Integrating the Human Experience in Climate-adaptive Urban Green Infrastructure: A Digital Approach

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PhD Research Plan

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Content

Summary

Climate change and ongoing global urbanization present profound challenges to cities worldwide, and the climate adaptation transformation of urban environments has become a key priority in urban policies. In response, cities are increasingly adopting urban green infrastructure, such as public green spaces, green streets, urban forests, and rain gardens, to mitigate and adapt to climate change while advancing broader sustainability goals. Beyond their environmental values, recent evidence suggests that urban green infrastructure can also enhance human experience and well-being. However, current climate-adaptive urban green infrastructure practices predominantly focus on the environmental benefits, while the human experience is often overlooked, and an integrated framework balancing human benefits with environmental functions remains lacking. Understanding how climate-adaptive urban green infrastructure contributes to human experience and ensuring that it supports both environmental and human benefits remains a central and unresolved question.

Conventional research methods for investigating human–environment interactions, though valuable, are often time- and labor-intensive and lack scalability. As a result, they face challenges in addressing the diverse, systemic, and spatially distributed characteristics of urban green infrastructure, leading to limited empirical insight. Advances in digital technologies offer significant potential to address this gap. Urban data, among which crowdsourced data (e.g., social media data), transactional data (e.g., property value data), etc., may allow for extensive and quantifiable observations and analysis of human-environment interactions in urban green infrastructure, opening new avenues for empirical inquiry. On the other hand, the use of virtual reality technologies and computational design methods can better enable the application of empirical insights in iterative design experiments, supporting more robust and evidence-based urban green infrastructure practices.

Therefore, this research aims to integrate emerging digital technologies to examine the human experience of climate-adaptive urban green infrastructure and explore how it can be balanced with environmental performance in more holistic planning and design applications. The driving vision of this research is to ensure that urban green infrastructure not only benefits the environment, but also enhances human perception and experience. The research question is, how can we understand and integrate human experience into climate-adaptive urban green infrastructure, leveraging digital technologies? The research lies at the intersection of urban green infrastructure, human-centric approach, and digital technologies.

The prospective results of this research will contain three main parts. Firstly, it aims to develop a human-centric theoretical foundation synthesizing existing research evidence and conceptualizing the human benefits of climate-adaptive urban green infrastructure. Secondly, building on this basis and focusing on cities in the Netherlands as case studies, it aims to employ emerging data and digital analytic techniques to conduct empirical investigations and understand the mechanisms underlying the relationship and interaction between climate-adaptive urban green infrastructure and human perceptions and experiences. Thirdly, it aims to explore the application of research insight by developing toolkits supporting more holistic urban green infrastructure practices that simultaneously balance human benefits and environmental performances leveraging computational

approaches and multi-objective optimization methods.

This research will help bridge the gap between human experience and urban climate adaptation efforts, advancing planning and design of urban green infrastructure in ways that, while conducive for environment, also serve human needs and benefits. It will provide practical guidance and applicable tools for practitioners to incorporate and align human experience and environmental performance in future practices. Its theoretical and methodological development will also support researchers and policymakers in conducting more critical assessments and making better-informed decisions, ultimately improving how urban environments contribute to well-being and adaptive capacity.

1 Background

1.1 Global climate change

The impacts of climate change are increasingly affecting our environment and society (IPCC, 2023). Climate change detrimentally influences ecosystem and environmental health, resulting in habitat degradation, water scarcity, and changes in species and populations (Pecl et al., 2017). These effects are exacerbated by ongoing urbanization and large-scale landscape transformation (IPCC, 2001). Climate change also poses social risks, particularly through the increasing frequency and severity of climate-related disasters such as heatwaves, droughts, and floods, which cause substantial public health and economic losses (EEA, 2022; Hsiang et al., 2017) (Fig. 1). As global urban populations are projected to continue growing, climate change impacts are expected to further intensify (Hartig et al., 2014; Markevych et al., 2017).

(a) (b)

Fig. 1. Climate change causes: (a) environmental damage (source: reuters.com/world/europe/german-belgian-flood-deaths-rise-157-search-continues) and (b) social and well-being damage (sources: abcnews.go.com/International/earliest-heat-wave-greece-closes-acropolis-public-schools)

1.2 Emphasis on climate adaptation of cities

Urban areas are both major contributors to greenhouse gas emissions and, due to their geographic characteristics, building density, and impervious surfaces, among the most vulnerable to climate change impacts, making them priority areas for climate adaptation (Carter et al., 2015; IPCC, 2001).

Climate adaptation is defined as “the process of adjustment to actual or expected climate and its effects, in order to moderate harm or exploit beneficial opportunities” (IPCC, 2023). It can include a wide range of physical, organizational, institutional, and nature-based measures aimed at making different sectors and urban systems more resilient to climate change and impacts (IPCC, 2023; Sussams et al., 2015). Recognition of climate adaptation’s effects has grown significantly globally, reflected by recent initiatives such as the European Environment Agency's report "Urban Adaptation to Climate Change in Europe" and the Netherlands' “National Climate Adaptation Strategy”, providing frameworks for guiding adaptation efforts (EEA, 2012; Ministerie van Infrastructuur en

Waterstaat, 2016) (Fig. 2).

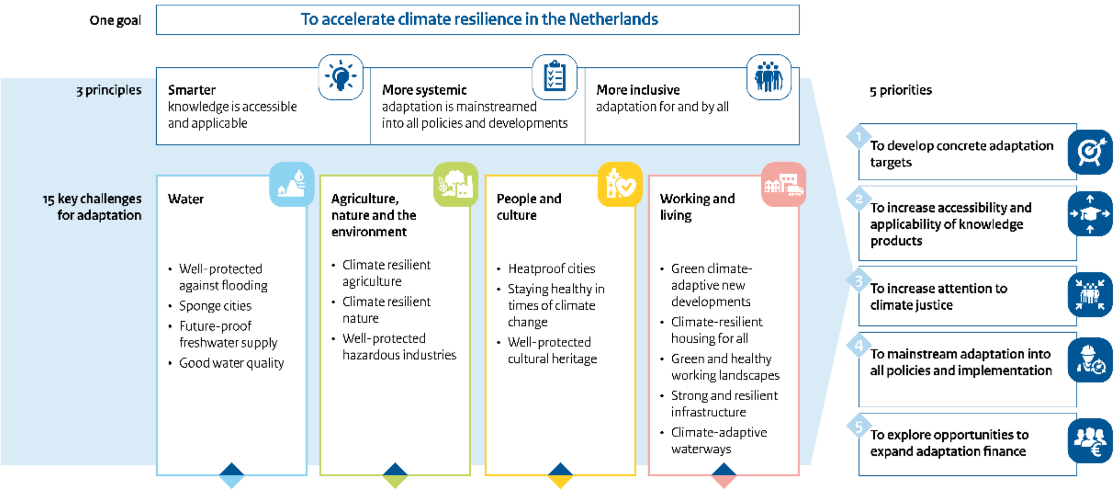


Fig. 2. National climate adaptation implementation program of the Netherlands (source: Ministerie va n Infrastructuur en Waterstaat, 2016)

1.3 Climate adaptation transformation of urban environment with urban green infrastructure

An important strategy of urban climate adaptation is urban green infrastructure. Green infrastructure refers to “a strategically planned network of natural and semi-natural areas with other environmental features, designed and managed to deliver a wide range of ecosystem services” (European Commission, 2015). Green infrastructure for climate adaptation can encompass a wide spectrum of spaces and structures covering conventional urban greenery such as green spaces, green streets, and urban forests, alongside emerging solutions such as rain gardens, green roofs, and vertical greening systems (Benedict & McMahon, 2012; Coutts & Hahn, 2015; Escobedo et al., 2019) (Fig. 3). These interventions aim to reduce urban vulnerability and exposure to climate change through multiple environmental benefits including temperature regulation, drought resilience, stormwater management, air quality improvement, and ecological conservation, and potentially generating additional economic and social value (Demuzere et al., 2014; Lovell & Taylor, 2013; Pauleit et al., 2019). For instance, sustainable drainage systems like bioretention and bioswale replicate natural watershed processes to capture precipitation, minimize runoff, reduce peak discharge rates, and filter contaminants, expanding urban infiltration capacity and mitigating flood risks (Ahiablame et al., 2012). Urban street trees and forests can provide cooling effects and air purification, addressing high temperatures and heat wave risks in metropolitan areas (Bowler et al., 2010).

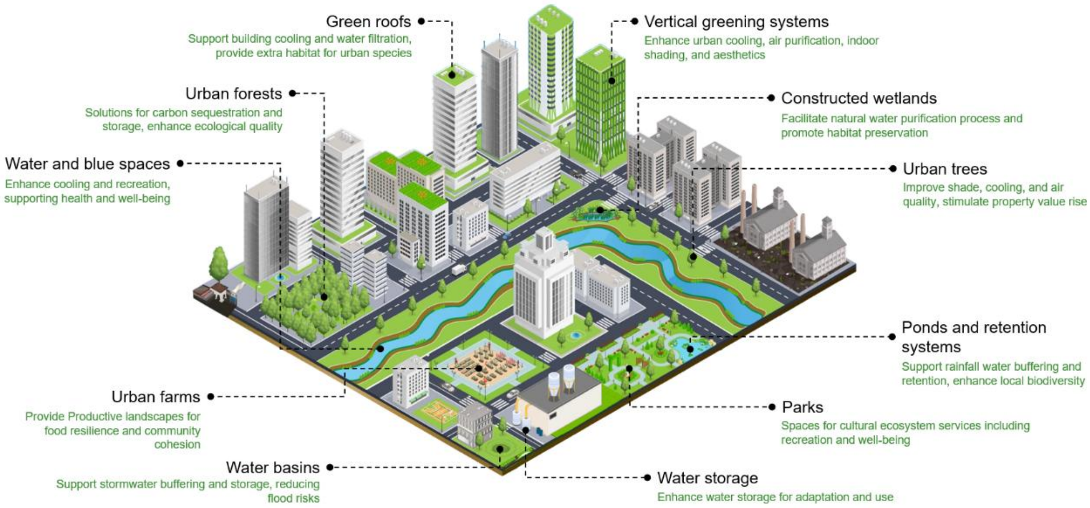


Fig. 3. Climate-adaptive urban green infrastructure (source: adapted from Cook et al., 2024)

Urban green infrastructure planning and implementation have gained widespread support. In the Netherlands, major cities including Amsterdam and Rotterdam have launched green infrastructure initiatives (e.g., "Green Infrastructure Vision 2050" and "Green Agenda 2023-2026" respectively) which propose extensive urban greening to combat heat waves and flooding (Gemeente Amsterdam, 2020; Gemeente Rotterdam, 2024), such as through the addition of 20 ha of green infrastructure. The Netherlands Enterprise Agency (Rijksdienst voor Ondernemend Nederland, 2024) has outlined 26 climate adaptation design measures and provided detailed guidance on climate benefits, costs, construction, and maintenance requirements to facilitate their implementation. Decision-support tools were also developed, which include the CLIMACAT platform developed by TU Delft's Geo-Database Management Center that provides online catalogs of climate adaptation design implementation (Kawasaki et al., 2024). In addition to policy and academic efforts, recent years have also witnessed the completion of multiple innovative green infrastructure projects, including Rotterdam's water squares and Dakpark rooftop garden, and Amsterdam's water playground, which exhibit innovative solutions for climate adaptation (Fig. 4).

(a) (b) (c)

(d) (e) (f) (g)

Fig. 4. Examples of climate-adaptive urban green infrastructure in the Netherlands. (a): resilient water front greenspace(source: landezine.com/tidal-park-keilehaven-by-de-urbanisten); (b): biodiverse green space (source: landezine.com/sponge-garden-by-de-urbanisten); (c): water square (source: duurzaam010.nl/nieuws/rotterdam-hergebruikt-regenwater); (d): roof park (source: landezine.com/four-harbour-roof-park-by-buro-sant-en-co); (e): green roof (source: unesco.org/en/sustainable-cities/unesco-sustainable-cities); (f): water basin (source: wikipedia.org/wiki/Waterspeelplaats_Het_Blad); (g): informal vegetation (source: landezine.com/secret-village-by-blooming-buildings)

2 Knowledge gaps and problem statement

2.1 The human effect of urban green infrastructure

With increasing practices of urban green infrastructure, there is also growing recognition that such interventions should not only deliver environmental and climatic benefits but also enhance the experiences of urban residents (Coutts & Hahn, 2015; Demuzere et al., 2014; Kumar et al., 2019; Lovell & Taylor, 2013; Tzoulas et al., 2007).

Climate-adaptive green infrastructure is increasingly viewed as a potential tool for fostering high-quality public spaces and improving public health and well-being. On one hand, the widespread presence of green infrastructure in urban environments inevitably affects people's daily lives and experiences (Hegetschweiler et al., 2017; Venkataramanan et al., 2019). Distinctive green infrastructure interventions like water squares and green roofs naturally attract public attention, potentially influencing perceptual and emotional responses and shaping user evaluations (Gobster et al., 2007). Green infrastructure perceived as safe and attractive may provide opportunities for recreation, restoration, and physical activity, contributing to improved health and quality of life (Hartig et al., 2014; Markevych et al., 2017). Such positive perceptions are also often reflected in multiple aspects of urban systems and experiences, for instance increased property values, eventually also leading to broader socio-economic benefits (Donovan & Butry, 2010; Netusil et al., 2010). On the other hand, successes of climate-adaptive green infrastructure can also depend on public understanding and support. Negative perceptions or preferences may hinder implementation, diminish social benefits, and adversely affect individual well-being (Ngiam et al., 2017; Samus et al., 2022) (Fig. 5).

With continuous urbanization process and urban spaces becoming increasingly valuable, enabling green infrastructure to fulfil multiple functions also presents an opportunity for cost-effective urban development.

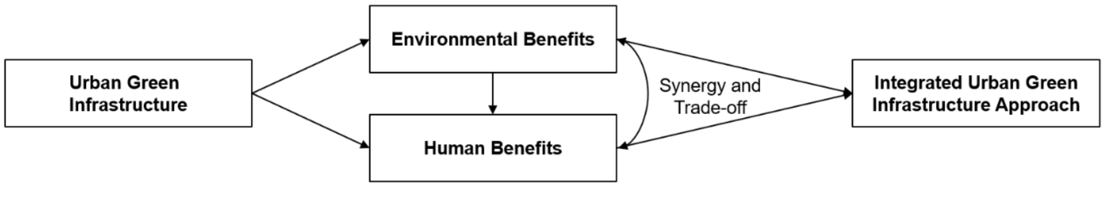


Fig. 5. Human effect of urban green infrastructure

2.2 Problem statement and research gap

There is a key gap in current climate-adaptive urban green infrastructure studies and practices: most existing efforts focus on the environmental functions and performances of green infrastructure, whereas the human experience and well-being outcomes of such interventions are often overlooked.

At the policy level, current agendas and guidelines both in the Netherlands and globally mainly emphasize climate adaptation performances, particularly urban flood management and heat mitigation. The Netherlands' National Climate Adaptation Strategy identifies six major climate effects—heat, urban system failures, crop failures, ecological damage, diseases, and cumulative effects—and multiple secondary effects, but provides limited attention to direct human experience and benefit, and mainly addressing these from macro perspectives (e.g., public health) (Ministerie van Infrastructuur en Waterstaat, 2016). City-level policies like Rotterdam's "Green Agenda 2023-2026" also stress climate adaptation objectives but do not directly consider human experience implications (Gemeente Rotterdam, 2024).

At the research level, green infrastructure's climate functions have been widely documented in the literature. In comparison, research on human experience and benefits remains limited and fragmented. Our initial literature search only identified approximately 25 studies that examined human perceptual, stress, and affective experience aspects related to green infrastructure among the literature (Z. Wang et al., n.d.). Reviews by Nieuwenhuijsen (2021) and Suppakittpaisarn et al. (2017) found "little evidence" regarding the relationship between climate-adaptive green infrastructure and humans, concluding this domain remains "largely unknown" (Nieuwenhuijsen, 2021).

This research gap presents three interrelated challenges (Fig. 6):

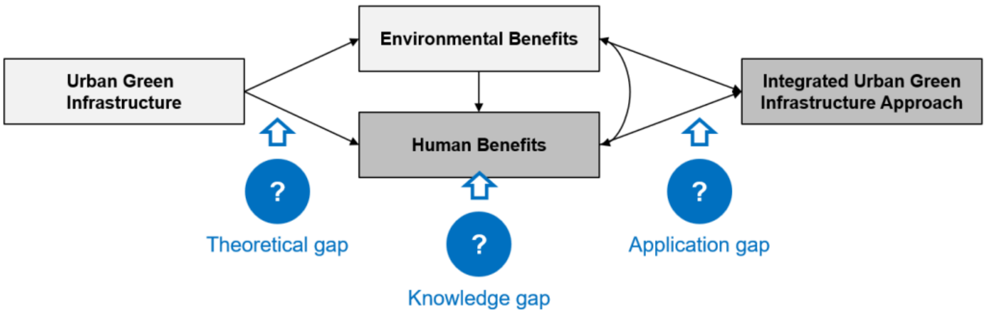


Fig. 6. Research gaps

(1) Theoretically, there is a lack of an integrated perspective for understanding the human outcomes of climate-adaptive urban green infrastructure.

(2) Empirically, it remains unclear in what ways climate-adaptive urban green infrastructure affects people's experiences and well-being.

(3) Practically, there is a need for effective strategies and methods to incorporate and balance human benefits with environmental performances in planning and design of urban green infrastructure.

Lack of integrative perspective of urban green infrastructure

Because of the lack of synthesis of knowledge, it remains unclear how climate-adaptive urban green infrastructure and its characteristics may influence which experiential and well-being benefits of urban residents (e.g., perceptions, emotions, etc.), with an integrative perspective incorporating human aspects into green infrastructure still absent. Existing environmental research primarily focuses on ecological functions and not human dimensions; on the other hand, environmental psychology studies have examined human experiences but rarely in climate adaptation context.

Limited knowledge and evidence of human experiences

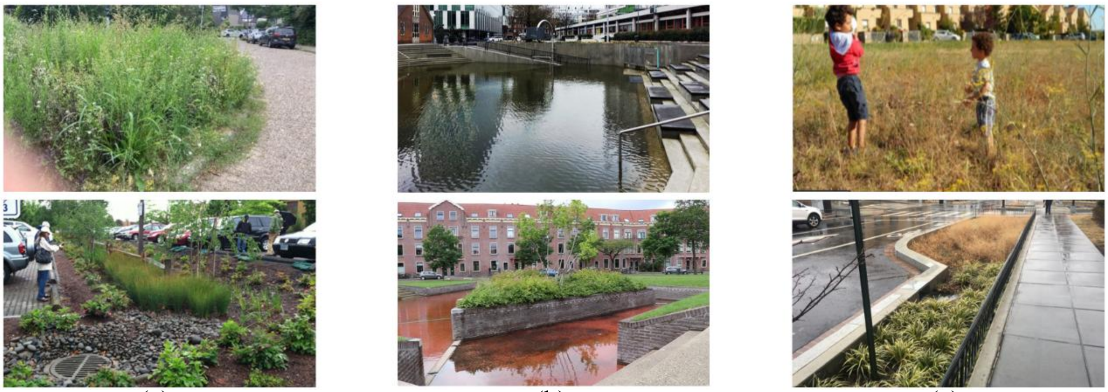
Due to few empirical studies, scholars have noted a *"sheer lack"* of knowledge on the relationship between climate-adaptive urban green infrastructure and human experiences (Nieuwenhuijsen, 2021). There is limited and sometimes inconsistent evidence regarding whether and how climate-adaptive designs affect human experiences such as perceptions and affective responses, and the pathways and mechanisms of such relationships have been insufficiently researched.

Need for practical support incorporating human dimensions

Existing green infrastructure guidelines are mainly oriented towards climate performance, revealing a lack of practical support for incorporating and synergizing human and environmental benefits in such interventions. The complex task of simultaneously balancing environmental and human outcomes in practices potentially also renders conventional design approaches inefficient in delivering optimum solutions.

2.3 Implications of the research gap

These research gaps have led to issues in implemented climate-adaptive urban green infrastructure. Research in the Netherlands, China, and the U.S. has found that green infrastructure projects lacking human-centric considerations could result in low usage and poor satisfaction (Cottet et al., 2013; de la Fuente de Val, 2023; Derkzen et al., 2017; J. Li et al., 2022; O'Donnell et al., 2020). An investigation in Enschede reported that residents perceived stormwater bioswale systems negatively, describing them as overgrown, poorly maintained, and unsuitable for recreational activities (Boogaard et al., 2006). In Hoeksche Waard, 84% of surveyed residents viewed biodiverse greenspaces as messy and unappealing, perceiving them as "unwanted green" (Redactie Hoeksch Nieuws, 2024) (Fig. 7).



(a) (b) (c)

Fig. 7. Issues with climate-adaptive urban green infrastructure lacking human consideration. (a): ecological greenspace may be viewed as messy and not properly maintained (source: hoekschnieuws.nl/2024/08/05/groenonderhoud-in-de-hoeksche-waard-ondanks-nieuwe-plannen-en-inspanningen-nog-steeds-niet-op-orde); (b): stormwater green infrastructure may be perceived as unappealing and undermine public health and well-being (source: sustainableleiden.wordpress.com/tag/climate-proof-cities/); (c): green infrastructure may cause conflict with other urban functions, e.g., physical activity (source: wikiwand.com/en/articles/green_infrastructure)

Unsatisfactory perceptions not only influence green infrastructure's attractiveness but can also affect public confidence in climate adaptation efforts and undermine policy support. A number of studies show that residents oppose certain climate-adaptive strategies, such as biodiverse vegetation, wild planting, and stormwater retention systems, and may resist their implementation in the neighborhood or are unwilling to provide economic support because of their perceived unattractiveness or impracticality (Cristiano et al., 2023; Derkzen et al., 2017; Miller & Montalto, 2019).

At a broader level, they may lead to missed opportunities for green infrastructure to deliver co-benefits serving both environmental and social goals, resulting in inefficient investments, reduced cost-effectiveness, and policies that fail to reflect the complex needs of urban communities (Choi et al., 2021; Sharifi et al., 2021; Tzoulas et al., 2007).

3 Methodological opportunities

3.1 Limitations of conventional methods

Constraints of research methods may be a reason leading to limited research efforts. Traditional human–environment interaction research methods like observations, interviews, and focus groups, though considered accurate and reliable, are labor- and cost-intensive and lack scalability (Teeuwen et al., 2024; Z. Wang et al., 2025). Given the widespread distribution, diverse forms, and varying scales of current green infrastructure practices, such methods face challenges in comprehensively and efficiently capturing people's experiences across such broad and varied landscapes. Existing research is thus mostly focused on specific cases or types, particularly parks.

Additionally, the emerging nature of climate-adaptive urban green infrastructure has resulted in limited development of design methodologies, with current practices largely dependent on experiential knowledge and guidelines (Graça et al., 2022). However, balancing increasingly emphasized human outcomes with environmental performance involves complex synergies and trade-offs, which create interdependencies that make the design process more intricate and less intuitive, requiring simultaneous consideration and coordination of multiple, potentially conflicting objectives. Conventional design approaches may prove inadequate or inefficient for achieving optimal outcomes.

