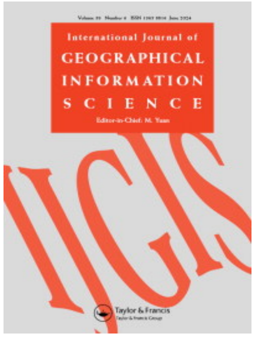

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REVIEW ARTICLE

Street view imagery-based built environment auditing tools: a systematic review

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ABSTRACT

The use of street view imagery (SVI) and advanced urban visual intelligence technologies has revolutionized built environment auditing (BEA) practice, by enabling high-resolution BEA at large scales. This study reviewed 96 studies of BEA published before October 2023. The Google SVI was employed in 92.7% of the included studies. Manual processing of SVI was used in BEA in most studies (81.3%), while deep learning methods were mostly used in the remaining studies. Validated auditing tools were used in 71% of the studies. Streets were the most frequently audited objects (54.2%), followed by sidewalk (51%), traffic (49%), and land use (34.4%). Objective attributes exhibited higher reliability in BEA, compared to subjective attributes (e.g. neighborhood environmental perception). The Active Neighborhood Checklist and Microscale Audit of Pedestrian Streetscapes were the two most widely used SVI-based BEA tools. Several key areas for improving the accuracy and reliability of SVI-based BEA were identified: building standardized datasets of built environment features for more accurate auditing, combining multi-source SVI for more comprehensive assessments, and adapting auditing tools to the contexts in developing countries. This study would contribute to a deeper understanding of built environmental influences on health, and facilitate informed decision-making in urban planning and public health efforts.

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KEYWORDS
Street view; built environment; auditing; computer vision; environmental health

Introduction

Built environment refers to the human-made places where we live, work, and engage in daily life. Considered a necessary component of the *exposome* (the totality of exposures from conception onwards) and usually characterized by in-field documenting

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methods, the built environment has been drawing increasing attention from a variety of fields over the past decade (Sallis *et al.* 2020, Jia 2021). It plays an essential role in shaping and affecting individuals' perceptions and behaviors, and consequently, exerting a profound influence on their health status (Forsberg and von Malmborg,2004 Winters *et al.* 2010, Robinson *et al.* 2018, Jia *et al.* 2019c). For instance, higher land use mix, featuring elements, such as speed limits and traffic safety concerns extracted from an in-field documenting method namely the Neighborhood Environment Walkability Survey, were associated with increased physical activities of adults from eight Latin American countries (Ferrari *et al.* 2020). However, such associations were the opposite in some other studies. For example, traffic safety concerns extracted from the same documenting method showed a negative association with active transport to school among adolescents in New Zealand (Rahman *et al.* 2023). The probable reason was that in-field documenting methods varied significantly across different regions and research contexts, and involved human perception and subjectivity. Therefore, associations between the built environment and health outcomes remain unclear due to uncertainties and variations in traditional in-field documenting methods.

Traditional in-field documenting methods often used to audit built environment require investigators to undergo specialized training as auditors, which, however, are costly, time-consuming, and may also suffer from inter-auditor inconsistencies in perception and behavior (Li *et al.* 2022b). To overcome these problems and better characterize the intricate and multi-faceted built environment, built environment auditing (BEA) has emerged as a promising approach for quantifying environment attributes with good accuracy (Forsberg and von Malmborg 2004). Photographs have been introduced as a BEA-assisting tool to systematically document street space and support urban inquiry. For example, photographs in 1890 were used to assess the living conditions of poor communities in New York City of the US (Riis 1890). In the early 20th century, photographs were more used in research on urban neighborhoods in several US cities (Lindner 2019). In another US study in 1960, the effect of photograph-extracted built environment features on residents' perception of their neighborhood environment was studied (Lynch 1964). In 1970, time-lapse photography, which captures scenes over an extended time period to produce a short video, was used to study how people used public spaces in New York City the US (Whyte 1980). However, in those early efforts, it is necessary for researchers to manually photograph the study areas.

The recent ability to capture digital multi-perspective photographs by a moving vehicle has greatly advanced BEA by allowing us to record street scenes comprehensively and objectively (Roman *et al.* 2004, Anguelov *et al.* 2010). Therefore, street view imagery (SVI) has emerged as a valuable resource informing various urban research endeavors, particularly in the realm of streetscape visual object detection (Biljecki and Ito,2021 Stiles *et al.* 2022). SVI comprises publicly available image datasets, captured by vehicles moving along streets, and further processed to provide panoramic views of cities. This technological innovation has shifted the implementation of BEA methods from manually on-site to (semi-)automatically on the computer (Kelly *et al.* 2013). The rapid proliferation of map services, providing a large amount of publicly available geo-tagged street-level images, has made it increasingly feasible to conduct virtual auditing through SVI (Zhang *et al.* 2019, Yin *et al.* 2023). The SVI has been used in BEA since 2010 and evolved from the replacement of filed work to (semi-)automatic auditing tools (Clarke *et al.* 2010, Nguyen *et al.* 2018). SVI typically originates from two major sources: company-owned photos, such as Google Street View, and user-contributed photos. The latter refers to content sourced from ordinary individuals or the general public, as opposed to images directly from the company. This dual sourcing broadens the scope of coverage, encapsulating areas that moving vehicles might not have reached. The coverage of SVI varies widely by region and service provider, with urban areas better covered than rural areas. For example, providers like Google usually have urban and tourist areas extensively covered, and have remote and less populated regions sparsely covered or even lacking SVI. These datasets have been accessible by commercial online map providers, which allow auditors to observe the built environment at a streetscape level, at a large scale, and in high safety and efficiency.

