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Urban Comfort Assessment in the Era of Digital Planning: A Multidimensional, Data-driven, and AI-assisted Framework

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Summary

Ensuring liveability and comfort is one of the fundamental objectives of urban planning. Numerous studies have employed computational methods to assess and quantify factors related to urban comfort such as greenery coverage, thermal comfort, and walkability. However, a clear definition of urban comfort and its comprehensive evaluation framework remain elusive. Our research explores the theoretical interpretations and methodologies for assessing urban comfort within digital planning, emphasising three key dimensions: multidimensional analysis, data support, and AI assistance.

KEYWORDS: urban planning, street view imagery, streetscape, human-centred GeoAI, AI agent

1 The Multidimensional Nature of Urban Comfort

Comfort is defined as the degree of satisfaction with the environment of a person (Frontczak et al., 2012; Shin, 2016). In the built environment, there are many environmental factors that have been proven to be associated with human comfort sensation, including visual elements (Klemm et al., 2015; Liu et al., 2023; Yang et al., 2025), physiological data of individuals (Chwalek et al., 2024), occupant behaviour (Miller et al., 2025), meteorological indicators (Xie et al., 2019; Miller et al., 2023; Mosteiro-Romero et al., 2024), the design of public places (Santos Nouri et al., 2018), the dynamics of life quality (Lei et al., 2025) and so on. Urban comfort, in this context, refers specifically to the experience of comfort within the urban environment. It is inherently a multidimensional concept due to the complexity and variability of the urban physical environment. Unlike general comfort, which can be defined at the individual level, urban comfort emerges as a collective and spatially embedded phenomenon, shaped by the interplay between environmental attributes and human perception. The diverse components of the urban environment evoke a wide range of perceptions in individuals (Salesses et al., 2013; Dubey et al., 2016; Qiu et al., 2023; Yang et al., 2023; Ito et al., 2024), making it unsuitable for reduction into a single numerical index or one-dimensional measure, as it is often the case with other concepts in planning such as walkability. In addition,

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comfort is highly subjective, varying significantly from person to person based on their preferences, experiences, and expectations (Castaldo et al., 2018; Wang et al., 2018), which adds another layer of complexity to the understanding of urban comfort.

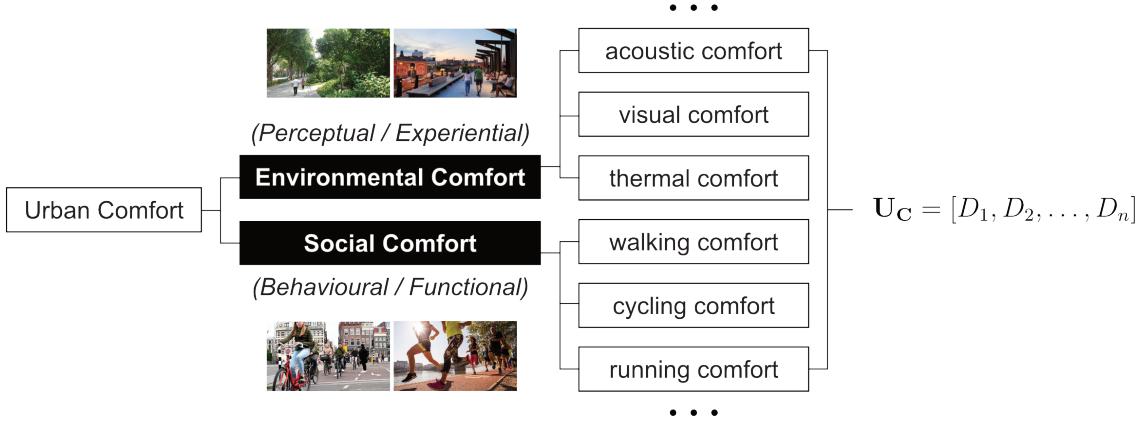


Figure 1: Proposed multidimensional framework of urban comfort.

Broadly, urban comfort can be categorised into two main dimensions: environmental comfort and social comfort, as described in **Figure 1**. Environmental comfort primarily refers to the perceptual and experiential satisfaction of people with the physical aspects of the built environment, such as thermal comfort (Rupp et al., 2015), visual comfort (Lam et al., 2020), and acoustic comfort (Yang and Kang, 2005). In contrast, social comfort relates to how well the urban environment supports human interactions and behavioural needs. It emphasizes the functional ability of spaces to facilitate desired user activities, such as walkability, accessibility, and safety. Examples include walking comfort (Ma et al., 2021) and cycling comfort (Ayachi et al., 2015), which reflect how urban infrastructure influences ease of movement and user experience.