The advent of new digital technologies offers promising opportunities to overcome these limitations.

3.2 Online crowdsourced data

Online crowdsourced data like social media data represents a promising emerging approach for human-environment interaction research. Social media provides continuous flows of user-generated content about urban lives and experiences, reflecting people’s perceptions(Richards & Friess, 2015), sentiments (Dodds et al., 2011), and behaviors (Cranshaw et al., 2012) in urban spaces. By leveraging deep learning techniques including computer vision and natural language processing, it is increasingly possible to extract these sophisticated insights through both visual and textual information from online platforms, enabling better description and modeling of many previously difficult-to-capture human-environment interaction processes (Birenboim et al., 2021; Ghermandi & Sinclair, 2019; Spek et al., 2009). Their wide coverage also better supports research of larger geographical and temporal spans, greatly expanding the scope of human-environment interaction research (Batty, 2013)(Fig. 8).

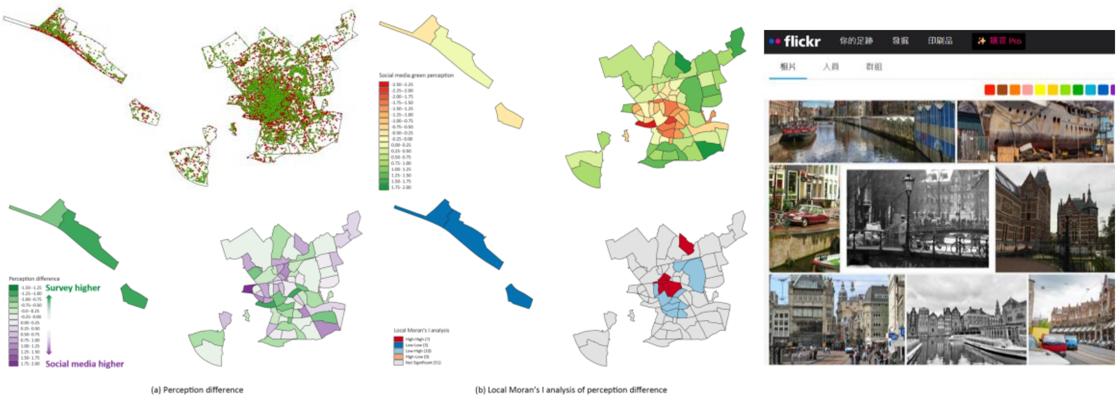


Fig. 8. Online crowdsourced data analysis for human-environment interaction research (source: Wang et al., n.d.)

It is worth noticing that despite offering apparent advantages, online crowdsourced data are also sometimes questioned for their potential limitations, among which unstructured data, lack of accuracy, and potential representative biases. Some existing efforts have corroborated such data type’s effectiveness in reflecting human-environment interaction processes, though more insight is needed (Biljecki & Ito, 2021; Wilkins et al., 2021). One potential channel is through calibration and triangulation with other objective data types and information, such as urban transaction data, which is believed to reflect public willingness-to-pay and value perceptions (Donovan & Butry, 2010).

3.3 Virtual reality

Another key advancement is the availability of virtual reality (VR) technologies, exemplified by head-mounted displays (HMD) such as the HTC Vive, which typically use computer simulations to create immersive 3D virtual environments that offer realistic representation and manipulation of real-world spaces. Unlike urban data that offers extensive information, VR enables researchers to observe and assess people's responses to urban environments (i.e., design scenarios) in controlled experimental settings, thereby offering detailed and highly accurate insight (Fig. 9).

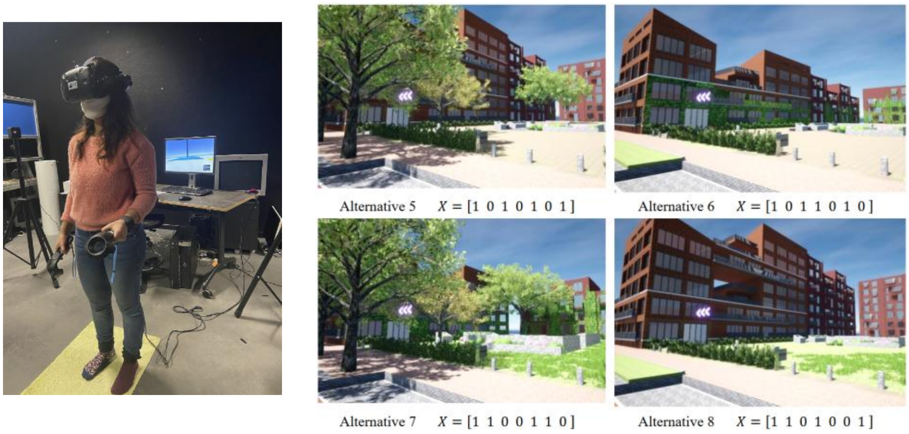


Fig. 9. VR-based design experiment (source: Zhao et al., 2024)

3.4 Multi-objective optimization methods

In addition to empirical data and virtual technologies, advances in computational design offer opportunities to apply empirical evidence in informing decision-makings in complex design problems (Fig. 10). Multi-objective optimization, a type of design optimization algorithms, refers to a computational approach that systematically adjusts decision variables within specified constraints and identifies optimal trade-offs between conflicting objectives, producing a set of *Pareto-optimal* solutions that are optimal for given design problems (Elwy & Hagishima, 2024; X. Zhang et al., 2024). It has the potential to enable simultaneous consideration of multiple performance criteria, such as environmental impact and human experience, thereby supporting more informed design decisions in complex tasks that would be difficult with conventional design approaches (Kim et al., 2023; S. Zhang et al., 2025).

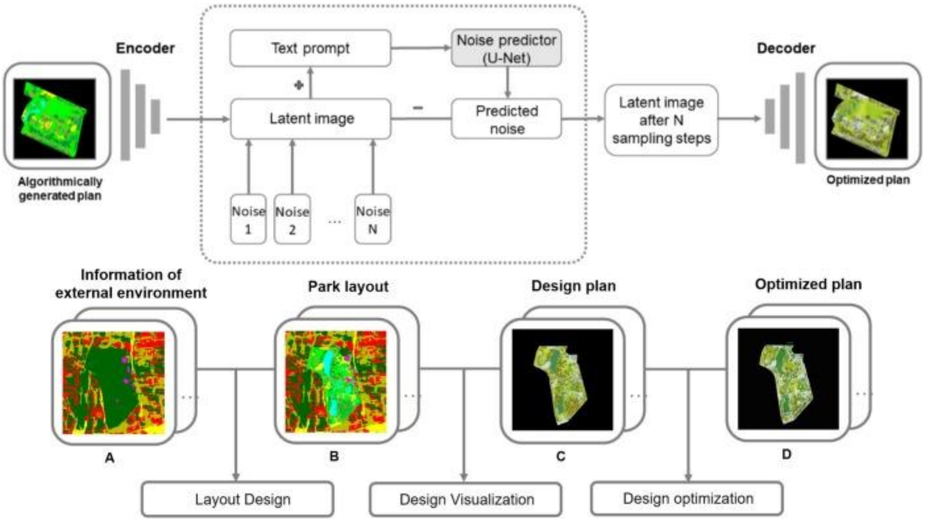


Fig. 10. Example of computational design generation and optimization workflow (source: Chen et al., 2025)

4 Research objective and questions

4.1 Research aim

Accordingly, this thesis aims to integrate emerging digital technologies to examine human experiences of climate-adaptive urban green infrastructure, and explore how to incorporate human benefits in more holistic and integrated future planning and design practices. The research lies at the intersection of urban green infrastructure, environmental psychology and behavior, and digital technologies.

4.2 Main research question

The main research question of this thesis is:

How can we understand and integrate human experience into climate-adaptive urban green infrastructure, leveraging digital technologies?

4.3 Sub research questions

To answer this question and address the identified gaps, we propose three sub-questions:

- What is the relationship between human and climate-adaptive urban green infrastructure? (Theoretical question)
- How do climate-adaptive urban green infrastructure and its planning and design characteristics affect people's experiences? (Empirical question)

- How can human benefits be incorporated into climate-adaptive urban green infrastructure practice? (Practical question)

4.4 Research framework

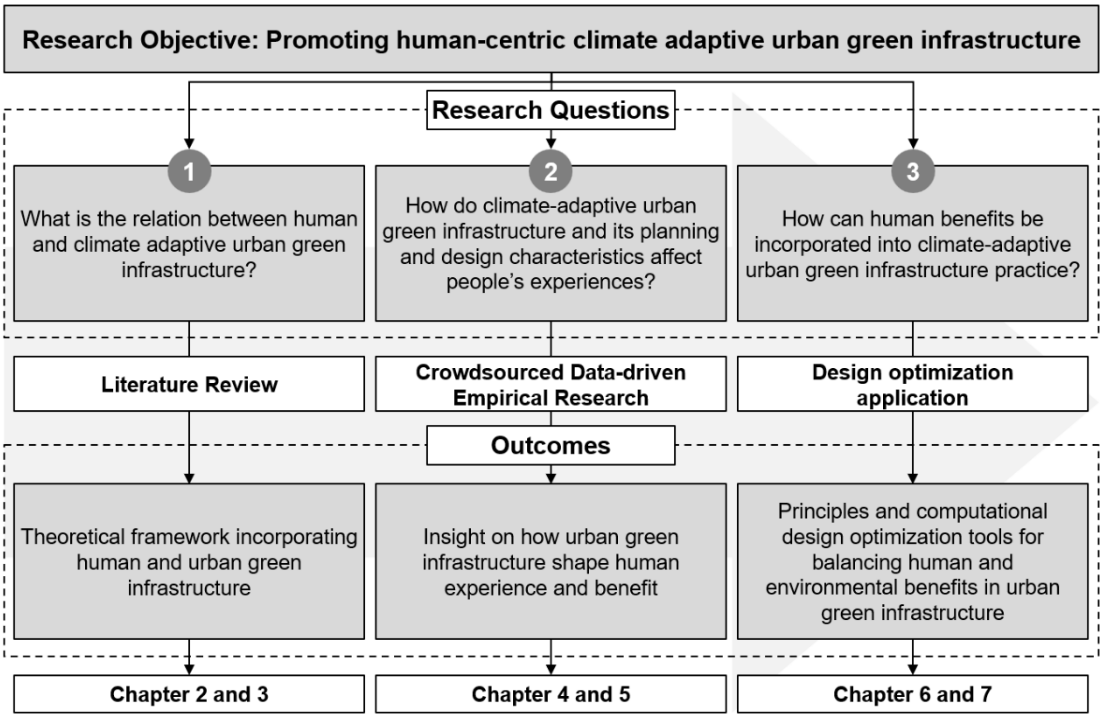


Fig. 11. Research framework

5 Research design and methodology

5.1 Research design and structure

To achieve the research objective, we propose a three-step framework aligned with the three sub-questions (Fig. 11). Step 1 aims to conduct literature reviews and develop a human-centric theoretical foundation synthesizing existing research evidence and conceptualizing the human outcomes of climate-adaptive urban green infrastructure. Step 2 aims to apply emerging crowdsourced data, urban data, and virtual technology to empirically investigate how climate-adaptive urban green infrastructure influences public experiences focusing on perceptions, emotions, and evaluations. Step 3 aims to translate findings into planning and design principles, as well as computational design optimization tools for supporting the synergy of human benefits and environmental performances in future climate-adaptive urban green infrastructure practices. The research workflow is detailed in Fig. 12.

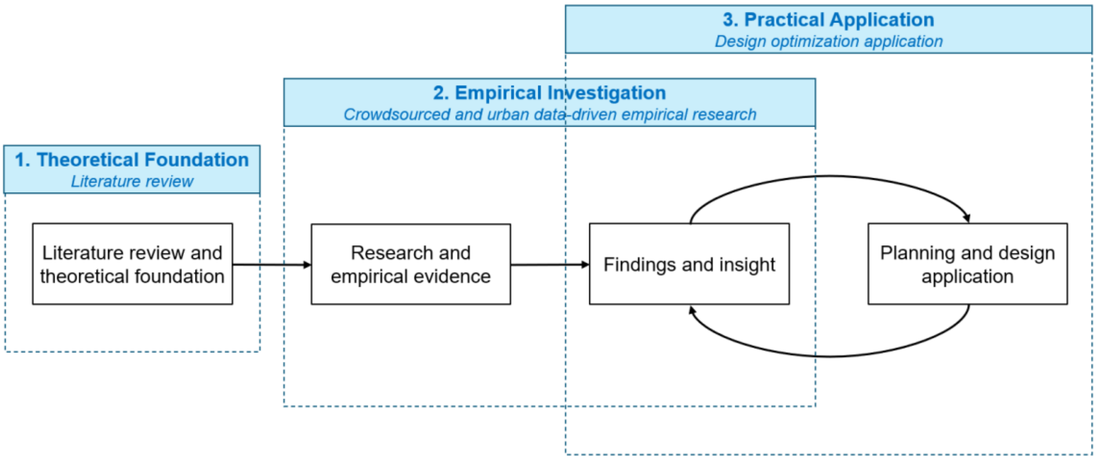


Fig. 12. Research workflow

5.2 Research site and case selection

This study focuses on cities in the Netherlands (e.g., in the Randstad region) as the research site. The Netherlands is actively pursuing climate adaptation transition, with plans for climate adaptation developed at both national and municipal levels. This makes Dutch cities both suitable and urgent contexts for investigating climate-adaptive urban green infrastructure and its impact (Fig. 13).

Fig. 13. Major cities in the Randstad of the Netherlands

Amsterdam and Rotterdam have each introduced green infrastructure strategies and implemented pilot projects, making them ideal case study sites (Fig. 14). Moreover, both cities offer rich open-access urban data—such as the "Maps Amsterdam" and "Rotterdam Wijkprofiel" databases—which provide valuable geographic and socio-demographic information for research.

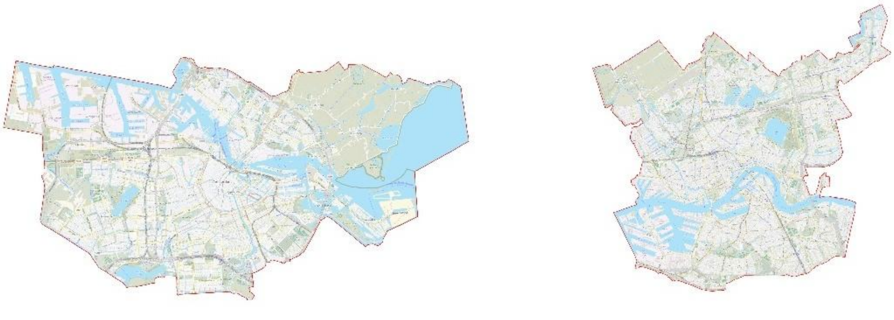


Fig. 14. The central regions of Amsterdam and Rotterdam as case studies

Where relevant, and leveraging the advantages of emerging digital tools, this thesis may also be extended to other European or East Asian cities to enable cross-cultural and cross-climatic comparisons.

Subsequent design and optimization applications will focus on representative cases of climate-adaptive green infrastructure informed by earlier phases of the research. One potential case is the Benthemplein Water Square in Rotterdam's Agniesebuurt neighborhood, implemented in 2013. This project combines public green space with stormwater retention functions, exemplifying the integration of environmental benefits and social use (Fig. 15). Additional case options include the Dakpark rooftop park in Rotterdam and the water playground in Amsterdam.

Fig. 15. Rotterdam water square as potential case study site (source: landezine.com/water-square-bent hemplein-by-de-urbanisten)

5.3 Research section one: theoretical foundation

Research question:
What is the theoretical foundation for understanding human impacts of climate-adaptive urban green infrastructure?

Sub questions:

- What types of human outcomes may be associated with climate-adaptive urban green infrastructure?
- Which planning and design characteristics of climate-adaptive urban green infrastructure may influence human outcomes?

- How are environmental performance and human outcomes related in the context of climate-adaptive urban green infrastructure?
- What methodological approaches are most suitable for studying the relationship between human and green infrastructure?

Research method:
Literature review

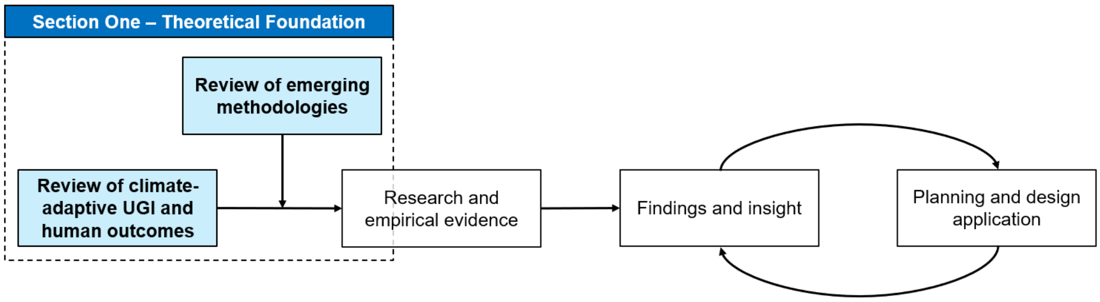


Fig. 16. Workflow for research section one

Section overview:
This first section aims to establish the theoretical foundation for the relationship between human and climate-adaptive urban green infrastructure, and lay the groundwork for this thesis (Fig. 16). Employing systematic literature reviews, it aims to review and synthesize existing knowledge, examining the potential linkages between climate-adaptive green infrastructure and various human outcomes and benefits, as well as their interplay with green infrastructure's environmental performance, thereby proposing an integrative conceptual framework. The goal is to clarify definitions, delineate the scope, organize current knowledge, and provide a theoretical basis for subsequent empirical investigation.

This section also reviews recent methodological innovations in human-environment interaction research field, and critically assesses their applicability, advantages, and limitations regarding our research scope and objectives.

5.4 Research section two: empirical investigation and insight

Research question:
How do climate-adaptive urban green infrastructure and its planning and design characteristics affect people's experiences?

Sub-questions:
- How do people perceive climate-adaptive urban green infrastructure?
- How does climate-adaptive urban green infrastructure influence human emotions and experiences?
- How does climate-adaptive urban green infrastructure influence human evaluations?
- How do planning and design characteristics of climate-adaptive urban green infrastructure

shape these human responses?
- How well does online crowdsourced data capture human experiences related to green infrastructure?
- How well does property value data reflect and calibrate human evaluations before and after green infrastructure interventions?

Research method:
Social media analysis, urban data analysis, virtual experiment

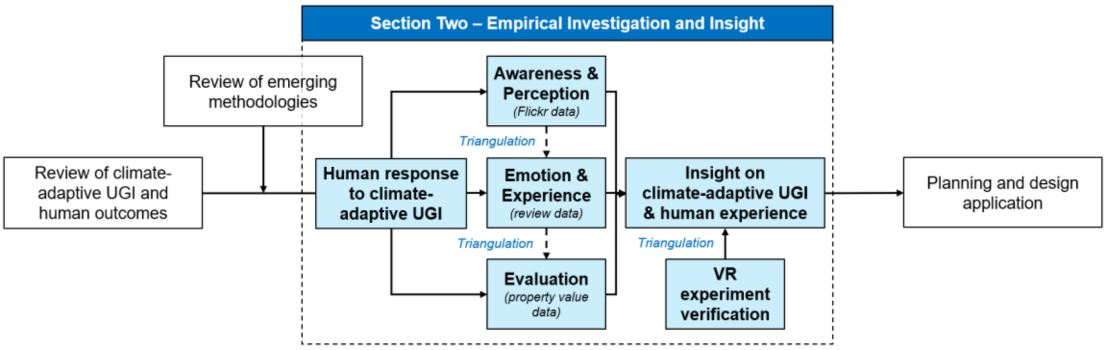


Fig. 17. Workflow for research section two

Section overview:
The second section aims to apply emerging data and technologies to empirically investigate how climate-adaptive urban green infrastructure and its attributes affect human experiences, with a focus on human perception, emotion, and evaluation as key experiential processes (Fig. 17). For instance, Flickr social media image data can be applied for analyses of public perceptions of green infrastructure, Google Maps review data can be applied for analyses of public affective responses and experiences of green infrastructure, and urban property value data can be applied for reflecting public evaluations and willingness-to-pay affected by green infrastructure. Incorporation of both crowdsourced subjective data and objective transactional data aims to ensure a more nuanced perspective.

Admittedly, urban data could face potential limitations related to data quality issues and data bias. With the data-derived insight, the last part of this section aims to conduct VR experiments to verify, triangulate, and fine-tune our data findings. We aim to select representative green infrastructure cases in the Netherlands, and reconstruct and present them in VR environment through digital modeling or laser scanning. Participants will be recruited and exposed to these different cases and potentially also different design schemes, with their subjective evaluations and physiological responses measured and analyzed.

Employing this mixed-methods approach, the section aims to generate empirical evidence and uncover mechanisms linking green infrastructure to human experience.

5.5 Research section three: application of insight in planning and design experiment

Research question:
How can human experiential benefits be incorporated into climate-adaptive urban green infrastructure practice?

Sub-questions:

- What are the planning and design strategies integrating human benefits into climate-adaptive urban green infrastructure?
- How can computational design methods (e.g., multi-objective design optimization) be utilized to support climate-adaptive urban green infrastructure practices balancing human benefits and environmental performance?

Research method:
Computational design experiment

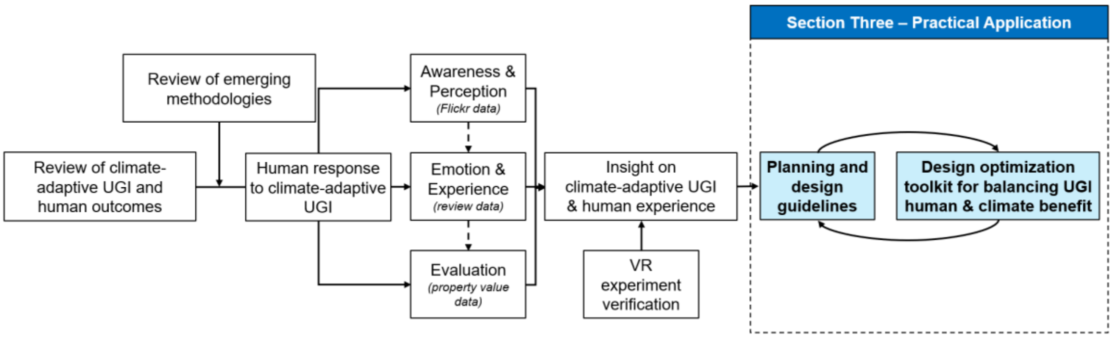


Fig. 18. Workflow for research section three

Section Overview:
The third section aims to explore the application of research findings (Fig. 18). It first aims to translate research findings and propose climate-adaptive urban green infrastructure principles, which could complement current green infrastructure guidelines (e.g., Rijksdienst voor Ondernemend Nederland, 2024).

Based on this, it aims to develop a computational design optimization toolkit intended to provide optimized design solutions for future green infrastructure projects balancing both human and environmental impacts. The toolkit aims to employ generative algorithms, i.e., multi-objective optimization algorithms, which employ section two's empirical evidence on human-environment interaction mechanisms for human benefits optimization criteria (i.e., perception and emotion), and established climate adaptation performance simulation models as environmental performance optimization criteria (i.e., heat reduction and ventilation). Employing a figure-based (e.g., masterplans) computational design approach, it aims to generate Pareto-optimal solutions that achieve the synergy balancing both dimensions. By developing such computational design optimization processes into a toolkit, it aims to present users with real-time feedback on the impacts of different design alternatives and present the optimum optimized solutions, from which practitioners can further develop detailed design schemes.

