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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 21st 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

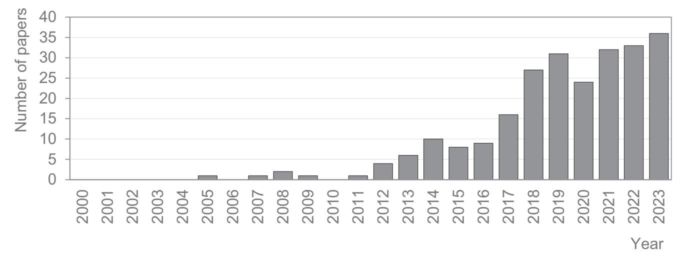

Fig. 2. Share of papers by publication time.

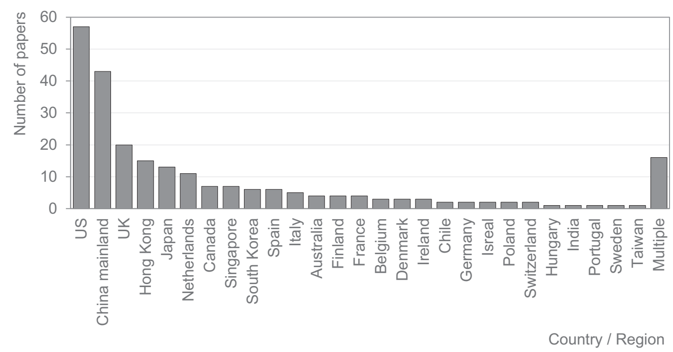

Fig. 3. Share of papers by research country/region.

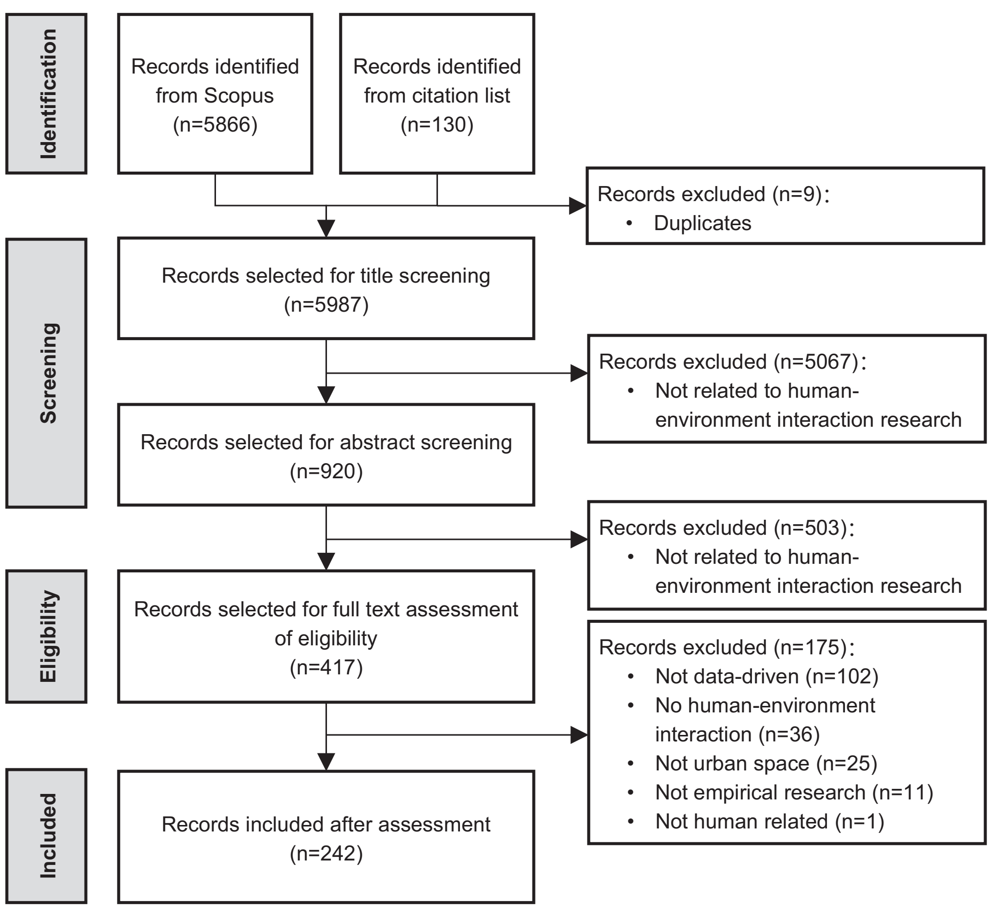

Fig. 1. Flow diagram for literature selection.

