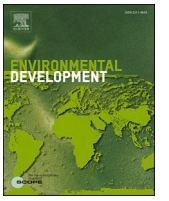
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Monitoring human behaviors in natural environments using sensor and vision technologies: A scoping review of analytical approaches and applications

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ABSTRACT

Understanding how people interact with natural environments is essential for evidence-based environmental planning and development. Recent advances in sensor-based technologies and computer vision have enabled new ways to monitor human behaviors in natural settings; however, a systematic synthesis of how these approaches have been applied, what behavioral dimensions they capture, and how they inform management decisions remains limited. This scoping review synthesizes 246 peer-reviewed studies published between 2000 and 2024, following the PRISMA-ScR guidelines, that employed sensor-based, vision-based, or hybrid technologies to empirically monitor human behaviors in outdoor natural environments, including urban green spaces and protected areas. We show that different monitoring technologies systematically shape which dimensions of human behavior become observable. Across the reviewed literature, human–nature interactions can be consistently understood through three primary behavioral dimensions: presence, movement, and activity and interaction. Sensor-based approaches predominantly capture presence and movement patterns, providing broad spatial and temporal coverage, whereas vision-based approaches enable detailed identification of activities and contextual interactions. Hybrid approaches increasingly integrate these complementary strengths. Rather than functioning as a separate behavioral category, spatial distribution of activities emerges as a cross-cutting analytical perspective, present in the majority of studies and frequently co-occurring with all three behavioral dimensions. By reframing the literature around behavioral dimensions rather than technological categories, this review highlights how methodological choices shape the visibility and interpretation of human behavior. The findings provide practical guidance for researchers, planners, and environmental managers in selecting appropriate monitoring approaches to support evidence-based decision-making and adaptive management of natural environments.

1. Introduction

Natural environments, including urban green spaces, blue spaces, and protected areas, support physical, psychological, and social well-being (Kwon and Silva, 2020; Markevych et al., 2017; Steg and de Groot, 2018). Activities such as walking, resting, and recreation

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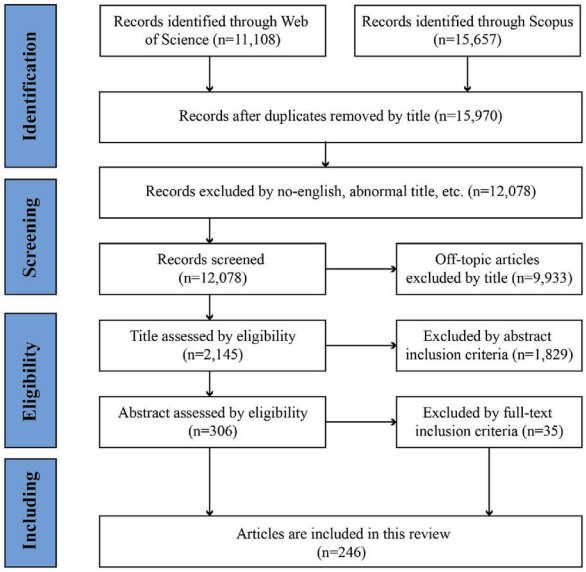


Fig. 1. Study selection process based on the PRISMA protocol.

can reduce stress and improve mood and cognitive functioning (Bratman et al., 2019; Marselle et al., 2021; Müller-Riemenschneider et al., 2013). Patterns of use also influence sustainability, resource allocation, and management effectiveness (M. Chen et al., 2025). Understanding how, where, and when people interact with nature is therefore important for evidence-based planning and management (Ghermandi et al., 2022; Kabisch et al., 2015).

Monitoring human behavior in natural areas involves several dimensions, including visitation frequency, movement, and activity. Traditional methods such as field observation, surveys, interviews, and participatory research provide contextual insight but often have limited spatial and temporal coverage and require substantial labor (Brown et al., 2014; Gehl et al., 2013; Miller et al., 2021). Digital sensing and computer vision now support more automated and scalable observation (Rout et al., 2021). GPS devices, mobile applications, wearables, and wireless sensors capture visitor volumes and trajectories, while image and video analysis can identify visible activities and interactions (M. Chen et al., 2024; Salazar-Miranda et al., 2023; X. Zhang et al., 2025). These technologies extend rather than replace traditional methods.

Recent research on behavior in natural areas is often shaped by available data and technical expertise rather than by explicit behavioral or management questions (Abbiasov et al., 2024; Gupta et al., 2024; Hu et al., 2020). Existing reviews also tend to focus on individual data sources, such as smartphone GPS or social media, within narrow spatial contexts (Rout et al., 2021). Consequently, knowledge remains fragmented regarding which dimensions of behavior different technologies reveal and how the findings support planning and management. A comparative framework is needed to explain how monitoring approaches construct, represent, and enable comparison of behavioral evidence across settings.

This scoping review addresses these gaps by synthesizing research on the monitoring of human behaviors in natural environments using sensor-based and vision-based approaches across both urban and non-urban contexts. Rather than treating technologies as purely technical categories, the review examines how different monitoring approaches capture different behavioral dimensions, and how these differences shape analytical outcomes and management relevance. The review is structured around five core themes: visitor volumes, visitor trajectories, activity classification, spatial distribution of activities, and other emerging topics such as perception and human wildlife interactions.

Three questions guide the review. First, which sensor and vision monitoring approaches have been used in natural environments? Second, which behavioral dimensions and spatial contexts do they address, and how do technologies shape the resulting evidence? Third, what strengths, limitations, and methodological considerations affect their use in environmental planning and management? The review aims to support informed method selection and sustainable management.

This study is guided by the view that monitoring technologies shape the dimensions of human behavior that can be observed. Sensor-based approaches tend to capture presence and movement, while vision-based approaches capture activity and contextual interaction. This perspective informs both the analytical structure of the review and the interpretation of findings.

2. Methods

We conducted the review in accordance with the PRISMA-ScR guidelines for scoping reviews (Tricco et al., 2018).

Table 1
Technologies and data used by researchers to understand human activities in natural areas.