To test our proposed toolkit, we aim to conduct co-creation sessions with practitioners, using design case studies to test its applicability and effectiveness. Practitioners' feedback would be leveraged to iteratively improve the toolkit. In short, the objective is to operationalize previous analyses into evidence-based design decision-making tools, facilitating the transition of practices in this domain from more conventional approaches focusing on a single dimension toward a more integrative approach optimizing both dimensions, supporting more holistic and human-centric future green infrastructure.

6 Expected outcomes

6.1 Theoretical foundation and framework

This study is expected to develop an integrative theoretical framework that conceptualizes the relationship between climate-adaptive urban green infrastructure and human benefits, which could address the current theoretical gap, enhance the synthesis of research findings in this field, and provide a more comprehensive foundation for future academic inquiry.

Expected publications:

- Towards an integrative green perspective: A systematic review of human perceptions and well-being and their interactions with environmental benefits in climate-adaptive urban green infrastructure (working paper, planning to submit to *Landscape and Urban Planning*)
- Understanding human-environment interaction in urban spaces with emerging data-driven approach: A systematic review of methods and evidence (Wang, Z., Yang, Y., Nijhuis, S., & van der Spek, S. 2025. *Cities*, 167, 106346. https://doi.org/10.1016/j.cities.2025.106346)

6.2 Empirical knowledge

The study is expected to generate empirical evidence on how climate-adaptive urban green infrastructure influences human experience, and through the application of digital technologies including crowdsourced data and urban property value data, could offer scalable and fine-grained insights expanding the current knowledge field.

Expected publications:

- How well does crowdsourced social media data capture public urban greenness perception? A comparative analysis in Rotterdam, the Netherlands (resubmitted to *Computers, Environment, and Urban Systems*)
- Mapping urban greenery: The spatial relationship among NDVI, green view index, and greenery perceptions of social media in Rotterdam (submitted to *Environmental Impact Assessment Review*)

- Understanding affective and cognitive responses to urban green infrastructure: A crowdsourced approach
- How does urban green infrastructure influence urban property values? A longitudinal study in Rotterdam, the Netherlands

6.3 Planning and design toolkit

Lastly, this study is expected to synthesize strategies that can be incorporated into current Dutch climate adaptation guidelines. It also aims to develop and test computational design optimization toolkit, which could be converted into platforms and systems for supporting future urban planners and policymakers.

Expected publications:
- Optimizing urban green infrastructure for environment improvement and human experience: A multi-objective approach

Other expected outcome:
- An online platform for computational design optimization of climate-adaptive urban green infrastructure

7 Relevance and impact

In face of growing challenges associated with climate change and urban densification, urban green infrastructure needs to transcend narrow focus on adaptation and adopt a more comprehensive approach.

This thesis contributes to this shift by offering empirical insights and practical toolkit for policymakers and designers seeking to create more humanized and responsive green infrastructure. By supporting attractive and high-quality design solutions, the research findings can help align future green infrastructure with human characteristics and needs, thereby optimizing resource allocation, preventing inefficient deployment, and maximizing both environmental and social benefits of these interventions.

The study employs emerging digital technologies, including online crowdsourced data, VR environment, and computational design models, which expand methodological approaches for investigating human-environment interactions in urban green infrastructure and demonstrate novel applications of digital technology in this domain.

8 Limitations

This study's scope is limited to examining human perception, emotion, evaluation, and, reflected by property value, willingness-to-pay as responses to climate-adaptive urban green infrastructure.

Human-environment interactions within green infrastructure likely encompass more complex processes and mechanisms than those addressed in this research. Moreover, due to longitudinal data limitations, this study mainly employs a cross-sectional methodology. However, resident responses to urban green infrastructure may change over time, and this temporal dimension remains unexplored in the current investigation.

Although this research aims to encompass diverse green infrastructure typologies, the innovative and evolving landscape of contemporary practice may limit comprehensive representation of all typologies or design approaches. Additionally, the design optimization framework concentrates on two primary climate adaptation functions: heat mitigation and ventilation enhancement, as well as two primary human responses: perception and affective response. Other significant aspects, including water management, require further investigation in subsequent studies.

9 Practical information

9.1 Supervision

The author will collaborate with Prof. Peter van Oosterom (promoter), Prof. Steffen Nijhuis (co-promoter), and Prof. Stefan van der Spek (daily supervisor). Meetings with the promoters are arranged monthly (i.e., every 4 weeks), with all promoters attending. Progress update and discussions will be held when necessary, with the main promoter. This interdisciplinary supervisory team brings together a wealth of expertise that aligns well with the theoretical, technical, and practical aspects of this proposed study, and the arrangement both enhances the robustness and depth of the research and ensures that the findings are practically applicable and relevant across multiple domains.

The author will also participate in other academic events in the faculty, such as the monthly PhD GIS group meeting and landscape architecture PhD group meeting.

9.2 Resources and tools

Crowdsourced data sources:

- Flickr API
- Google Maps Places API

Property value data sources:

- Waardering Onroerende Zaken (WOZ) data (the Netherlands)

Other data sources:

- Maps.amsterdam (Amsterdam)
- Gisweb (Rotterdam)
- Actueel Hoogtebestand Nederland (AHN, the Netherlands)

- Rijksinstituut voor Volksgezondheid en Milieu (RIVM, the Netherlands)
- Centraal Bureau voor de Statistiek (CBS, the Netherlands)
- OpenStreetMap (OSM, global)

Programming language:
- Python
- Javascript

VR equipment:
- Oculus Quest 3 / CAVE system

Software:
- ArcMap
- QGIS
- Rhinoceros
- Unreal Engine

9.3 Research timeline

Table 1. Research timeline

Stage	Task	1st Year		2nd Year		3rd Year		4th Year	
		1/2	1/2	1/2	1/2	1/2	1/2	1/2	1/2
1	Literature review of research methods								
	Literature review and theoretical framework								
	Research proposal								
2	Pilot Study								
	Perception study of climate-adaptive urban green infrastructure								
	Affection and experience study of climate-adaptive urban green infrastructure								
	Housing property value study of climate-adaptive urban green infrastructure								
	Summarizing findings and evidence								
	Virtual planning and design experiment								
3	Summarizing planning and design strategies								
	Developing toolkit for urban green infrastructure planning and design optimization								
4	Finalizing the thesis								
	Defense								

9.4 Journal publication plan

Relevant journals:
- Applied Geography
- Building and Environment
- Cities
- Computers, Environment, and Urban Systems
- ISPRS Journal of Photogrammetry and Remote Sensing
- Journal of Cleaner Production
- Land Use Policy
- Landscape and Urban Planning
- Sustainable Cities and Societies

9.5 Conference attendance plan

First Year (2025)

- Accepted Conference: IFLA World Congress, Nantes, France. (Sep 2025. Website: https://ifla2025.com/)

Second Year (2026)

- Intended Conference: AGILE conference, Tartu, Estonia. (June 2026. Website: https://agile-gi.eu/)
- Backup Conferences: DLA (Digital Landscape Architecture) conference (est. June 2026. Website: https://www.dla-conference.com/)

Third Year (2027)

- Intended Conference: ACADIA (est. Nov 2027. Website: https://www.acadia.org/)
- Backup Conferences: CAAD Futures (est. Jul 2027. Website: https://caadfutures2025.hku.hk/), or eCAADe (est. Sepr 2027. Website: https://ecaade.org/)

Fourth Year (2028)

- Intended Conference: ISPRS Congress (est. August 2028. Website: https://www.isprs.org/society/congress.aspx)
- Backup Conferences: AHFE (Applied Human Factors and Ergonomics) International Conference (est. July 2028. Website: https://ahfe.org/)

Additional conferences in the Netherlands

- NCG Symposium, and AMS Scientific Conference

9.6 Master's thesis supervision plan

The author is expected to be able to supervise master's theses in areas of urban data analysis, geographic analysis, environmental behavior and psychology research, architectural design, urban public space design, and landscape design. Possible MSc thesis topics include:

- Large-scale urban perception analytics with emerging online crowdsourced data
- Urban green infrastructure and changes in WOZ urban property value
- Assessments and realistic design experiments of urban green infrastructure in VR environment.

9.7 Graduate school course planning

Table 2. Course planning

	Completed	In progress	Planned	**Total**
Discipline-related skills				
Python Programming for Geomatics	5			
Research Proposal for Architecture and the Built Environment		4		
Urban and Regional Research			5	
Academic Writing Retreat			4	
				18
Research skills				
The Informed Researcher - Information and Data Skills	1.5			
Navigating Academic Publishing	1			
Basic Problem Solving & Decision-making	1			
How to select-make a questionnaire and conduct an interview	2			
Research Data Management 101	2			
Writing the first journal article	2			
Poster presentation, major international audience		1		
Addressing a small audience			0.5	
Addressing a major international audience			1	
Supervising a MSc student / BSc project groups			3	
				15
Transferable skills				
The PhD Network Hub (on-campus)	1			
Time Management I – Time Management Foundation	1			

Time Management III – Mastering Individual Challenges	0.5				
Project Management for PhD Candidates	2				
PhD Start-up Module A-I	0.5				
PhD Start-up Module A-II	0.5				
PhD Start-up Module A-III	0.5				
PhD Start-up Module B	0.5				
Data visualisation - a Practical Approach		1			
Designing Scientific Posters		2			
LinkedIn for Researchers		1			
Cross Cultural Communication Skills in Academia			1		
Scientific Storytelling				2	
Foundations of Educational Design				1	
Coaching Individual Students				1	
Career Development courses				1	
					16.5

9.8 Self-reflection of first year

During my first year as a doctoral candidate at AE+T (also second year at TU Delft), I have achieved several milestones in academic development. I have successfully transitioned into the doctoral role, and completed around half of the mandatory doctoral education program requirements and supplementary training components.

Regarding my PhD research, I have also conducted preliminary research activities, with pilot studies generating promising preliminary findings. My work in the past year has translated into several academic outputs: one published paper, two manuscripts submitted and currently under peer review, one working paper in preparation for submission, and an international conference poster presentation.

The guidance and supervision from professors and intellectual exchange with colleagues in the past year have been very helpful in refining my research focus and methodological approach. These interactions have enhanced my understanding of both my research domain and the PhD's education process.

I am confident that I am now well-positioned to advance to the next phase of my doctoral studies. Moving forward, I aim to enhance research efficiency through improved familiarity with relevant tools and methodologies, while expanding my engagement in collaborative networks. My goal is to contribute meaningfully to both research and practice in my field of architecture, urban analytics, landscape, and environment psychology and behavior.

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Appendix 1 - Understanding human-environment interaction in urban spaces with emerging data-driven approach: A systematic review of methods and evidence

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Understanding human-environment interaction in urban spaces with emerging data-driven approach: A systematic review of methods and evidence

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ABSTRACT

The development of information technologies and the advent of extensive digital data since the 21[st] century have enabled more profound explorations and interpretations of the relationship between humans and the urban environment. This study systematically reviews the application of emerging data-driven methods in measuring human-environment interaction in urban spaces. The synthesis of 242 studies reveals a diversified application landscape of data-driven methods, employing street view imagery data, social media data, positioning data, physiological data, and video data, each carrying distinct information and addressing various research inquiries. We also review the new insights generated by their application, which offered evidence for analyzing and evaluating a wide range of established frameworks and classic theories concerning human perceptual, cognitive, emotional, and behavioral aspects in urban spaces. Based on these findings, we describe the trends, advancements, and limitations of this rising research field, and make recommendations for future researchers adopting data-driven methods to understand relationships between humans and environments in urban spaces.

1. Introduction

As global urbanization continues to reshape human living patterns, understanding the interaction between humans and the urban environment offers significant potential for advancing evidence-based planning and design practices that support more livable future cities (Karakas & Yildiz, 2020). Urban spaces—including streets, parks, and squares—function as essential venues for this interaction, enabling residents' movements, relaxation, and social participation (Carr et al., 1992). Creating high-quality urban spaces through such understanding has become a central agenda for sustainable urban development (UN-Habitat, 2017).

Since the mid-20th century, growing research has recognized that urban spatial conditions shape human perception and experience, thereby influencing emotional states and generating distinct behavioral patterns. This has led to the development of many ground-breaking theories that extensively examined and described human-environment interaction processes. Theoretical contributions from Cullen (1961), Alexander et al. (1977), and Berlyne (1974) elucidated the connections between environmental perception and physical urban characteristics. Lynch (1960) introduced the concept of urban legibility, extending human understanding of cities to the cognitive dimension. Kaplan and Kaplan (1989a, 1989b) and Ulrich (1984), employing psychological and health studies, empirically validated the positive cognitive and well-being impacts of urban nature. Pioneering observational approaches, Jacobs (1961), Whyte (1980), and Gehl (1987) identified behavioral patterns and proposed principles for vibrant spaces. These seminal theories have had a lasting impact on human-environment interaction research and inspired strategies for designing urban spaces that positively impact human experience.

Research in this field has traditionally relied on established methods such as surveys, observations, interviews, and censuses. The recent rapid advancements in information technologies and interdisciplinary influences have provided studies with broader data types and analytical capabilities, allowing for more multidimensional and fine-grained capture of human-environment interaction. This represents an emerging

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data-driven research trend that brings new possibilities to the human-environment interaction field (Batty, 2013a; Miller & Goodchild, 2015). Unlike conventional methods, emerging data-driven approaches rely on digital systems and advanced sensors to gather and analyze large-scale, diverse datasets that directly reflect human-environment interaction processes (Goodchild, 2007; Kitchin, 2014). These datasets range from what some call "big data"—such as social media and urban sensor data—to other cutting-edge digital information—such as interdisciplinary physiological measurements—offering unprecedented research perspectives and dimensions (Batty, 2013b). Coupled with enhanced computational power, software capabilities (e.g., Geographic Information System), and artificial intelligence methods (e.g., machine learning), these approaches also often demonstrate enhanced efficiency and scalability, overcoming cost and extrapolability limitations inherent in traditional methods (Marshall, 2012; Ohly et al., 2016). This trend has in recent years stimulated innovative projects including the PEACH (Lachowycz et al., 2012) in the UK and the Place Pulse (Salesses et al., 2013) in the U.S. that developed data-driven methods to quantitatively observe human responses to urban environments, offering new insights and profound impact.

The growing research interest and surge in publications in this area underscore the need for a systematic review. Existing reviews have typically focused on other domains such as urban auditing (Calabrese et al., 2015), tourism (Li et al., 2018), and management (Wilkins et al., 2021), and have often covered only specific data types (Biljecki & Ito, 2021; Ghermandi & Sinclair, 2019; Karakas & Yildiz, 2020; Kiefer et al., 2017). These reviews are not fully grounded in the human-environment interaction domain that this review focuses on, of which a more comprehensive picture remains lacking. Furthermore, reviews of how emerging data-driven approaches contribute to the knowledge base in this area are also notably absent. The characteristics of emerging data employed in human-environment interaction research as well as what and how they can contribute to investigations remain unclear, potentially obscuring broader prospects and hindering further research efforts in a technically complex and rapidly evolving domain.

This paper addresses the research gap by conducting a systematic review of the application of emerging data-driven approaches in human-environment interaction research in urban spaces. Especially, we adopt a disciplinary perspective and aim to address three questions:

1) What are the key characteristics of these new data-driven studies compared to traditional research in this field?
2) What types of data are applied, and how are they utilized to support research on human-environment interaction?
3) What insights are generated from data application, and how have they advanced foundational theories in the field?

The paper is structured as follows: Section 2 covers the methodology, Section 3 presents quantitative findings, and Sections 4 and 5 respectively review new data types and evidence. Section 6 discusses emerging trends, challenges, and future research opportunities. Section 7 concludes the paper.

2. Methods

This review adopts the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (Page et al., 2021) as the methodological approach, and is oriented along previous systematic review exercises in this field (Ghermandi & Sinclair, 2019; Wilkins et al., 2021).

2.1. Framework for human-environment interaction

Human-environment interaction can be studied from multiple perspectives (e.g., Markevych et al., 2017). This study adapted the comprehensive framework proposed by Nasar (2014) to conceptualize it through four core dimensions: (1) Perception refers to direct human sensory reactions to and preferences for environments, serving as the starting point of interaction. (2) Cognition involves how people categorize, remember, and represent urban experiences. (3) Emotion and well-being are influenced by urban stimuli, eliciting various affective responses. (4) Behavior is ultimately shaped by the combined influence of the above processes along with environmental characteristics.

Nasar's framework was employed because of its wide recognition and its theoretically grounded yet practical lens for categorizing the diverse types of human responses, which aligns with our research aim of examining emerging data-driven approach applications across these aspects. Admittedly, due to the complexity of the field and potential controversies arising from different disciplinary perspectives, we acknowledge that this framework may not encompass all dimensions. Our findings can provide insights for future scholars applying the knowledge in broader research contexts.

2.2. Search strategy

This research defines emerging data-driven approaches as those employing novel data sources that directly capture human-environment interaction processes. Specifically, they typically exhibit three distinctive characteristics: First, the employed data or digital methods directly reflect human perceptual, cognitive, emotional, or behavioral responses to urban spaces. Second, the data types represent recent innovations, particularly those that, according to scholarly consensus, have been widely adopted only since the 21st century (Kitchin, 2014). Third, they involve new data collection, processing, and analytical paradigms that extend beyond conventional descriptive or analytical methods.

Given that many studies employ multiple data sources, we include research that combines emerging data with traditional data sources, while excluding studies that rely exclusively on conventional data collected through observation, survey, census, or GIS methodologies.

Accordingly, four categories of search terms were defined: data-driven (e.g., data, dataset, technology), human-environment interaction (e.g., perception, cognition, emotion, behavior), human (e.g., people, individual, resident), and urban space (e.g., urban environment, built environment, urban space). The complete search terms are provided in Appendix A. Given the multidisciplinary nature of this topic, broad search terms were used to achieve high sensitivity and collect more relevant articles. For instance, we used both terms directly tied to our focus like "data*" and more general terms like "technolog*", "sensor*", and "device*" to account for other expressions of data-driven research, aiming to ensure a comprehensive search. Following PRISMA protocol, records were also identified from reference lists.

Scopus was selected as our literature search source due to its extensive coverage as one of the largest peer-reviewed literature databases. This approach aligns with previous systematic reviews in urban research (e.g., Biljecki & Ito, 2021).

2.3. Inclusion criteria

Articles in English and published in peer-reviewed journals or conference proceedings with full-text availability were included in the identification phase. As the preliminary search returned many irrelevant records, the search was further refined by limiting the subject area (e.g., environmental science, social sciences) and keyword (e.g., urban planning, built environment), and restricting publications to those from 2000 to 2023, considering the nature of emerging data.

Subsequently, all identified records from the initial pool were screened and selected based on the following criteria:

(1) Only papers focused on human-environment interaction within our theoretical framework were included, papers centered solely on urban (e.g., management) or human aspects (e.g., biology) were excluded.

(2) Only papers employing emerging data-driven approaches that directly capture human-environment interaction processes were included, papers using only conventional data (e.g., census) or digital tools without directly reflecting human-environment interaction (e.g., geographic data) were excluded.
(3) Only papers situated in urban spaces were included, papers of irrelevant contexts (e.g., rural) or scales (e.g., regional scale) were excluded.
(4) Only papers reporting empirical research were included.

2.4. Selection process

The literature search was conducted during December 2023 and July 2024. The search yielded 5987 publications in total. The inclusion criteria were carefully applied at each stage during record screening. After scanning the titles, 920 studies remained in the pool, of which 417 were retained after abstract screening. After full-text reading and eligibility assessment, 242 articles met the inclusion criteria and were selected for this systematic review (Fig. 1). The selection process is detailed in Appendix B, and the included articles are available in Appendix C.

3. Overview of results

3.1. Characteristics of the literature

The collected literature shows a rise in interest in this research field. The first identified article was published in 2005, but over 90 % of the articles were published after 2014 (Fig. 2). Many of the studies are conducted in the U.S. (n = 57) and mainland China (n = 43), which

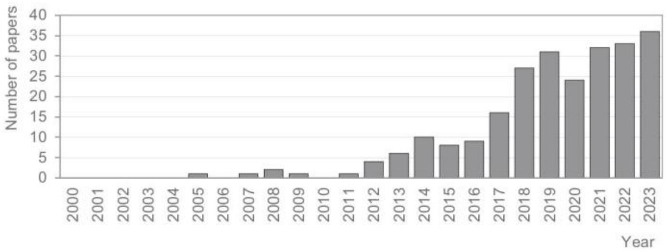

Fig. 2. Share of papers by publication time.

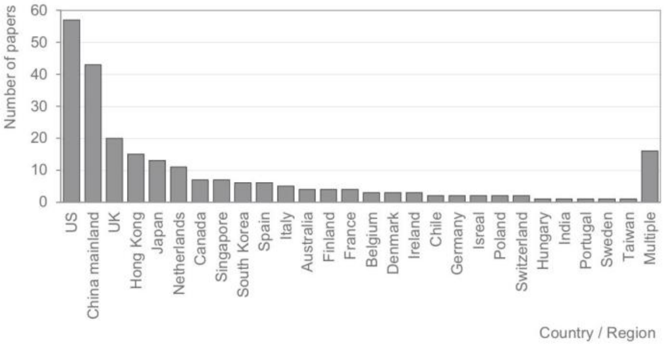

Fig. 3. Share of papers by research country/region.

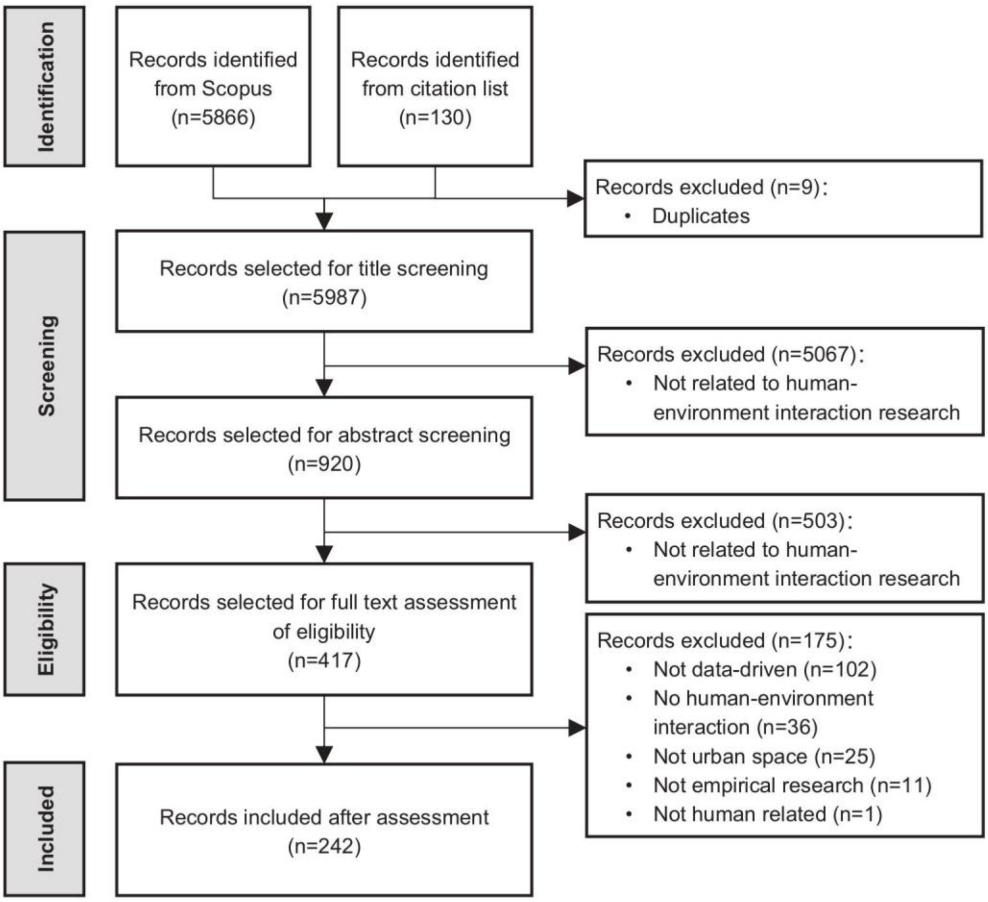

Fig. 1. Flow diagram for literature selection.

combined contributed to over 40 % of the articles, followed by the UK ($n = 20$), Hong Kong ($n = 15$), Japan ($n = 13$), and the Netherlands ($n = 11$) (Fig. 3). Most studies are conducted in the Global North, with the Global South remaining underrepresented.