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).

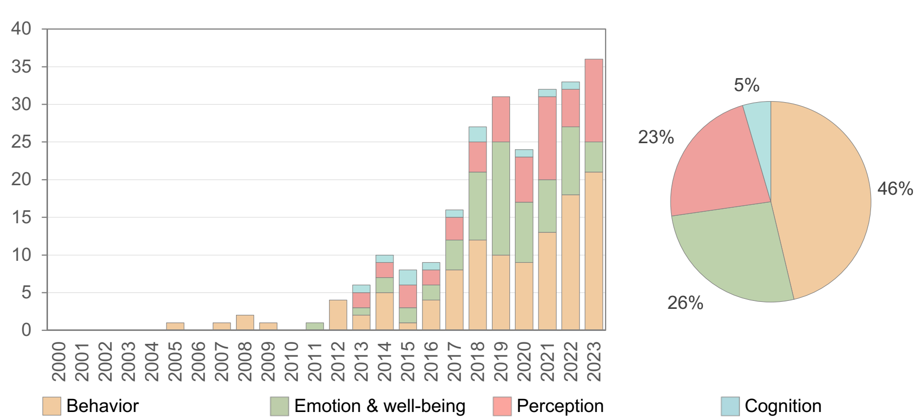

Fig. 4. Share of human-environment interaction theme by year.

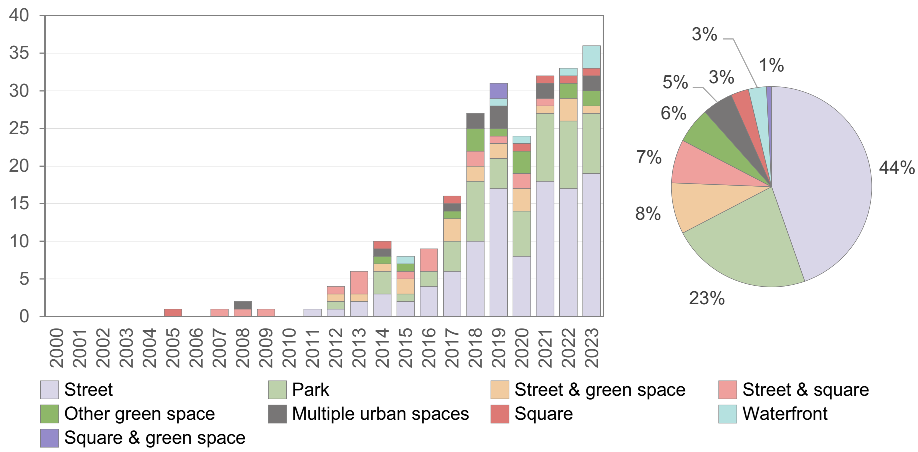

Fig. 5. Share of urban space typology by year.