Technology	Data type	Description	Number of papers
GPS devices	Routes and points (automatic)	Tracks from handheld GPS devices, such as Garmin units, that capture spatial trajectories.	62
GPS applications	Social media (geolocated images)	User-shared, GPS-tagged images from platforms such as Flickr, Twitter, and Instagram.	51
	Social media (geolocated text)	Textual posts with embedded location metadata, such as geotagged tweets or captions.	47
	Routes and points (automatic)	Smartphone applications, such as Strava and AllTrails, that record movement with GPS.	13
	Non-geolocated text	Application reviews, hashtags, or posts without coordinates but associated with named places.	17
Wearable sensors	Activity intensity	Accelerometer-based sensors, such as Fitbit and ActiGraph devices, that measure activity levels.	33
Wi-Fi, Bluetooth, and beacons	Volume and movement estimates	Detection of nearby devices to estimate foot traffic and spatial density.	5
Counters	Volume and movement counts	Sensors that detect motion or presence, including infrared and seismic devices.	12
Computer vision	Video	Continuous or time-lapse footage from CCTV, webcams, or drones, processed with computer vision for activity recognition, counting, and movement tracking.	12
	Social media (geolocated images)	User-generated photographs from social media platforms with embedded GPS coordinates, analyzed with computer vision to classify activities, assess spatial distribution, or monitor visitation patterns.	9
	Routes and points (automatic)	Pedestrian routes extracted from video, aerial imagery, or other visual sources.	8
	Other photographs	Static camera or drone imagery used for computer vision analysis.	3
	Non-geolocated text	Textual labels or captions associated with images in computer vision datasets.	1
	Activity intensity	Activity levels inferred from images or video with object-detection models.	1
Hybrid (sensor and computer vision)	Geolocated photographs and computer vision	GPS-tagged photographs analyzed with computer vision to identify activities.	19
	Movement and activity recognition	GPS or sensor tracking combined with computer vision-based behavior recognition.	11

2.1. Search strategy and selection criteria

We conducted a comprehensive literature search using the Web of Science and Scopus databases, which are known for their rigorous quality control standards. Instead of general queries, we used a structured Boolean search strategy to systematically capture the intersection between monitoring technologies and natural environments.

The search paired nine technology terms with ten groups of environment terms, producing 90 combinations (Appendix A). The technology terms represented vision, sensor, and user-generated data approaches and were identified through a preliminary literature scan. The environment terms covered common urban and protected settings, including parks, green spaces, urban forests, and waterfronts.

Where applicable, singular and plural forms were included to reduce omissions, and every combination was searched in the title, abstract, and keyword fields. Eligible articles had undergone peer review and were published from January 1, 2000, through December 31, 2024. Appendix A reports all terms and 90 combinations. Publications from 2025 cited elsewhere provide context only and were not included in the 246-study dataset.

Studies were included when they: 1) examined an outdoor setting; 2) were published in English; 3) reported empirical research using sensor or vision technologies to monitor human behavior in natural areas; 4) focused on visitor presence, movement, or activity rather than only psychological outcomes; and 5) for studies using images or video, applied computer vision algorithms rather than manual coding alone. Studies that relied only on manual image or video coding, including drone studies without algorithms, were excluded (Park et al., 2020; Park and Ewing, 2017).

As shown in Fig. 1, the search identified 26,765 records, including 11,108 from Web of Science and 15,657 from Scopus. After duplicate removal, 15,970 records remained, and preliminary eligibility checks reduced this number to 12,078. Title screening retained 2145 articles, abstract screening retained 306, and full-text assessment produced a final sample of 246 studies. Data were coded in Excel and managed in Zotero.

2.2. Data extraction and analysis

For each included article, we extracted data on study characteristics, technologies used, analytical themes, and key findings. A structured data extraction form was developed and iteratively refined through pilot testing. The form included three components: (1) basic information (e.g., title, publication year, authors, country), (2) methodological attributes (e.g., data types, technologies,

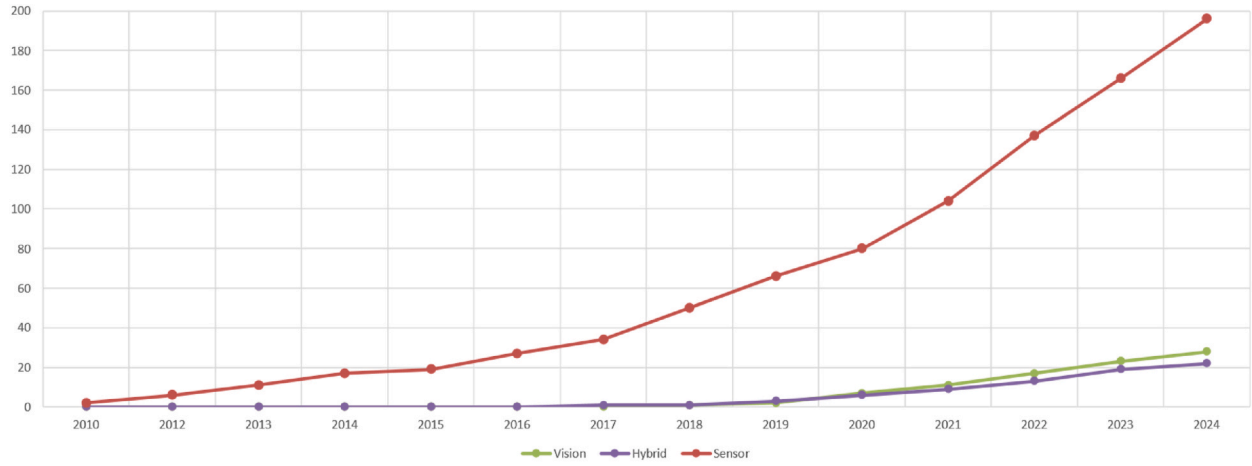


Fig. 2. Cumulative publication trends by method: sensor, vision, and hybrid.

analytical approaches, sample size), and (3) study outcomes (e.g., findings, strengths, and limitations).

To promote consistency and reliability, two researchers independently tested the extraction form on a randomly selected subset of studies. They compared the results, resolved discrepancies through consensus, and refined the coding framework before applying it to the full dataset. This process improved clarity, consistency, and reproducibility in data coding.

Five analytical themes (Section 3.2) emerged inductively during the full-text review. Two researchers collaboratively compared the objectives, methods, and findings of the studies and grouped them by recurring analytical focus. The coding emphasized the behavioral information produced, including presence, movement, and activity, and informed the analytical framework used in the review.

We used Excel and Python 3.8.2 to summarize the literature, identify trends, and produce visualizations.

3. Results

3.1. Technologies and data types used to monitor human behavior in natural areas

The 246 peer-reviewed studies were classified as sensor, vision, or hybrid approaches. Sensor methods were most common, while vision and hybrid approaches increased in recent years (Table 1; Fig. 2). This growth expanded the field from monitoring presence and movement toward identifying activity types and interaction contexts. Appendix C summarizes publication locations.

3.1.1. Sensor-based monitoring of human behavior

Sensor technologies include handheld GPS devices, GPS applications, wearable sensors, wireless systems, and counters (Table 1). They are used primarily to estimate visitor presence and reconstruct trajectories, although wearables can also measure activity intensity.

