	2023	UTCI	Numerical simulation	CFD	Street
(Wu et al., 2023)	China	Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing	2023	temperature-humidity index	Meteorological station	Machine learning	City
(Blizer et al., 2024)	Israel	Remote Sensing	2024	Ta	Meteorological station	Machine learning	City
(Briegel et al., 2024)	Germany	Geoscientific Model Development	2024	UTCI	Meteorological station	Machine learning	City
(Chajaei & Bagheri, 2024)	Netherlands	Urban Climate	2024	Ta	Numerical simulation (UrbClim)	Machine learning	City
(Cureau et al., 2024)	Italy	Environmental Research	2024	PET	Field measurement + wearable sensors	Spatial interpolation	City
(Kotharkar et al., 2024)	India	Sustainable Cities and Society	2024	others (heat stress index)	Meteorological station	Point-based exposure assignment	City
(Zafarmandi et al., 2024)	Iran	Sustainable Cities and Society	2024	UTCI/PET	Field measurement	Point-based exposure assignment	Person-based
(Singh et al., 2024)	India	Sustainable Cities and Society	2024	PET	Field measurement	Point-based exposure assignment	Person-based
(Colaninno et al., 2025)	Spain	Sustainable Cities and Society	2025	Tmrt	Field observation	SOLWEIG	Street
(Cureau et al., 2025)	United States	Energy and Buildings	2025	PET	Field observation	RayMan + PUCM + LHEB / JOS-3 (numerical simulation)	Street
(Ma, Chau et al., 2025)	China	Architectural Science Review	2025	PET	Numerical simulation	ENVI	Street
(Wu et al., 2025)	China	Sustainable Cities and Society	2025	Skin temperature	Wearable sensors	Point-based exposure assignment	Person-based
(Ma, Zeng et al., 2025)	China	Building and Environment	2025	Tmrt	Numerical simulation	Deep learning	Street
(Nath & Deka, 2025)	India	Environmental and Sustainability Indicators	2025	PET	Field observation	Spatial interpolation	City
(Qin et al., 2025)	China	Sustainable Cities and Society	2025	Tmrt/UTCI	Meteorological station	Deep learning	City
(Requena-Ruiz et al., 2025)	France	International Journal of Biometeorology	2025	Ta	Wearable sensors	Point-based exposure assignment	Person-based
(Sampaio et al., 2025)	Brazil	Sustainable Cities and Society	2025	Ta	Numerical simulation (WRF)	Machine learning	City
(Yang et al., 2025)	China	Building and Environment	2025	Thermal neutral temperature	Field observation	Point-based exposure assignment	Person-based
(Zhang et al., 2025)	Singapore	Sustainable Cities and Society	2025	UTCI	Numerical simulation (ENVI)	Machine learning	Street
(Zhong et al., 2025)	China	Sustainable Cities and Society	2025	Tmrt	UAV	Point-based exposure assignment	Street
(Zhou, Geng et al., 2025)	China	Sustainable Cities and Society	2025	UTCI	Meteorological station data	Spatial interpolation	City
(Ouyang et al., 2025)	China	Building and Environment	2025	PET	Field measurement + wearable sensors	Point-based exposure assignment	Person-based
(Giordano et al., 2025)	Italy	Urban climate	2025	Ta	Urban sensors	Point-based exposure assignment	City
(Zhong et al., 2026)	United States	Building and Environment	2026	Tmrt	Field observation (LiDAR + TIR + meteorology)	Numerical simulation	Street
(Feng et al., 2026)	China	International Journal Of Biometeorology	2026	skin temperature/ heart rate/ tympanic temperature	Wearable sensors	Point-based exposure assignment	Person-based
(Fang et al., 2026)	China	Building and Environment	2026	Ta/PET	Wearable sensors	Point-based exposure assignment	Person-based

Table A2
SHS-related literature statistics.

