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Developing the Urban Comfort Index: Advancing liveability analytics with a multidimensional approach and explainable artificial intelligence

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Abstract

Urban comfort is a means of measuring the dynamic quality of urban life as an outcome of the interaction between humans and urban environments, capturing spatio-temporal phenomena in cities. We design a multidimensional urban comfort framework encompassing 44 features, to comprehensively represent urban living environments, based on 3D urban morphology, socio-economic features, human perception, and environmental factors. We develop a graph-based approach to measure urban comfort through an index and explain its driving forces by exploiting spatial relationships between urban comfort and surrounding features. Explainable artificial intelligence (XAI) is leveraged to interpret feature importance and inherent complexity in urban contexts, advancing conventional methods that are limited to linear relationships. We implement the framework in Amsterdam, generating a city-wide comfort index. Compared to the baseline random forest model, our graph-based approach demonstrates competitive performance in measuring the urban comfort index, achieving an MAE of 1.03, an RMSE of 2.04, and an R-squared value of 93.6%. Meanwhile, we visualise how the urban comfort index changes across quarters, examining the spatio-temporal dynamics at the neighbourhood level. Furthermore, we employ XAI to explain the positive and negative impacts of urban features by categorising neighbourhoods into high and low-comfort groups, indicating the varied contributions of urban features. Exploring the usability of the urban comfort index, we simulate various urban strategies in a neighbourhood of interest benefiting from urban digital twins (e.g. improving air quality to mitigate its negative impact on urban comfort). The urban comfort study demonstrates the potential to address information gaps by incorporating multidimensional features in cities, thereby providing insights into understanding and interpreting local comfort. It can further serve as an instrument to inform neighbourhood design, suggest feasible strategies, and indicate far-reaching implications for urban health and wellbeing.

Keywords: Graph neutral networks, Urban complexity, Human-centric planning, 3D GIS, Urban simulation

1. Introduction

The quality of life of urban residents has been broadly studied across multiple domains, from sociology to urban studies, associated with public health and wellbeing (Marans and Stimson, 2011b; Pacione, 2003; Marans and Stimson, 2011a; Jaroszewicz et al., 2023; Alfaro-Navarro et al., 2024). However, cities today are facing urban challenges in diverse ways, for example, such as unequal access to public facilities and unaffordable housing due to extensive urbanisation (Zhang, 2016; While and Whitehead, 2013; Castells-Quintana and Royuela, 2015; Ziogas et al., 2023; Hu et al., 2023; Yin et al., 2023), as well as the essential to adapt to climate change and build resilience against natural events and resource fluctuations (Godfrey and Julien, 2005; Lau et al., 2010; Maheshwari et al., 2020; Aboagye and Sharifi, 2024). The growing interest in the quality of human life in both academia and practice confirms its multitude of important benefits and long-term value (Samavati and Veenhoven, 2024; Syamili et al., 2023; Patino et al., 2023). Urban liveability, as a multidimensional concept to evaluate and monitor the quality of life in the long term, has been widely adopted by governments and initiatives as an instrument for facilitating policymaking and city planning (Ley, 1990; Long et al., 2024; Higgs et al., 2019). Various indices and platforms are developed, such as the 'Leefbaarometer'[1] in the Netherlands, and 'Liveability for 21 largest cities'[2] in Australia. The evaluation of urban life quality most relies on statistical data (e.g. census survey data) collected by governments, leading to insufficient resolution, and may not fully capture the dynamics of residents' life experience and their living environments (Harvey and Aultman-Hall, 2016; Kovacs-Györi et al., 2020). In fact, a number of social and economic indicators, such as the accessibility to public transport and social infrastructure, affordable

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[1] https://www.leefbaarometer.nl/home.php

[2] https://auo.org.au/measure/scorecards/

housing, and local work opportunities (Higgs et al., 2019), are predominately used in the assessment, whereas existing approaches overlook humans' subjective experiences in cities and a dynamic and comprehensive representation of urban environments. For example, subjective perception in urban environments is crucial for understanding city life, including the effects of urban green spaces on restoration and visual quality (Grahn and Stigsdotter, 2010; Ma et al., 2024), the relationship between human active mobility and street design (Homolja et al., 2020), and residents' sense of place (Zhang et al., 2018; Su et al., 2023). Further, while studies on characterising urban life quality specific to local contexts vary in indicators and methods, explanations of the driving forces behind these measurements have not been fully discussed. The proliferation of crowdsourcing and human-centric analysis opens the door to addressing the limitations embedded in liveability studies, as well as demonstrates the potential to facilitate the current research landscape. Hence, we introduce the term *urban comfort* to describe the quality of urban life, aiming for a holistic representation of the urban experience and using it interchangeably with urban liveability in some cases. In this sense, urban comfort is an outcome of the interplay between humans and urban environments. We define urban comfort as a multifaceted concept that captures and reflects the spatio-temporal dynamics of urban life quality through a lens of human perspective.

Comfort as subjective reflections at the human scale has been discussed in multiple domains. For example, many studies in the built environment focus on improving indoor building environments by understanding human comfort, such as air conditioning and thermal comfort (Ahmed, 2003; Lei et al., 2024c; Jayathissa et al., 2020), as well as indoor noise and acoustic comfort (Oquendo-Di Cosola et al., 2022; Lau and Choi, 2021). The discourse of comfort is further extended to characterise outdoor conditions and human activities, investigating the relationships between outdoor environments and human comfort, e.g. walking comfort (Deng and Wong, 2020; Liu et al., 2023). The state of the art in comfort studies demonstrates a consistent trend across various domains, contributing to a comprehensive dialogue on urban health and human wellbeing (Piselli et al., 2018; Migliari et al., 2022). Despite these advancements, a significant gap remains in understanding how various aspects of urban environments collectively impact urbanites' comfort and life experience, particularly concerning spatio-temporal changes. Aligning with this line of research, urban comfort is conceptualised as a collection of urban features in the built environments and human sensing information, advancing the present discourse of life quality. In this regard, we take the diversity of urban environments into account, for example, environmental factors and urban morphology, aiming to uncover the complexity and dynamics of cities. Besides the well acknowledged socio-economic aspect of this topic, we include human perception as an addition, i.e. how people perceive and sense their living environments. Further, in pursuit of a comprehensive depiction of urban layout, we adopt urban digital twins (Lei et al., 2023c) to advance the measurement of urban comfort, in particular, 3D buildings as a pillar in urban digital twins will be leveraged to represent morphology. Urban digital twins refer to a virtual representation of the urban environment integrated with 3D semantics and rich information, demonstrating the potential to simulating numerous what-if urban scenarios and ultimately facilitating city management (Ferré-Bigorra et al., 2022; Ketzler et al., 2020). However, the current research landscape of urban digital twins is dominated by technical discourse, overlooking their usability of addressing socio-economic topics by incorporating human perspectives (Lei et al., 2023a; Nochta et al., 2021; Lei et al., 2023c). In this sense, this work presents also an advancement in the adoption of urban digital twins, exploring their role in facilitating socio-economic issues related to city development. The implementation of urban comfort can subsequently offer insights and values for emphasising the socio-technical direction in urban digital twins. In this context, the term urban comfort takes a further step to investigate yet unstudied aspects of urban life quality, revealing the interactions between humans and urban environments.

Considering these highlighted innovations, we investigate three research questions: 1) What features impact urban comfort, and how do they affect the spatio-temporal dynamics of urban comfort in cities; 2) how do advanced techniques help understand the interactions between humans and urban environments; and 3) how an index quantifying urban comfort can be established and adopted to facilitate urban planning and policymaking.

Defining urban comfort as a holistic and human-centric representation of life quality, we develop a multidimensional framework to encapsulate urban dynamics, encompassing a variety of criteria from 3D urban morphology, socio-economic factors, human perception, and environmental factors (as illustrated in Figure 1). Considering that urban comfort is also a reflection generated from the interplay between humans and urban surroundings (Batty, 2016; Ortman et al., 2020), spatial relationships are essential to be incorporated into the assessment and interpretation. Therefore, we adopt a graph-based neural network approach to measuring urban comfort, exploiting the spatial patterns of urban areas and multidimensional features. Explainable AI (XAI) is further employed to interpret the impact of urban features on urban comfort, disclosing the non-linear interactions between features. This study will bifurcate into two aspects: 1) capturing the spatial and temporal phenomena of urban comfort and explaining the driving forces with spatio-temporal variations; and 2) proposing a use case of urban digital twins to substantiate their usability of advancing socio-economic studies. This work is among the first to 1) propose a multidimensional framework that incorporates not only socio-economic indicators but also human experience and environmental parameters; 2) leverage crowdsourced and publicly available data (e.g. street view images) to enhance information richness and facilitate future wide adoption; and 3) integrate 3D data to represent the vertical dimension of built environments, paving the way for the adoption of urban digital twins in the socio-economic domain. Further, our research tends to initiate the decision-making process and foster better planning and design in the long term (Ferré-Bigorra et al., 2022), for example, by serving as a tool to provide recommendations and solutions for neighbourhoods with inadequate urban comfort through the simulation of various urban strategies.