Urban comfort is deeply intertwined with the characteristics of the urban environment (Gulyás et al., 2006). People experience different levels of comfort in heterogeneous urban settings (Kim et al., 2022), and even within the same environment, individuals may perceive comfort differently across various dimensions (Du et al., 2023). This dual-layer relationship indicates that urban comfort is not only context-dependent but also multidimensional. Instead of considering urban comfort as a single scalar value, it is more accurate to conceptualise it as a vector \mathbf{U}_C that captures the multidimensional nature of urban comfort across several dimensions. Mathematically, this can be expressed as $\mathbf{U}_C = [D_1, D_2, \dots, D_n]$, where:

- D_i represents each dimension of urban comfort (e.g., thermal comfort, visual comfort).
- \mathbf{U}_C is the vector of all the dimensions of comfort, reflecting the multidimensional aspects of urban comfort without reducing them to a single aggregate value.

Our vector-based approach acknowledges that different dimensions of urban comfort can interact with each other, contributing differently to the perception of comfort depending on the urban context

and individual preferences. The complexity of assessing urban comfort lies in understanding how these dimensions coexist and influence each other, rather than simply aggregating them into a single index. This perspective reinforces the need for a comprehensive evaluation framework that captures the nuanced and multidimensional experiences of individuals within urban environments.

In this study, we clarified the multi-dimensional nature of urban comfort and its math expression by definition. In the following sections, we further propose the four steps of urban comfort assessment and the role of AI algorithms in modelling urban comfort for digital planning, as shown in **Figure 2**.

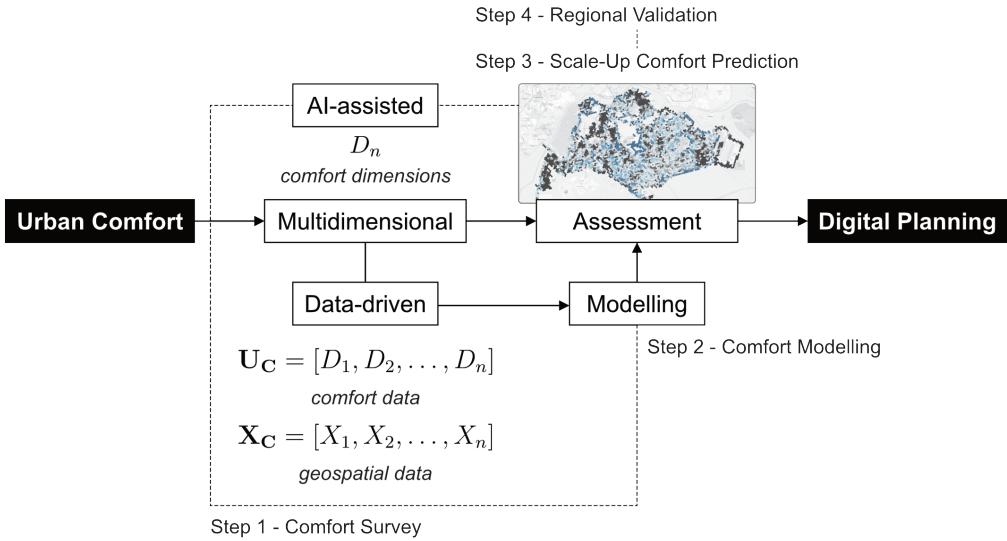


Figure 2: Urban comfort assessment framework in this study.

2 Four-Step Framework for Data-Driven Urban Comfort Assessment

To effectively evaluate urban comfort in its multidimensional attributes, we propose a structured, data-driven assessment framework encompassing four key steps: conducting comfort surveys, developing comfort models, scaling up urban comfort predictions, and performing regional validation, as illustrated in **Figure 3**. Each step is data-supported, leveraging three essential data streams: geospatial data to characterise the urban environment in the comfort survey, survey results to capture human comfort perception, and additional comfort survey data from distinct sites for model validation.