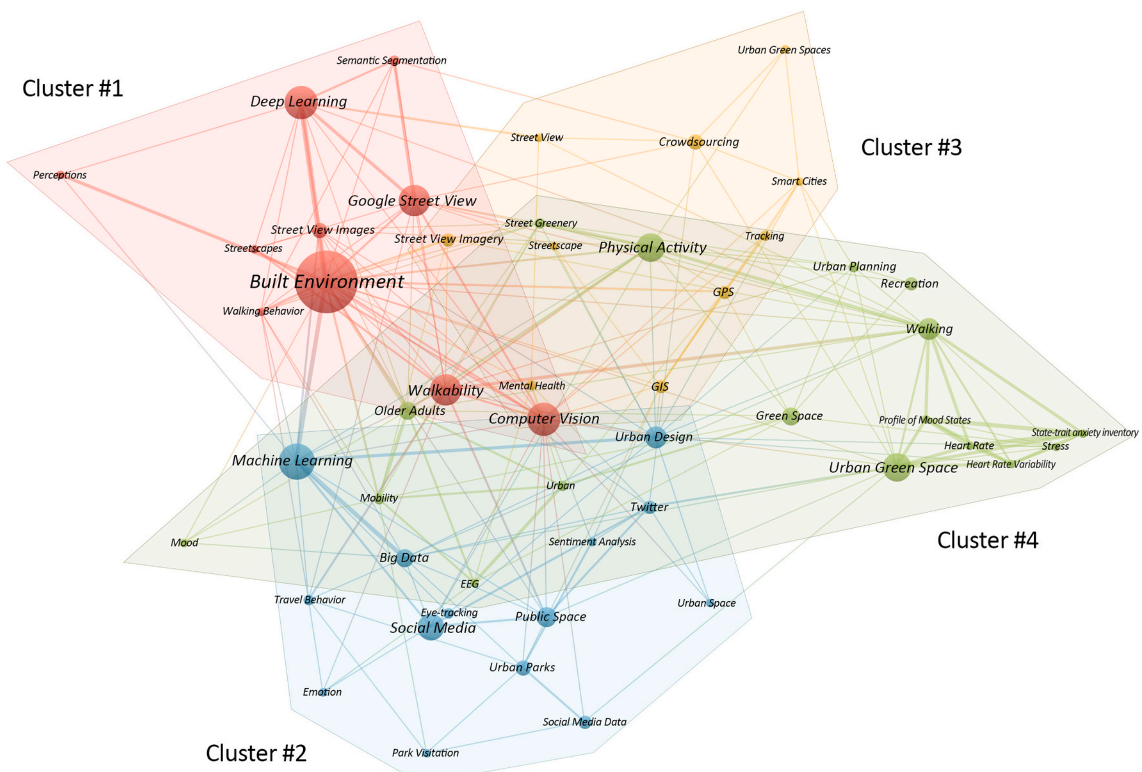

Fig. 6. Co-occurrence analysis of keywords.

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 ($n =$

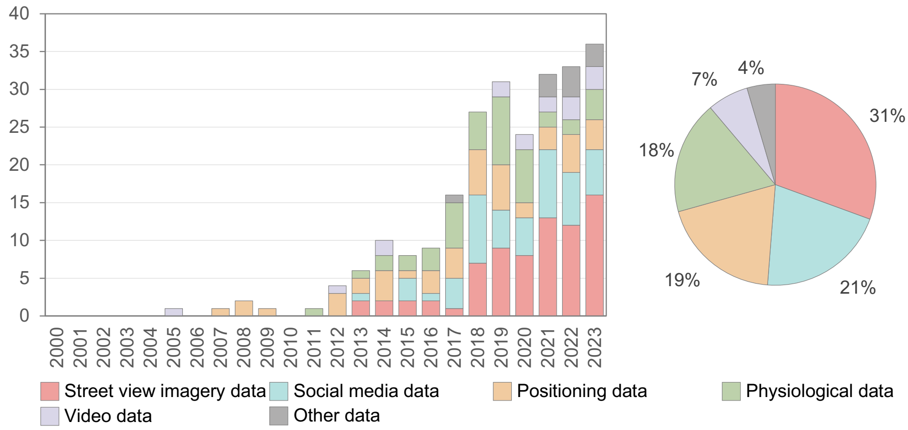

Fig. 7. Share of data type by year.

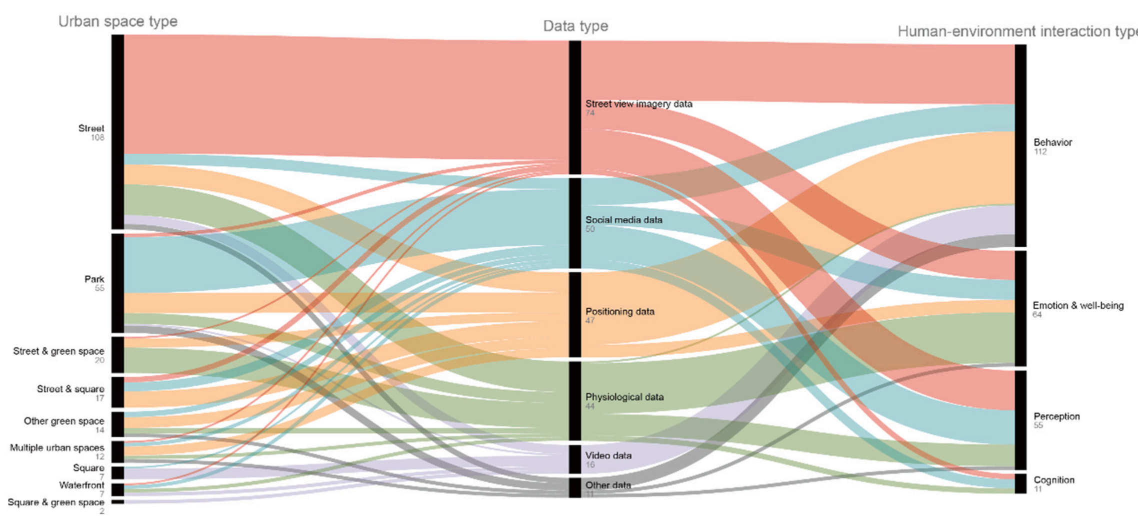

Fig. 8. Relationship of research settings, data types, and research themes.