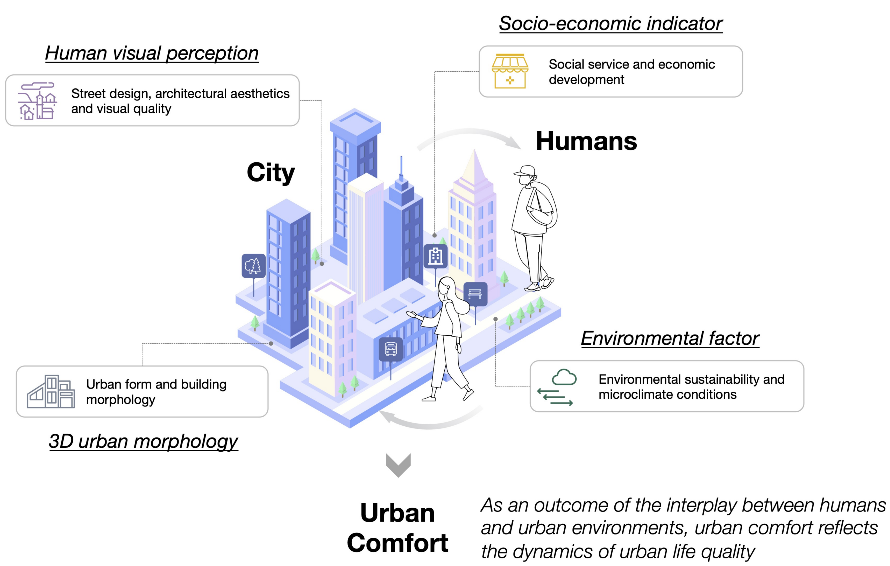


Figure 1: A general concept of urban comfort, encapsulating 3D urban morphology, socio-economic indicators, human perception and environmental factors.

2. Background and related work

Three tendencies are summarised from the literature review for urban comfort research. *First*, the present research landscape exploits how socio-economic indicators influence urban life quality, highlighting their importance in developing related indexes (Tapsuwan et al., 2018; Musa et al., 2018; Allirani et al., 2024,?; Mouratidis, 2021). For example, Zhan et al. (2018) conducted a comprehensive survey in China to assess satisfaction with urban liveability. The findings suggest that the convenience of public facilities (e.g. healthcare, education and recreation) and socio-cultural environment (e.g. social inclusion and sense of belonging) are significant contributors to urban life quality. The accessibility of transport, such as the provision of active transport and walkability, is another critical indicator in the life quality assessment (Long et al., 2024; Higgs et al., 2019). While socio-economic conditions have an impact on local life, urbanites are continuously exposed to a multi-sensory environment that encompasses factors such as noise, wind, heat, humidity, air pollutants, and various interactions with streetscape (e.g. buildings, vegetation, and urban furniture). Further, considering the role of spatial patterns and building form in the cities (Oliveira, 2016; Biljecki and Chow, 2022), such urban morphology not only features urban functions and accommodates social activities but also contributes to the visual appearance of cities, associated with visual quality (Elzeni et al., 2022; Chen et al., 2021; Ito et al., 2024). Such determinants stemming from the urban environment as a whole influence life quality, shaping a sense of place and consequently impacting residential mobility and neighbourhood developments, such as renewal or gentrification (Brown, 2020; Lee and Perkins, 2023; Emami and Sadeghlou, 2021). Therefore, in this work, we aim to develop a multidimensional human-centric framework that will be among the first to encapsulate urban comfort.

Second, the performance of urban liveability indicators is usually discussed to interpret the results of liveability index. A sensitivity analysis is commonly used in the literature to explain the contribution structure of the proposed liveability framework (Cao et al., 2021; Xiao et al., 2022; Benita et al., 2021). However, sensitivity analysis implies a linear relationship between indicators and outcomes, which may oversimplify the complexity of cities and can not capture the nonlinear interactions between urban indicators. Further, sensitivity analysis has limitations in explaining the dynamics of life quality, for example, missing the combined effects of multiple interacting urban features (e.g. street design and the sense of safety), making such a method less flexible in dynamic urban contexts. Thus, it remains ambiguous how selected urban features promote or downgrade urban comfort (Martino et al., 2021; Wang and Miao, 2022). In this context, we take advantage of AI technologies — explainable AI (XAI), in urban analytics (Liu et al., 2024). XAI offers a promising way to interpret the integrated and dynamic impact of urban features on urban comfort, which can be considered as an addition to justifying the inclusion of relevant indicators in many cases. This advancement not only provides explanations but also implies potential solutions and suggestions for enhancing urban comfort. For instance, when urban comfort is recognised as the outcome of urban planning and design (Xiao et al., 2022; Alijani et al., 2020), the theoretical impact of planning a neighbourhood with more street trees is effective in making people feel comfortable, encouraging outdoor activities, and subsequently supporting urban health and enhancing local vitality as well (Lowe et al., 2020, 2022).

Third, prior studies on urban comfort often use simple data sources (e.g. tabular data) with limited spatial information (Higgs et al., 2019; Long et al., 2024). However, the dynamic nature of urban comfort makes a 2D analysis fall short in altogether representing the surroundings, particularly aspects such as building scale, visual quality, and vegetation density (Lang et al., 2020; Bruyns et al., 2020; Raman, 2010). The inherent limitations may introduce biases, propagating challenges of uncovering the interplay between people and the environments. Inspired by recent innovations, we apply human-centric urban digital twins in this work, advancing the current analysis by representing urban environments in 3D and simulating scenarios related to urban comfort variations. The concept of human-centric urban digital twins, representing physical entities, people, systems, and real-world interactions in near real-time, has been increasingly adopted in 3D GIS and urban studies, offering great potential to solve the rising number of urban issues and challenges (Dembski et al., 2020; Lei et al., 2023c). Benefiting from the characteristics of urban digital twins, it will aid decision-making and support urban management for diverse stakeholders. Urban digital twins are thus considered an innovative technology that can capture the dynamics of urban comfort, as well as simulate a variety of scenarios to strategically enhance local urban comfort.

3. Methodology

We summarise our methodology in Figure 2 and describe details in the subsections.

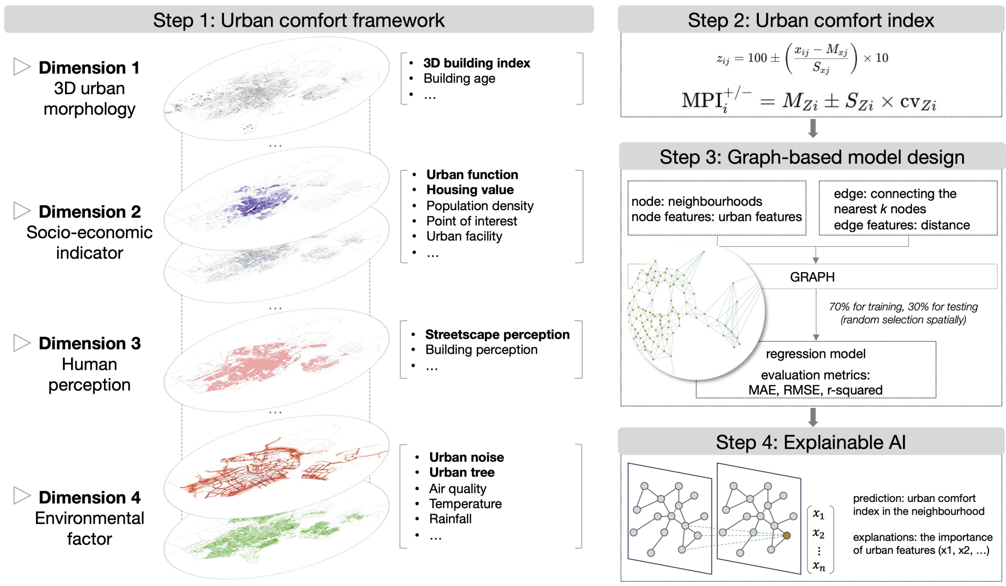


Figure 2: The workflow including four main step. First, the urban comfort framework incorporates four dimensions with 44 urban features: (1) 3D urban morphology, (2) socio-economic features, (3) human perception, and (4) environmental factors. Second, the Mazziota-Pareto Index (MPI) is adopted to measure the urban comfort index. Third, a graph-based approach is designed to exploit spatial relationships between neighbourhoods and urban features. Lastly, explainable AI (XAI) is leveraged to interpret the impact of each urban feature.