As shown in **Figure 3**, the process begins with a comfort survey conducted at a specified urban location, recording geospatial characteristics ($X_1 \dots X_n$) and various comfort dimensions ($D_1 \dots D_n$). Subsequently, the collected geospatial and comfort data undergo modelling to capture the non-linear relationship between the urban environment and human comfort. This model enables scaling up predictions to more urban areas across the city based on extended geospatial data, facilitating an

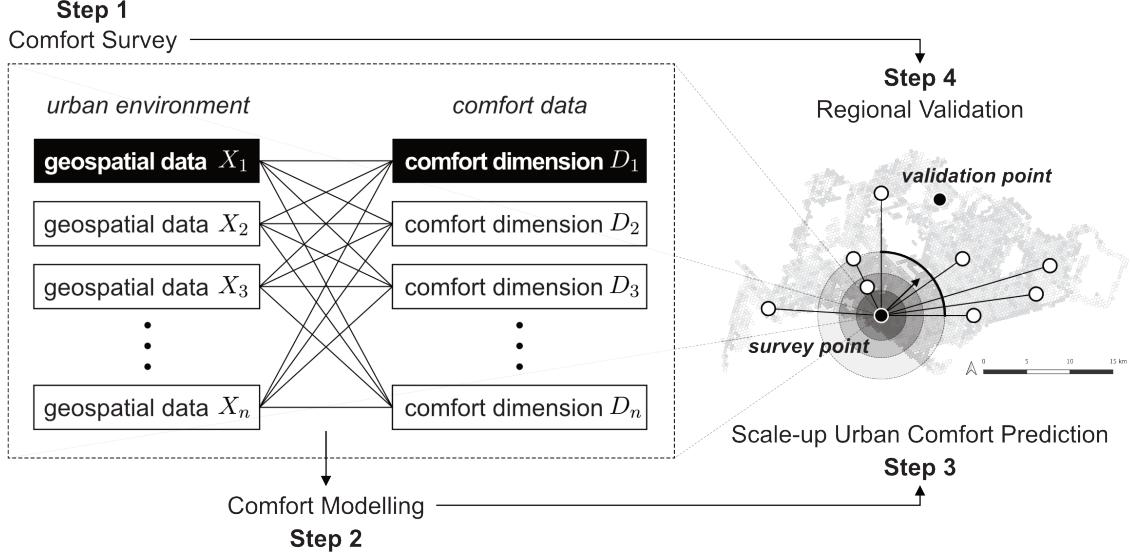


Figure 3: Data-driven urban comfort assessment framework.

urban-scale comfort assessment. Finally, the comfort model is validated using survey data from an additional, designated validation location.

3 AI-assisted Comfort Modelling in the Era of Digital Planning

Data-driven, multidimensional urban comfort modelling can be further enhanced by artificial intelligence to support digital planning more effectively (**Figure 4**). AI models offer significant advantages, including high-dimensional data representation, non-linear relationship modelling, scalability, generalisability, and spatial-temporal understanding, making them better suited than traditional methods for tackling the complexities of comfort modelling. For instance, convolutional neural network (CNN) excels in feature extraction from image data and are widely used in processing satellite and street view imagery (SVI) as data representation tools. Advanced AI models, such as deep neural network (DNN), demonstrate robust predictive performance with non-linear problems like human comfort and possess strong scalability and generalisation, enabling application to untrained data. Comfort models developed for one urban area can be extended to predict comfort in other regions. Additionally, long-short-term memory network (LSTM) is well-suited for time-series data, making them valuable for handling large volumes of temporally-labelled geographic data in dynamic urban observations.

These AI technologies, when integrated, can significantly enhance comfort modelling and mapping within our data-supported urban comfort assessment framework, offering powerful tools for digital urban planning. As depicted in **Figure 4**, typical applications include identifying areas with low comfort for prioritisation in urban renewal, highlighting critical urban environmental elements needing quality improvement, and conducting continuous geospatial analyses based on spatial-temporal