Handheld GPS devices such as Garmin and Trackstick record precise routes and points for targeted movement studies (Heikinheimo et al., 2020; Rice and Pan, 2021). Combining GPS with participatory GIS can add local knowledge and context that location traces alone cannot provide (Wolf et al., 2018). These devices are especially useful for reconstructing visitor trajectories within natural areas.

GPS applications and platforms such as Strava, Instagram, Weibo, and TripAdvisor provide geotagged routes, photographs, and text for large-scale analysis of visitation and activity patterns (Gu et al., 2016; Li et al., 2020; Lu et al., 2021; S. Zhang and Zhou, 2018; Y. Song et al., 2020). Mobile operator data and commercial mobility services can provide aggregated visitation estimates (Guan et al., 2021). Sports applications combine several sensors, while social media reviews provide information about visitor experiences (Heikinheimo et al., 2020; Roberts et al., 2017). These sources primarily represent population-level patterns of presence and movement.

Bluetooth, beacon, and WiFi systems estimate presence and movement by detecting nearby devices or signal strength. Bluetooth has been used at outdoor events (Versichele et al., 2012), beacons have been combined with GPS in public spaces (Osaba et al., 2018), and WiFi positioning has supported pedestrian tracking and counts (Hu et al., 2020; Traunmueller et al., 2018). These systems offer scalable, aggregated mobility data, although their accuracy and spatial range differ.

Wearable sensors, including accelerometers and smartwatches, measure activity intensity and classify actions such as walking or running (Berke et al., 2011; Kondo et al., 2009). Their accuracy depends on consistent use, which can be difficult in long studies (Jago et al., 2006). Environmental sensors, including seismic devices, can detect footsteps with fewer privacy concerns (Zhao et al., 2021). These methods provide detailed evidence of physical engagement with natural environments.

Infrared counters and pyroelectric sensors also monitor visitor presence and movement, particularly in remote settings where complex infrastructure is impractical (Pettebone et al., 2010; Rogowski and Piotrowski, 2022). Although they provide less detail than tracking or vision systems, they remain useful for reliable counts.

3.1.2. *Vision-based recognition of human activity*

Computer vision supports detailed activity recognition from images and video. Object detection, depth estimation, time lapse analysis, optical flow, drones, and surveillance systems can identify and track people in outdoor settings (Barekatain et al., 2017; Göçer et al., 2019; Hou et al., 2020; Jin et al., 2020; Niu et al., 2022; Szczepanek, 2020; Wei et al., 2022). These methods primarily detect activity types and interactions.

Static cameras, webcams, and drones provide images for classifying activities and mapping their spatial distribution. Kane et al. (2021), for example, used beach camera and drone imagery to examine visitor density, location, and mask use during the pandemic. Such methods connect observed behavior with environmental and social context.

Video from webcams, surveillance systems, drones, and social media can support activity recognition, crowd estimation, and movement tracking (Kane et al., 2021; Park, 2020; Szczepanek, 2020; Wei et al., 2022). Geotagged images from Flickr, Instagram, and Twitter can also be processed with computer vision models to classify activities and map visitation patterns (Ghermandi et al., 2022; Matasov et al., 2023). These sources enable large-scale analysis of activities and contextual interactions.

Routes and points can be extracted automatically from surveillance footage, aerial imagery, and other video sources using computer vision methods such as optical flow and object tracking (Jin et al., 2020; Wei et al., 2022). For example, Wei et al. (2022) used surveillance video and a custom trajectory extraction workflow to model pedestrian movement in natural areas. Vision-based approaches can therefore complement location data by linking trajectories to observed behavior.

3.1.3. *Hybrid approaches to understanding human behavior in natural areas*

Hybrid approaches integrate geolocated movement data with computer vision to provide a multidimensional view of human behavior in natural areas. By linking spatial traces from GPS or application platforms with recognition of activities or environments, these methods can reveal both where people go and what they do or perceive.

For example, Ghermandi et al. (2022) used geotagged Flickr images to classify activities and examine their spatial distribution across green spaces. Matasov et al. (2023) combined VK.com GPS traces with YOLO models applied to user-uploaded images to identify temporal changes in park use. Walden-Schreiner et al. (2018) combined trail-counter data with computer vision analysis of Flickr photographs to compare visitation volumes with engagement patterns.

Hybrid strategies either apply computer vision to geotagged photographs or combine movement traces with activity recognition. The resulting data link location with behavioral context and can represent presence, movement, and activity together (Heikinheimo et al., 2020; X. P. Song et al., 2020a, 2020b).

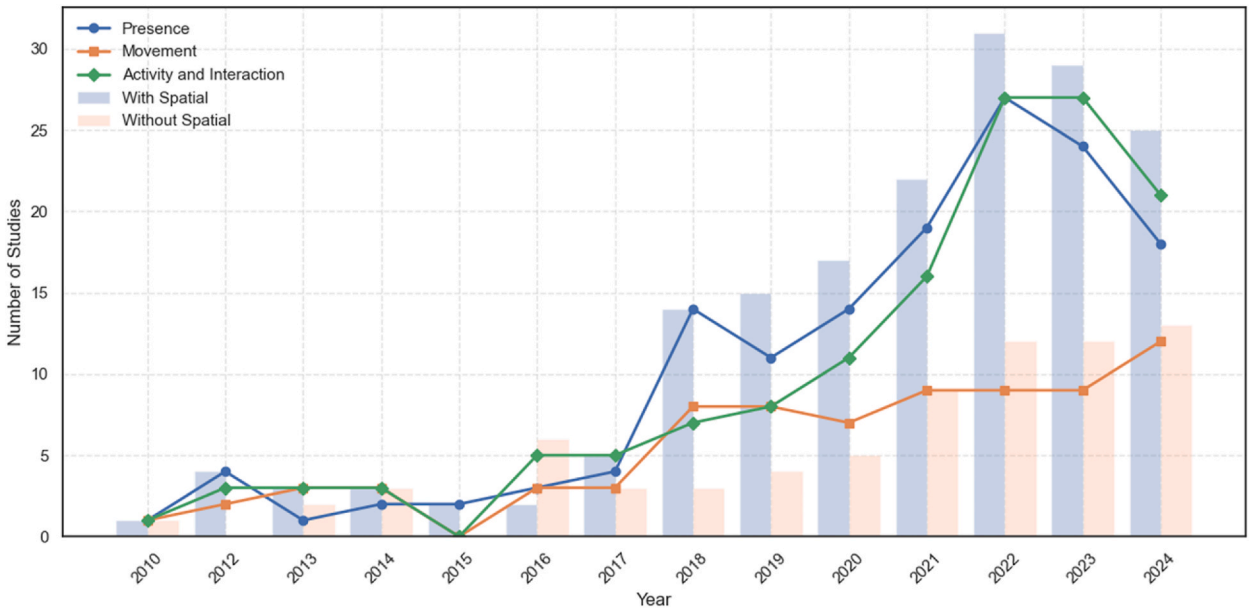


Fig. 3. Temporal distribution of themes from 2010 to 2024.