Nearly half of the articles ($n = 112$) address human behavior in urban spaces, followed by emotion and well-being ($n = 64$), perception ($n = 55$), and lastly, cognition ($n = 11$). While behavioral aspects have been the main focus in the early stages, in recent years there has been a diversification of research attention (Fig. 4).

Streets are the most predominant urban space investigated, accounting for nearly half of the articles ($n = 108$), followed by parks ($n = 55$). Among the other urban space typologies, waterfronts ($n = 7$) and squares ($n = 7$) are relatively sparsely researched (Fig. 5).

VOSviewer (van Eck & Waltman, 2010) was employed to conduct co-occurrence analysis of the keywords of the literature for analyzing research themes, and identified four main clusters (Fig. 6). By examining each cluster and its associated articles, we found that these clusters largely align with different data-driven approaches, and thus categorized the themes of each cluster and their corresponding data type as follows:

(1) Cluster #1 includes studies applying street view imagery data, featuring keywords like "google street view", "walking behavior", and "perception".
(2) Cluster #2 includes studies applying social media data, featuring keywords like "social media", "sentiment analysis", and "park visitation".
(3) Cluster #3 includes studies applying positioning data, featuring keywords like "gps", "tracking", and "mental health".
(4) Cluster #4 includes studies applying physiological data, featuring keywords like "heart rate", "mood", and "stress".

Beyond these common themes, we also observed the adoption of other emerging data in the literature. Notably, video data, first utilized as early as 2005, has emerged as another important data type and is thus grouped as a major data-driven approach in this review. Other emerging data types with more limited application include accelerometer data, wearable camera data, and unmanned aerial vehicle sensing data (Fig. 7).

The relationship between data types, urban space typologies, and human-environment interaction processes of the collected articles was further analyzed (Fig. 8). Street view data-driven studies predominantly focus on streets, reflecting the unique strengths of this data type, while their research themes regarding human-environment interaction are more diverse. Social media data are frequently employed in park studies, while also showing a wide application across different human-environment interaction processes. Physiological data are often used to support street experiments or comparative studies between streets and greenspaces, and are notably applied to other human-environment interaction processes except behavior. In contrast, positioning and video data are almost exclusively utilized in behavioral research, reflecting their common role as tracking data.

3.2. Analytical framework

We developed a framework with three dimensions to organize the literature: the employed emerging data type, the researched human-environment interaction processes, and the relationship between findings and established theories (Fig. 9).

First, drawing from the clustered research themes and existing classifications (Huang, Yao, et al., 2021; Li et al., 2018; van der Spek, 2008), studies were categorized into six categories based on the data employed (Section 4): street view imagery data, social media data, positioning data, physiological data, video data, and other data, with the first five types being the focus and further subdivided based on their characteristics (Fig. 10).

Second, studies were grouped based on human-environment interaction processes—perception, cognition, emotion and well-being, and behavior—and their findings were classified depending on their comparison to established theories into four types (Section 5): (1) "supportive", when confirming established theories (though studies may not address all aspects of the original theories); (2) "mixed", when showing both supportive and contradictory or not statistically significant evidence; (3) "contrary", when not generating any supportive evidence or providing clear evidence against established theories; and (4) "non-responsive", when studies neither cited established theories nor provided clear responses (Fig. 11).

4. Data in reviewed studies

4.1. Street view imagery data

Street view imagery data allow for directly reflecting perceived urban landscape through eye-level panoramic street photos. Articles applying this data emerged around 2013 and account for around one-third of the literature ($n = 74$).

4.1.1. Technical characteristics

Street view imagery is usually obtained from online map providers, especially Google Street View (Dubey et al., 2016; Lu, 2019; Salesses et al., 2013), Baidu (Chen, Lu, et al., 2022), and Tencent (Helbich et al., 2019), with some studies also obtaining them from databases (e.g., OpenStreetMap, Mapillary), dashcams, or custom-collection (Biljecki & Ito, 2021). Images from map providers are typically collected by vehicle-mounted cameras and subsequently standardized into 360° views (Lu et al., 2018).

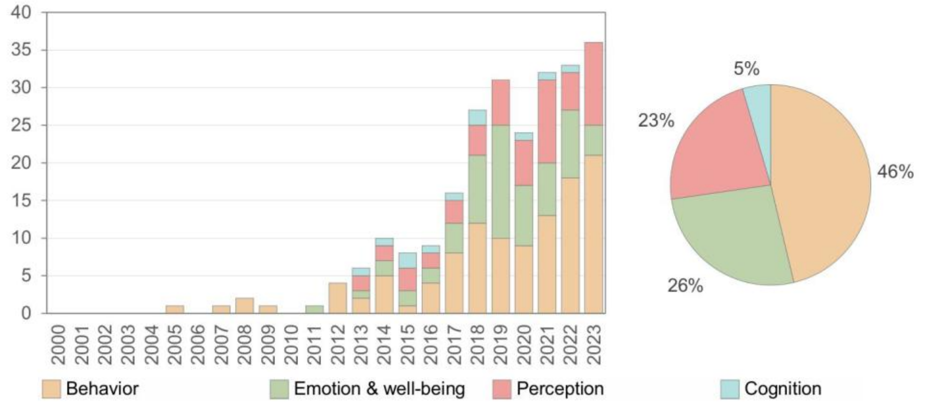

Fig. 4. Share of human-environment interaction theme by year.

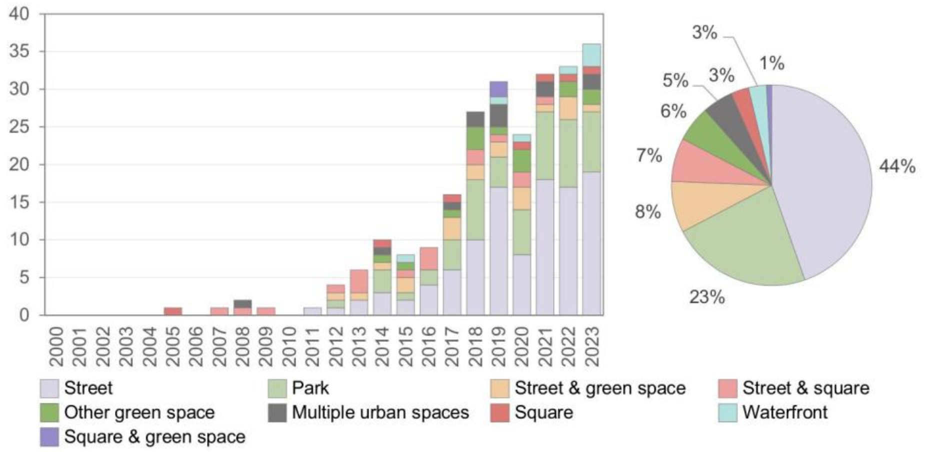

Fig. 5. Share of urban space typology by year.

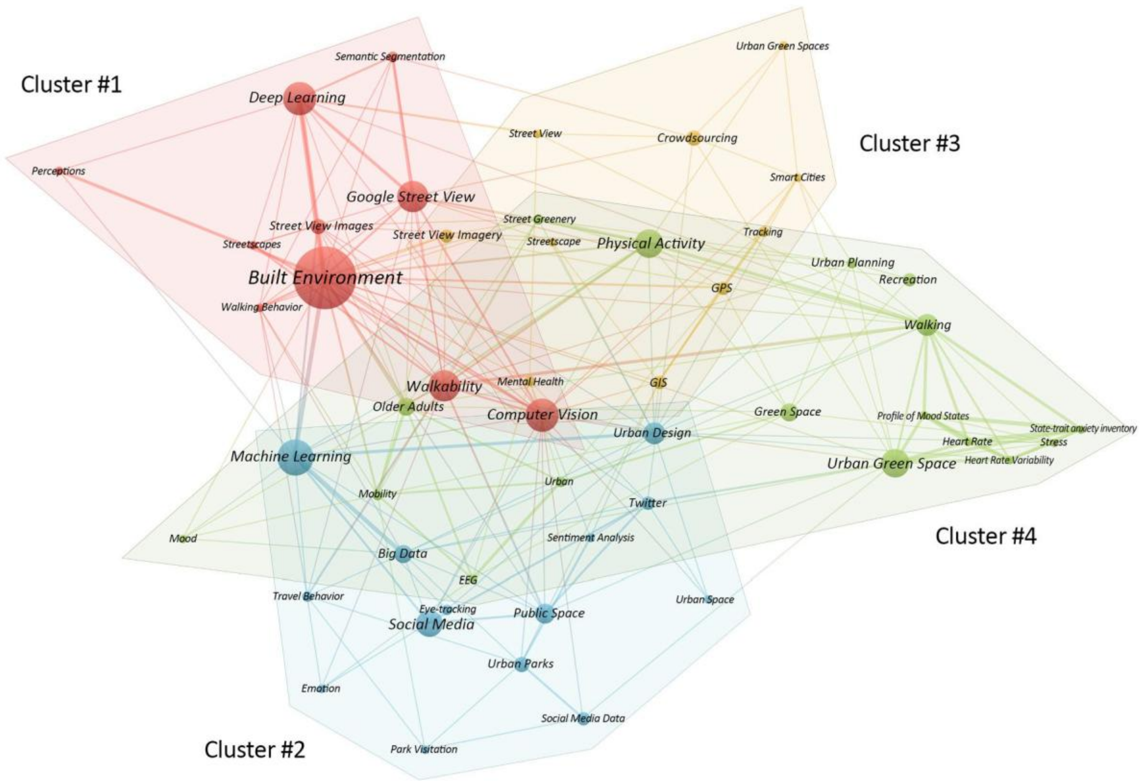

Fig. 6. Co-occurrence analysis of keywords.

4.1.2. *Analytic technique*

Images from map providers are commonly acquired through web interfaces or application programming interfaces (APIs).

Street view images can either be applied to directly reflect or approximate public's perceived urban conditions (Lu et al., 2018; Wang, Lu, et al., 2019), or employed as stimuli for participants to remotely experience and navigate realistic streetscapes in experiments (Dubey et al., 2016; Naik et al., 2014; Quercia et al., 2014; Salesses et al., 2013). Both approaches increasingly involve further processing of images to extract eye-level spatial-visual information, typically through low-level feature (e.g., color and texture) calculation (Yang, Ao, et al., 2021) or deep-learning based high-level information (e.g., semantic information) extraction (Ki & Lee, 2021; Yin & Wang, 2016; Zhang et al., 2018) (Fig. 12).

4.1.3. *Research focus*

Research employing street view data can be categorized into two main groups. Early works often adopt the second approach, employing street images as readily available material for perception experiments ($n = 22$). Typical processes involve bulk downloading street images and asking participants to rate each image's perceptual attributes, such as beauty (Quercia et al., 2014), safety (Salesses et al., 2013), and uniqueness (Dubey et al., 2016). For instance, the Place Pulse project developed a web interface for pairwise comparisons of street images regarding six urban spatial qualities, gathering evaluations from over 80,000 participants on 110,000 images worldwide (Dubey et al., 2016).

Other studies, typically combining street view imagery with other approaches like census and questionnaire, utilize these images to approximate and audit perceived urban qualities, often assessing their association with residents' behavior ($n = 33$) and health outcomes ($n =$

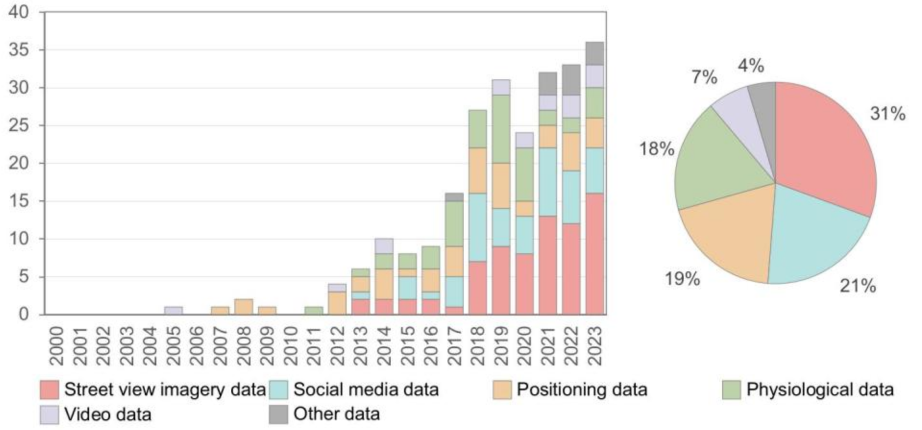

Fig. 7. Share of data type by year.

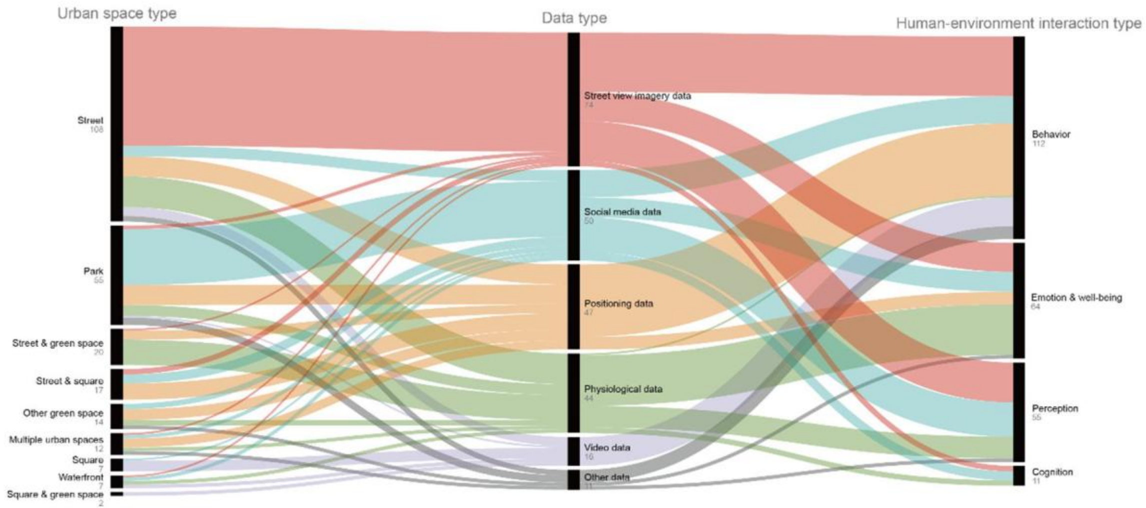

Fig. 8. Relationship of research settings, data types, and research themes.

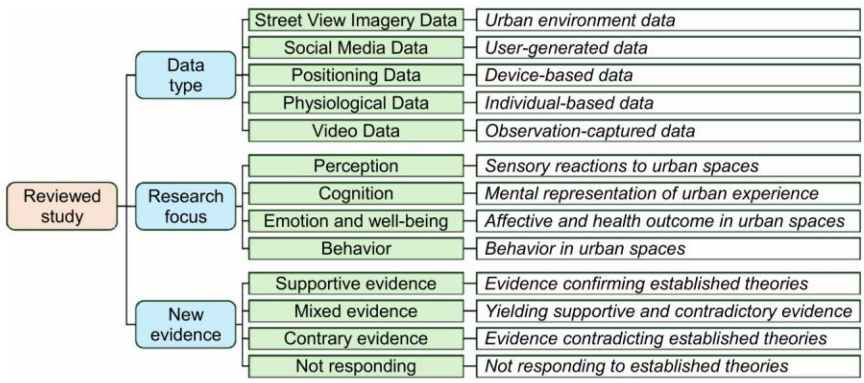

Fig. 9. Analytical framework.

16). A recurring focus is on exploring the relationship between urban greenness levels calculated from street images and residents' well-being and health-promoting behavior, such as positive mood (Chen, Li, et al., 2022), depression (Helbich et al., 2019), health (Wang, Liu, et al., 2019), and physical activity (Lu et al., 2018; Yang et al., 2022; Yang, Ao, et al., 2021). Other urban space qualities calculated include walkability (Wang, Lu, et al., 2019), street design features (Koo et al., 2021), sky exposure (Nagata et al., 2020), and vehicular traffic (Villeneuve et al., 2018).

4.2. Social media data

Social media services have led to rich user-generated content published online (Goodchild, 2007), which is utilized in this group of articles ($n = 50$) to gain first-person insights into users' experience and interaction in urban spaces.

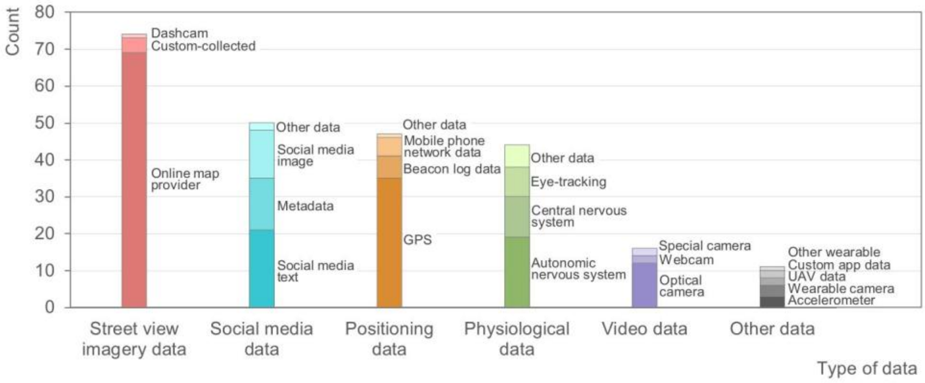

Fig. 10. Share of papers by data type.

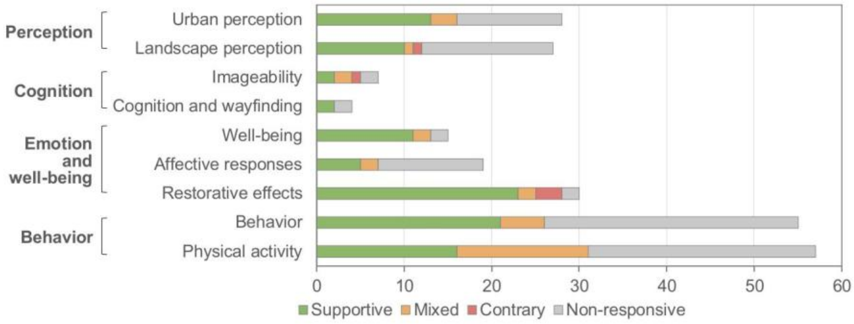

Fig. 11. Share of papers by research theme and evidence.

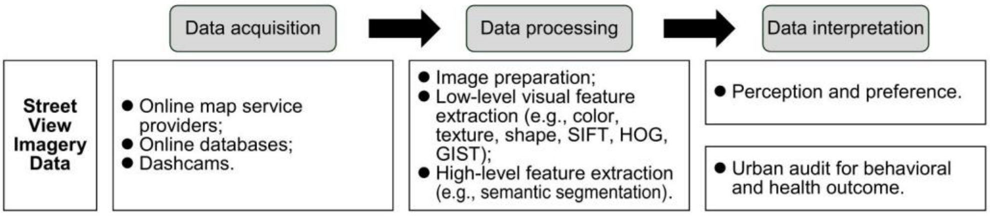

Fig. 12. Technical characteristics of street view imagery data.

4.2.1. *Technical characteristics*

Three major types of social media data have been identified. Text-based data (n = 21), typically retrieved from X (formerly Twitter), Facebook, and Tripadvisor, encompass information on user impressions (Song et al., 2021), feelings (Plunz et al., 2019; Roberts et al., 2019), viewpoints (Wan et al., 2021), and evaluations (Liu & Xiao, 2021) of urban environment. Image-based data (n = 13), typically retrieved from Instagram and Flickr, may contain visual information reflecting users' states (Zhu et al., 2021) and interest (Heikinheimo et al., 2020; Kothencz et al., 2017; Richards & Friess, 2015). Metadata (n = 14) refer to geographical and temporal information from online platforms, such as social media posts' timestamps and geolocations, online check-in data, and location-based services, and can reflect user behavioral traces and crowd dynamics (Hamstead et al., 2018; Hu et al., 2015; Volenec et al., 2021).

4.2.2. *Analytic technique*

Most articles in this category collect data through social media APIs (Huang, Obracht-Prondzynska, et al., 2021; Roberts et al., 2019), a convenient service but may face limitations related to cost and access limits (Ghermandi & Sinclair, 2019). Other channels include data brokers (Chen et al., 2018; Li, Li, et al., 2023), manual searches (Sim et al., 2020), and scraping (Zhu et al., 2021). Pre-processing is often needed for raw data, such as removing noise (Tan & Guan, 2021), retaining pertinent information (Kovacs-Györi et al., 2018), and resolving over-representation issues (Huang, Obracht-Prondzynska, et al., 2021).

Several analytical techniques for social media data have been identified. Descriptive insights are extracted using manual coding (Heikinheimo et al., 2020) and content analysis (Wan et al., 2021). More advanced techniques for text include topic modeling for identifying latent themes (Song et al., 2021) and sentiment analysis for quantifying emotions (Plunz et al., 2019). Computer vision-based object and semantic analyses for images are also applied (Song et al., 2020). Lastly, geographic metadata usually require spatial analysis, such as DBSCAN (Hu et al., 2015) and kernel density estimation (Huang, Obracht-Prondzynska, et al., 2021) (Fig. 13).