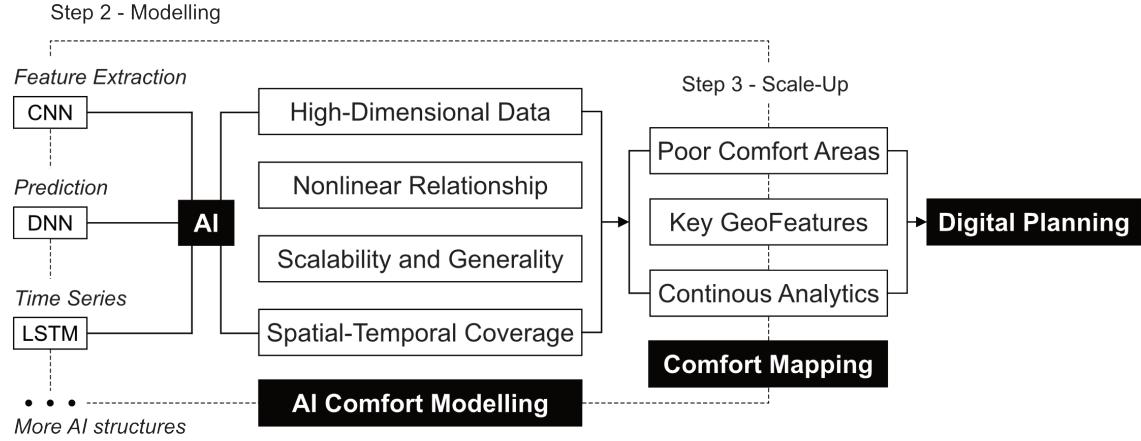


Figure 4: AI-assisted comfort modelling features for digital planning.

analytics to inform urban planning decisions (Yap et al., 2023; Liang et al., 2023; Yang et al., 2025).

4 Case Study: Thermal Comfort Analytics in Singapore

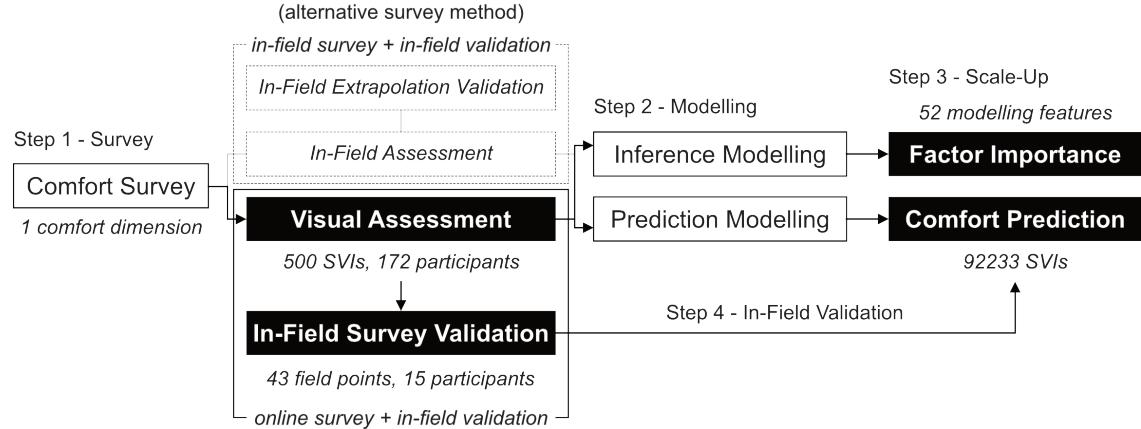


Figure 5: Urban comfort assessment framework in the case study.

To implement our proposed four-step, AI-assisted urban comfort assessment framework, we selected Singapore as the study area for a focused analysis of urban thermal comfort, given its strong emphasis on urban liveability and resilience in a high-density, tropical environment. As illustrated in **Figure 5**, this case study adheres rigorously to the framework's stages: conducting a comfort survey, developing comfort models, scaling up urban comfort predictions, and performing in-field validation.

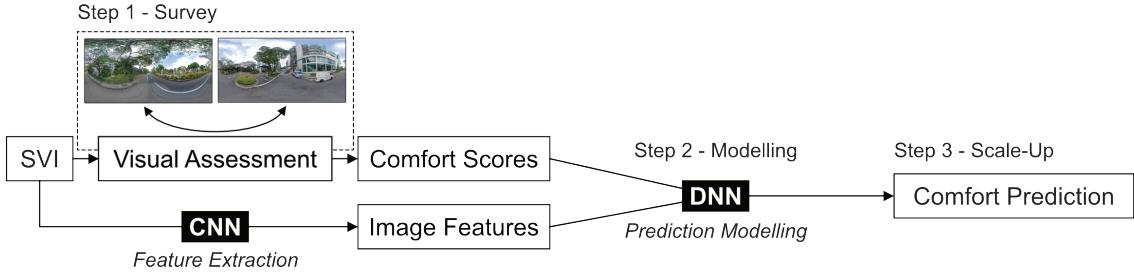


Figure 6: SVI-supported visual assessment as a replacement for in-field comfort survey.