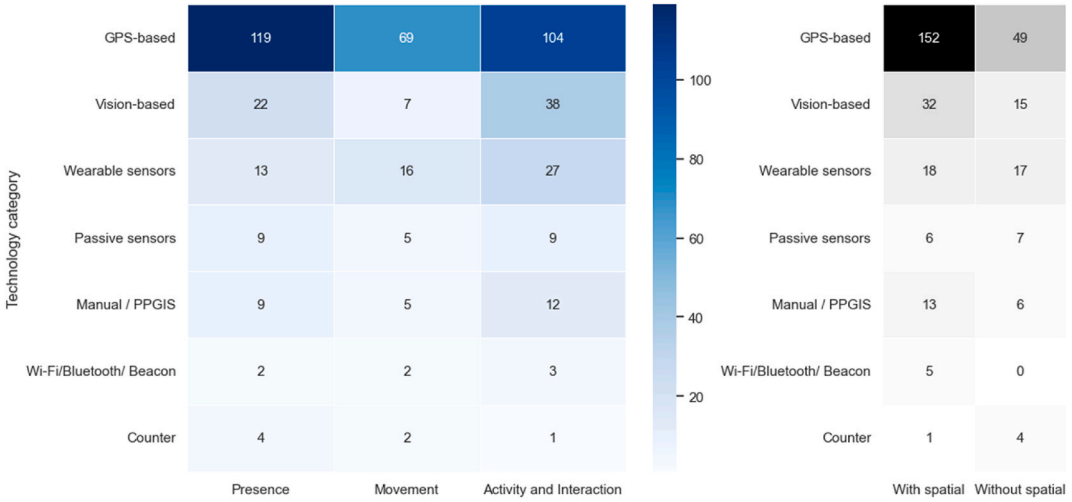


Fig. 4. Technology type by analytical theme among the 246 reviewed articles.

3.2. Review themes

3.2.1. Overview of behavioral dimensions in natural environments

The reviewed literature can be interpreted through three primary behavioral dimensions: presence, movement, and activity and interaction. Presence refers to the number of people visiting natural areas. Movement focuses on visitor routes and spatial navigation within or between sites. The activity and interaction dimension captures what people do in natural environments, including activity type, intensity, perception, and human-wildlife interaction. Spatial distribution is not a separate behavioral category but a cross-cutting analytical lens that describes how the three dimensions are arranged across space.

A total of 246 unique articles were included in the review, and most (n = 214) addressed multiple behavioral dimensions, producing an average of 2.25 dimensions per article. Presence was examined in 142 studies, movement in 77, and activity and interaction in 136. Spatial distribution was analyzed in 173 studies and frequently co-occurred with all three dimensions, supporting its interpretation as an integrative analytical lens rather than a standalone category.

All three behavioral dimensions increased over time, especially from 2018 to 2022 (Fig. 3). This growth coincided with wider access to digital data and advances in machine learning. Presence and movement dominated earlier studies, while activity and interaction grew with the use of vision methods. Spatial analysis remained common across all dimensions.

Monitoring approaches were associated with distinct behavioral dimensions (Fig. 4). Sensors, especially GPS, primarily captured presence and movement, whereas vision methods more often identified activity and interaction. Hybrid approaches linked movement with activity. Appendix D shows that spatial distribution overlapped with presence (n = 102), movement (n = 49), and activity and interaction (n = 94), confirming its role as a shared analytical lens.

3.2.2. Presence

Presence refers to the number of people visiting natural areas and is commonly used to assess site popularity, identify peak-use periods, and monitor long-term changes in demand. Common applications include identifying high-demand areas and peak hours (S. Chen et al., 2022), observing park visit trends over multiple years (Y. Song and Wei, 2024), and managing on/off trail usage in protected areas (Geng et al., 2024). Sensor-based approaches, particularly GPS-based methods, dominate this dimension, providing scalable tools to capture patterns of presence across space and time.

Presence studies examine visitor numbers and variation across places and time. Researchers have related visitation to residence, amenities, transit, and external events using mobile phone records, social media check-ins, and other spatial data (Guan et al., 2021; Kim et al., 2023; Li et al., 2020; Lu et al., 2021; Y. Song et al., 2023). Computer vision has also supported crowd-density estimation (Hou et al., 2020; Kane et al., 2021; Lee, 2021). These methods reveal where and when people are present but provide limited evidence about activities or experiences.

3.2.3. Movement

Movement refers to the routes and behavioral rhythms of individuals or groups navigating natural environments. Unlike presence, it emphasizes paths and sequences rather than aggregate counts. Studies often use GPS loggers, smartphone tracking, or volunteered geographic information to reconstruct routes and examine how visitors engage with trails, landmarks, and route complexity.

Research commonly examines walking, running, or cycling in parks, cities, and protected areas. For example, GPS studies in national parks have identified route variation and the influence of landscape features on loop length (Meijles et al., 2014). Salazar-Miranda et al. (2023) used computer vision to derive trajectories from video, extending movement analysis beyond sensor data.

Some studies integrate accelerometer data, reported itineraries, or environmental exposure to examine trail use and activity intensity (Berke et al., 2011; Korpilo et al., 2018). Crowdsourced platforms such as Strava also support longitudinal, large-scale trajectory analysis (Venter et al., 2023). These approaches can inform trail design, identify heavily used areas, and reveal accessibility gaps. Movement describes how people navigate natural environments but does not directly identify the activities or interactions that occur along a route.

3.2.4. Activity and interaction

Activity and interaction describe what people do in natural environments and how they engage with environmental features. Studies examine activity type and intensity, recreation, social interaction, perception, and ecological relationships. Image data and machine learning increasingly support classification of actions such as walking, picnicking, and wildlife observation (Barekatain et al., 2017; Ghermandi et al., 2022; Tan et al., 2023).

Computer vision models trained on images or video classify visible activities. Tan et al. (2023) identified 12 types of park events, including art, family, sport, and education. The Okutama Action dataset distinguishes interactions between people, interactions with objects, and individual actions such as reading or running (Barekatain et al., 2017).