4.2.3. *Research focus*

A key theme of articles in this category is perception (n = 19), grounded in the assumption that user-generated content reflects people's interests and preferences. For example, users' motivation to share photos is linked to enjoyment of environments (Richards & Friess, 2015; Wilkins et al., 2022), and studies have used geo-tagged image density to determine users' greenspace preference (Tieskens et al., 2018). Image

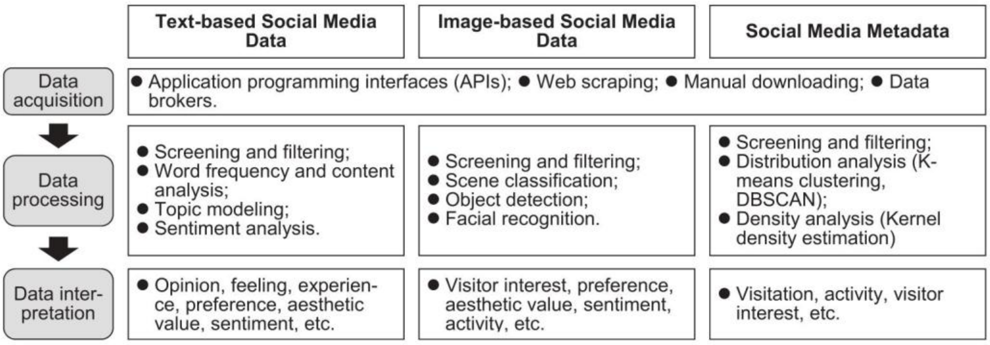

Fig. 13. Technical characteristics of social media data.

content is considered to reflect attention and interest (Liu & Xiao, 2021), and thus analyzed to infer public's aesthetic values (Kothencz et al., 2017) and sense of place (Wan et al., 2021).

Several other themes are also notable. Fifteen articles focus on behavior analysis, typically employing post quantities and distributions as indicators for urban space visitation (Donahue et al., 2018; Hamstead et al., 2018) and usage intensity (Grzyb & Kulczyk, 2023). Identification of specific behavior patterns is also possible (Roberts, 2017; Song et al., 2022). Another 11 articles, using sentiment lexicons (Plunz et al., 2019; Roberts et al., 2019) and, less commonly, facial recognition (Zhu et al., 2021), analyze emotions. Finally, 6 publications examine the presence of various orientation elements in online posts to study spatial cognition (Dunkel, 2015; Huang, Obracht-Prondzynska, et al., 2021).

4.3. Positioning data

Positioning data ($n = 47$), the earliest applied emerging data type identified in the literature, are employed to track human movements across extensive spatial and temporal scales (Nijhuis, 2008).

4.3.1. Technical characteristics

Three types of positioning data have been identified. Global Positioning System (GPS), the most widely used technology in the articles ($n = 35$), provides location data through satellite signals typically using portable devices and smartphones (van der Spek, 2008). It generally offers sufficient precision (7 to 13 m) and sampling rates (1 to 10 Hz) suitable for tracking pedestrian-level activities (Shoval & Isaacson, 2007).

Mobile phone network data ($n = 6$) are collected through radio waves from telecommunication base stations by operators (Girardin et al., 2008). Typically coming in the form of datasets, they have larger spatiotemporal coverage but lower accuracy (100 to 500 m) and sampling frequency (De Nadai et al., 2016; Yue et al., 2017).

Beacon log data ($n = 5$) are collected through Wi-Fi and Bluetooth, available on most smartphones, by fixed access points (Bonne et al., 2013; Versichele et al., 2012). These technologies theoretically offer detailed location data within small ranges, but positioning and tracking remain challenging due to operational constraints (Hou et al., 2023).

4.3.2. Analytic technique

Two positioning data collection methods have been identified. Early studies typically rely on GPS trackers (van der Spek et al., 2009) to monitor individuals' locations, which requires participant cooperation but can offer detailed location information and integrate other instruments (e.g., accelerometers) (Marquet et al., 2022; Rundle et al., 2016). Recently, available positioning datasets from third-party apps (e.g., fitness apps) (Salazar Miranda et al., 2021; Sevtsuk et al., 2021) or telecommunication operators (Liu et al., 2023; Yue et al., 2017) are increasingly utilized, which offer larger samples but have limited precision due to privacy problems (Horanont et al., 2013).

Raw positioning data could feature noise, outliers, and signal losses (Shoval & Isaacson, 2007), requiring pre-processing techniques like map matching to correct errors and offsets (Korpilo et al., 2017; Sevtsuk et al., 2021) or filtering to clean irreparable errors (Meijles et al., 2014). Processed data allow analysis of user counts (Liu et al., 2023) and locations (Almanza et al., 2012; Rout & Galpern, 2022), and support calculations like route choice (Sarjala, 2019) and activity patterns (Santos et al., 2016) (Fig. 14).

4.3.3. Research focus

Most literature in this group ($n = 40$) address human behaviors. Studies have applied mobile phone network data to investigate population distribution (Girardin et al., 2008), handed out GPS trackers to monitor tourists' movement (Shoval, 2008; van der Spek et al., 2009), and set up Bluetooth devices to count pedestrian flow (Versichele et al., 2012). Scholars also applied positioning data in walking (Salazar Miranda et al., 2021; Vich et al., 2019) and physical activity (Andersen et al., 2015; Rundle et al., 2016) research.

Seven articles also explored emotional aspects by integrating experience sampling method (ESM) into special GPS tracking apps, which allow participants to report moods in different urban environments in real-time (Doherty et al., 2014; Glasgow et al., 2019; Shoval et al., 2018).

4.4. Physiological data

This group of articles ($n = 44$) employs biometric equipment, enabled by advancements in neuroscience and bioinformatics, to collect physiological data reflecting human responses to urban spaces.

4.4.1. Technical characteristics

Three categories of human physiological data have been utilized in the articles. Autonomic nervous system measurement is the predominant approach ($n = 19$), which monitors unconscious bodily functions including cardiac activity, electrodermal activity (EDA), and muscular reactions triggered by environmental exposure (Stigsdotter et al., 2017). For example, stress events may affect heart rate and skin conductance, and can be measured with electrocardiography and EDA sensors (Chrisinger & King, 2018; Stigsdotter et al., 2017; Xiang et al., 2021).

Another 8 studies measure central nervous system, specifically the brain. The activation of brain neurons causes local electrical currents and different extracellular potentials in cortex regions (Karandinou & Turner, 2017), which can be measured with Electroencephalogram (EEG) devices and offer insights into brain activities (Olszewska-Guizzo et al., 2020).

Lastly, 11 studies apply eye-tracking to measure human gaze behaviors and visual patterns, which, given human spatial information is mainly acquired visually (Kiefer et al., 2017), are considered to reflect individuals' perception and cognition of their surrounding environment (Simpson et al., 2019; Zhou et al., 2023).

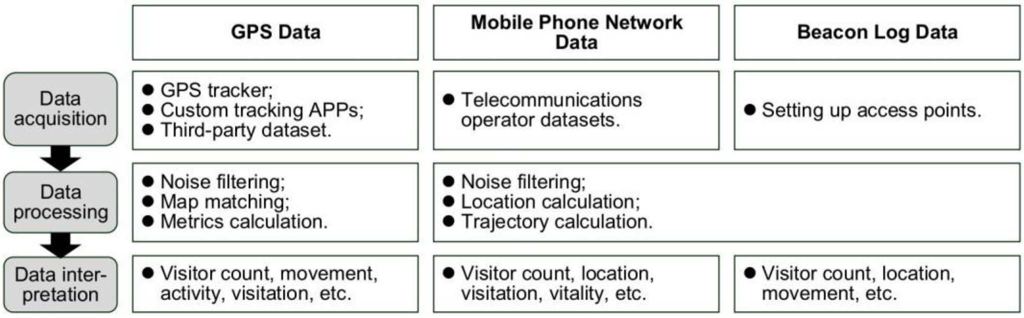

Fig. 14. Technical characteristics of positioning data.

4.4.2. Analytic technique

All articles in this category involve laboratory or field experiments in which participants are exposed to environmental stimuli while sensors collect physiological data.

Raw data on central and autonomic nervous systems are typically recorded as electrical signals, and, susceptible to noise, often require pre-processing to remove contamination (Mavros et al., 2022). Complex signals from EEG are commonly further transformed, such as through Fourier transform, for direct analysis (Olszewska-Guizzo et al., 2020).

Eye-tracking data's processing and analysis focus on three attributes (Kiefer et al., 2017). Fixation, calculated through fixation counts (Emo, 2014) and duration (Liu et al., 2021), is associated with attention engagement. Eye movement, calculated through saccade and scanpath (Ma et al., 2023), reflects attention directions and the amount of processed information. Finally, other measures such as pupil diameter and blink frequency (Zhou et al., 2023) can reflect individuals' cognitive load and stress responses (Fig. 15).

4.4.3. Research focus

This group of papers reveals three main themes. Most studies ($n = 28$) apply physiological measures, considered a more objective option to conventional self-reports, to explore human emotion aspects (Olszewska-Guizzo et al., 2020). Key emotions and mental states measured include stress (Resch et al., 2020), arousal (Xiang et al., 2021), restoration (Song et al., 2013; Song et al., 2015), and excitement (Neale et al., 2017), with particular attention on natural elements' effects (Aspinall et al., 2015; Tilley et al., 2017).

Twelve studies also employed certain physiological data to infer people's perceptions and preferences. For instance, Hollander and Foster (2016) utilized participants' brain meditation and attention states to reflect street design qualities. Several studies also applied eye-tracking data to understand users' attention (Liu et al., 2021; Zhang, 2023).

We also identified 3 studies addressing cognition and 1 addressing behavior, where physiological data are applied to offer insights into the neural and mental basis of human-environment interaction processes like wayfinding (Karandinou & Turner, 2017).

4.5. Video data

Lastly, we noted 16 articles that leverage video data, often incorporating computer vision processing techniques, to observe human behaviors in urban spaces.

4.5.1. Technical characteristics

Video data analytics is viewed as the digital transformation of traditional time-lapse behavior research (Schlickman, 2020). Most identified studies employ cameras (Li et al., 2022) or thermal sensors (Nielsen et al., 2014) to continuously monitor an urban space, with video durations ranging from minutes (Niu et al., 2022), hours (Schlickman, 2020), to several weeks (Liang et al., 2020). Recently, online webcam footage has also been explored as an available video data source (de Montigny et al., 2012).

4.5.2. Analytic technique

Automated and quantitative analysis of video data through computer vision methods is a notable recent advancement in this group (Yan & Forsyth, 2005). Key steps involve detecting and tracking human figures from video frames via object detection algorithms (Li, Yabuki, & Fukuda, 2023), georeferencing positions to geographic coordinates and correcting perspective distortion (Liang et al., 2020), and codifying data into spatial grids for analysis (Ceccarelli et al., 2023) (Fig. 16).

4.5.3. Research focus

All identified literature in this category employs videos to analyze behavior. Studies calculated user counts (de Montigny et al., 2012), positions (Massaro et al., 2021), trajectories (Nielsen et al., 2014), moving speeds (Liang et al., 2020), and behavioral types (Li et al., 2022) through video data and explored their association with spatial

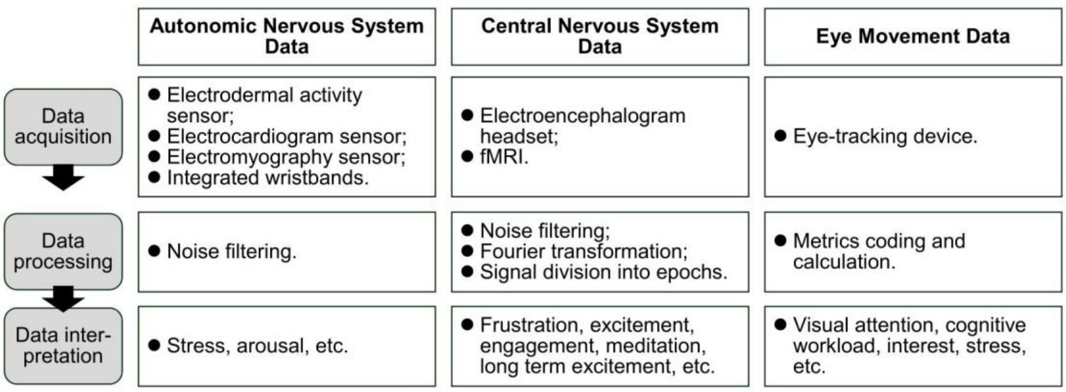

Fig. 15. Technical characteristics of physiological data.

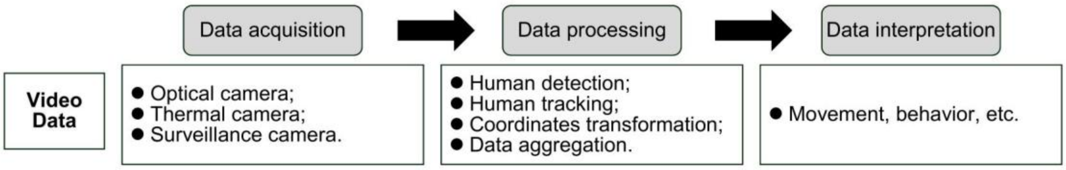

Fig. 16. Technical characteristics of video data.

configuration (Ceccarelli et al., 2023), landscape design (Schlickman, 2020), and street furniture (Sánchez-Vaquerizo & Llach, 2019). Recent research has extended to the identification of social interaction (Loo & Fan, 2023), providing indications for design qualities (Niu et al., 2022).

5. New evidence of reviewed studies

Section 5 reviews the insights derived from emerging data-driven approaches and their contributions to existing theories on human-environment interaction in urban spaces, structured by the human-environment interaction processes covered and the responses to existing theories. Our findings indicate that 58 % of the studies ($n = 139$) drew on existing frameworks, with 42 % of the studies ($n = 102$) generating supportive evidence, 13 % showing mixed results ($n = 32$), and 2 % presenting contradictory findings ($n = 5$).

5.1. Perception

Human perceptions have been addressed in 55 studies. Twenty-eight studies mainly focused on general urban spaces, with 16 citing established theories, and 13 yielding supporting evidence. Notable advances include the use of precise biometric measures to validate classic preference patterns, such as eye-tracking experiments linking active street edges with people's increased visual attention (Simpson et al., 2019) and EEG evidence linking pedestrian-oriented designs with increased measured interest (Hollander & Foster, 2016). Previously-unavailable large datasets also enabled validations of known preference patterns (e.g., for visual enclosure) in broader contexts (Harvey et al., 2015; Kruse et al., 2021; Quercia et al., 2014). Wilson and Kelling's (1982) Broken Window Theory and Jacobs' (1961) "eyes on the street" were also corroborated by street view-based safety perception research (Kang et al., 2023; Li et al., 2015; Xu et al., 2023; Zhang et al., 2021). However, 3 studies delivered mixed results partially challenging established preference patterns for certain urban spatial elements (Rossetti et al., 2019; Verma et al., 2020; Zhang et al., 2018). It is important to note that differing definitions and calculations may contribute to variations in findings (Zhang et al., 2018).

Another 27 studies mainly covered greenspaces (parks, green spaces, etc.), with 12 addressing established theories and 10 yielding supportive evidence. Social media analysis validated vegetation (Liu & Xiao, 2021) rather than artificial elements (Kothencz et al., 2017) as a key predictor of satisfaction, with preferences potentially differing among visitor groups (Huai et al., 2022; Song et al., 2020). Visual complexity (Kaplan & Kaplan, 1989b) was also proved preferable (Liu et al., 2021). Jacobs' (1961) theory on safety perception was endorsed as well (Zhou et al., 2022), as eye-tracking evidence linked visual obstruction in parks with negative aesthetic evaluations (Ma et al., 2023). However, Wan et al.'s (2021) study in Hong Kong parks partially challenged Herzog's (1985) theory, failing to establish any correlation between water features and preferences as extracted from Instagram posts. Tieskens et al.'s (2018) research on social media photos in Dutch greenspaces expanded previous understandings, identifying preferences for monumental buildings.

5.2. Cognition

Spatial cognition has been addressed in 11 studies. We identified 7 studies on urban imageability, with 5 citing Lynch's (1960) theory and 2 supporting. These supportive studies innovatively employed social media (Liu et al., 2016) and street view images (Quercia et al., 2013) to substantiate Lynch's arguments. However, by classifying urban orientation elements from extensive social media posts, Huang, Obracht-Prondzynska, et al. (2021) partially questioned Lynch's five elements, with "edge" and "node" lacking empirical evidence. Yoshimura et al.'s (2020) research, employing street image-based memory tests, also contradicted Lynch's legibility theory and raised doubt on mental image formation.

Four studies explored wayfinding in urban spaces, with 2 citing and confirming existing theories. Emo (2014) used eye-tracking to show that individuals preferred routes with stronger connectivity, emphasizing the importance of spatial structures for navigation. Another study using EEG found increased Beta activity during decision-making, offering neural insights into spatial cognition processes (Karandinou & Turner, 2017).

5.3. Emotion and well-being

We identified 64 articles addressing emotion and well-being aspects. Fifteen studies covered well-being and health outcomes, with 13 citing established theories and 11 yielding supportive evidence. Studies typically employed street view data to quantify perceived environmental qualities like greenness (Jimenez et al., 2022; Yang et al., 2023), water (Helbich et al., 2019), walkability (Kim et al., 2023), and aesthetics (Hart et al., 2018), and have identified positive associations between these qualities and physical and mental well-being. However, contradicting other research findings (e.g., Molina-García et al., 2021; Wang, Yuan, et al., 2019), 2 studies reported mixed results on infrastructure's (Nguyen et al., 2019) and perceived safety's (Pearson et al., 2021) effects on well-being.

A critical pathway of urban spaces' well-being impact is through affective responses (Markevych et al., 2017). Among 19 articles in this group, 7 referenced existing theories, with 5 generating supportive evidence. Employing physiological data as objective markers, field studies confirmed the effects of compactness and enclosure on stress responses (Li et al., 2016). For example, on-site EDA experiments linked crowding to aversive emotional responses (Engelniederhammer et al., 2019), providing physiological evidence for Hall's (1966) Proxemic Theory. Virtual validation via social media and street images further confirmed these findings (Chen, Li, et al., 2022; Luo & Jiang, 2022). Nonetheless, we identified 2 experiments producing mixed results regarding affective responses to visual complexity (Xiang et al., 2021) and walkability (Glasgow et al., 2019), though both acknowledged indicator selection as a potential factor.

We identified 30 studies focusing on restorative effects of natural elements in urban spaces, with 28 citing Kaplan and Kaplan (1989a, 1989b) and Ulrich (1984), and 23 supporting their theories. Physiological and GPS data have facilitated quantitative observations of restorative effects, marked by improved attention levels and lowered blood pressure and heart rate (Aspinall et al., 2015; Neale et al., 2017; Song et al., 2013, 2014, 2015). Innovative attempts also linked greenery to positive pedestrian facial expressions (Wei et al., 2021) and favorable emotions online (Zhu et al., 2021). Studies further explored potential influences of temporal (Roberts et al., 2019), spatial (Wang et al., 2016), landscape (Olszewska-Guizzo et al., 2020; Wei et al., 2022), soundscape (Jeon et al., 2023), demographic (Kondo et al., 2020), and behavioral variables (Lin et al., 2020; Mavros et al., 2022). However, Plunz et al.'s

(2019) examination of New York Twitter posts yielded inconsistent results concerning parks and positive sentiments. Lin et al. (2019) found other factors like environmental spaciousness can influence greenery's restorative potentials. Roe et al.'s (2019) and Yu et al.'s (2018) studies with physiological measurements also both contested greenery's consistent restorative effect, while Birenboim et al. (2019) hinted at the need for cognitive overload as a prerequisite.

5.4. Behavior

We identified 112 studies focusing on behavior. Fifty-five studies addressed general environmental behavior aspects, with 26 citing existing theories and 21 yielding supportive evidence. Location and video tracking have provided high-granular data verifying classic design principles (Chen et al., 2018; Donahue et al., 2018; Korpilo et al., 2018; Rout & Galpern, 2022) and corroborated Whyte's (1980) and Gehl's (1987) theory on domino effect (Yan & Forsyth, 2005), street furniture (Sánchez-Vaquerizo & Llach, 2019), triangulation (Loo & Fan, 2023), and edge effect (Schlickman, 2020). Jacobs' (1961) urban vitality theory was also supported by emerging data on crowd flow, corroborating positive effects of mixed-use (Yue et al., 2017), density (Delclòs-Alió et al., 2019), and smaller blocks (Garrido-Valenzuela et al., 2023). We also noted 5 studies yielding mixed results. De Nadai et al. (2016) and Li et al. (2022) did not fully confirm the spatial design-urban vitality link in research of broader cultural contexts employing big data. Large-scale location datasets also partially contradicted known effects of green-space design on behavior (Hamstead et al., 2018; Liu et al., 2023; Meijles et al., 2014).

Another 57 studies focused on physical activity and walking, with 31 addressing classic theories and 16 generating supportive evidence. Researchers confirmed urban spatial attributes' impact on walking using diverse data sources—commuting trajectories (Salazar Miranda et al., 2021), accelerometers (Almanza et al., 2012), street view-based surveys (Villeneuve et al., 2018), and social media posts (Roberts et al., 2017). Urban greenery was a major focus, with evidence linking it to increased walking propensity (Lu et al., 2018; Yang et al., 2020), time (Yang, Liu, et al., 2021), steps (Marquet et al., 2022), and physical activity (Lu, 2019; Villeneuve et al., 2018; Zhang et al., 2023). We also identified 15 studies with mixed results. Four studies employing street view data showed inconsistent effects of street features including greenery (Wang, Liu, et al., 2022) and sidewalks (Doiron et al., 2022) on walking, and 4 large-scale investigations also did not empirically confirm the impact of configuration and function factors as theorized by Cervero and Kockelman's (1997) 3D framework (Lu, 2018; Sarjala, 2019; Yang, Liu, et al., 2021; Yang et al., 2019). Data-driven approaches have enabled exploration of the potential roles of purpose and need of behavior (Koo et al., 2023; Steinmetz-Wood et al., 2020) as well as cultural and climatic influences (Chen, Lu, et al., 2022; Ki et al., 2023) in explaining mixed findings.

6. Discussion

This section discusses the characteristics, trends, and potential limitations of emerging data-driven approaches in human-environment interaction research, outlining future research possibilities.

6.1. Advances and challenges in emerging data-driven research

6.1.1. New capabilities amid quality limitations

Our systematic review demonstrates that multiple data-driven approaches have been applied in human-environment interaction research. This aligns with previous review findings (Li et al., 2018) and indicates that considerable development has been achieved in the field, with the scope of applications expected to continue expanding (Biljecki & Ito, 2021). Within our literature, five key data types emerge, with their research trends and technical characteristics summarized in Table 1.

Table 1
Strengths and weaknesses of new data.

	Research Focus	Strength	Challenge
Street view imagery data	• Behavior • Perception	• Large sample size • Easy data collection	• Varying data quality • Varying data availability
Social media data	• Perception • Behavior • Emotion and well-being	• Easy data collection • Non-intrusive	• Low data quality • Varying data availability • Sampling bias • Privacy issue
Positioning data	• Behavior	• Large sample size • High spatiotemporal granularity • Non-intrusive	• Varying data quality • Sampling bias • Contain limited information • Privacy issue
Physiological data	• Emotion and well-being • Perception	• Objectivity • High temporal granularity • Real-time data collection	• High research cost • Varying data quality • Require expertise in collection & analysis
Video data	• Behavior	• High spatiotemporal granularity • Non-intrusive • Unbiased sampling • Real-time data collection	• Varying data quality • Require expertise in analysis • Privacy issue

A significant advantage of emerging data is their ability to offer more direct observations of human-environment interaction. They provide opportunities for more precise descriptions and real-time modeling of processes that were previously difficult to capture (e.g., psychological responses) or could only be obtained through post-hoc surveys or self-reporting (e.g., spatial behaviors) (Olszewska-Guizzo et al., 2020; van der Spek et al., 2009). This enhanced granularity and accuracy show promising potential in extending existing knowledge and revealing more nuanced human-environment interaction mechanisms (Olszewska-Guizzo et al., 2020; Schlickman, 2020).