In the comfort survey phase, we opted for a more efficient online approach using street view images instead of the traditional in-field survey combined with in-field validation, as shown in **Figure 6**. This method leverages information embedded in street view images and utilises AI-based CNN feature extraction to replace in-field surveys that typically require extensive environmental measurements, participant involvement, and significant human and financial resources. Nonetheless, for model validation, we still conducted a field comfort survey to confirm the model’s reliability.

For comfort modelling, we developed two types of models: a comfort prediction model and a comfort inference model (**Figure 5**). The prediction model employs a DNN to achieve high accuracy and generalisation capabilities, enabling us to apply it to 92,233 street view images across Singapore to predict thermal comfort levels along urban streets. The inference model, based on linear regression, interprets feature weights, allowing us to identify which factors significantly influence urban thermal comfort. Finally, we mapped Singapore’s urban thermal comfort (**Figure 7**), clearly identifying spatial areas with higher and lower comfort levels. As an addition, this mapping can provide valuable insights for urban planners to pinpoint zones requiring efforts to enhance street-level thermal comfort.

5 Contributions and Limitations

This paper establishes a multidimensional framework for understanding urban comfort, introducing four key steps for assessing urban comfort. Additionally, it examines the supportive role of AI in urban comfort modelling within the context of digital urban planning. In the case study, we apply this framework to assess urban-scale thermal comfort in Singapore, utilising CNN, DNN, and other advanced technologies for thermal comfort modelling. The resulting urban thermal comfort map of Singapore represents a valuable resource for digital urban planning efforts.

However, this study has several limitations. First, considering the notion of data sources, we incorporate three key modelling methods in this framework to support the objective. However, this approach does not fully account for the diverse auxiliary roles that various AI technologies could play in urban comfort modelling, depending on specific use cases. Future research could explore how different AI techniques—such as reinforcement learning, generative models, or multi-agent systems—can further enhance urban comfort assessment and digital planning. Second, the

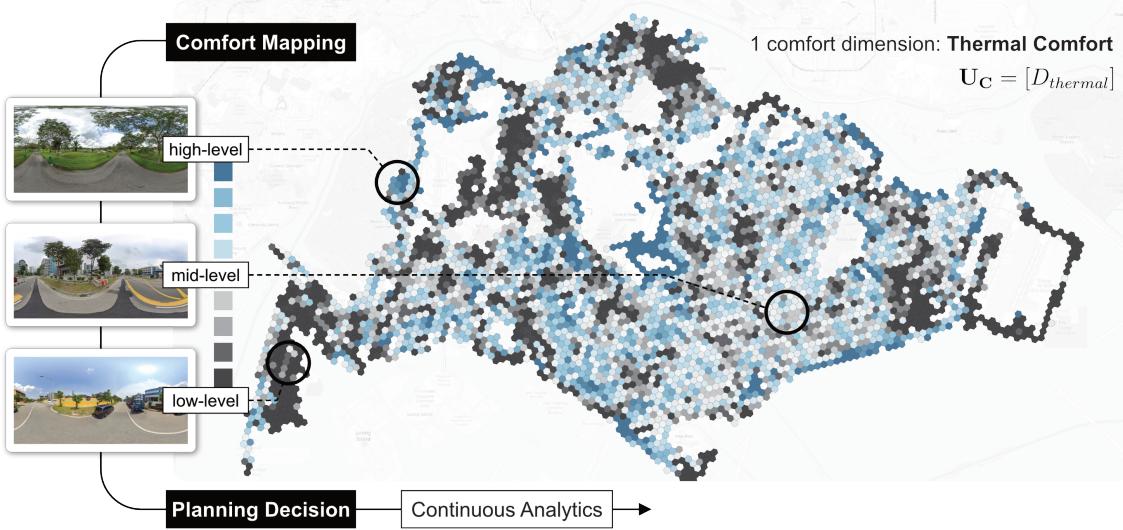


Figure 7: Comfort mapping for thermal comfort analytics in Singapore.

case study focuses solely on thermal comfort as a one-dimensional aspect of urban comfort, without extending to the multidimensional comfort model proposed in the framework. Future studies should consider developing and validating a multidimensional comfort model to substantiate the reliability of this conceptual framework for urban comfort assessment.

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