Geotagged images from Twitter, Instagram, Weibo, and Flickr can be labeled and clustered to identify activity patterns (Ghermandi, 2022; Matasov et al., 2023; Roberts et al., 2017; Tenkanen et al., 2017; X. P. Song et al., 2020a, 2020b). Sports applications such as Strava provide activity distributions for running, cycling, water activities, and winter recreation (Dong et al., 2023; Venter et al., 2023).

Wearable sensors measure steps and activity intensity, often among specific groups such as older adults and children (Berntsen et al., 2010; Bürgi et al., 2016; Dunton et al., 2013; Han et al., 2016; Holliday et al., 2017; Jago et al., 2006). Studies relate activity to environmental features, participant characteristics, and health conditions (Kondo et al., 2009). Computer vision can also classify levels of physical activity (Carlson et al., 2017).

Activity and interaction also include perception and ecological relationships. Social media images and text have been used to infer cultural ecosystem services, aesthetic preferences, safety, and emotional responses (Ghermandi et al., 2022; Roberts et al., 2017). Camera traps reveal overlap between human and wildlife activity and show that species respond differently to recreation (Lewis et al., 2021; Procko et al., 2022). These studies extend behavioral monitoring beyond movement to experience and ecological effects.

4. Discussion

4.1. Advantages, limitations, and considerations of sensor and vision technologies

Table 2 compares technologies by representativeness, deployment requirements, information richness, and analytical focus. GPS

Table 2
Advantages, limitations, and considerations.

Tools	Advantages	Limitations	Considerations
GPS devices	High positional accuracy Suitable for route analysis Independent of smartphones	Limited participant pool Manual deployment required Data-intensive processing	Best for targeted tracking studies Participant compliance required Potential privacy risks from detailed movement tracking
GPS applications	Broad spatial and temporal coverage Low cost Automated data logging	Limited demographic representativeness Signal loss in dense areas	Requires widespread smartphone use Depends on platform access policies and API restrictions Requires privacy protection
Wearable sensors	Focus on selected participant groups Collection of physical and physiological indicators	Time and labor intensive Costly Small participant groups	Participant compliance and comfort Requires informed consent and ethics approval for human participant data
Bluetooth, Wi-Fi, and beacons	High accuracy in dense areas with many users Low investment Passive monitoring does not disturb visitors Applicable outdoors and indoors	Limited coverage or range Limited representativeness, including children and older adults without smartphones	Hardware reliability Deployment strategy for optimal coverage Regulations may limit tracking in public spaces
Counters	Objective visitor counting Simple and cost effective	No demographic or behavioral information Affected by weather or context	Useful for monitoring entrance volume Minimal privacy concerns because data are aggregated
Computer vision	Automated activity detection with artificial intelligence models Applicable outdoors and indoors	Limited coverage or range Affected by environmental conditions, including lighting and weather High initial setup and maintenance costs	Image privacy and ethical concerns Requires anonymization techniques such as face blurring

applications support scalable trajectory analysis but can underrepresent older users (Sessions et al., 2016). Computer vision can capture all visible users within a scene but requires greater setup and maintenance (Biljecki and Ito, 2021; Tan et al., 2023). Bluetooth and Wi-Fi systems can be inexpensive and scalable (Hu et al., 2020). GPS records paths but not activity types, while vision and wearable sensors provide richer activity information (Link et al., 2022). These differences should guide method selection.

4.1.1. Sensor-based technologies: GPS, applications, wearables, Bluetooth, and Wi-Fi

GPS loggers and smartphone applications provide detailed spatial and temporal data for studying trails, catchment areas, and movement flows (Guan et al., 2021; Korpilo et al., 2018; Meijles et al., 2014). Applications and aggregated mobility data support large-scale comparisons but may overrepresent younger, urban, and technically engaged users (Venter et al., 2023). GPS is spatially precise but cannot easily distinguish active use from passive presence without contextual data (Fernandez et al., 2024; Zhai et al., 2021).

Wearable sensors measure activity intensity and are valuable for health research and studies of specific age groups, but cost and participant compliance limit scale (Berke et al., 2011; Donahue et al., 2018; Jago et al., 2006; Zhai et al., 2021). Bluetooth and WiFi systems can estimate crowd density through passive device detection at low cost, although results depend on device ownership, settings, and signal conditions (Hu et al., 2020; Osaba et al., 2018).

Sensor data still require safeguards for consent, anonymization, and regulatory compliance (Fernandez et al., 2024; Korpilo et al., 2018). GPS and Bluetooth records also need contextual alignment with landscape features. Despite these limitations, sensor methods remain valuable for mapping mobility, visitation, and physical activity.

4.1.2. Vision-based technologies

Vision methods use cameras, drones, and social media imagery to classify visible actions such as walking, sitting, and group recreation (Ghermandi et al., 2022; Kane et al., 2021; Tan et al., 2023). They do not depend on device ownership and can include all visible users within a camera field, although coverage remains limited to that field (Biljecki and Ito, 2021).

Computer vision generates semantic information from scenes. Models such as YOLO and scene recognition networks detect activities and interaction types in social media images, drone footage, and surveillance video (Matasov et al., 2023). These methods identify activities that location sensors may miss and can support analysis of aesthetic preferences and recreational values (Donahue et al., 2018; Gugulica and Burghardt, 2023).

Vision models are sensitive to lighting, camera angle, and occlusion, and general datasets may not represent environmental behavior well (Tan et al., 2023). User generated imagery also favors attractive or iconic locations and may underrepresent less photographed areas (Biljecki and Ito, 2021; Donahue et al., 2018).

Vision data can include identifiable people and sensitive activities. Face blurring, local processing, and aggregated visual descriptors can reduce privacy risks (Salazar-Miranda et al., 2023). Platform restrictions, changing access policies, and data ownership also affect reproducibility (Tenkanen et al., 2017). When carefully managed, vision methods provide rich contextual evidence for spatial behavior, cultural ecosystem services, and design preferences.

4.1.3. Hybrid approaches

Hybrid approaches combine spatial traces with visual or activity data to show where people go and how they engage with natural environments (Ghermandi et al., 2022; Walden-Schreiner et al., 2018). They can distinguish active from passive use and connect behavior with cultural meaning (Gugulica and Burghardt, 2023; Matasov et al., 2023). Earlier studies combined sensors with manual interpretation, while recent work uses computer vision. Both approaches address the limitations of individual data sources.

Hybrid systems can strengthen analyses by cross-validating behavioral evidence across modalities and improving activity classification. They are especially useful for connecting spatial patterns with perceptual or aesthetic dimensions. However, differences in spatial and temporal resolution can complicate synchronization, metadata integration, and interpretation (Guan et al., 2021).