Another commonly cited strength is large data volume, characterized by broader coverage areas (Dubey et al., 2016), longer observation periods (de Montigny et al., 2012), and more continuous sampling frequencies (Aspinall et al., 2015), which is often associated with improved data availability and easier collection processes. Unlike descriptive and small-scale observational studies, data-driven approaches could allow for capturing larger samples and support statistical analysis that potentially yield more complete information about human responses (Hamstead et al., 2018; Heikinheimo et al., 2020). The automatic generation and collection of data from sources like social media and video further enable long-term tracking of public opinions and behavioral patterns that would be difficult with traditional methods (Loo & Fan, 2023).

A co-benefit of larger data volume is the applicability of these approaches and their relative ease of large-scale implementation. Our review identified a limited but growing number of studies that directly compare and validate human-environment interaction across different cities and contexts (Rossetti et al., 2019; Zhang et al., 2018), thereby identifying potential variations (Salesses et al., 2013). This could contribute to the broader generalizability of findings.

However, the strengths of emerging data could come at the expense of limitations in datasets. A widely reported issue is inferior data quality, observed across nearly all data types. Due to the often absence of quality control mechanisms, emerging data are typically characterized by noise and heterogeneity, including artifacts in physiological data (Neale et al., 2017), noise in social media data (Dunkel, 2015), and outliers in positioning data (Meijles et al., 2014). Data bias is another challenge, as data often come from unknown gathering processes and are not randomly sampled, potentially containing biases related to gender, age, socioeconomic status, and user motivation (Calabrese et al., 2015). Previous studies show that social media features younger and more educated user groups (Ghermandi & Sinclair, 2019), yet such biases are difficult to quantify and correct without referencing ground truth data (Heikinheimo et al., 2020). These limitations have raised doubts about usability and reliability among some scholars (Huang, Yao, et al., 2021). Nevertheless, we observed that many studies have not explicitly acknowledged or addressed data quality concerns, potentially compromising research validity and thus warranting attention in future research.

6.1.2. Analytic innovations and limited protocols

Many advances in data-driven research can be attributed to developments in processing and analytical techniques, particularly given that emerging data were often not originally collected for human-environment interaction research purposes. We especially identified interdisciplinary contributions from data science and computer science fields. Machine learning methods, including computer vision and natural language processing, are increasingly applied to data types such as street view imagery and social media, demonstrating impressive capabilities and efficiency in processing and analyzing visual and textual material (Song et al., 2021; Zhang et al., 2018).

The challenge of interdisciplinary approaches lies in the requisite specialized expertise. Collected articles highlighted difficulties in sensor setup (Aspinall et al., 2015), data processing (Versichele et al., 2012), and result interpretation (Birenboim et al., 2019). Emerging data types often lack established processing and analytical protocols, which requires researchers to develop their own approaches (Wilkins et al., 2022). These may present barriers to broader adoption of data-driven approaches.

We observed another concern regarding the lack of validation. Many analytical methods are inherently experimental in nature, and reliable evidence concerning their validity remains insufficient. For example, using social media data to infer landscape preferences may lack theoretical grounding and could contradict established findings (Wilkins et al., 2022). Questions about the effectiveness and interpretability of machine learning methods also remain (Spencer et al., 2019). Apart from a few exceptions like Heikinheimo et al.'s (2020) research, very few studies have investigated how different data sources and analysis methods perform or compared them against traditional approaches, which is a clear gap demanding further research effort.

6.1.3. New perspectives, but not always new insight

A slight majority of the collected articles addressed established theories in human-environment interaction research. We observed in some cases that emerging data provide innovative perspectives and insights, expanding the scope and knowledge in existing discourse. For instance, creative use of mobile phone network data for measuring neighborhood vitality provides quantitative spatial and statistical evidence for Jacobs' and Gehl's theories (Yue et al., 2017). Also, use of biometrics linked restorative effect with physiological changes and brain activities, offering information on underlying mechanisms and influencing factors (Olszewska-Guizzo et al., 2020). However, we also noticed that some studies appear to primarily replicate known findings using new methods, offering limited significant contributions. This echoes observations by Biljecki and Ito (2021), who pointed out that some papers are "largely replications or offer minor incremental improvements". A potential reason is technological barriers, which may result in homogenization in research.

We also identified a small number of studies that yielded conclusions not entirely consistent with established theories, yet the underlying causes of these discrepancies have not been adequately explored. Whether these differences stem from the limitations of established theories, biases inherent in emerging data, or actual shifts in human–environment relations over time remains an open and under-researched question.

Lastly, nearly half of the literature did not reference any existing frameworks in the field, a trend particularly prevalent outside the emotion and well-being research that has strong interdisciplinary traditions. We believe this finding has two sides: it confirms Batty's (2013a) concern that the lack of theoretical grounding may limit the value of data-driven methods in providing meaningful and actionable insights. Conversely, we anticipate that the complexity and heterogeneity of data-driven approaches may stimulate new research areas that transcend traditional theoretical boundaries.

6.1.4. Uneven research attention

Despite surging publications, certain aspects of human-environment interaction remain understudied. Compared to behavioral aspects, spatial cognition and perception lack adequate empirical attention. Many seminal theories—Cullen's serial vision, Tuan's sense of place, Gehl's social behavior, and Bosselmann's distance cognition—are also underrepresented in recent work. Future studies could investigate broader spectrum of interaction mechanisms that may prove equally important for urban experiences.

Global South is inadequately researched compared to Global North, with China being an exception. This could limit the generalizability of research findings across different contexts. Human-environment interaction is potentially influenced by cultural, socioeconomic, environmental, and climatic factors that vary substantially between regions. For example, green exposure level in Global South cities is only one-third of that in Global North cities (Chen, Wu, et al., 2022), showing fundamental differences requiring attention. The underrepresentation of Global South, which is facing rapid urbanization and unique environmental challenges, may result in missed local insights, widened knowledge gaps, and false policy recommendations.

We also noted disparities in interest regarding data types and urban space typologies: video data application remains scarce, and attention to squares and other urban spaces is limited compared to streets and parks. This can be explained by data availability and accessibility constraints, warranting innovative data collection and interpretation approaches.

6.1.5. Other challenges

Most data-driven research faces the ethical challenge of using private information. Though data are often publicly-available or obtained with informed consent, these do not necessarily guarantee voluntary use, especially given how they are scrutinized in research (Rout et al., 2021). It is also privacy concerns that increasingly complicate tasks or access of certain data types like mobile phone network data. In short, questions remain unresolved regarding the legal obtainment and ethical use of data.

6.2. Future opportunities

Integrated approach: Given data's inherent quality issues, no dataset alone is arguably "big" enough to fully capture the complexities of human-environment interaction (van der Spek et al., 2009). Combining methods—whether by merging complementing emerging data or integrating conventional qualitative methods—can address sampling biases and information gaps, potentially offering a broader perspective. However, determining the right methodology is crucial, as excessive integration risks complicating data management and interpretation. We also observe innovative methods maximizing information from smaller datasets (e.g., Salazar-Miranda et al., 2023), which highlight the value of balancing data richness with analytical feasibility which prioritizes coherence over sheer volume or novelty.

Rigorous methodologies: Because of the often absence of standards for data processing and analysis, it is essential to not only develop quality control protocols and standardized processing procedures for new data types, but also adopt solid theoretical underpinnings and rigorous methodologies ensuring reliability and credibility. Though artificial intelligence presents a methodological advancement, considering many machine learning methods are not designed for urban analysis and may face challenges like output quality control, it remains important to exercise caution and uphold sharp awareness and rigorous approach when researching actual urban issues (Kitchin, 2014).

Broader research attention: We stress that many human-environment interaction processes still require stronger empirical evidence, and Global South contexts and other contextual factors demand further scrutiny. We also anticipate broader exploration in areas with limited significant output, and call for data to be fully utilized to address not only past issues but also new frontiers beyond traditional research.

Better privacy protection: Ethical and privacy concerns need addressing, as the absence of robust protocols may hinder the field's long-term development. Admittedly, privacy protection extends beyond this review and requires both technical solutions and non-technical efforts (legislative, regulatory, and governance).

6.3. Limitations

This review has several limitations. We adopt Nasar's framework for human-environment interaction and only include research applying emerging data-driven approaches directly reflecting human-environment interaction processes. This delimitation is necessary to maintain focus but may exclude studies that employ different theoretical foundations or draw on emerging data beyond the scope of our research. The interdisciplinary and evolving nature of this field also means that, despite adopting systematic methods, thorough coverage of research is challenging, and new approaches and research are constantly emerging.

As previously emphasized, our collected articles show uneven focuses regarding research areas, methods, and locations, suggesting that potential biases need to be considered when interpreting our results and their applicability, particularly to underrepresented contexts and regions. Lastly, the time scope of our search query may have inadvertently emphasized certain research traditions and contexts, potentially limiting the diversity of methodological approaches and theoretical perspectives included in our analysis.

7. Conclusion

Rapid technological progress since the 21st century has enabled the integration of new data into observing and analyzing human-environment interaction in urban spaces. This study systematically reviewed 242 articles employing emerging data-driven approach in human-environment interaction research. The main contribution of this research is providing a comprehensive overview of this rapidly evolving research field, synthesizing insights from diverse research directions across methodology and knowledge dimensions. The findings can serve as guidance for researchers, urban designers, and policymakers.

This review identified multiple emerging data types utilized in human-environment interaction research, with street view imagery, social media data, positioning data, physiological data, and video data being the five main categories. These emerging data types each feature unique characteristics and strengths, require varying processing and analytic techniques, and have been applied in different research directions. Furthermore, many emerging data-driven studies have connected with established theories in the field, and created new evidence that enables rigorous examinations of classical urban theories, providing empirical validation as well as alternative perspectives.

Our review demonstrates that emerging data possess promising potential, especially in both scope and precision. Their application has stimulated innovative research methodologies and expanded horizons in human-environment interaction research field. However, data are not panaceas and still suffer from a range of limitations related to their inherent problems, methodological issues, uneven application domains, and privacy concerns. This review stresses the need for future data-driven human-environment interaction research to leverage their advantages responsibly and exercise judiciousness. With great scrutiny, emerging data can assume an important role in fostering an inclusive, livable, and sustainable urban future.

CRediT authorship contribution statement

Zian Wang: Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization. **Yifan Yang:** Writing – review & editing, Visualization, Conceptualization. **Steffen Nijhuis:** Supervision, Conceptualization. **Stefan van der Spek:** Writing – review & editing, 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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2025.106346.

Data availability

No data was used for the research described in the article.

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Appendix 2 - How well does crowdsourced social media data capture public urban greenness perception? A comparative analysis in Rotterdam, the Netherlands

Wang, Z., Yang, Y., Van Oosterom, P., Nijhuis, S., & Van Der Spek, S. (n.d.). *How well does crowdsourced social media data capture public urban greenness perception? A comparative analysis in Rotterdam, the Netherlands (working paper)*.

How well does crowdsourced social media data capture public urban greenness perception? A comparative analysis in Rotterdam, the Netherlands

Abstract

Perceived greenness of environment is closely linked to urban greenery's health and well-being benefits for residents. Conventional greenness perception measurement relies on survey methods, which provide accurate and detailed information but are difficult to apply at large geographical scales. Alternative approaches employ large-scale geospatial indices including NDVI and GVI to measure objective greenness levels, but may face limitations in reflecting subjective perceptions of urban greenness. In this Rotterdam-based study, we proposed an innovative greenness perception measurement approach combining crowdsourced Flickr social media image data and deep learning techniques, and conducted comparative analysis with conventional survey results and objective geospatial indices to critically assess its capacity and performance. Results show that social media-based approach effectively captured overall perceived greenness patterns and exhibited the best consistency with survey results among included measures. However, it did not fully align with survey findings and exhibited statistical and spatial differences. Regression analyses reveal that social media-based greenness perception better reflects greenery availability and visual conditions but may be difficult to capture broader accessibility and attractiveness qualities that survey represents, which are more associated with long-term usage. Additionally, we identified potential limitations of social media approach including fluctuations, platform and user biases, and spatial over-representations, while integrative and complementary approach may enable more comprehensive and inclusive insight. With our findings we aim to enhance understanding of urban greenness perception and its assessment methods, and provide evidence to inform future methodological selection and green infrastructure planning and design.

1 Introduction

In the context of global climate change and rapid urbanization, urban greening has increasingly been recognized as an essential strategy to address multifaceted urban challenges and achieve environmental and social goals (UN General Assembly, 2015). Research shows that green spaces regulate urban environments through ecosystem services (Korkou et al., 2023; Tzoulas et al., 2007) and contribute positively to human health and well-being, including improved restoration and self-reported happiness, increased physical activity, enhanced social interaction, and lower risks of psychological distress and mortality (Hartig et al., 2014; Markevych et al., 2017). Residents' perception of the urban environment, particularly perceived greenness, is a key factor closely connected to the health and well-being benefits they gain (Lackey & Kaczynski, 2009; Leslie et al., 2010; Rieves, Freis, et al., 2024). Perceived greenness has been found to directly affect residents' use of greenspaces, including visitations (Ries et al., 2009) and physical activities (Tabatabaie et al., 2019; Tilt et al., 2007). Better perceived greenness of the neighborhood also correlates with improved quality of life, satisfaction, and well-being (Loder et al., 2020; Sugiyama et al., 2008; Van Herzele & de Vries, 2012). Moreover, an increasing amount of evidence suggests that perceptions of environmental greenness are shaped not only by the presence of greenery but also by the integration of diverse and multifaceted environmental qualities (Orstad et al., 2017). Therefore, understanding and assessing residents' perceptions of environmental greenness is important for better designing green infrastructure aligning with user preferences and needs while supporting informed and human-centered planning decisions.

Traditionally, residents' perceived greenness measures are obtained using surveys, such as through self-reports and questionnaires. Such approaches are reliable and accurate, but face constraints for time- and labor-intensiveness and limitations in scalability (Teeuwen et al., 2024). Although recent efforts have attempted to combine surveys with digital tools, such as through public participatory geographic information system (PPGIS) method (Y. Wang et al., 2019), scalability challenges remain. An alternative class of methods relies on large-scale, readily-available datasets, such as geospatial datasets, to quantify objective measurements of greenness, which are subsequently used to approximate public's green exposures or perceptions (Larkin et al., 2021; Rieves, Freis, et al., 2024). Common approaches include using remote sensing indices, such as Normalized Difference Vegetation Index (NDVI), which measures photosynthesizing vegetation present on the land surface to reflect the relative greenness of urban environments. NDVI features easy access and broad coverage, but is often considered unable to fully reflect residents' perceptions because of its top-down perspective (Leslie et al., 2010). A recently emerging method uses street-level imagery, such as Google Street View, to calculate urban greenness levels approximating human perspective, known as Green View Index (GVI) (Larkin et al., 2021; H. Zhang et al., 2025). As a type of geospatial big data-derived index, GVI is considered "similar" to human perceptions and has witnessed increasing application in perception research (Biljecki & Ito, 2021), but consistent validation evidence for reflecting residents' perceived greenness remains limited.

Against this background, social media data, as a form of crowdsourced big data, potentially provides a novel approach for large-scale investigations of subjective and individual-level urban greenness perceptions. User-generated content on social media platforms encompasses people's voluntarily expressed views and perspectives, containing valuable insights into urban experiences (Ghermandi & Sinclair, 2019; W. Zhang & Su, 2024). Among them, social media image data could offer rich information about both the physical urban environment and users' interests (Dunkel, 2015; Song, Richards, & Tan, 2020). Analyzing such images could enable researchers to understand which landscape elements attract public attention, thereby supporting analysis of urban greenery's perceptual dimensions from a new perspective (Oteros-Rozas et al., 2018). This type of data also offers extensive coverage and detailed spatial and temporal records, making it suitable for large-scale perception studies (Dunkel et al., 2023).

While social media data has been widely applied in greenspace research, particularly in parks (e.g., Donahue et al., 2018; Sessions et al., 2016; Wood et al., 2013), its potential for measuring greenness perception at the broader urban scale remains underexplored (Z. Wang et al., 2025). It is currently unclear whether social media-based methods can effectively capture perceived measures of urban greenness, and validation studies based on survey results are lacking. Concerns over social media's limitations including data quality and bias further raise questions about its validity and accuracy, which have yet to be empirically addressed in this research area. Another knowledge gap involves how this potential approach performs compared to established and popular measurement methods such as NDVI and GVI, leaving researchers unable to assess the relative advantages and limitations of the social media-based method. As urban greenery continues to receive attention in current research and practice, more efficient methods for assessing subjective greenness perception are required.

This study addresses these gaps by proposing a novel social media data-based perceived greenness assessment method. We validate it against conventional survey-based greenness perception results to examine its effectiveness and accuracy. We also compare our proposed method with widely-used NDVI and GVI indices to understand consistencies and differences among varying greenness measurement approaches. To be specific, we employ Rotterdam as the case study and focus on three research questions:

- To what extent can social media data accurately capture perceived greenness of urban environment as measured by surveys?
- What are the characteristics, strengths, and limitations of social media-based greenness perception measurement compared to conventional survey methods?
- How does the performance of social media-based greenness measurement compare with established objective measurement indices such as NDVI and GVI in reflecting residents' perceived greenness?

The remainder of this paper is organised as follows: Section two synthesizes the theoretical background and current measuring methodologies of greenness perception; Section three details our methods for quantifying greenness perception; Sections four and five present and discuss our findings and analysis; and finally, Section six presents key conclusions and implications for future research and practice.

2 Background

2.1 Perceived greenness of urban environment

Perceived greenness refers to subjective evaluations of greenery in one's environment. Environmental psychology and behavior research conceptualizes perception process as the interpretation and appreciation of landscape based on conscious sensory engagement (Zube et al., 1982). It closely relates to preferences and behaviors, shaping how people engage with and experience the environment (Kaplan & Kaplan, 1989; Stigsdotter et al., 2017). Human perception of landscape is active and selective (de Fockert et al., 2001; Dunkel, 2015); as a result, while existence of greenery plays a crucial role in shaping human perceptions, evidence increasingly indicates that perceived environmental greenness may be subject to complex influences, differing from simple green availability conditions (Falfán et al., 2018; Gulwadi et al., 2019; Loder et al., 2020; Orstad et al., 2017). For example, greenery visibility and accessibility were found to influence people's ease and convenience of contact and engagement with nearby green environments, contributing to utilization and thus awareness (Gulwadi et al., 2019; Lackey & Kaczynski, 2009). Urban greenery's qualities and attractiveness are also critical factors. Different greenery types and aesthetics may be perceived differently: exposure to forests or trees may be beneficial, while exposure to grass may not (Reid et al., 2017). Amenity and facility qualities have also been found to enhance greenery attractiveness. Lackey and Kaczynski (2009) concluded that parks with more features and playground facilities are more likely to enhance awareness of local greenness. In addition, recent evidence also sheds light on potential effects of broader neighborhood socio-economic conditions, which may modify how people perceive greenspaces around them (Rieves, Reid, et al., 2024).

2.2 Conventional methods for assessing greenness perception

Traditional methods typically assess public greenness perception through surveys, which involve self-report questions, such as perceived amount of greenery, access to parks, or the quality of natural features (Leslie et al., 2010; Orstad et al., 2017). Some research also developed dedicated scaling tools (Dzhambov et al., 2018; Rieves, Freis, et al., 2024; Sugiyama et al., 2008).

Survey methods are recognized for their reliability and accuracy, as well as their capability to provide detailed information, thus have been used by a number of studies (Leslie et al., 2010). However, their collection is often constrained by cost, time, and geographical limitations (Teeuwen et al., 2024), sometimes confining studies to specific communities or limited sample sizes. Recent efforts also attempted to integrate surveys with digital technologies to expand their scope. For instance, Wang et al. (2019) employed PPGIS approach in online investigations of Helsinki residents' perceptions of urban forests. Schrammeijer et al. (2021) developed a mobile phone application to collect visitors' feedback on an Amsterdam park in real-time. However, these digital approaches still necessitate and depend on active participant engagement and face scalability and application limitations.

2.3 Objective indices for measuring greenness

Widely-availably geospatial data are used to calculate objective measures of urban greenness, which are often employed to approximate or represent residents' green exposure and perception. NDVI is a typical objective index, which assesses relative greenness by measuring the difference between red and near-infrared light reflection from remote sensing and satellite imagery, with higher values indicating greater vegetation coverage (Labib et al., 2020). NDVI's advantages include ease of access, broad coverage, and high sampling frequency, making it a dominant approach in greenspace research (Rieves, Reid, et al., 2024). However, as a top-down vegetation index, NDVI cannot capture three-dimensional urban greenery characteristics that reflect human perspectives and experiences (Leslie et al., 2010). It can also hardly distinguish greenery types and quality, which are potential factors influencing greenness perceptions (Orstad et al., 2017). Several studies have examined the association between NDVI and subjective greenness perception, typically finding low consistencies (Gulwadi et al., 2019; Leslie et al., 2010; Rieves, Freis, et al., 2024).

Addressing limitations of NDVI, street view imagery-based GVI index has emerged as an increasingly popular approach (Dubey et al., 2016). In contrast with top-down indices, street view imagery provides high-resolution urban information through panoramic photographs that resemble pedestrians' observations (Biljecki & Ito, 2021). By assessing the presence and proportion of green elements in these images, GVI enables measurement of urban greenness from a human-centric perspective (Larkin et al., 2021). GVI is generally recognized for having "greater compatibility with human perception", and has been found to exhibit greater explanatory power regarding urban greenery's health and well-being benefits compared to NDVI (Sánchez & Labib, 2024). Nevertheless, direct validations comparing GVI with survey-based perceived greenness measurements remain limited. Falfán et al (2018) reported moderate correlations between GVI and survey-based results in two Mexican cities, whereas Rieves, Reid, et al. (2024) found no significant associations with many greenness perception indicators.

2.4 Social media data and its application in greenery research

Crowdsourced data, such as social media data, could combine first-person perspectives with large volumes and broad spatial-temporal coverage, potentially representing a means of overcoming current methodological constraints in greenness perception measurements (Ghermandi & Sinclair, 2019). Social media consists of several types of data including images, text, and metadata. Among which, social media images are considered capable of extending established photo-based perception analysis methods, including visitor-employed photography (VEP) and photovoice approaches, by enabling large-scale and rapid perception assessments at individual-level (Dunkel, 2015; Dunkel et al., 2023). Emerging deep learning techniques such as computer vision further enable extraction of complicated information from these unstructured data (H. Zhang et al., 2025). Compared to traditional methods, social media data may be limited in detailed information, but demonstrates better scalability and cost-effectiveness, representing a viable alternative approach (Komossa et al., 2020).