3.1. Designing a multidimensional framework to measure urban comfort

Evaluating urban comfort has gathered continuous interest in academia and practice; however, a consensus has yet to be generated regarding its definition and conceptualisation (Benita et al., 2021; Liang et al., 2020; Wang and Miao, 2022). The inclusion of multidimensional indicators indicates a tendency to understand urban comfort from a comprehensive and empirical aspect. Other than focusing on how economic developments impact local life, the current approaches shift to taking account of sociology-related metrics, e.g. urban activities and availability to services and amenities (Zhan et al., 2018; Cao et al., 2021). Nevertheless, such research predominantly investigates how objective urban features impact urban comfort in the city, failing to consider the role of local residents, in particular the perception of their neighbourhoods. Our research develops an integrated approach incorporating 3D urban forms and environmental factors. It provides a dynamic and holistic representation of urban surroundings, going beyond the prominent metrics commonly considered in the literature. Meanwhile, we include human-generated perception, offering a subjective perspective on urban environments in terms of visual quality.

We examine research papers related to life quality measurement, screen instruments developed by governments and initiatives that align with our research motivations, and finally decide on four dimensions in our framework: (1) 3D urban morphology, (2) socio-economic features, (3) human perception and (4) environmental factors. Such a conceptual framework aims to integrate objective and subjective features related to urban environments, encapsulating urban life of residents and helping stakeholders (e.g. policymakers and city planners) better understand urban comfort from a diversity of perspectives. We further explain each dimension and its components in detail, demonstrating how this multidimensional framework can comprehensively represent urban comfort.

First, 3D urban morphology encompasses the shapes of buildings and architectural patterns, characterising urban form in more detail (Cai et al., 2022). 3D city models and urban digital twins are increasingly adopted as virtual representations of urban environments, in particular involving a vertical dimension, aiming to reproduce holistic features from the real world (Biljecki et al., 2015; Schrotter and Hürzeler, 2020; Hämäläinen, 2021; Caprari et al., 2022; Dembski et al., 2020). Given the role of urban buildings in the city, we adopt a set of *3D building metrics* developed by Labetski et al. (2023) to capture building morphology. Additionally, we consider 2D building attributes as a supplementary source, such as *geographic locations*, *building age*, and *building style*, to outline basic information about urban buildings. Further, we use the portion of urban objects segmented from street view imagery (SVI) to complete and enhance the representation of urban environments with visual elements of the streetscapes, for example, *buildings*, *roads*, *sidewalks*, and *street furniture*. It is also widely discussed in the research landscape that the proportions of streetscapes significantly affect human comfort and the success of placemaking (Harvey et al., 2017; Su et al., 2023).

Second, following prevailing discussions, we incorporate a socio-economic dimension to reveal the quality of life and well-being of urban residents. This dimension comprises a range of factors that impact the everyday life of residents, including the availability and access to services and facilities (Long et al., 2024), opportunities for work and leisure (Ruth and Franklin, 2014), and the affordability of housing (Badland and Pearce, 2019; Reid et al., 2024). For example, we include mixed *urban functions* as an indicator to understand local activities, such as the percentages of working, living, and recreation, implying the vibrancy related to lifestyle (Tu et al., 2017). In response to the new tradition of compact cities in urban development, many cities have implemented the concept of mixed-use to accommodate diverse needs, such as job prospects, shopping, and public services around the living area (Raman, 2010). It is believed to be a critical feature implying not only life convenience but also an enhancement of the living experience of local residents. Along this line, we include the availability of multiple amenities, demonstrating access and proximity to *points of interest* (POIs), e.g. schools, parks, and grocery stores, as well as transport options such as train stations and bus stops. It can suggest the level of well-planned neighbourhoods and implies a relationship with social equity and cohesion, where greater access to urban facilities contributes to a higher quality of life and more perceived comfort (Bartik and Smith, 1987; Frey, 2017; Xiao et al., 2017). Further, we consider *housing prices* as a feature reflecting economic development and affordability, and population density to denote a rough profile of demographics. The indicator *population density* is a multifaceted indicator associated with the provision of services and amenities, as well as the balance of neighbourhood development, illustrating both the benefits and challenges of high population growth (Clark et al., 2002; Gottlieb, 1994).

Third, human perception is an innovative dimension of our framework, adding valuable insights into how people perceive their living environment. We consider two types of human sensing information: *the perception of architectural constructs* and *the perception of streetscapes*, advanced through the use of SVI and computer vision. Architectural constructs, including building layout and design, are essential elements in defining a city's visual aesthetics (Imamoglu, 2000; Devlin and Nasar, 1989). The perception of urban buildings is evaluated from six aspects: complexity, originality, order, pleasantness, excitement, and style, on a scale from 0 to 10. The evaluation is adopted from Liang et al. (2024), whose dataset is trained from participants' responses. Streetscape is designed and shaped by the horizontal and vertical elements in the urban environments, influencing comfort for human users (Harvey et al., 2017). It is widely used as an instrument to evaluate place representations from a human perspective, such as how safe people feel in a given area. In this work, streetscape perception is based on Place Pulse 2.0 (Dubey et al., 2016), a crowdsourced dataset describing streets from 56 cities with six perceptual attributes: safe, lively, boring, wealthy, depressing, and beautiful (Salesses et al., 2013; Dubey et al., 2016; Zhang et al., 2018).

Fourth, environmental factors contributes to comfort from a biological and meteorological perspective (Williams, 1991; Chen et al., 2020; Fujiwara et al., 2024). The elements of microclimate are outcomes of planning and policymaking, indicating a number of implications for human health that cannot be overlooked (Alijani et al., 2020; Shi et al., 2022). Among the most discussed topics in urban microclimate, features such as thermal conditions and greenery are well acknowledged as determinants influencing human activities and behaviour (Armson et al., 2012; Park et al., 2021; Yang et al., 2023; Antoniou et al., 2019). However, such a micro-environment aspect remains a lack of detailed investigation when discussing urban comfort and the quality of urban life. Inspired by the inclusion of air quality and noise in measuring neighbourhood satisfaction (Higgs et al., 2019; Silva and Mendes, 2012), we consider the impact of environmental factors for building the urban comfort measurement, aiming to include a variety of micro-environment features. For example, *temperature*, *rainfall*, *noise*, and *air quality* are included in this dimension. Elaborating on these environmental characteristics, our framework tends to be a holistic and dynamic instrument for understanding urban comfort from multifaceted perspectives and uncovering the interactions between various indicators and comfort.

3.2. Measuring and evaluating urban comfort

A variety of indicators outlined in Section 3.1 contribute to the urban comfort index, with features having either a positive or negative impact on urban comfort. For example, higher levels of noise, air pollutants, and unfavourable human perceptions of the surroundings are generally less desirable. Reviewing the methods used in socio-economic and policymaking domains, the Mazziotta-Pareto index (MPI) is widely accepted as a composite instrument (Mazziotta and Pareto, 2018; Scaccabarozzi et al., 2024; Mundetia et al., 2018; Higgs et al., 2019).

$$MPI_i^{+/-} = M_{Z_i} \pm S_{Z_i} \times cv_{Z_i}$$

where M_{Z_i} is the mean of the standardised values for unit i, S_{Z_i} is the standard deviation of the standardised values for unit i, and cv_{Z_i} is the coefficient of variation. It enables the aggregation of multiple indicators at spatial units and summarises their impact into a single index (Mazziotta and Pareto, 2016). Compared to other measurements, a key aspect of the MPI method is the penalisation of imbalances among positive and negative indicators, using a range of standard deviations to match the polarity of indicator values.

$$z_{ij} = 100 \pm \left(\frac{x_{ij} - M_{xj}}{S_{xj}} \right) \times 10$$

where x_{ij} is the value of the j-th indicator for the i-th unit, M_{xj} is the mean of the j-th indicator across all units, and S_{xj} is the standard deviation of the j-th indicator. Data-wise, the MPI method reduces the dimensionality of the data while preserving essential information, helping enhance efficiency and mitigate the impact of outliers. In our research, we generate urban comfort scores by applying the MPI method to the included indicators. Following the formula structure, the 100 is a constant used as the baseline score for standardising the values (Mazziotta and Pareto, 2016), making the index more interpretable and comparable. Therefore, we define in this work, that urban areas scoring above 100 are considered more comfortable for living and activities, while areas scoring below 100 are regarded as having less urban comfort.