Hybrid methods also increase privacy risks because combining spatial and visual data can permit reidentification even when each source is anonymized. Relevant safeguards include real time anonymization, local processing, and transparent disclosure of monitoring practices (Salazar-Miranda et al., 2023). Data integration also requires technical expertise and standardized protocols to support scalability and reproducibility (Rout et al., 2021).

Despite these limitations, hybrid approaches offer methodological flexibility and interpretive depth. They are well suited to research that connects movement patterns with activity types, landscape affordances, or social and environmental perceptions.

4.2. How monitoring technologies shape behavioral knowledge

This review identifies three primary behavioral dimensions: presence, movement, and activity and interaction, with spatial distribution serving as a cross-cutting analytical lens. Sensor-based approaches dominate the study of presence and movement, while vision-based methods are more prevalent in analyses of activity and interaction. This uneven distribution shows how monitoring technologies shape which dimensions of human behavior become observable and how they are interpreted. Different technologies do not simply collect data differently; they produce different forms of behavioral knowledge.

Sensor data usually represent behavior as counts, density, and movement across space and time, whereas vision data represent activity types, poses, and interactions within scenes. This distinction explains why sensor studies cluster around visitor volume and trajectories while vision studies emphasize activity classification. Hybrid studies connect these complementary forms of evidence and support more complete assessments of park use (Carlson et al., 2017; Matasov et al., 2023; Walden-Schreiner et al., 2018).

Presence and movement dominate the literature because visitor counts and trajectories are readily captured with WiFi probes and mobile sensing (Hu et al., 2020). These studies describe visitation intensity, movement flows, and accessibility, confirming the field's strong emphasis on mobility.

Activity and interaction are less common but have grown in recent years. These studies identify recreation, social interaction, and engagement with environmental features. They provide richer descriptions of behavior, but their smaller number shows that detailed activity analysis remains limited.

Spatial distribution overlaps with all behavioral dimensions and is best understood as an analytical perspective rather than a separate behavior. Studies use it to connect presence, movement, or activity with environmental conditions, and hybrid methods increasingly link trajectories with contextual information (Carlson et al., 2017; Matasov et al., 2023; Walden-Schreiner et al., 2018).

Overall, studies emphasize presence and movement more than activity and interaction. Spatial distribution links these dimensions, but most research still provides only a partial view of human interaction with nature. The dimensions made visible depend on the selected monitoring approach.

Beyond methodological considerations, these findings have broader interdisciplinary implications for environmental development and governance. By clarifying how monitoring technologies shape the visibility of human-nature interactions, this study provides a foundation for integrating behavioral data into policymaking, urban planning, and environmental management.

Distinguishing among presence, movement, and activity can support more targeted decisions. Planners and managers can align monitoring strategies with goals such as managing visitor pressure, designing circulation, or enhancing experiential quality and cultural ecosystem services (Gugulica and Burghardt, 2023; Zapata-Caldas et al., 2022). More broadly, the framework integrates technological, social, and environmental perspectives and supports adaptive, evidence-based governance across spatial and institutional contexts.

At the level of knowledge production, our synthesis extends existing critiques of digitally mediated behavioral evidence. Reviews of smartphone GPS and social media monitoring show that these sources expand spatial and temporal coverage but organize behavior primarily as location, visitation, and movement (Tenkanen et al., 2017; Rout et al., 2021). Venter et al. (2023) further demonstrate that crowdsourced recreational data can be systematically biased even when aggregate patterns are precise. Image based and hybrid studies broaden this evidentiary field by identifying activities, perceptual cues, and contextual interactions (Ghermandi et al., 2022; Matasov et al., 2023), yet image availability and platform participation remain spatially selective (Biljecki and Ito, 2021; Donahue et al., 2018). Taken together, this literature supports our finding that technologies do not simply differ in accuracy or scale. They make some behavioral dimensions more visible than others. Researchers should therefore distinguish direct observations from interpretations and combine digital monitoring with contextual observation, surveys, or qualitative evidence when motivations, experiences, informal social practices, or culturally situated uses are central to the research question.

For environmental planning and management, the literature likewise indicates that different data sources support different decisions. Automated counters estimate visitor pressure at entrances and trailheads (Pettebone et al., 2010), while GPS and participatory GIS reveal routes, conflict areas, and spatial management needs (Korpilo et al., 2018; Wolf et al., 2018). Computer vision can distinguish visible activities and interactions that counts and trajectories cannot capture (Salazar-Miranda et al., 2023; Tan et al., 2023). Walden-Schreiner et al. (2018) showed the value of comparing trail counts with crowdsourced images, and more recent hybrid studies have linked geolocated imagery with machine learning to examine both where and how people use natural environments (Ghermandi et al., 2022; Matasov et al., 2023). Building on these studies, our synthesis suggests that method selection should begin with the management question rather than with data availability. Visitor counts may be sufficient for capacity assessment, trajectory data for circulation and access, and activity or interaction data for evaluating recreational use and engagement. Decisions that balance access, visitor experience, and ecological protection require triangulation across methods and clear communication of the limits of each source.

4.3. Privacy, data protection, and ethical considerations

Monitoring technologies are shaped by privacy, data protection, and ethical constraints as well as technical capabilities. Location and image data raise concerns about ownership, consent, and misuse (Salazar-Miranda et al., 2023). The suitability of each method therefore depends on its institutional and regional context.

Regulation and data access vary across regions. The General Data Protection Regulation in Europe imposes strict requirements on personal and location data. Platform policies and institutional practices also shape access to social media and mobility data (Ghermandi et al., 2022; Guan et al., 2021; Lu et al., 2021; Rout et al., 2021). Consequently, the same method may be feasible in one context and restricted in another.

GPS traces can reveal individual routines, while images may identify people or sensitive activities (Procko et al., 2022;

Salazar-Miranda et al., 2023). Combining spatial and visual data can increase the risk of reidentification even when each source is anonymized. Data minimization, anonymization, and clear communication are therefore essential (Rout et al., 2021).

Method selection also involves practical and ethical tradeoffs. Computer vision and large-scale tracking provide richer evidence but require greater data access, computation, and regulatory oversight (Ghermandi et al., 2022; Tan et al., 2023). Counters and aggregated data offer less detail but can be easier to deploy responsibly in remote or resource-constrained settings (Pettebone et al., 2010; Rogowski and Piotrowski, 2022).