Social media data have demonstrated important and promising applications in greenspace research. Li et al. (2024) conducted content and sentiment analysis on social media posts in 50 Shanghai greenspaces to reveal visitors' attention and feedback. Zhang and Su (2024) analyzed Twitter posts in Singapore parks to understand user perceptions and satisfaction with greenery presence. Song, Richards, and Tan's (2020) research on Flickr users' photography behaviors identified interests and visiting preferences of different visitor groups. Other studies have applied this data in counting park visitations (Donahue et al., 2018), understanding aesthetic preferences (Tieskens et al., 2018), and mapping cultural ecosystem services (Richards & Friess, 2015).

Existing social media-based perception studies have mostly focused on urban greenspaces, particularly parks. However, despite advantages in spatial coverage, such data have witnessed limited application in broader city-scale investigations of greenness perception. Guerrero et al.'s (2016) research was an exception, which experimented with the application of Instagram images and tags for exploration of Copenhagen's urban nature distribution and awareness. Nonetheless, their analysis did not extend to greenness perception or its detailed analysis.

Validations on social media data's ability to reflect subjective perceptual information were limited and yielded inconsistent results. Komosssa et al. (2020) discovered consistencies between interviews and Flickr content analysis for outdoor recreation preferences in two peri-urban landscapes. In comparison, Wilkins et al. (2022), applying a similar method, found significant differences between Flickr photo content and survey-reported landscape preferences. Moreno-Llorca et al.'s (2020) research noted social media analysis's accuracy only in perceptions of landscape and species. Other studies further yielded inconsistent results, and few have explored this data type's feasibility in urban greenness perception assessment (Kothencz et al., 2017).

This data type faces several other potential issues. Social media data are often considered biased in user representation and behavior, and may not represent random samples of the target populations (L. Li et al., 2013; Komossa et al., 2020). Social media site selection may also influence data characteristics, though notably, van Zanten et al.'s (2016) research found that different platforms captured similar landscape values. As a form of big data, this crowdsourced information faces questions for quality control and accuracy issues (Wilkins et al., 2022). Finally, ethical access and efficient analysis of extensive personal data represent an ongoing challenge (Ghermandi & Sinclair, 2019).

This study aims to propose a novel approach for exploring the potential of social media image data in city-scale greenness perception measurement, and to assess its validity and performance through comparisons with traditional survey-based results and other widely-used geospatial indices, thereby providing insights for future urban greenery research and practices.

3 Method

This research adhered to ethical guidelines for human research of Delft University of Technology and was approved by Human Research Ethics Committee (TUDelft-HREC, #5257).

3.1 Research area

Rotterdam was selected as the case study. As the Netherlands' second-largest city, Rotterdam spans approximately 326 km2 and has a population exceeding 600,000 (CBS StatLine, 2025). Located in the South Holland province, the city experiences a temperate maritime climate. Rotterdam contains extensive and diverse green and blue spaces and has implemented consistent initiatives to preserve and enhance its green infrastructure. The city's latest plan, "Rotterdam Green Agenda", stresses the further addition of 20 ha of green infrastructure to mitigate climate change, enhance biodiversity, and promote more livable urban environment (Gemeente Rotterdam, 2024). In addition, Rotterdam is an economic center and home to the largest port in Europe. It is also known for diverse socio-economic and demographic conditions as well as large tourism industry. Thus, Rotterdam provides the opportunity for comprehensive observations and analyses of urban greenness perception from multiple intersecting perspectives. Our research encompasses Rotterdam's city area, incorporating 64 neighborhoods, while excluding the western port areas that are disconnected and feature few residents (Fig. 1).

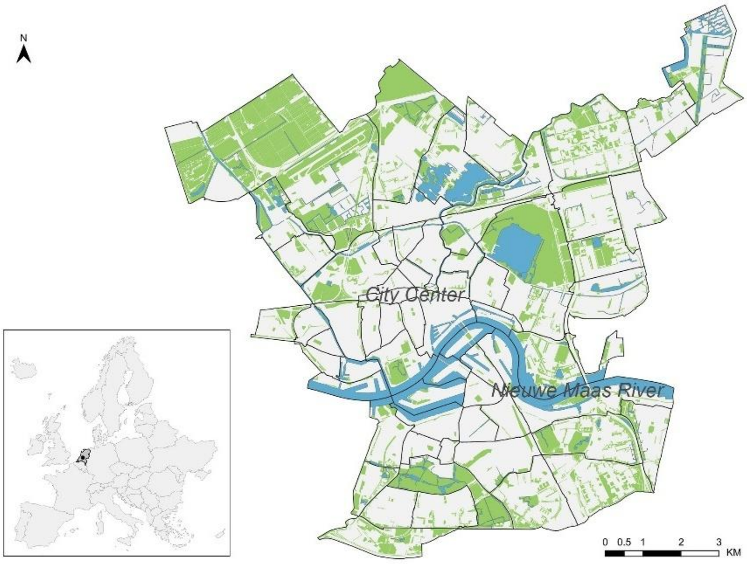

Fig. 1. Study area

3.2 Research design

The research framework consists of five steps (Fig. 2). First, the selected greenness perception results and measurements, including our proposed new method, were collected and calculated. Conventional survey-based perceived greenness results were obtained from Rotterdam's 2024 Neighborhood Survey (Enquête Wijkonderzoek). Then, geo-tagged images uploaded to social media site Flickr within Rotterdam were collected and analyzed to compute social media-based greenness perception. We also incorporated objective geographical indices of NDVI and GVI for comparisons. Due to privacy constraints preventing access to individual data, we employed *buurt* (neighborhood), the smallest census unit in the Netherlands, as our analytical unit. In the second step, the statistical results and spatial patterns of the included measurements were presented and analyzed. Building on this, correlation analyses were conducted to understand the relationship and consistency of these measurements. To further examine the performance of the proposed social media-based approach, the fourth step conducted detailed qualitative and quantitative analyses of its spatial consistency and heterogeneity in the association with survey results. Lastly, regression analyses were adopted to analyze potential explanations for both social media- and survey-based greenness perception measurements and their differences.

Data used in this study were derived from multiple sources (see supplementary materials). Most spatial data were obtained from the Rotterdam GisWeb database and BGT database via PDOK platform. Raw street and greenery data were derived from OpenStreetMap (OSM) and calibrated with the Dutch CBBS land use data. Rotterdam Neighborhood Survey results were obtained from Neighborhood Profile (Wijkprofiel) dataset. Social media and street view images were collected via API from Flickr and Google Maps respectively. NDVI was collected from Copernicus Sentinel-2 mission employing Google Earth Engine API.

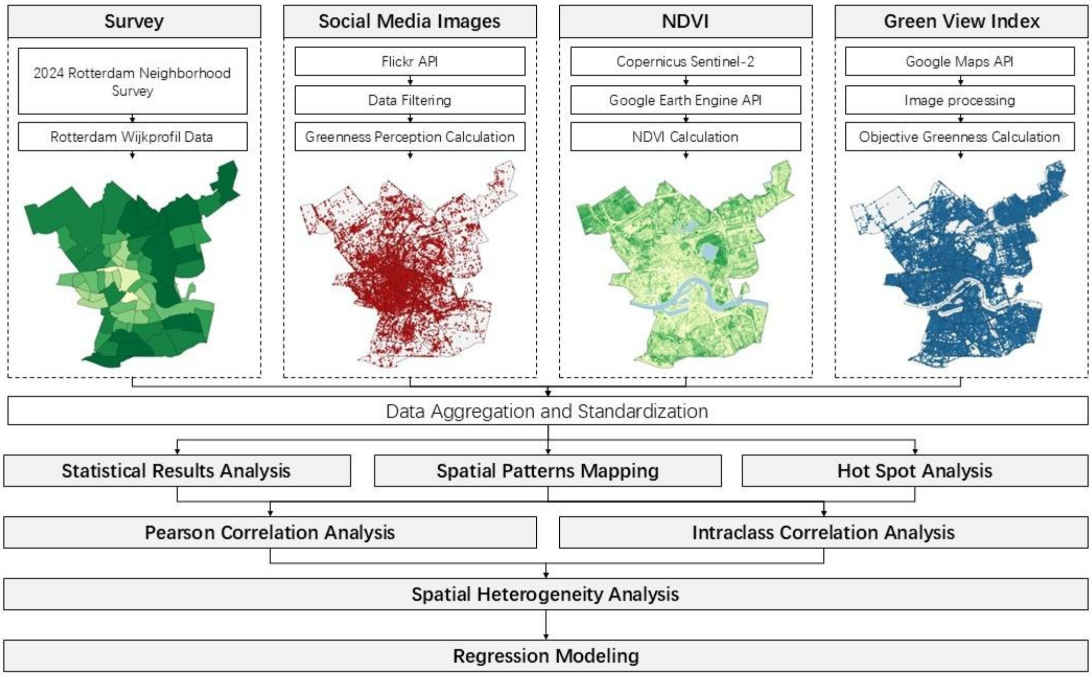

Fig. 2. Research design

3.2.1 Survey-based greenness perception

We employed Rotterdam's 2024 Neighborhood Survey data, which were collected between March and October 2023 and included approximately 30,000 Rotterdam participants, as survey-based greenness perception results. We focused on one survey question: "To what extent do you consider greenery in your neighborhood to be sufficient?" The question employed a five-point Likert scale, and responses were averaged and aggregated across neighborhoods, with higher scores reflecting more positive perceptions of neighborhood greenness. Details are provided in supplementary materials.

3.2.2 Social media-based greenness perception

This study employed social media imagery as the data source, which, compared to textual data, has been found to provide more detailed urban spatial-visual information and potentially offer more comprehensive record of the perceived environment (Dunkel, 2015). Flickr, a prominent photo-sharing platform, was selected for its substantial data quality and favorable accessibility, as well as continuous geo-tagging (in contrast with the POI-based approach of most social media sites), better aligning with our city-scale analyses. The Netherlands' high social media penetration rate (87%) supports the suitability of social media data sources for analyses.

Processing of Flickr data involved three main stages. First, all geo-tagged images taken in Rotterdam between 2010 and 2024, along with associated metadata, were collected using the Flickr API in December 2024, yielding 80,708 images. Long data collection time was aimed to ensure better data coverage across the entire study area and address potential data fluctuations and noise. For privacy protection, we only accessed open-access images and only collected users' publicly-available place of origin information as personal data, with all information anonymized or encoded.

Secondly, to filter and eliminate dataset noise, NIMA, a CNN-based image technical quality classification model (Talebi & Milanfar, 2018), was applied to filter low-quality images inadequate for subsequent analyses, and the dataset was further manually inspected to retain only outdoor images, resulting in 47,823 qualified images. Lastly, semantic segmentation was performed on the selected images using a pre-trained fully convolutional network (FCN) model trained on the ADE20k dataset. The proportion of vegetation pixels in each image was calculated to quantify perceived greenness levels (Fig. 3), with results aggregated to the selected neighborhood units to represent social media-based greenness perception measurements. Additionally, to account for potential user representativeness bias effects on results, we separately calculated the social media greenness perception of Dutch users by excluding the images taken by foreign users.

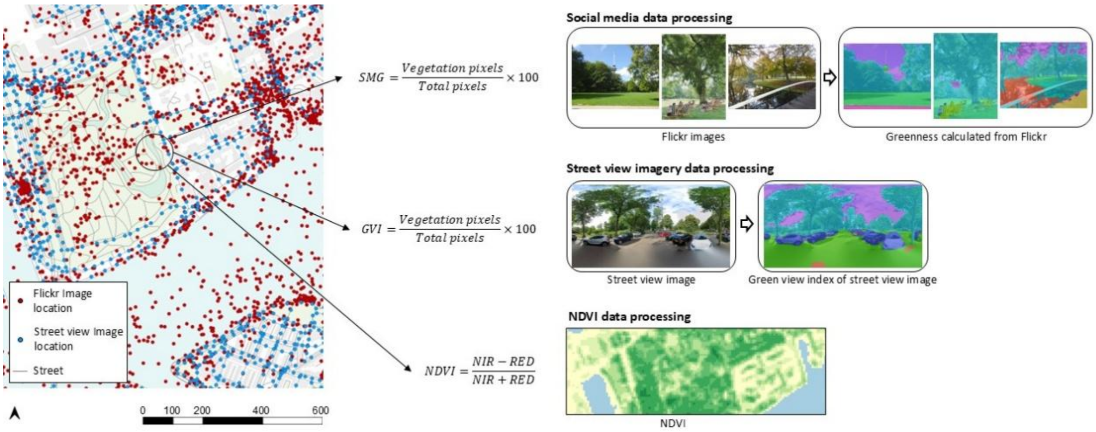

Fig. 3. Processing of social media data, street view imagery, and NDVI

3.2.3 Objective greenness indices

Rotterdam's NDVI was calculated using 10 m-resolution satellite images from Copernicus Sentinel-2, and subsequently aggregated to neighborhood units. Following Teeuwen 's methods, only NDVI values greater than 0 were retained and calculated.

GVI index was calculated employing Google Street View and the aforementioned semantic segmentation model to represent street-level greenness level. Streets in Rotterdam were segmented at 30 m intervals to establish sample points, from which approximately 90,000 street view images covering all streets in Rotterdam were obtained using Google Street View API in December 2024. Subsequently, consistent with H. Zhang et al.'s (2025) research, collected panoramic images were cropped based on human field of view to minimize distortion. The same semantic segmentation model was then applied, and the proportion of vegetation pixels was calculated to quantify street-level greenness levels (Fig. 3).

3.3 Analytic methods

Mapping analyses and hotspot analyses: spatial distribution and clustering patterns of included greenness measurements were first analyzed employing mapping and hotspot analyses. For better comparison, we followed T. Li et al.'s (2021) methods and categorized greenness measurements into five categories from very low to very high. For matching with survey results, all measurements were subsequently standardized using Z-score standardization. The formula is:

$$Z = \frac{X - \mu}{\sigma}$$

where X represents the original data, Z represents the standardized data, μ represents the mean of the data, and σ represents the standard deviation of the data.

Subsequently, Getis-Ord Gi* statistic was employed to identify statistically significant clusters of high (hot-spots) and low (cold-spots) greenness values for spatial patterns analysis.

Correlation analyses: to compare the correlations and disparities among different methods, we employed Pearson correlation coefficient (PCC) to examine the relationships between them. Friedman's ANOVA was also employed to assess differences in results across different social media user sub-groups. Further, intraclass correlation coefficient (ICC) was employed to evaluate the agreement between multiple measurements and survey results, which, compared to PCC, allows for checking the agreement among multiple methods.

Spatial heterogeneity analyses: for more detailed comparisons of the spatial consistency and heterogeneity of our proposed social media-based greenness perception and survey results, we defined perception difference as the difference in value between these measurements in each neighborhood:

$$P_i^{\text{diff}} = P_i^{\text{soc}} - P_i^{\text{sur}}$$

where P_i^{diff} represents perception difference of neighborhood i, P_i^{soc} represents social media-based greenness perception, and P_i^{sur} represents survey-based greenness perception.

Subsequently, we analyzed the spatial distribution patterns of perception differences and qualitatively discussed disparities in typical neighborhoods.

Regression analyses: to examine the mechanisms and factors underlying such differences between the two approaches, we employed regression analyses to model social media- and survey-based greenness perception as functions of urban environmental and socio-economic variables. Established frameworks and existing findings generally indicate that greenness perceptions may be influenced by three major groups of greenery attributes (Biernacka et al., 2020; Markevych et al., 2017): availability, referring to the existence of greenery; accessibility, referring to the possibility and ease of accessing greenery; and attractiveness, referring to the qualities of greenery regarding various dimensions including vegetation, facility, aesthetics, etc. We also controlled for the potential influence of socio-economic variables, including neighborhood economic and demographic conditions. Based on this framework, we established a series of potential indicator sets, with rationale and details provided in the supplementary materials.

Two types of regression models were applied, ordinary least squares (OLS) regression, and spatial regression models including spatial lag model (SLM) and spatial error model (SEM). SLM addressed potential spatial spillover effect, whereby greenness perception in a neighborhood is influenced not only by local conditions but also, due to city images, public opinions, and social contacts, potentially by the greenness perception in neighboring areas. SEM was employed to control for spatially structured omitted variables that may affect greenness perception but are not captured by the included covariates. Spatial dependency of both greenness measurements was examined through Global Moran's I before spatial regression, with the results confirming spatial autocorrelation. Regression models were checked for multicollinearity issues (VIF<5).

4 Results

4.1 Statistics and spatial patterns of the perceived and objective greenness measurements

The descriptive statistical results of the four included perceived and objective greenness measurements are shown in Table 1. Survey results indicated that residents generally perceived Rotterdam neighborhoods' greenness conditions positively. As shown in Fig. 4, the other three measurements yielded broadly comparable results. Social media-based greenness perception generally fell between NDVI and GVI in terms of minimum, mean, and max values, as well as standard deviation. However, it featured a relatively high coefficient of variation, indicating pronounced fluctuation. In comparison, NDVI index exhibited broader value range with higher maximum and average values, and showed more balanced proportions across different greenness value categories. GVI index exhibited the most concentrated value range and the smallest coefficient of variation, with distribution skewed towards lower greenness values.

Table 1. Statistical results of the included measurements

	Min	**Mean**	**Med**	**Max**	**Std**	**CV**	**0-5%**	**5-15%**	**15-25%**	**25-35%**	**35-100%**
Survey	0.270	0.749	0.770	1.000	0.175	0.234	N/A	N/A	N/A	N/A	N/A
Social media	0.020	0.170	0.178	0.340	0.083	0.487	4.7%	34.4%	42.2%	18.8%	0.0%
NDVI	0.020	0.227	0.225	0.417	0.087	0.383	4.7%	14.1%	40.6%	34.4%	6.3%
GVI	0.047	0.140	0.138	0.231	0.035	0.249	1.6%	56.3%	42.2%	0.0%	0.0%

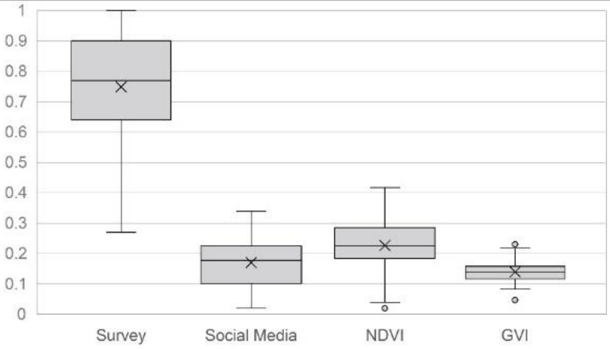

Fig. 4. Box plot of the included measurements

The spatial distribution and hotspot clustering of measurements are illustrated in Fig. 5. Raw data (non-standardized) revealed similar spatial patterns of greenness captured by different measurements, showing a trend of low greenness in central areas and high greenness towards peripheral areas. Hotspot analyses indicated that low-value clusters were predominantly distributed in the city center and along both banks of Nieuwe Maas River, while high-value clusters were mainly located in southern and northern suburbs. Despite these similarities, measurements also showed varying value distributions and clustering patterns. Standardized results allow for more direct comparisons. Survey results indicated low perceived greenness in central neighborhoods and along the southern bank of Nieuwe Maas River, with high perceived greenness relatively evenly distributed in peripheral neighborhoods. Social media-based greenness perception demonstrated similar patterns, but, along with other measurements, captured fewer statistically significant cold-spot neighborhoods in the city center compared to survey. In comparison, NDVI and GVI indices showed more pronounced differences. NDVI captured more low-greenness neighborhoods along the Nieuwe Maas river rather than in the city center, and identified more high-greenness neighborhoods in northwestern suburbs. GVI also mainly captured low-greenness values along the Nieuwe Maas river. It also showed more pronounced local variations and more discontinuous spatial distributions.

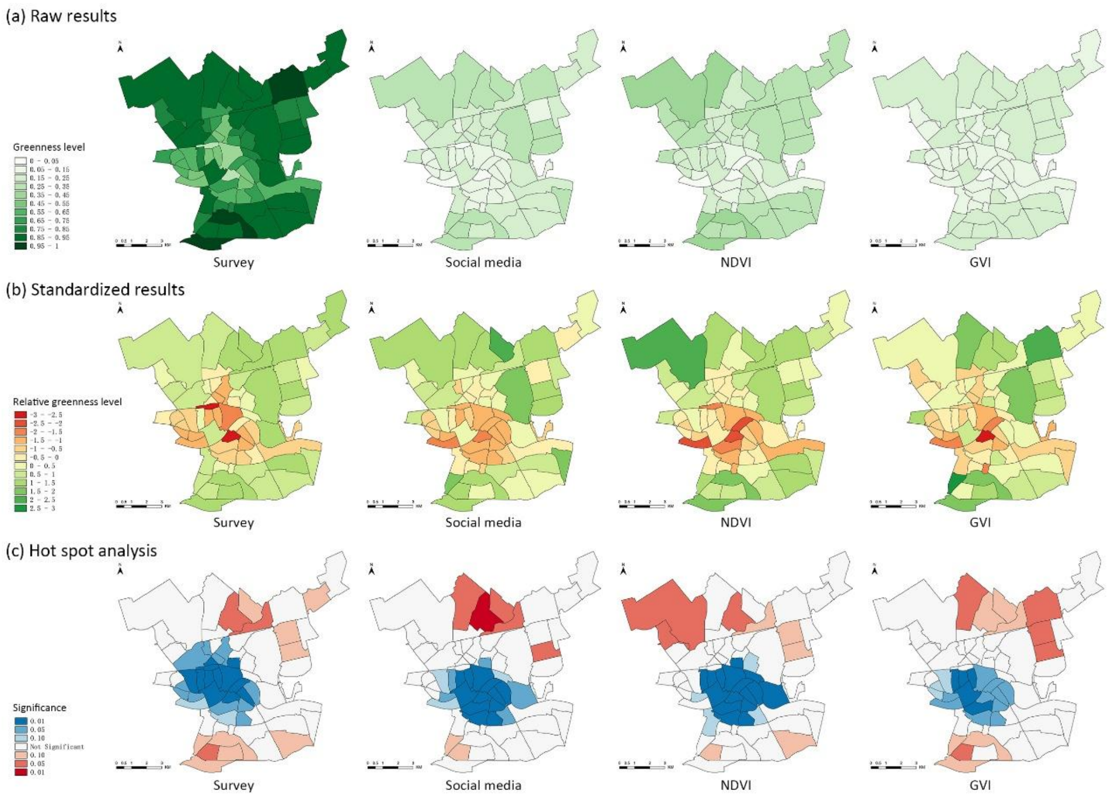

Fig. 5. Spatial patterns and hot spot analysis of the included measurements. (a): Raw (non-standardized) results; (b): Standardized results; (c) Hot spot analysis. From left to right: survey, social media, NDVI, and GVI results.

4.2 Relationship and consistency of the perceived and objective greenness measurements

Table 2 presents the results of pairwise Pearson correlation analyses among perceived and objective greenness measurements. Results indicated that all correlations were statistically significant (p <

0.01), albeit with varying strengths. The absolute intraclass correlation for four measurements was 0.771 ($p < 0.001$), confirming overall consistency.

Social media-based greenness perception demonstrated the highest correlation with survey results among all measurement pairs, suggesting it better captured actual perceptions of urban greenness conditions. NDVI and GVI demonstrated relatively lower but still significant correlations with survey results. Surprisingly, NDVI exhibited a higher correlation coefficient with survey results than GVI.