3.3. Building a graph-based approach to explaining urban comfort

GeoAI, or geospatial artificial intelligence is an interdisciplinary field representing the intersection of geography and artificial intelligence (Gao, 2021), empowering the research to investigate geospatial phenomena and enhance the understanding of human habitation (Gao, 2021; Liu and Biljecki, 2022; Mai et al., 2022; Casali et al., 2022). The emergence of graph neural networks (GNNs) in GeoAI models introduce a new dimension by integrating geographic theories directly into the models, thereby making them spatially explicit (De Sabbata et al., 2023; Liu and Song, 2024). Benefiting from the development of XAI techniques, graph-based approaches can be specifically tailored for urban and geospatial applications, unveiling the mystery and enhancing the transparency and accountability of AI-driven urban research (Liu et al., 2024; Xu et al., 2019).

Our multidimensional framework with a variety of urban features highlights the value of spatially explicit information for exploring urban comfort. Thus, we adopt GNNs to model the spatial patterns of urban areas (Liu et al., 2024; Jin et al., 2023; Silva and Silver, 2024), which is visualised in Figure 3. While numerous research papers examine the impact of urban features on life quality and urban comfort, spatial characteristics are not fully investigated for this purpose. The motivations for employing a graph-based neural network approach are twofold. First, a GNN model capture intricate spatial relationships between neighbourhoods, leveraging the graph structure of urban features (Lei et al., 2024b), and then predict urban comfort index with MPI scores as targets. The high complexity and dimensionality of such a model, involving multiple layers and various parameters, render traditional statistical inference methods less effective in this case. When urban data availability is a challenge in some cities, this approach can serve as an alternative for measuring comfort and developing a generic representation of local areas. Second, advanced by XAI techniques (Hoffman et al., 2018), a graph-based model can better explain the implicit contributions of various indicators to urban comfort. Similar to other deep learning algorithms, GNNs are highly non-linear and involve numerous parameters learned from data without assuming any specific underlying statistical distribution. Hence, different from classical statistical models, GNNs learn complex patterns directly from the input data itself. Thus, integrating with XAI techniques, the model can facilitate the interpretability regarding feature impact. Such a graph-based model will outperform the conventional methods (e.g. sensitivity analysis), which fall short of capturing the complexity and dynamics of urban interactions.

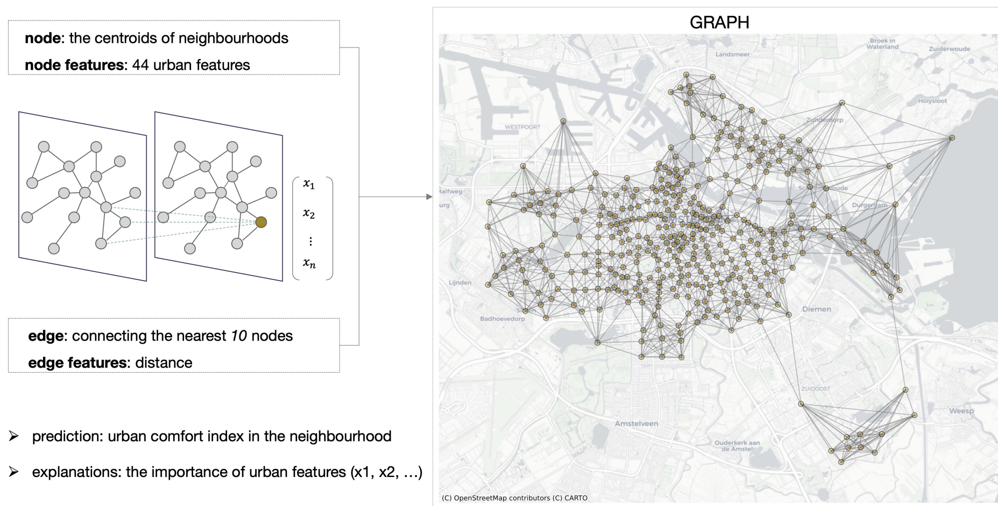


Figure 3: Spatial relationships between neighbourhoods in our graph-based model. Basemap: (c) OpenStreetMap contributors, (c) CARTO.

The GraphSAGE algorithm is adapted for constructing spatial networks among urban areas, benefiting from inductive learning and information aggregation (Hamilton et al., 2017). It is highly customisable, allowing for dynamic spatial representation and hyperparameter tuning (e.g. graph size and depth). XAI is a cutting edge technique popular for explaining the predictions of machine learning models. GraphLIME (Huang et al., 2022), an adaptation of the LIME method:

$$\xi(v) \leftarrow \arg\min_{g \in G} g(f, \mathbf{X}_n),$$

where f denotes the GNN model, v is an interpretable explanation model and node v is explained, addresses the challenges posed by graph-based models, for example, the difficulty in interpreting aggregated features from multiple neighbourhoods. Thus, we combine the GraphSAGE algorithm and GraphLIME to build an interpretable model for urban comfort index, aligning with our research motivations.

3.4. Conducting experiments

To implement this conceptualised framework and assert its applicability, we conducted our experiments in Amsterdam, carefully considering urban challenges and data availability in the local context. Amsterdam has launched an official project to measure urban liveability every two years. However, the current indicators may fall short of reflecting a holistic evaluation of living conditions, in particular in the context of climate change. Further, the multidimensional framework is developed for examining urban comfort in a holistic manner, and thus the completeness of urban data is a crucial determinant when we choose the study area. Given the open data initiatives (Spaans et al., 2013; Zuiderwijk and Janssen, 2014), Amsterdam extends collaborative connections between research institutions and government departments, providing a wide range of publicly accessible local data. Some research efforts have been made, taking advantage of the availability of data in the Netherlands, e.g. a country-wide walkability index (Lam et al., 2022), comprehensive 3D city models (Peters et al., 2022), and property value analysis (Huisman and Mulder, 2022). While the framework can be customised to align with local environments, the data richness in the Netherlands ensures a thorough investigation of the usability of our framework, covering as many urban features as possible, which affirms our motivation of considering the Netherlands as the focus of the implementation. We use 2022 as the study period in this work, aligning with the completion of government data release (e.g. housing value) and other appropriate spatial data (e.g. neighbourhood divisions).

A visual example of some used features is is provided in a neighbourhood in Amsterdam, as illustrated in Figure 4. Data sources used in the experiment are mainly from open government data and publicly accessible data. In detail, we retrieve most data from the government website — Maps Amsterdam[3], in particular for building information, socio-economic indicators and part of environmental factors (e.g. noise and air quality). Other than government information, we also leverage data from crowdsourced platform (i.e. OpenStreetMap), freely accessible data (i.e. Google Street View Images, PlacePulse 2.0, building perception dataset from Liang et al. (2024), 3D building metrics dataset from Labetski et al. (2023)). Further, we apply interpolation techniques and spatial aggregation

[3] https://maps.amsterdam.nl/

to process and harmonise data at the neighbourhood level. For finer-scale data (e.g. building information and streetscape data), we aggregate values directly to neighbourhoods by computing mean or sum values, depending on the nature of the dataset. For coarser-scale data (e.g. weather data and air quality), we interpolate data values before aggregation to ensure data consistency across spatial and temporal scales (Paulhus and Kohler, 1952; Afrifa-Yamoah et al., 2020).

Implementing our framework in Amsterdam can serve as a supplementary instrument for better understanding urban issues, filling information gaps, and suggesting potential solutions for local stakeholders. Further, a successful adoption can also inspire future customisation in other cities, where there is a need to comprehensively interpret urban comfort, taking into account its spatial and temporal dynamics.