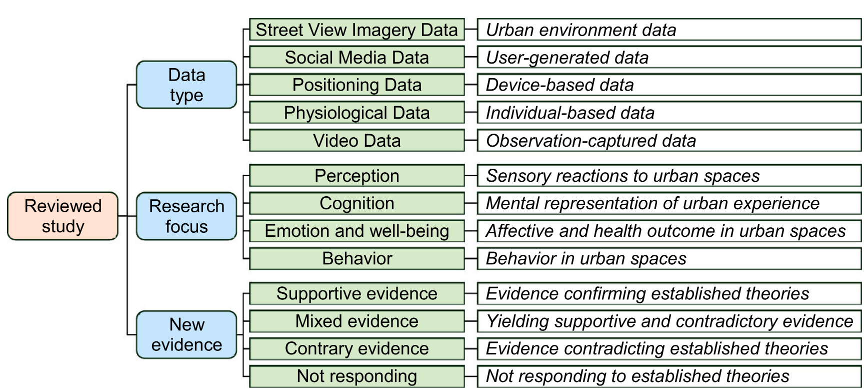

Fig. 9. Analytical framework.

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.

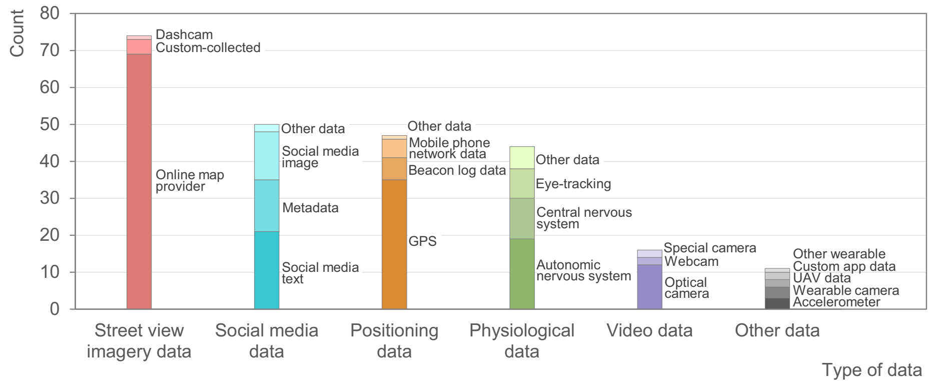

Fig. 10. Share of papers by data type.

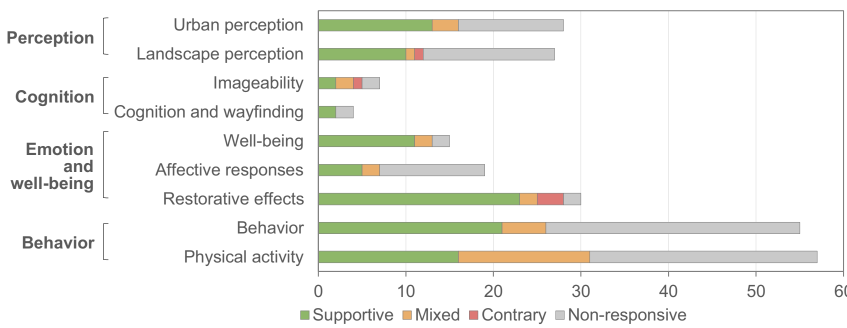

Fig. 11. Share of papers by research theme and evidence.

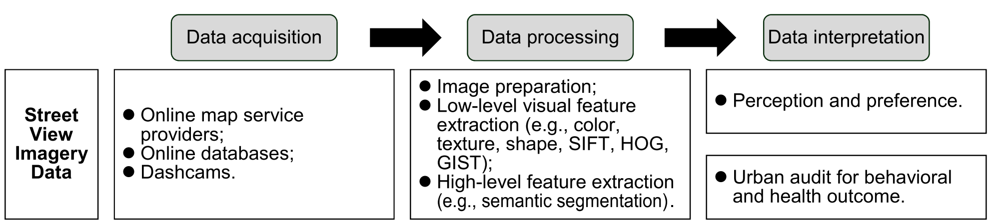

Fig. 12. Technical characteristics of street view imagery data.