We further examined the impact of potential demographic and representative bias in social media data on its performance. Analysis of user origins of the collected Flickr dataset revealed that 73% of users with known locations were foreign users. However, Friedmans' ANOVA test did not identify statistically significant differences between user subgroups ($p = 0.30$). Social media greenness perception calculated for Dutch users, while maintaining significant and relatively strong correlations with survey results, showed decreased correlation coefficients compared to the full dataset.

Table 2. Pearson correlation analysis of the included measurements

		Survey	Social media	Social media (excluding foreign users)	NDVI	GVI
Survey	Pearson Correlation	1				
	Sig					
Social media	Pearson Correlation	0.773**	1			
	Sig	0.000				
Social media (excluding foreign users)	Pearson Correlation	0.688**	0.905**	1		
	Sig	0.000	0.000			
NDVI	Pearson Correlation	0.737**	0.860**	0.765**	1	
	Sig	0.000	0.000	0.000		
GVI	Pearson Correlation	0.706**	0.757**	0.689**	0.777**	1
	Sig	0.000	0.000	0.000	0.000	

** indicates significance at the 0.01 level.

4.3 Spatial heterogeneity between survey and social media-based greenness perception measurements

To better understand the relationship between social media and survey greenness perception, their perception difference was computed. As shown in Fig. 6, the two measurements exhibited both similarities (neighborhoods in white) and differences (neighborhoods in green indicating higher survey values compared to social media, neighborhoods in purple indicating the opposite). Spatial heterogeneity and its distribution were relatively discontinuous and more localized. Hotspot analyses showed that statistically significant clusters of survey greenness perception exceeding social media were present in neighborhoods south of Nieuwe Mass River and northeastern suburbs. These neighborhoods generally feature modern residential communities in urban periphery, covering both high and low perceived greenness levels. In comparison, clusters of social media-based greenness perception exceeding survey results appeared in city center. Notably, these neighborhoods primarily cover dense and populous areas and were perceived as low greenness in both measurements. However, further examination revealed that these differences could not be explained by social media usage intensity ($p = 0.10$), suggesting influences of other spatial factors.

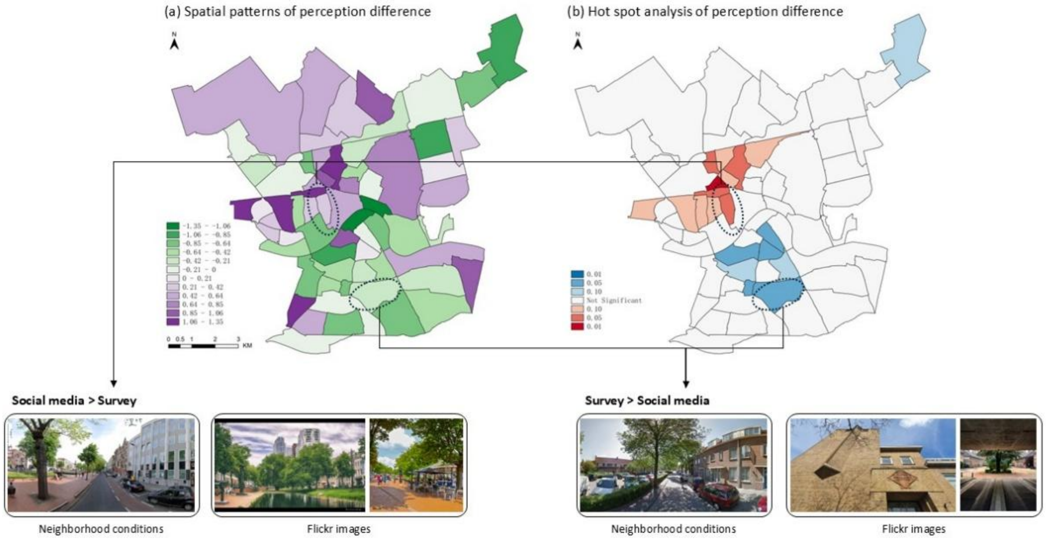

Fig. 6. Spatial heterogeneity analysis of survey- and social media-based greenness perception. (a): Spatial patterns of perception difference. (b): Hot spot analysis of perception difference

4.4 Comparative regression analysis of survey and social media-based greenness perception measurements

Regression analyses allow for exploring the factors and mechanisms underlying perception difference between survey and social media-based greenness perception (Table 3). Models were constructed with these two greenness perception measurements as dependent variables and a series of potential environmental and socio-economic factors as independent variables, employing both linear and spatial regression methods. Results indicated that approximately half of the independent variables show significant associations, explaining approximately 70% of both greenness perception measures. Regression residuals conformed to normal distributions, all VIF values were below 5, and model fit and performance were comparable. SLM and SEM models in both regression model groups were insignificant, indicating that spatial regression was not applicable.

Table 3. Regression analysis of survey- and social media-based greenness perception

	Survey-based greenness perception						**Social media-based greenness perception**					
	OLS		SLM		SEM		OLS		SLM		SEM	
	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig
const	1.67	0.17	2.04	0.06	1.63	0.13	1.03	0.38	1.17	0.27	1.05	0.32
Availability of greenery	0.58	0.55	0.45	0.60	0.59	0.50	2.05	0.04 *	1.93	0.02 *	2.07	0.02 *
Availability of water	-0.67	0.27	-0.40	0.47	-0.65	0.23	-2.05	0.00 ***	-1.78	0.00 **	-2.05	0.00 ***
Accessibility of greenery	1.86	0.00 ***	1.87	0.00 ***	1.86	0.00 ***	0.23	0.64	0.24	0.59	0.23	0.60
Accessibility of water	0.06	0.87	0.01	0.97	0.05	0.87	0.13	0.71	0.11	0.71	0.12	0.69

Vegetation type	-5.43	0.01 **	-5.90	0.00 ***	-5.41	0.00 **	-4.68	0.01 *	-4.79	0.00 **	-4.71	0.01 **
Facility	-0.53	0.01 **	-0.42	0.02 *	-0.54	0.00 **	-0.28	0.14	-0.21	0.22	-0.27	0.10
Playground	0.01	0.00 **	0.01	0.00 **	0.01	0.00 ***	0.01	0.08	0.01	0.09	0.01	0.05
Construction density	-0.36	0.24	-0.33	0.22	-0.35	0.20	-0.52	0.08	-0.46	0.08	-0.54	0.05 *
Average income	0.01	0.42	0.01	0.38	0.01	0.35	0.02	0.01 *	0.02	0.01 **	0.02	0.00 **
Senior population	0.03	0.05 *	0.02	0.14	0.03	0.02 *	0.05	0.00 **	0.05	0.00 **	0.05	0.00 ***
Lambda					-0.06	0.77					-0.03	0.87
Rho			0.24	0.06					0.21	0.10		
R-squared	0.70		0.72		0.70		0.71		0.73		0.71	
AIC	125.41		124.89		125.36		123.08		122.62		123.06	
BIC	149.16		150.80		149.11		146.83		148.52		146.81	
Local Moran's I	-0.014		-0.064		-0.004		-0.011		-0.102		-0.001	

OLS: Ordinary least squares model; SLM: Spatial lag model; SEM: Spatial error model. *, **, and *** indicate significance at the 0.05, 0.01, and 0.001 levels, respectively.

For survey-based greenness perception, urban greenery's accessibility and attractiveness were positively associated with better perceived greenness. Residents living in neighborhoods with more accessible greenery, more playgrounds and fewer other facilities in greenery, as well as more trees/shrubs versus herbaceous plants were more likely to report higher perceived greenness. In contrast, social media-based greenness perception showed different predictive factors. Results indicated that urban greenery's availability, i.e., increased greenery provision, was a positive predictor of social media greenness perception, but no significant association with greenery accessibility was found. Also, vegetation type was associated with social media-based greenness perception, but no evidence indicated significant effects of facilities and amenities.

Among socio-economic variables, we found that senior population composition, as well as neighborhood average income in the social media model, were significant predictors of perceived greenness.

5 Discussion

With growing recognition of urban greenery's health and well-being benefits, there is an increasing need for more effective methods to assess greenness perception. This research develops an innovative social media image-based approach for city-scale greenness perception measurement and, employing Rotterdam as the case study, evaluates its effectiveness and performance through comparative studies with both conventional survey results and widely-used NDVI and GVI indices.

5.1 Effectiveness of social media-based greenness perception

Our results showed that social media-based greenness perception captured comparable patterns to other established methods and exhibited the strongest correlation with survey among all included measurements. This indicates that social media data can effectively reflect subjective perceptions of urban greenness. To our knowledge, this is among the first studies to validate this data source's applicability to city-scale greenness perception assessment, which extends increasing evidence on its feasibility in greenspace research (Donahue et al., 2018; Kothencz et al., 2017; W. Zhang & Su, 2024) and demonstrates its new application scenario. This result is not unexpected, as past studies adopting photographic methods like VEP and photovoice approaches have corroborated the parallel between perception and photography, with photographs effectively reflecting the process of subjective experience of and engagement with the environment (Dunkel, 2015; Oteros-Rozas et al., 2018; Song, Richards, He, et al., 2020). Stedman et al. (2004) suggested that images record the content people choose to capture (and exclude), thus revealing individual ways of perceiving the landscape. Furthermore, recent evidence indicates that social media images' content and distributions also reflect users' activities and usage of greenery (Donahue et al., 2018), thereby uncovering traces of behavioral patterns in the environment which potentially better represent residents' actual experiences (Song, Richards, He, et al., 2020; Song, Richards, & Tan, 2020). Our results are consistent with Komossa et al.'s (2020) findings on social media image data accuracy in peri-urban landscapes, but contrast with Wilkins et al.'s (2022) park-based case study. What distinguished our research from Wilkins et al. (2022) is that we investigated perceptions rather than more personalized preferences, and we extended beyond single locations to incorporate broader analytic units and data.

In this context, social media demonstrates several methodological advantages. While social media data may lack survey approach's detailed information, it offers advantages in larger sample sizes, easier access, and more rapid calculation, thus potentially excelling in cost-effectiveness (Ghermandi & Sinclair, 2019), evident in our method where Flickr approach required substantially less time and limited monetary cost. Such data type's broader spatial coverage and precise embedded metadata may also enable perception studies both at large geographic scales and, in data-rich areas such as city centers, facilitate more fine-grained and sensitive analyses (Dunkel, 2015; Komossa et al., 2020), which can be explored in future studies.

Notably, our research also discovered critical limitations of social media approach. Because of methodological differences, social media-based greenness perception's value range diverges from survey results, suggesting that such measure is more reliable in indicating relative rather than absolute perceptions. Results also revealed social media measures' greater fluctuations, consistent with findings by Moreno-Llorca et al. (2020). This may be caused by social media images' unstructured and unstandardized generation and collection process, presenting challenges for processing and analysis (Ghermandi & Sinclair, 2019). Lack of quality control may also contribute, as some irrelevant content and advertisement images—often clustered in certain areas (Dunkel et al., 2023)—can be hard to detect and may remain in the dataset despite our manual filtering, affecting reliability. Moreover, a repeated concern is social media's representative bias (L. Li et al., 2013). Consistent with Song, Richards, He, et al.'s (2020) findings, we observed over-representation of tourists in our Flickr dataset, confirming existing evidence that social media did not capture a random sample of the target population (Komossa et al., 2020; Wilkins et al., 2022). Surprisingly, we discovered that greenness perception did not differ significantly among user groups, and excluding international users did not improve correlations with survey results, contradicting findings by Song, Richards, He, et al. (2020) and Huai et al. (2022). A possible explanation is other demographic bias. Social media users' gender, age, and other demographic variables have also been found to affect their perception patterns (Komossa et al., 2020; L. Li et al., 2013). For example, Di Minin et al. (2015) and Hausmann et al. (2018) revealed that Flickr platform's user base included more professional photographers and nature enthusiasts, which could affect their interests and interactions with urban greenery (Falfán et al., 2018; Ode et al., 2009). However, due to privacy reasons we did not access this information. Social media's usage pattern could also be a contributing factor, as previous research noted that individuals visiting unique and attractive destinations and more beautiful sceneries are more likely to publish image than those visiting familiar parks, potentially overrepresenting visitor perspectives (regardless of nationalities) and amplifying biases (Sessions et al., 2016; Song, Richards, He, et al., 2020).

Accordingly, we believe that while social media approach demonstrates effectiveness in capturing subjective greenness perception and offers benefits in certain aspects, such approach's limitations need to be acknowledged and potentially controlled in future research, and their impacts require further scrutiny.

5.2 Disparities between social media- and survey-based greenness perception

Despite social media's better correlations among included measurements, spatial heterogeneity and regression analyses between social media- and survey-based greenness perception also revealed their meaningful differences. Social media-based greenness perception was primarily associated with greenery availability and visual attributes (i.e., vegetation), whereas survey results were influenced by broader environmental indicators, particularly covering greenery accessibility and amenity qualities. This indicates that social media data captured greenness perceptions related to, but not identical to, those identified by survey methods: it effectively reflected greenery's direct and visual perceptions but may be limited in capturing broader quality conditions that are more associated with long-term usage. Given Flickr's dataset biases and overrepresentation of visitors, this is not surprising, as existing evidence has identified contradicting perception patterns of visitors and residents in urban greenery, favoring aesthetics and functionalities respectively (Deng et al., 2017). Presence of vegetation and its suitable combinations may enhance visual aesthetics and sense of safety, both factors influencing people's awareness of and willingness to enter greenspace (Gatersleben & Andrews, 2013; H. Zhang et al., 2013). In comparison, X. Li et al. (2008) found that ease of access is a primary concern for long-term users rather than visitors and strongly affects their likelihood of revisiting greenery (J. Zhang & Tan, 2019; Y. Zhang et al., 2017). Presence of well-planned amenities and facilities is also a key expectation of long-term users that influences their satisfaction and frequency of utilizing greenspaces (Ayala-Azcárraga et al., 2019; Kaczynski et al., 2008). This represents a novel finding and suggests that social media approach and survey may potentially capture distinct aspects of urban greenness perception.

Spatial analysis further reveals specific manifestations of these differences (Fig. 6). In city center neighborhoods with statistically significant clusters of social media-based greenness perception exceeding survey, we identified many Flickr images featuring the famous Westersingel greenspace

(39.7%), while few residents live along this greenspace (11.5%). This may illustrate that well-known and visually-appealing destinations amplify greenness perception calculated from social media due to their overrepresentation in the dataset, even though they may not exhibit favorable accessibility or usability conditions for residents. Conversely, in the southern residential neighborhood where social media results were lower than survey, Flickr images primarily feature shots of unique residential architecture rather than residential greenery, again reflecting social media data favoring more unique scenes and destinations (Dunkel et al., 2023; Song, Richards, He, et al., 2020; Wilkins et al., 2022). Consequently, notwithstanding convergent trends, substituting survey methods with social media approach risks inadvertently losing detail and introducing bias, leading to incomplete insight.

These observations underscore the need for critical methodology considerations: having information on what social media-based approach can (and cannot) effectively capture would be essential for selecting suitable methodology in future research aligning with research needs and contexts and for facilitating more cautious and nuanced interpretations of the results it delivers

5.3 Comparative performance of greenness measurement methods

Among included three data-driven greenness measurements, we found that social media-based measurement showed a stronger correlation with survey compared to NDVI and GVI. This indicates social media's better effectiveness and affirms Rieves, Reid, et al.'s (2024) and Falfán et al.'s (2018) findings on the limitations of objective geospatial indices in approximating human perceptions. This comparative better performance may be attributed to three advantages. First, social media imagery may better reflect the actual profile perspectives from which people typically perceive urban greenery, compared to top-down indices like NDVI (Falfán et al., 2018; Komossa et al., 2020). Second, compared to the passive greenery exposure captured by GVI, social media may better reflect subjective attention and perception due to users' selective recording of environments (Song, Richards, He, et al., 2020). Third, social media may provide more continuous coverage, particularly within urban public spaces like parks (e.g., see Fig. 3), which contrasts with GVI data that are typically confined to vehicular roads (Biljecki & Ito, 2021). Notably, we did observe relatively strong correlations between survey and NDVI/GVI, which did not fully align with several comparative studies (Leslie et al., 2010; Rieves, Freis, et al., 2024). This may result from our larger neighborhood analytical scales, potentially smoothing local variations.

Statistical and spatial analyses further revealed limitations of NDVI and GVI indices, warranting attention. We discovered that NDVI exhibited comparably different distributions of high-greenness neighborhoods, for instance identifying high greenness levels in northwestern areas mainly consists of farmland and airport infrastructure. This supports Labib et al.'s (2021) findings that NDVI, despite its strength in representing total vegetation cover, may be insensitive to detailed greenery characteristics including type and accessibility that may affect greenness perception. Regarding GVI, we surprisingly found that it showed weaker correlation with survey results than both social media and NDVI. This contradicts multiple studies suggesting GVI better reflects subjective perceptions by providing street-level perspectives (Larkin et al., 2021; Sánchez & Labib, 2024); however, our results do align with Rieves, Reid, et al.'s (2024) empirical findings. While GVI captures urban visual information similar to human perspectives, it may not necessarily represent how pedestrians experience urban environment. For instance, Ki et al. (2023) found that street view images, collected from road lanes, differ significantly from pedestrian perspectives due to distortions, obstructions, and different viewpoints. Also, insufficient road density may lead to limited street view data availability in certain areas and affect result accuracy (Biljecki & Ito, 2021), potentially explaining our observed GVI variations in northwestern and southeastern suburbs. Through comparison, our results question the effectiveness of both NDVI and GVI indices in directly capturing subjective greenness perceptions, underscoring the need for careful selection of measurement methods in future research.

5.4 Implications for research and practice

This study reveals the distinct characteristics and therefore suitable application scenarios of different greenness measurement approaches. Social media represents an effective and comparably more accurate tool among the included measurements for assessing public greenness perception, particularly suitable for large-scale and low-cost perception assessments. Social media approach also better reflects users' subjective attentions and usage conditions, and may offer advantages in representing certain user groups like visitors. Such data's extensive coverage may also provide opportunities for future cross-temporal and multi-scale investigations.

Nonetheless, our results also identified inherent fluctuations, demographic and platform bias, and different value distribution problem of social media data. We believe that conventional survey methods remain relevant and essential, especially when accurate details and representative sampling are required. We also observed that widely-used objective indices of NDVI and GVI showed comparably limited consistency in reflecting subjective greenness perceptions, though they remain useful: for instance, NDVI may be suitable for objective ecological assessments, and GVI may be appropriate for quantifying local greenery conditions or measuring passive green exposures. These indices are also more directly transferable and actionable for practitioners and policymakers and, due to their standardized methods, better suited for inter-regional comparisons.

Our findings highlight the importance of methodological complementarity for more comprehensive and compelling insights, with methodology and data fusion representing a direction for future research. Evolving advancements in artificial intelligence also promise to expand analytic capabilities of social media and other similar data types, promising new research opportunities. Additionally, research is also needed to further understand performances of different measurement approaches in different urban morphological, cultural, and climatic contexts and across different seasons. Thereby facilitating more robust greenness perception assessment frameworks.

Beyond methodological implications, this study also provides information for future urban green infrastructure practice and management. We noted that urban greenery availability, accessibility, and attractiveness are all potentially associated with public's greenness perception, which further confirms mounting evidence on the multidimensional nature of perception of urban greenery (Gulwadi et al., 2019; Hipp et al., 2016; Y. Zhang et al., 2017) and underscores the need for more comprehensive green infrastructure agendas transcending mere greenery coverage metrics. Our results also revealed that several Rotterdam neighborhoods, particularly ones in the city center and Nieuwe Maas waterfront, consistently demonstrated poor greenness levels across subjective and objective measurements. Given the high population density and tourist activities in these neighborhoods, their green environment warrants additional attention in future planning and design interventions.

5.5 Limitations and future work

A few limitations remain and could be addressed in future research. Regarding social media dataset, following privacy protection we did not extract users' demographic variables, preventing analysis of their potential influences. Notably, evidence remains mixed on whether demographic variables affect human perceptions and requires further scrutiny (Teeuwen et al., 2024). Also, while we followed widely validated methods in image coding and perception analysis, considering the potential subjectivity of perception, incorporating direct participatory investigation with photographers would be conducive to refining the results and is the aim of our subsequent research.

Secondly, to match data sources we aggregated all collected data at the neighborhood level, which could potentially introduce the modifiable areal unit problem (MAUP), evident in our identified better alignment of measurements. Aggregated data also prevents analysis of personal factors in greenness perception, such as individual's connectedness to nature. Collecting individual-level data could be an option for future research but cost-effectiveness needs to be balanced. Also, temporal misalignment exists as we aggregated both social media and street view data over multiple years to maintain quantity and quality. Aggregating data also constrained our study to a cross-sectional design and limited causal interpretations.

Lastly, our study only explored the applicability of Flickr data, whereas future research can extend to other online image and text data sources. We also only explored the case of Rotterdam and our findings' applicability to other locations or scales remains uncertain. Subsequent research could look at the potential impact of climatic, contextual, and cultural variations of perception by conducting comparative studies on regional or global scales, which also aligns with the key advantage of crowdsourced data.

6 Conclusion

Public greenness perception is closely related to urban greenery's health and well-being benefits. Addressing constraints of existing greenness perception measurement methods, this study proposes an innovative approach by employing crowdsourced social media image data and computer vision techniques, and, taking Rotterdam as the case study, critically examines its effectiveness and performance through comprehensive comparative analyses with conventional survey results as well as currently widely-used objective indices.

Our results indicate that the proposed social media-based approach effectively captured the perceived greenness patterns in Rotterdam, and exhibited the strongest correlation with survey results among all included measures, outperforming NDVI and GVI indices which exhibited multiple limitations. Nevertheless, correlation and spatial analyses revealed that social media-based greenness perception does not completely align with survey results, showing statistical differences and spatial variations leading to perception differences. Regression modeling indicated that social media approach captures perceived greenness conditions related to but different from survey results: it better reflects urban greenery presence and visual conditions, associated with greenery availability and vegetation; however, it may face limitations in capturing broader qualities of urban greenery that survey results better reflect, which are associated with greenery accessibility, amenities, and facilities that relates to long-term experience and usage. Furthermore, results also reveal social media measurements' different value distribution, more pronounced fluctuations, overrepresentation of popular destinations, and influences of platform and demographic biases, indicating potential limitations of this approach.

This study delivers one of the first empirical evidence of social media image data's applicability and capability in reflecting city-scale subjective greenness perception, and critically verifies its performance, strengths, and potential limitations in capturing actual perceived greenness conditions of the environment against multiple existing subjective and objective measurements. Our study provides a novel methodological approach for future research on greenness perception. Our conclusions suggest that social media approach offers a more scalable and rapid alternative to conventional surveys; however, solely relying on this data source may lead to detail losses and amplified biases. Therefore, we propose that integrative and complementary approaches can enable more comprehensive assessment of complex urban greenness perception patterns and potentially incorporate broader stakeholder perspectives. Our findings can assist methodological selection in future greenness perception investigations and inform more critical interpretation of research findings. Additionally, our analyses offer new insight into multifaceted influencing factors and mechanisms of greenness perception that may inspire more targeted green infrastructure policies and practices addressing people's needs.

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