3D urban morphology

Index	Feature	Value
1	building_age	1704
2	fractality_3d	0.30631383
3	cubeness_3d	0.788132149
	…	
18	exchange_3d	-0.104608871

Human perception

Index	Feature	Value
1	building_style	4.504533023
2	building_boring	3.923660084
3	street_safer	5.356807299
	…	
12	street_livelier	5.882793226

Socio-economic indicators

Index	Feature	Value
1	property_value	5271
2	poi	162
3	mixed_living	0.441207
	…	
7	population	2369.627434

Environmental factors

Index	Feature	Value
1	tree	240
2	sky	0.20603692
3	no2	20.99113001
	…	
7	noise	38.4337757

Figure 4: An example of data integration for urban comfort measurement in Amsterdam. It highlights the spatial distribution of selected features included in our multidimensional framework, such as 3D building index from 3D urban morphology, visual perception of buildings from human perception, property value as one of socio-economic indicators, urban trees from environmental factors.

The experiment in Amsterdam contains a multidimensional framework with 44 urban features, MPI measurements, graph-based model construction, and explanation. Regarding the graph-based model design, each neighbourhood is considered a *node*, with various indicators serving as *node features*. To exploit spatial relationships, we connect each neighbourhood with its *10* nearest neighbours, where the connection is an *edge* in the model, and the distance is used as the *edge weight*. Considering the issue of geographical isolation, we exclude neighbourhoods that cannot be spatially connected with their neighbours, such as those segmented by administrative boundaries. Root mean squared error (RMSE), mean absolute error (MAE), and R-squared value (R2) are employed as evaluation metrics to examine model performance.

4. Results

We generate a city-wide urban comfort index in Amsterdam, and explain how both objective and subjective features contribute to the spatio-temporal dynamics of urban comfort. We summarise the feature importance by leveraging the graph-based model and explainable AI, which exploit the spatial connectivity of neighbourhoods and outperform standard machine learning algorithms across various metrics, e.g. RMSE (2.04), MAE (1.03), and R-squared value (93.57%). For example, the density of urban trees and the availability of points of interest (POIs) consistently have a positive impact on neighbourhood urban comfort, whereas population density and housing value also positively affect urban comfort in some cases. Notably, certain aspects of buildings along the street negatively contribute to urban comfort, for example, the perceived building style.

4.1. Urban comfort demonstrates spatial variation and temporal dynamics

Figure 5 illustrates the spatial distribution of the urban comfort index for 2022 and its quarterly changes at the neighbourhood scale in Amsterdam. We apply seven classes to quantify the divergence of urban comfort across the city, with higher scores indicating better urban comfort and a score of 100 set as the baseline. We determine seven classes to make a balance between granularity and interpretability, allowing us to capture nuanced variations in urban comfort while ensuring that the results remain meaningful. The multidimensional index indicates that lower urban comfort is generally found within inner Amsterdam compared to areas in the middle and some peripheral regions. While these findings reflect discrepancies with the acknowledged distribution of infrastructure (e.g. the city centre commonly benefits from greater access to services and amenities), subjective perception of facilitate provisions may play an important role in shaping human-centric urban comfort. Considering urban challenges associated with the rapid growth of cities, policy initiatives often focus on addressing inequities in social provisions in suburban areas, which, to a certain extent, impact urban comfort. However, our findings suggest that such deductions may not comprehensively represent local life. Urban life results from a multidimensional interplay of various uncertainties and dynamics (e.g. climate conditions, personal experiences, and the quality of social infrastructure). We explore this case in detail in Section 4.2, evaluating our findings within the local context.

Diving into the dynamics of urban comfort, we examine how it varies over the seasons in 2022, considering differences in environmental factors (e.g. temperature, rainfall, and air quality). The right column in Figure 5 illustrates the temporal variation of urban comfort, showing changes across each quarter. We observe an increase in urban comfort index in the city centre and nearby suburbs from the first quarter (Q1) to the second quarter (Q2). This trend expands to more peripheral regions in Amsterdam from Q2 to the third quarter (Q3). In detail, around 50% of neighbourhoods experience positive changes from Q1 to Q2 and from Q2 to Q3. However, there is a slight decrease from Q3 to Q4, with 46.21% of neighbourhoods showing improved urban comfort. This seasonal variation highlights the influence of environmental factors on urban comfort, as factors like temperature, rainfall, and air quality fluctuate throughout the year. The findings underline the importance of considering temporal dynamics when evaluating urban comfort, as seasonal variations can significantly impact the overall quality of life. In Section 4.4, we dive deeper into these observations, providing a detailed analysis of how different seasons and their associated features affect urban comfort in various neighbourhoods across Amsterdam.

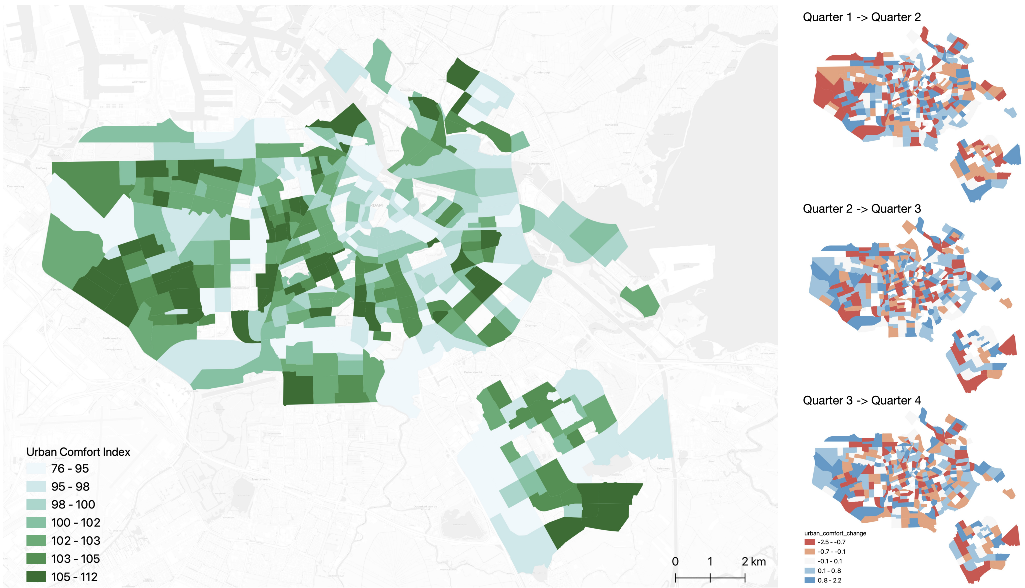


Figure 5: Urban comfort index in Amsterdam. Its distribution highlights spatial and temporal variations across neighbourhoods in Amsterdam. The left map shows the urban comfort index for each neighbourhood, with 100 as the baseline; higher values indicate greater comfort. The right column illustrates the changes in the urban comfort index across quarters.

4.2. Evaluating urban comfort index with the official instrument

Exploring the results from the spatial distribution, we compare our findings with the ‘Leefbaarometer’ instrument published by the Netherlands government. We choose two illustrative regions as examples: Amsterdam-Centrum and Amsterdam-Gein. The former, the city centre, demonstrates deficient urban comfort in our measurement but is classified with excellent liveability in the Leefbaarometer. The latter, an outer suburban region, shows satisfactory urban comfort in our index but is indicated as a less liveable area by the official measurement. Given the distinct differences between our urban comfort index and the official index, we leverage social media data to investigate these scenarios and evaluate the reliability of our findings. The results are summarised in Figure 6. This comparative analysis helps to highlight the unique aspects captured by our multidimensional framework and implies the future enhancement in conventional measurements of urban life quality.

Figure 6: The evaluation of urban comfort index, comparing it with official instruments and supplementary data from Google reviews. Word clouds generated from Google reviews demonstrate positive and negative comments for two highlighted regions. The percentages of positive and negative comments reveal human perspectives, substantiating the potential of the urban comfort index to fill an information gap through a mix of qualitative and quantitative methods. Source of the imagery: Leefbaarometer 2022 and Google reviews.

The adoption of social media data, also known as volunteered geographic information and user generated content in many cases, has proliferated in the research landscape (Martí et al., 2019; Yan et al., 2020). The publicly available and crowdsourced nature of such data enhances various studies by providing insights into urban phenomena and events on a human scale (Chen et al., 2018; Liu et al., 2017). In this regard, we aim to seek local perspectives on urban life across neighbourhoods in Amsterdam. Therefore, Google Places, one of the most prominent social platforms with a wealth of user reviews, has become an expansive data source for researchers to obtain observational information and comments related to how people experience and understand urban places (Song et al., 2021; Huai and Van de Voorde, 2022).