The lack of a uniform reporting standard among the majority of the existing BEA studies could result in misinterpretations of urban scenes, as well as inaccurate estimation of associations between the built environment and health outcomes (Brownson *et al.* 2009). With the increasing use of SVI in recent years, it is imperative to scrutinize the existing studies to promote a consistent reporting standard. However, a systematic review of the applications of SVI in built environment remains absent from the literature. This study aimed to systematically review the literature reporting on SVI-based BEA. By summarizing key information, such as BEA methods, environment attributes audited, and SVI types used in those studies, this study would shed light on the current challenges and facilitate the standardization and advancement of BEA. The findings would serve as a useful resource and a key reference for researchers in multiple fields, including geography, urban planning, public health, and emergency management.

Methods

We used the PubMed and Web of Science databases to search for refereed journal articles. To identify articles related to BEA and SVI, we used two sets of search terms: (1) 'built environment* audit', 'auditing', and 'virtual audit*'; (2) 'streetview*', 'street view*', 'street-view*', and 'street view image*'. We collected all the papers published from the inception of the electronic bibliographic databases up to October 2023. We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to conduct a systematic review (Moher *et al.* 2009), as depicted in Figure 1. Out of 429 initial results, we identified 96 eligible studies. These studies provided information on the following: publication date, first author, journal name, research themes, study area, study scale, study unit, built environment attributes audited, audited imagery, audited methodologies, reliability-calculated methodologies, audited results and their reliability, auditing tools, and variable types of attributes audited (whether continuous or categorical).

Following the data extraction from all the included studies, we systematically classified them into five distinct categories, namely: health and well-being ($n = 36$), socio-economics studies ($n = 15$), transportation and mobility ($n = 17$), urban morphology

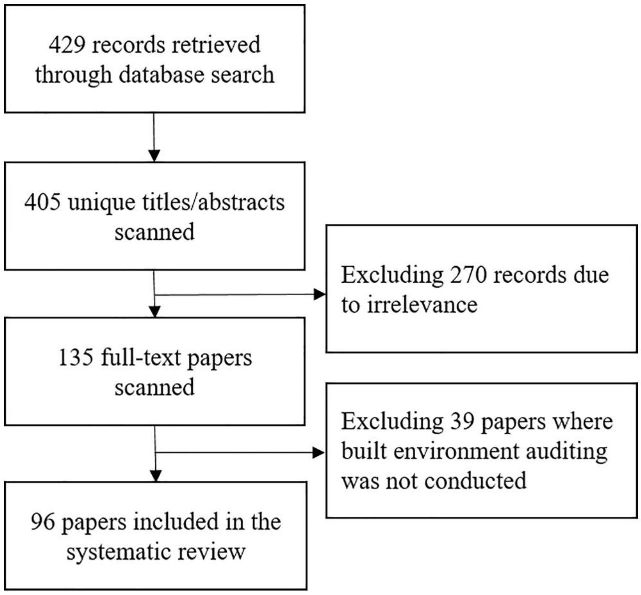

Figure 1. The flowchart that was followed when selecting and including studies on built environment auditing.

($n = 1$), and validating/developing the auditing tools ($n = 27$), in accordance with the classification system established by Biljecki and Ito (2021). Subsequently, we proceeded to delineate the applications of SVI in the field of BEA by identifying the aforementioned domains.

Results

Characteristics of the included studies

Through our inclusion criteria, we included a total of 96 studies, with characteristics shown in Table S1 (Supplementary Appendix). All included studies were published after 2010, marking a discernible increase trajectory in the annual number of publications over the past decade, as illustrated in Figure 2. These 96 studies were conducted in 36 countries across the world, specifically, the United States featured prominently with fifty-three studies, followed by seven studies in China and six in Canada. Belgium, Japan, and the United Kingdom each contributed three studies, while Australia, Brazil, and Spain each added two studies. Chile, Germany, Korea, New Zealand, and the Netherlands each hosted one study. Additionally, six studies had a multi-city focus in Europe, such as Ghent (Belgium), Paris (France), Budapest (Hungary), London (the United Kingdom), and the multi-city Randstad (the Netherlands). Two more studies in Melbourne (Australia), Ghent (Belgium), Curitiba (Brazil), Hong Kong (China), and Valencia (Spain), with one study each in San Francesco (the United States), and Oslo (Norway). The remaining study covered a remarkable 59 cities spanning 26 European countries. These studies were conducted at various geographic scales, including nationwide ($n = 2$), multi-state ($n = 2$), multi-city ($n = 25$), multi-county ($n = 3$),