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

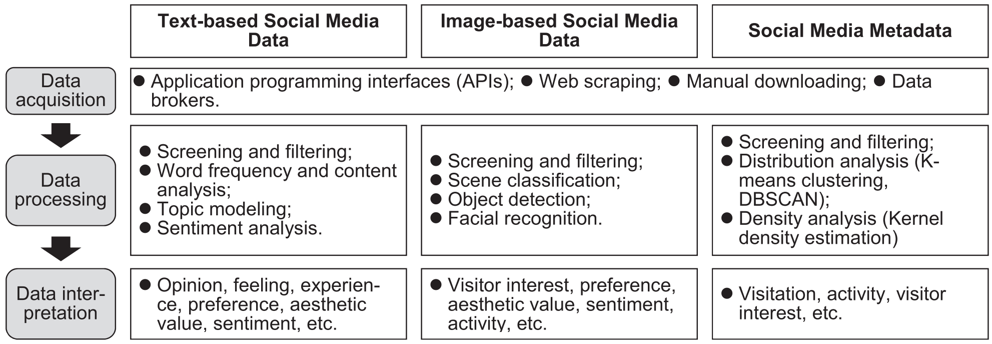

Fig. 13. Technical characteristics of social media data.

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).

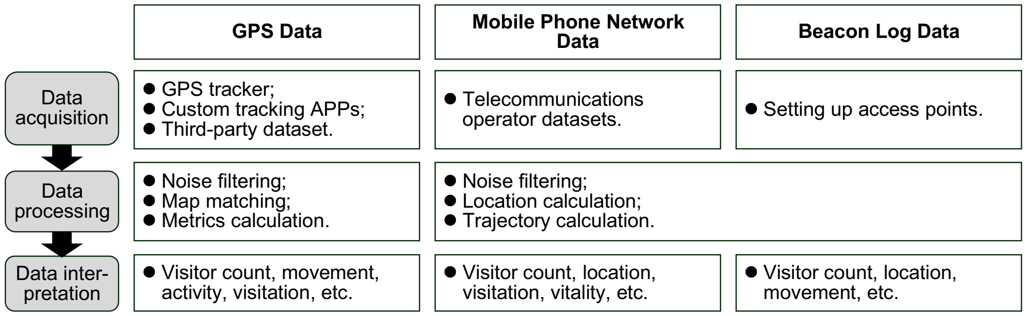

Fig. 14. Technical characteristics of positioning data.

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

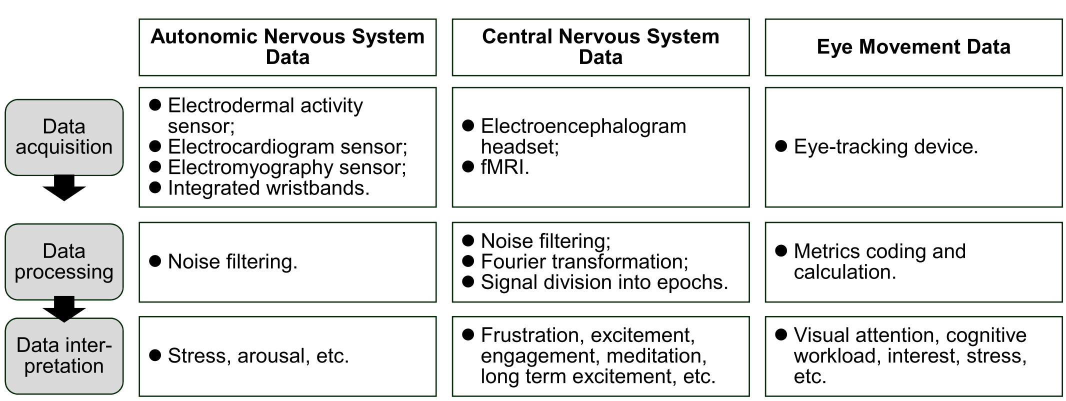

Fig. 15. Technical characteristics of physiological data.

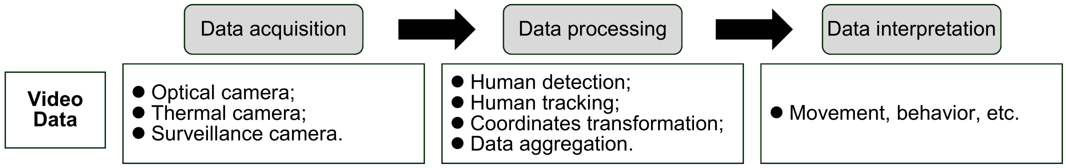

Fig. 16. Technical characteristics of video data.

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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