To retain as many comments from local residents as possible, we primarily focus on urban amenities that support daily life and provide social services. We consider 15 types of places, such as *urban parks*, *healthcare*, and *schools*. Further, we only include comments written in Dutch to filter out visitors to a certain extent, and accurately profile local residents in these two regions. Applying the defined search strategy, we retrieve comments using the Places API[4], building our dataset for further analysis. As a result, we obtained 20,740 reviews in the central area, with 15.02% negative comments, and 659 reviews in Gein, 14.87% of which were negative. A sentiment analysis was conducted as supplementary information (detailed in Figure 6). Many negative comments in the centre complain about unpleasant streets, crowdedness, and expensive prices, using words such as 'busy', 'expensive', and 'annoying'. In Gein, concerns related to availability and environmental maintenance were observed, with terms like 'dirty', 'strange', and 'waste'. While the Gein neighbourhood is less popular than the city centre, the percentage of negative comments on social infrastructure is lower than in the central region. This contemporary evaluation, using a mix of qualitative and quantitative methods, enhances our understanding that the urban comfort index has the potential to uncover more details that the official measurement may overlook. Further, it should be highlighted that our index is not intended to contrast the government project but to provide insights into a comprehensive representation of urban life in the city. Indeed, urban comfort results from city planning and strategic implementation, and thus, the inclusion of multidimensional features can shed light on the inherent differences across space and time.

4.3. Graph-based approach performs well in predicting urban comfort

We train the graph model across neighbourhoods over time in Amsterdam and achieve good performance in generating urban comfort dynamics, benchmarked against the baseline random forest model, a widely accepted method in the research landscape. To gauge the characteristics of the graph-based approach compared with the random forest algorithm, the same features are applied in both models, with specific parameters in random forest (i.e. max_depth=100, random_state=0). Table 1 summarises the evaluation. When predicting yearly urban comfort on a neighbourhood scale in 2022, the graph-based model delivers an RMSE of 2.04 and an MAE of 1.03, with an average R-squared value of 93.57% across four quarters. Whereas, the random forest model achieves an RMSE of 4.57 and an MAE of 1.56, with an average R-squared value of 85.59%. The predictions in Q3 achieve the best performance, with an RMSE of 1.31 and an MAE of 0.88, and an R-squared value of 95.85%, indicating a better fit of the model to the variables. We then evaluate the model performance in more detail, calculating the

[4] https://developers.google.com/maps/documentation/places/web-service/overview

percentage of predicted urban comfort that is overestimated and underestimated (Table 1). Overall, the graph-based approach tends to underrate urban comfort scores. Specifically, 68.70% of neighbourhoods are predicted with lower urban comfort in Q3, while 42.61% of neighbourhoods are overestimated in Q4.

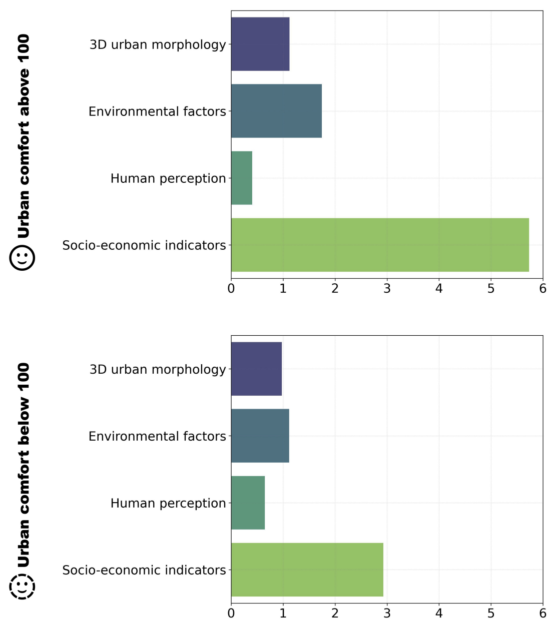
Despite this tendency, the graph-based model outperforms the state-of-the-art methods. We believe that the designed method is strongly predictive of urban comfort, which can be further generalised in other cities that face challenges of available urban data. Meanwhile, such an evaluation demonstrates robustness under spatial and temporal changes by modelling the spatial interactions between neighbourhoods in the city. It confirms a solid foundation for the subsequent adoption of XAI to interpret the impact of each feature on urban comfort dynamics.

Table 1: Comparative performance evaluation of random forest and GraphSAGE models. Metrics include MAE, RMSE, R-squared values for estimating urban comfort index; the percentages of overestimated and underestimated neighbourhoods in the graph-based approach.

	MAE	RMSE	R-squared (%)
2022	**Random forest**		
	1.56	4.57	85.59
	GraphSAGE		
	1.03	2.04	93.58
	Overestimate (%)	Underestimate (%)	
	35.65	64.35	
Quarter 1	**Random forest**		
	1.55	4.50	85.84
	GraphSAGE		
	0.99	1.56	95.08
	Overestimate (%)	Underestimate (%)	
	40.87	59.13	
Quarter 2	**Random forest**		
	1.70	4.50	84.62
	GraphSAGE		
	0.88	1.46	95.53
	Overestimate (%)	Underestimate (%)	
	35.65	64.35	
Quarter 3	**Random forest**		
	1.53	4.27	86.45
	GraphSAGE		
	0.88	1.31	95.85
	Overestimate (%)	Underestimate (%)	
	31.30	68.70	
Quarter 4	**Random forest**		
	1.80	5.57	82.93
	GraphSAGE		
	1.15	2.44	92.54
	Overestimate (%)	Underestimate (%)	
	42.61	57.39	

4.4. *Explaining the impact of features on urban comfort*

We divide our explanations of feature importance into two scenarios: neighbourhoods with high urban comfort (above the threshold of 100) and neighbourhoods with low urban comfort (below the threshold of 100). The yearly results are used as an instance, complemented by seasonal details. Figure 7 concludes the explanations from the graph-based model.



Top 3 positive features with importance — in quarter

	Top 1	Top 2	Top 3
Quarter 1	Tree (1.39)	Population density (1.32)	POI (1.13)
Quarter 2	Tree (1.47)	Housing value (1.37)	POI (1.11)
Quarter 3	Tree (1.98)	POI (1.77)	Facility (0.76)
Quarter 4	Tree (1.76)	POI (1.11)	Facility (0.97)

Top 3 negative features with importance — in quarter

	Top 1	Top 2	Top 3
Quarter 1	Buildings (-0.31)	Building originality (-0.31)	Building style (-0.24)
Quarter 2	Population density (-1.95)	Sky (-2.8)	Buildings (-0.18)
Quarter 3	Population density (-0.79)	Vegetation (-0.21)	Streetscape boringness (-0.19)
Quarter 4	Building complexity (-0.26)	Building originality (-0.23)	Building style (-0.23)

Figure 7: Explanations of feature importance from explainable AI (XAI), grouped by neighbourhoods in urban comfort index above and below the baseline. The bar charts highlight the the contribution of each dimension, and the two tables lists the top three positive and negative features for each quarter.

First, it is notable that socio-economic indicators and environmental factors have significant impact on urban comfort. In detail, in neighbourhoods with high urban comfort, greenery (1.75) from environmental aspect and points of interest (1.33) from socio-economic dimension have a notably positive impact. Additionally, the provision of urban facilities (e.g. bus stops) and local services (e.g. healthcare) underscores the significance of social support in building urban comfort, which are well recognised features in the research landscape. Urban functions related to living and working also play a role in enhancing local life quality, including the availability of residential spaces and proximity to workplaces (i.e. local economy). Such finding implies a growing need for mixed-use developments, which can enhance a balanced urban environment where living and working are well integrated. Further, from the perspective of urban buildings, physical characteristics such as housing value, building age, and morphology contribute positively to urban comfort. In a human scale, neighbourhoods with buildings perceived as more boring and ordered tend to have lower urban comfort. Similarly, regarding human perception of streetscapes, livelier and wealthier streets encourage more comfort compared to tedious streetscapes. In this sense, architectural design and placemaking, focusing on visual quality, influence urban comfort.