4.4. Research gaps and future directions

Several gaps remain. Visitor counts often come from fixed locations such as entrances and may miss movement through less prominent areas (Hu et al., 2020; Osaba et al., 2018; Versichele et al., 2012). GPS provides detailed trajectories but is usually limited to small samples or individual sites because of privacy, cost, and technical constraints (Berke et al., 2011; Korpilo et al., 2018). Regional studies often infer movement from geotagged photographs or reviews, which offer broad coverage but less temporal continuity and spatial precision (X. P. Song et al., 2020a, 2020b; Tenkanen et al., 2017). Future work should connect reliable counts with continuous movement data across larger areas.

Computer vision studies often rely on small, manually labeled datasets or general models that were not designed for environmental behavior (Tan et al., 2023). These models may miss subtle behaviors such as landscape appreciation, group interaction, and wildlife observation. Standardized datasets designed for outdoor recreation would improve consistency, transferability, and interpretation.

Representativeness is another limitation. Mobile technologies can underrepresent older adults, children, and marginalized groups, which is especially problematic for equity research (Zhao et al., 2021). Stratified sampling, offline data collection, and inclusive application design can improve demographic coverage.

Future research should integrate sensor and vision data to connect visitor numbers, trajectories, and activities (Ghermandi et al., 2022; Salazar-Miranda et al., 2023; Wolf et al., 2018). Passive wireless tracking requires further validation, and computer vision needs better recognition of complex activities (Hu et al., 2020; Osaba et al., 2018). These developments can strengthen evidence for environmental planning and human well-being.

GPS will remain valuable when combined with broader and more representative data. Multicity check-in data can reveal visitation patterns, while surveys and field observations add information about demographics and preferences (Heikinheimo et al., 2020; Korpilo et al., 2018; Li et al., 2020). Future studies should integrate active and passive data and examine how land use, transportation, nearby amenities, and environmental conditions influence park use.

5. Conclusions

This scoping review synthesizes how sensor-based, vision-based, and hybrid approaches are used to study human behavior in natural environments, with a focus on how these technologies capture different dimensions of human–nature interaction.

The findings show that monitoring technologies systematically shape the types of behavioral knowledge produced. Sensor-based approaches predominantly capture presence and movement, enabling large-scale analysis of where people are and how they navigate space. In contrast, vision-based approaches provide richer insights into activity and interaction, revealing what people do and how they engage with natural environments. Hybrid approaches increasingly bridge these dimensions by linking spatial patterns with behavioral and perceptual information.

These results show that methodological choices define which aspects of human behavior can be observed and analyzed. For researchers and practitioners, selecting a monitoring technology is both a technical and conceptual decision because it shapes research questions, analytical outcomes, and planning relevance. Recognizing this relationship enables more intentional monitoring strategies and supports effective evidence-based planning and management of natural environments.

CRediT authorship contribution statement

Mingze Chen: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft. **Keunhyun Park:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Writing – review & editing.

Declaration of competing interests

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. Complete search terms and keyword combinations

The complete search vocabulary and all 90 paired combinations are reported below. Nine technology terms were combined with ten groups of environment terms. Within each row, singular and plural variants separated by a semicolon were joined with OR, while the technology and environment components were joined with AND. Each combination was searched in the title, abstract, and keyword fields in both Web of Science and Scopus using the corresponding database field tags.

Technology search terms: Computer Vision; Sensor; Video; Camera; Track; Social Media; Counters; Smartphone; GPS.

Environment search term groups: Public space; Park/Parks; Waterfront/Waterfronts; Open space/Open spaces; Urban forest/Urban forests; Beach/Beaches; Garden/Gardens; Green space/Green spaces; Natural area/Natural areas; Blue space/Blue spaces.

ID	Technology search term	Environment search term(s)
1	Computer Vision	Public space
2	Computer Vision	Park; Parks
3	Computer Vision	Waterfront; Waterfronts
4	Computer Vision	Open space; Open spaces
5	Computer Vision	Urban forest; Urban forests
6	Computer Vision	Beach; Beaches
7	Computer Vision	Garden; Gardens
8	Computer Vision	Green space; Green spaces
9	Computer Vision	Natural area; Natural areas
10	Computer Vision	Blue space; Blue spaces
11	Sensor	Public space
12	Sensor	Park; Parks
13	Sensor	Waterfront; Waterfronts
14	Sensor	Open space; Open spaces
15	Sensor	Urban forest; Urban forests
16	Sensor	Beach; Beaches
17	Sensor	Garden; Gardens
18	Sensor	Green space; Green spaces
19	Sensor	Natural area; Natural areas
20	Sensor	Blue space; Blue spaces
21	Video	Public space
22	Video	Park; Parks
23	Video	Waterfront; Waterfronts
24	Video	Open space; Open spaces
25	Video	Urban forest; Urban forests
26	Video	Beach; Beaches
27	Video	Garden; Gardens
28	Video	Green space; Green spaces
29	Video	Natural area; Natural areas
30	Video	Blue space; Blue spaces
31	Camera	Public space
32	Camera	Park; Parks
33	Camera	Waterfront; Waterfronts
34	Camera	Open space; Open spaces
35	Camera	Urban forest; Urban forests
36	Camera	Beach; Beaches
37	Camera	Garden; Gardens
38	Camera	Green space; Green spaces
39	Camera	Natural area; Natural areas
40	Camera	Blue space; Blue spaces
41	Track	Public space
42	Track	Park; Parks
43	Track	Waterfront; Waterfronts
44	Track	Open space; Open spaces
45	Track	Urban forest; Urban forests
46	Track	Beach; Beaches
47	Track	Garden; Gardens
48	Track	Green space; Green spaces
49	Track	Natural area; Natural areas
50	Track	Blue space; Blue spaces
51	Social Media	Public space
52	Social Media	Park; Parks
53	Social Media	Waterfront; Waterfronts
54	Social Media	Open space; Open spaces
55	Social Media	Urban forest; Urban forests
56	Social Media	Beach; Beaches

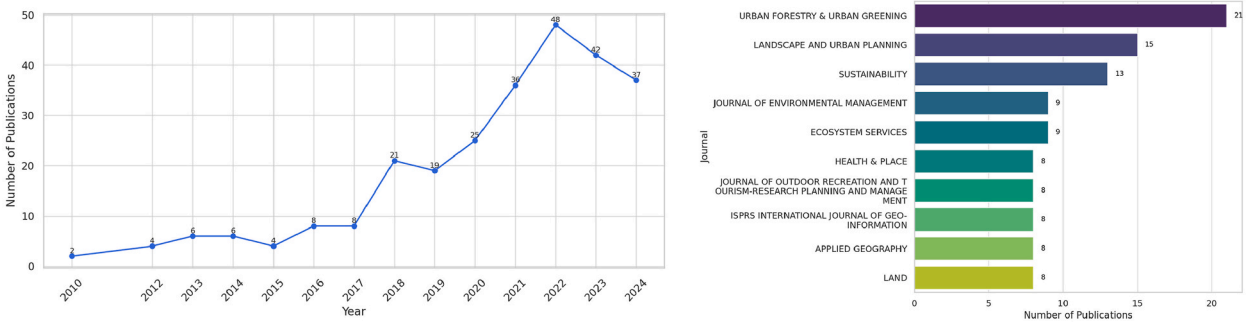
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(*continued*)