Cite	Location	Journal	Year	Indicator	Data source	Level
(Hashiguchi et al., 2010)	Japan	European Journal of Applied Physiology	2010	TCV	Contextual questionnaire	Individual
(Haque et al., 2012)	Bangladesh	Environmental Health	2012	Long-term heat perception	Contextual questionnaire	Community
(Ruddell et al., 2012)	United States	Climatic Change	2012	Long-term heat perception	Contextual questionnaire	Community
(Pantavou et al., 2013)	Greece	Building and Environment	2013	TAV + TSV	Contextual questionnaire	Individual
(Yang et al., 2013)	Singapore	Building and Environment	2013	TSV + TAV + TPV	Contextual questionnaire	Individual
(Lai et al., 2014)	China	Energy and Buildings	2014	TSV	Contextual questionnaire	Individual
(Lane et al., 2014)	United States	Journal of Urban Health-Bulletin of the New York Academy of Medicine	2014	Heat stress awareness	Contextual questionnaire	City
(Oliveira et al., 2014)	Portugal	Finisterra	2014	TSV + TPV	Contextual questionnaire	Individual
(Pantavou et al., 2014)	Greece	International Journal of Biometeorology	2014	TSV	Contextual questionnaire	Individual
(Li et al., 2016)	China	Energy and Buildings	2016	Heat stress awareness	Contextual questionnaire	Individual
(Murakami et al., 2016)	Japan	Ieee Access	2016	Perceived heat mapping	Social media	City
(Chen et al., 2018)	China	Building and Environment	2018	TSV + TAV	Contextual questionnaire	Individual
(Cheung & Jim, 2018)	China	Energy and Buildings	2018	TAV	Contextual questionnaire	Individual
(Broday et al., 2019)	Brazil / Portugal	International Journal of Industrial Ergonomics	2019	TSV	Contextual questionnaire	Individual
(Cheung & Jim, 2019)	China	Building and Environment	2019	TAV	Contextual questionnaire	Individual
(Jänicke et al., 2019)	South Korea	International Journal of Biometeorology	2019	Keyword frequency	Social media	City
(Lam et al., 2020)	China	Building and Environment	2020	TSV + TCV	Contextual questionnaire	Individual
(Vasilikou & Nikolopoulou, 2020)	United Kingdom / Italy	International Journal of Biometeorology	2020	TSV	Contextual questionnaire	Individual
(Li et al., 2021)	China	Buildings	2021	TCV	Contextual questionnaire	Community
(Lin et al., 2021)	China	Building Simulation	2021	TSV + TCV + TAV	Contextual questionnaire	Individual
(Othman et al., 2021)	Malaysia	International Journal of Biometeorology	2021	TSV + TPV	Contextual questionnaire	Individual
(Dzyuban et al., 2022)	Singapore / United States	Weather	2022	Keyword frequency	Social media	City
(Gu et al., 2022)	China	Atmosphere	2022	TSV + TAV	Contextual questionnaire	Individual
(Li et al., 2022)	China	Indoor and Built Environment	2022	TCV	Contextual questionnaire	Community
(Li et al., 2022)	China	Atmosphere	2022	TSV	Contextual questionnaire	Community
(Lim et al., 2022)	United States	Landscape and Urban Planning	2022	Heat stress awareness	Contextual questionnaire	Community
(Xiang et al., 2022)	China	Sustainable Cities and Society	2022	Keyword frequency	Social media	City
(Xiong & He, 2022)	China	Sustainable Cities and Society	2022	TSV + TCV + TAV	Contextual questionnaire	Individual
(Bundo et al., 2023)	Switzerland	Environmental Health	2023	Heat-related emotions	EMA	Individual
(Cohen et al., 2023)	Israel	Building and Environment	2023	TSV + TAV	Contextual questionnaire	Individual
(Derakhshan et al., 2023)	United States	Applied Geography	2023	Others	GPS	City
(Hao et al., 2023)	China	Building and Environment	2023	Others	GPS + social media	Community
(Huang et al., 2023)	China / United Kingdom	Building and Environment	2023	TSV + TPV	Contextual questionnaire	Community
(Lehnert et al., 2023)	Czech Republic	Landscape and Urban Planning	2023	Perceived heat mapping	Participatory mapping	City
(Ly et al., 2023)	United States	GeoHealth	2023	Others	GPS	City
(Wang et al., 2023)	China	Building and Environment	2023	TSV + TCV + TAV + TPV	Contextual questionnaire	Individual
(Guo et al., 2024)	China	Building and Environment	2024	TSV + TCV + TAV	Contextual questionnaire	Individual
(Ji et al., 2024)	China	Building and Environment	2024	TSV + TPV	Contextual questionnaire	Community
(Lyu et al., 2024)	United States	INTERNATIONAL JOURNAL OF GEOGRAPHICAL INFORMATION SCIENCE	2024	Heat-related emotions	Social media	City

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Table A2 (*continued*)

Cite	Location	Journal	Year	Indicator	Data source	Level
(Meidenbauer et al., 2024)	United States	BMC Psychology	2024	Heat-related emotions	EMA	Individual
(Tarpani et al., 2024)	Italy	City and Environment Interactions	2024	Others	Participatory mapping	Community
(Wang et al., 2024)	China	Urban Climate	2024	TCV + TPV	Contextual questionnaire	Community
(Zhang et al., 2024)	China	Building and Environment	2024	TSV	Route-based evaluation	Individual
(Bano et al., 2025)	India	Green Technologies and Sustainability	2025	Perceived heat mapping	Participatory mapping	City
(Che et al., 2025)	China	Weather Climate and Society	2025	Heat-related emotions	Social media	City
(Huang et al., 2025)	China	Sustainable Cities and Society	2025	TAV	Route-based evaluation	Individual
(Krüger et al., 2025)	Brazil	International Journal of Biometeorology	2025	TSV	Route-based evaluation	Individual
(Květoňová et al., 2025)	Czech Republic	Journal of Maps	2025	Others	Participatory mapping	City
(Li et al., 2025)	China	Energy and Buildings	2025	TSV + TCV + TAV	Contextual questionnaire	Individual
(Liang & Wang, 2025)	China	Environmental Research Letters	2025	Others	GPS	City
(Lin & Zhang, 2025)	China	Journal of Building Engineering	2025	TSV + TPV	Contextual questionnaire	Individual
(Liu & Hang, 2025)	China	Sustainable Cities and Society	2025	Heat-related emotions	Social media	City
(Soomro et al., 2025)	Pakistan	Sustainable Cities and Society	2025	Others	Social media	City
(Xu et al., 2025)	China	Sustainable Cities and Society	2025	Keyword frequency	Social media	City
(He et al., 2026)	China	Building and Environment	2026	Heat perception intensity	Social media	City
(Zhao et al., 2026)	China	Sustainable Cities and Society	2026	TCV	Route-based evaluation	Individual

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