Second, we find corresponding patterns in neighbourhoods with reduced urban comfort. Regarding the dimension of socio-economic indicators, the availability and accessibility of urban social support(e.g. facilities and diverse urban functions) are important for generating higher life quality. However, population density (-1.17) is a critical indicator that negatively impacts urban comfort. It suggests that overcrowdedness may lead to an uncomfortable living experience, propagating social issues such as a reduced sense of safety (Wen et al., 2020; Tandogan and Ilhan, 2016). Additionally, a high portion of building (-0.38) and vegetation (-0.23) in streetscapes induces undesirable comfort for residents. Such phenomenon can be interpreted from a sentimental perspective. For example, densely developed areas (e.g. with more compact and tall buildings) may make people feel stressed and unpleasant, and an excessive portion of greenery on the streets may trigger concerns about safety (Kuo et al., 1998; Mouratidis, 2019).

Moving from yearly to quarterly results, an alignment of positive feature importance is observed across temporal changes (summarised in the right tables in Figure 7). Indeed, the provisions of available and sufficient urban amenities and services can promote urban comfort at the neighbourhood scale. However, while crowdedness remains a negative impact on urban comfort in Q2 and Q3, human perception of urban buildings contributes more to decreasing urban comfort in the fourth quarter of 2022.

4.5. Use case: simulating strategies to enhance urban comfort

To investigate the usability of our urban comfort index and feature importance, we conduct a use case (Figure 8), simulating urban scenarios and proposing strategies to enhance local comfort. Taking the neighbourhood Frederik Hendrikbuurt-Zuidwest as an example, its comfort index is 99.32 in 2022, slightly below the baseline of 100.

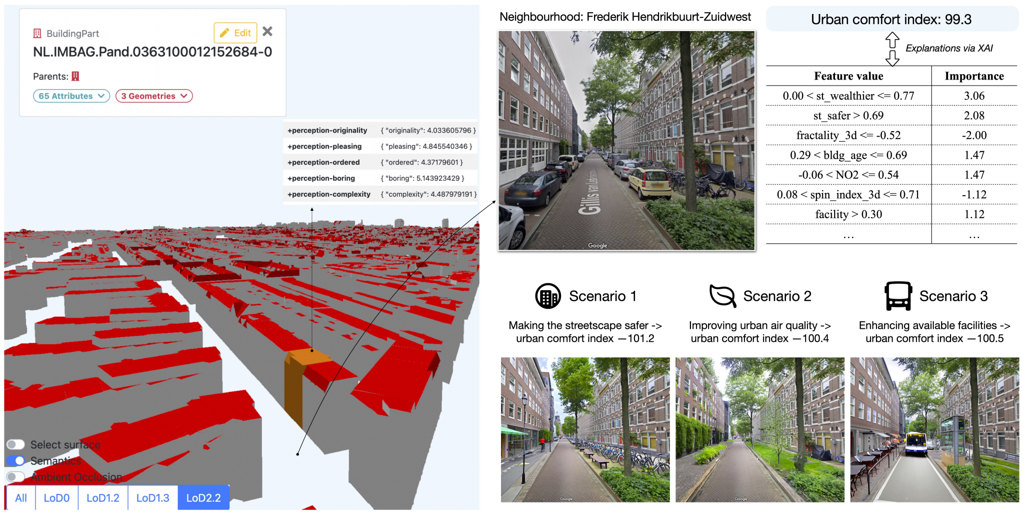


Figure 8: Scenario simulations for improving urban comfort in the neighbourhood of Frederik Hendrikbuurt-Zuidwest. Source of the imagery: Google Street View, ninja (Vitalis et al., 2020).

The graph-based approach combined with XAI explains the impact of urban features in detail. In this neighbourhood, human perception makes significant contribution to local urban comfort. For example, when street design makes people feel wealthier (3.06) and safer (2.08), it introduces positive impact on urban comfort. In the environmental dimension, air quality (reversed as a negative indicator) suggests a significant influence on urban comfort with a value of 1.47, which is indeed overlooked in the official instrument. Further, the explanations of feature importance demonstrate that 3D urban morphology, as an important part of urban environment, plays a role in generating urban comfort. For instance, the value of 3D fractality (-2.00) indicates that a number of similar architectural designs may decrease comfort. In this regard, such interpretations substantiate our motivation for including urban morphology and 3D building index as one critical dimension in the urban comfort framework.

Considering the practicability of neighbourhood improvement, we propose three urban scenarios advanced by 3D city models and urban digital twins: activating street design, improving urban air quality, and increasing available urban facilities. In *Scenario 1*, we increase the value of street safety while keeping other feature values the same, achieving a score of 101.30 for neighbourhood comfort. This scenario incorporates urban planning methods to visualise various strategies, such as a regenerative design of building facades to enhance visual quality. Additional considerations include well-lit sidewalks, visible cycling paths, and outdoor seating areas, creating a safe and lively atmosphere in the neighbourhood. For *Scenario 2*, we adopt several strategies to improve urban air quality. Given the negative impact of nitrogen dioxide (NO2) on urban comfort, we aim to decrease the concentration of NO2 to 10 $\mu g/m^3$ in this neighbourhood, an acknowledged level with less impact on human health (Zallaghi et al., 2014; Rao et al., 2014). This adjustment will increase the urban comfort index to 100.35. Design principles include encouraging the development of vertical gardens in residential buildings, introducing sustainable transportation modes, and setting up air quality monitoring stations, contributing to a sustainable and healthy neighbourhood. *Scenario 3* focuses on strengthening the accessibility and availability of urban facilities, especially public transport. By elaborating on design strategies such as setting up publicly accessible bus stops and including diverse urban furniture (e.g. drinking fountains, seating areas, and bike racks), we increase the number of facilities to 20 in this neighbourhood. The improvement facilitates an increase in the local urban comfort score to 100.52.

The proposed three scenarios enhance neighbourhood comfort with the help of XAI. However, this approach is purely quantitative and is limited to fully consider the interaction between urban features and city complexity in the reality. For example, adding more urban trees to the street may improve air quality to some extent but may have an unknown impact on the sense of safety (e.g. discussed in Section 4.4). Therefore, optimal consideration should be given when adopting various strategies to enhance neighbourhood.

Further, a number of validations should be taken into account for accommodating local contexts (e.g. planning regulations and public demands), whereas these scenario simulations provide quantitative insights on planning actions. In this regard, we deem that incorporating qualitative information can complement the findings from digital simulations, reviewing the feasibility in a holistic manner. For example, we can compare the simulation results with empirical information, such as similar strategic interventions in other neighbourhoods which share the similar local contexts. Meanwhile, consultations with experts (e.g. strategic planners) can be involved as a means of evaluating the potential impact of proposed scenarios, gathering insights from domain experts and practitioners. Prioritising the voice from local residents, we also need to encourage public engagement in the planning process. For example, interview and discussion sessions with residents of Frederik Hendrikbuurt-Zuidwest can be conducted in the future, understanding their vision of their neighbourhood, as well as validate the effectiveness of proposed scenarios and strategies in the local environment. Hence, besides digital simulations of urban scenarios and strategies, an integration of qualitative research, along with top-down and bottom-up approaches can be considered for further applicability and validation, when implementing our framework in real-world contexts.

Therefore, this use case remains of interest to future researchers and practitioners, offering insights into potential solutions and recommendations for urban design and planning. Further, compared to conventional tools, we highlight the role of 3D city models and urban digital twins in representing urban settings, enabling a realistic and semantic perspective for analysis and simulations.

5. Discussion

5.1. Urban comfort framework fills the information gap

The quality of urban life has been widely studied to examine how liveable and comfortable neighbourhoods and cities are, impacting urban health and wellbeing. However, to date, this field is limited in providing a holistic representation of humans and cities, as well as robust explanations of urban features. The term 'urban comfort' encapsulates a variety of urban features that impact the quality of life, aiming to reflect the inherent dynamics. Compared to existing measurements, our urban comfort framework stands out for its comprehensive inclusion of both human perception and urban surroundings. Additionally, advanced by graph-based neural networks and XAI, we are able to interpret the driving forces behind urban comfort. Unlike commonly used methods for explanations, deep learning models enable us to investigate how urban features are interwoven with urban comfort, rather than merely analysing the linear relationships between urban features. This approach is more appropriate for understanding the city as a complex system consisting of interactions between humans and urban environments. Applying our instrument in Amsterdam, the urban comfort index illustrates spatial and temporal variations. We compare the results with the Leefbaarometer project, which is officially launched by the Netherlands and updated biannually, leading to a discussion from two perspectives.