ID	Technology search term	Environment search term(s)
57	Social Media	Garden; Gardens
58	Social Media	Green space; Green spaces
59	Social Media	Natural area; Natural areas
60	Social Media	Blue space; Blue spaces
61	Counters	Public space
62	Counters	Park; Parks
63	Counters	Waterfront; Waterfronts
64	Counters	Open space; Open spaces
65	Counters	Urban forest; Urban forests
66	Counters	Beach; Beaches
67	Counters	Garden; Gardens
68	Counters	Green space; Green spaces
69	Counters	Natural area; Natural areas
70	Counters	Blue space; Blue spaces
71	Smartphone	Public space
72	Smartphone	Park; Parks
73	Smartphone	Waterfront; Waterfronts
74	Smartphone	Open space; Open spaces
75	Smartphone	Urban forest; Urban forests
76	Smartphone	Beach; Beaches
77	Smartphone	Garden; Gardens
78	Smartphone	Green space; Green spaces
79	Smartphone	Natural area; Natural areas
80	Smartphone	Blue space; Blue spaces
81	GPS	Public space
82	GPS	Park; Parks
83	GPS	Waterfront; Waterfronts
84	GPS	Open space; Open spaces
85	GPS	Urban forest; Urban forests
86	GPS	Beach; Beaches
87	GPS	Garden; Gardens
88	GPS	Green space; Green spaces
89	GPS	Natural area; Natural areas
90	GPS	Blue space; Blue spaces

Appendix B

Number of papers published by year (a) and journal (b)

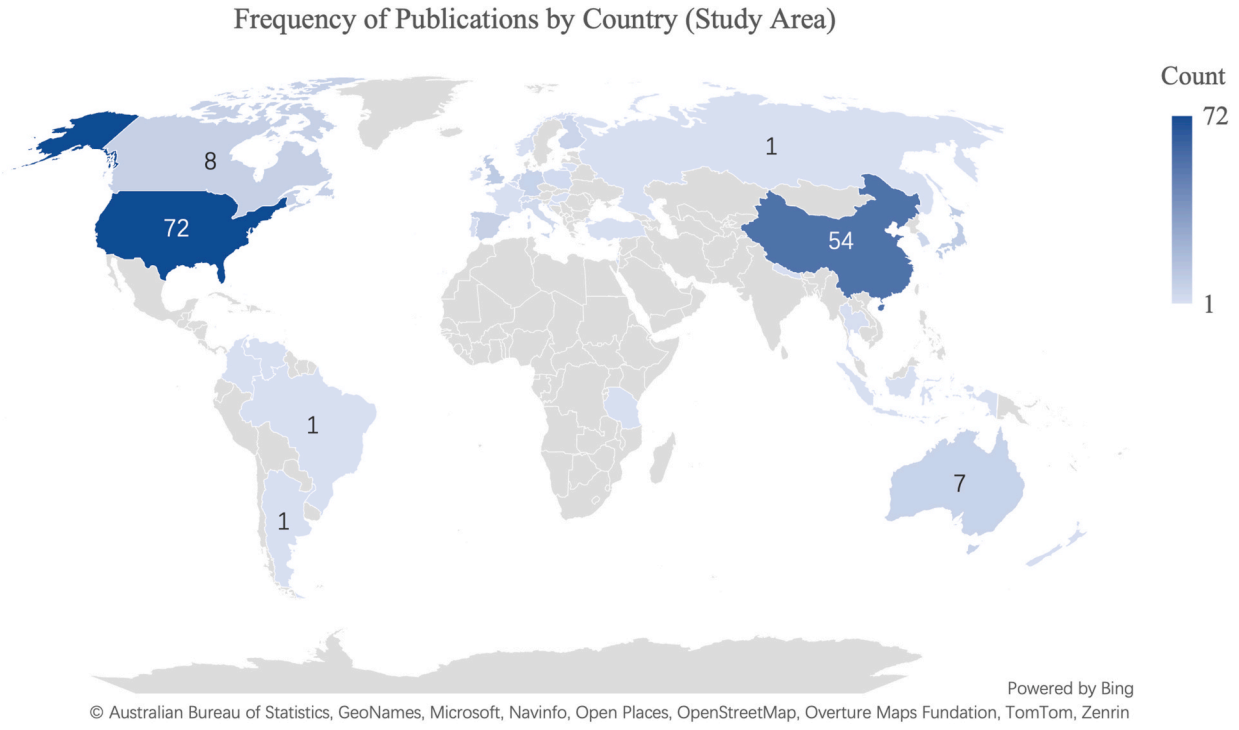


(a) (b)

The most frequently represented journals in Appendix B are Urban Forestry & Urban Greening (21 papers) and Landscape and Urban Planning (15 papers).

Appendix C

Frequency of publications by country (study area)



The United States was the most frequently studied country (72 papers), followed by China (54 papers), the United Kingdom (11 papers), and Japan (10 papers). Most studies examined one natural area or several areas within a single city, including urban parks, protected parks, and mountains. A smaller number covered multiple cities or global contexts. For example, Venter et al. (2021) analyzed mobility changes in blue and green spaces across 153 countries, while Lu et al. (2021) compared park visitation in Singapore, Hong Kong, Seoul, and Tokyo during the COVID-19 pandemic.

Appendix D

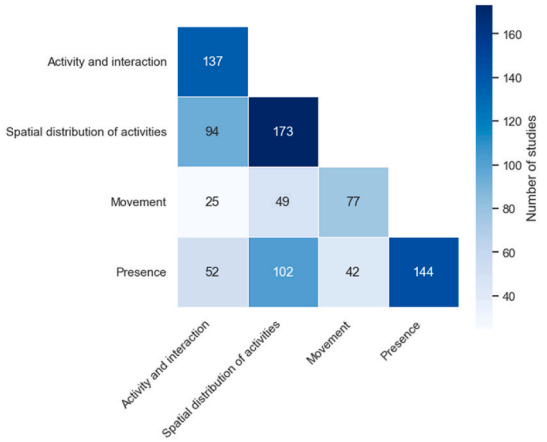


Fig. D.1. Theme co-occurrence matrix based on the 246 reviewed articles

Data availability

Data will be made available on request.

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