First, urban comfort index uncovers more detail that may be blurred in the official measurement. The Leefbaarometer project has nine categories to classify life quality, yet these categories can hardly demonstrate detailed differences. For example, neighbourhoods located in the city centre are evaluated in the same category with excellent life quality (Uitstekend). However, from a perspective of spatial heterogeneity, each neighbourhood is uniquely characterised by its local context. In this regard, the official instrument has limitations in distinguishing these inherent distinctions. As analysed in Section 4.1, our urban comfort index is unaligned with the official measurement in some areas, considering that we include more diverse urban features in the designed framework. However, by employing a mixed qualitative and quantitative analysis, we leverage social media data to explore representations of local areas and discuss the differences. The findings and details ensure the reliability of the urban comfort index. Therefore, we believe this work can offer insights into revealing variations at the neighbourhood scale and serve as a tool to address the information gap.

Second, integrating 3D building data with human perception plays a significant role in measuring urban comfort. Current discussions on urban life quality are hampered by limitations in quantifying diverse urban surroundings and the lack of a human lens. The concept of human-centric urban digital twins, with growing interest in analysing and solving urban issues (Ye et al., 2023; Lei et al., 2023c), inspires us to adopt it in our urban comfort framework. It not only enables a 3D representation of the city but also advances the subsequent use case to simulate different urban scenarios. Further, recent research on adding the perception of urban buildings in 3D city models highlights the role of humans in understanding urban morphology (Lei et al., 2024a). Following this line of research, we include 3D city models and human perception to represent urban environments with an integration of subjective and objective aspects, thus generating preliminary understandings of the interactions between 3D urban morphology, human perception, and urban comfort. The explanations from XAI further indicate a significant contribution of 3D morphology to urban comfort, confirming our motivation for including these indicators.

The assessment of urban quality of life differs from various aspects worldwide (Mittal et al., 2020), considering datasets (e.g. national census, public statistics or participatory information), indices (e.g. subjective or objective), techniques (e.g. statistical or geospatial analysis), and purposes (e.g. top-down approach for urban governance or bottom-up for research. In this work, our urban comfort index brings a plethora of innovative perspectives and potential use cases, contributing the growing body of literature on urban life, wellbeing and sustainable cities. Shedding light on the advancement of urban technology, such as graph neural networks and urban digital twins, this work can serve as an invaluable instrument with credible evidence to understand the heterogeneity and complexity of urban environments, as well as the dynamic interplay between urbanites and their surroundings.

5.2. *Explainable AI advances the interpretations of urban features on urban comfort*

Exploiting the spatial relationships between neighbourhoods, our graph-based model represents such spatial connectivity, capturing urban features aggregated in each neighbourhood. However, while the model is well constructed and evaluated, it remains challenging to interpret the impact of each feature, considering the black-box nature of this graph-based model. Meanwhile, the urban comfort index is a composite measure derived from multiple dimensions, of which the high dimensionality of selected features further complicates the difficulty of interpreting the contributions of individual features.

Employing LIME as our XAI technique, it enables us to gather explanations for individual predictions, making it particularly useful for understanding model behaviour in neighbourhoods of interest within the urban context. For example, we can identify the most influential features in specific neighbourhoods (such as Frederik Hendrikbuurt-Zuidwest as an example). Further, unlike classic means of explanation in the existing assessment (e.g. sensitivity analysis), the advancement of XAI moves forward to uncovering the non-linear interaction inherent to urban complexity, which collectively impacts urban comfort. In this regard, the findings from XAI can imply more comprehensive and in-depth insights to practitioners, taking into account the intricate and interacting urban environments. For example, adopting urban comfort index as an instrument, city planners can investigate key drivers of urban comfort in a local neighbourhood, thereby designing and taking potential interventions to improve the urban quality of life.

5.3. *Limitations and future work*

We discuss the limitations and future work from four perspectives. First, while the four dimensions in the framework gather comprehensive information about urban environments, future studies can consider including more detailed indicators to meet specific needs. In the case of Amsterdam, 44 urban features were selected to capture characteristics related to urban comfort, taking into account the literature and local urban challenges. However, when generalising the framework and method to other cities, local contexts should be considered. It means the urban comfort index can be tailored in future customisations, integrating additional features or updating the framework as needed. The second limitation addresses data availability and quality. The implementation of urban comfort index in Amsterdam aligns with the available data. Government data in the Netherlands stands out compared to other regions, yet there remains a sparsity in specific data categories. For example, not all buildings in Amsterdam can be retrieved with housing values, and the housing values only indicate a range of prices instead of specific values. Further, while environmental factors (e.g. weather data) significantly contribute to urban comfort, climate data is not easily accessible in this case (e.g. the limited number of weather stations). Therefore, we use interpolation techniques, which are commonly used in processing meteorological data, to enhance completeness and consistency for analysis. Many studies on urban life quality rely on government data; however, as previously mentioned, official data can be challenging in terms of availability and quality, potentially leading to unreliable results. In this regard, a highlight of our urban comfort index is the employment of crowdsourced data, which has been widely used in multiple domains with acknowledged value, such as human perception in this work. In future work, we intend to increase the variety of datasets and collect opinions from local practitioners as well. Third, the same way as in other domains (e.g. (Lam et al., 2022; Ye et al., 2022; Patias et al., 2021; Lei et al., 2023b)), the selection of dimensions and features may be considered subjective to some extent. Such an inclusion is based on our review of related work, exploration of datasets, examination of use cases and literature, and it strives to serve our research motivations. On the other hand, the proposed framework is intended to serve as a generic approach to indexing urban comfort, thus, it may also satisfy further purposes for future uses. For example, it enables giving more weight to a particular aspect that may be more important than some others in a particular context. Depending on the specific goals, the framework may be further extended with further dimensions. The urban comfort index with 44 features provides a holistic and robust instrument for different stakeholders to evaluate local comfort. At the same time, it provides the flexibility to further determine extra features based on particular use cases. Fourth, we have only implemented our framework in one city — Amsterdam, which may propagate uncertainties related to its scalability and transferability to other cities, given spatial heterogeneity and varying urban settings. Differences in urban contexts may impact the adoption of the urban comfort framework, in particular concerning data availability and framework features. However, as discussed above, the urban comfort framework is flexible and allows for customisation when tailored to other contexts. Therefore, we can take into account diverse urban environments and data accessibility, incorporating relevant features to better represent local life quality. For example, Amsterdam is a typical European city with its own distinct cultural and socio-economic characteristics. When adopting the framework in cities that differ from European settings, the indicators of local importance should be included (e.g. informal settlements in developing cities). Likewise, collaborating with local stakeholders and residents can further enhance the adaptability of our framework, reflecting urban life in a comprehensive manner. In this case, we can explore and refine the framework in a variety of urban settings, facilitating its robustness and scalability to serve as a more universal tool for evaluating and improving urban comfort.

6. Conclusion

In this work, we introduce a generic concept — urban comfort — which integrates four dimensions to represent quality of life in urban environments: 3D urban morphology, socio-economic features, human perception, and environmental factors. This holistic framework aims to measure dynamic urban comfort from a human-centric perspective, advanced by the inclusion of 3D analysis and micro environment.

Aligning with our research motivations, a graph-based approach is employed to interpret how diverse urban features impact urban comfort. We conduct experiments in Amsterdam, including 44 urban features for urban comfort measurement. The results demonstrate spatial variations at the neighbourhood scale, as well as quarterly changes in 2022. When observing differences compared to the official instrument, we introduce a mixed qualitative and quantitative method to make evaluations, using Google Places reviews as a crowdsourced dataset that helps us sense additional information. The evaluation enhances our findings, showing that urban comfort index has the potential to reveal detailed information across neighbourhoods, while the official index falls short in classifying the quality of life in more detail. Advanced by XAI, we gain a deeper understanding of feature importance. The availability and accessibility of urban amenities and social services (e.g. trees, facilities, and urban functions) positively contribute to urban comfort. Conversely, less visual quality (e.g. boring building appearance) and overcrowding decrease local comfort.

Further, we conduct a use case to illustrate the usability of urban comfort index and discuss its value in practice. Supported by 3D city models integrated with human perception, we design three scenarios by adopting relevant strategies, each of which enables an improvement in urban comfort. The proposed framework and the innovation of our method provide insights into measuring urban comfort from an inclusive perspective, facilitating urban planning and policymaking for researchers and practitioners.

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