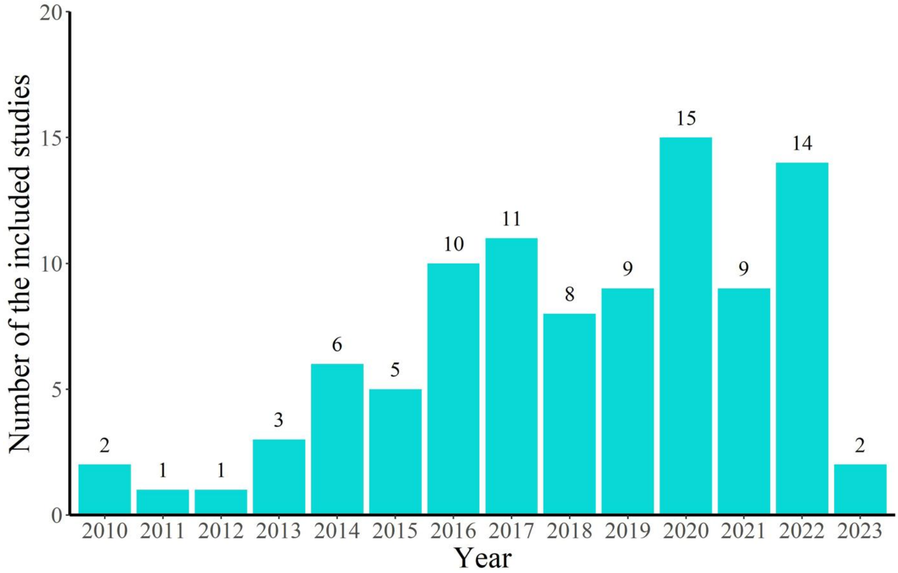

Figure 2. Number of the included studies published each year.

single-county ($n = 2$), single-state ($n = 5$), single-city ($n = 56$), and street ($n = 1$) (see Supplementary Appendix Table S1). The basic units of analysis in BEA ranged from neighborhoods, street segments, and street intersections.

Types of SVI and auditing tools

The vast majority of the studies (89 of 96, 92.7%) utilized Google SVI for BEA, while the remaining seven studies explored alternative SVI sources including Tencent SVI and Baidu SVI. Additionally, 13 studies employed other SVI sources, such as Bing Map, closed-circuit television, daum road view service, Google Earth, and Google Maps alongside Google SVI. In most studies (78 of 96, 81.3%), SVI was processed for BEA manually. Only 18 studies used computer vision and artificial intelligence technologies. Among these, deep learning techniques were particularly prevalent, employing convolutional neural network models like visual geometry group-16, visual geometry group-19, ResNet-18, SegNet, and DeepLab V3+. These models were specifically tailored for image segmentation tasks, offering fine-scale detection of eye-level objects, such as trees, sidewalks, and bike lanes.

BEA tools are defined as a range of developed toolsets or instruments utilized to audit and assess built environment attributes, including physical structures, facilities, and surroundings within a given study area, comprising both validated and unvalidated auditing tools. The validated auditing tools were defined as a series of commonly used auditing tools, which are based on well-established references and often implemented as platforms, toolsets, and frameworks. In contrast, unvalidated auditing tools are usually self-developed, lacking validation in other studies, and thus could only serve as conceptual methods without systematic implementation. The frequently used

Table 1. Purpose and applied scenes of validated auditing tools.

Auditing tools	Purpose	Applied scenes	Audited attributes
ANC	Accessing key street-level features related to physical activity	Physical activity-related studies	– Land use types – Sidewalks – Shoulders and bike lanes – Street characteristics – Quality of the environment for pedestrians
CANVAS	Measuring built environmental exposures of interest and environmental effect modifiers	Built environmental exposures and environmental effect-related studies	– Aesthetics – Physical disorder – Pedestrian safety – Motorized traffic and parking – Infrastructure for active travel – Sidewalk amenities – Human presence and social interactions
EGA-Cycling	Assessing the physical environmental characteristics of cycling routes to school	Cycling-related studies	– Land use types – Characteristics of street segment – Cycling facilities – Pedestrian facilities – Aesthetics
MAPS	Examining the associations between microscale environmental attributes and macro-level neighborhood walkability	Walkability-related studies	– Routes – Street segments – Crossings – Cul-de-sac
PEDS	Assessing the walking environment	Walkability-related studies	– Environment – Pedestrian facilities – Road attributes – Walking/Cycling environment
S-VAT	Identifying and comparing environmental characteristics to assess the obesogenicity of neighborhoods	Obesity-related studies	– Walking – Cycling – Public transport – Aesthetics – Land use mix – Grocery stores – Food outlets – Recreational facility-related items
SPACES	Assessing the walking and cycling environment	Active transport behaviors-related studies	– Walking/Cycling function – Walking/Cycling safety – Walking/Cycling aesthetics – Walking/Cycling destinations
SSO	Examining some phenomenon or aspect of behavior	Social-related studies	No uniform audited attributes
SWEAT-R	Understanding the influence of the physical environment on physical activity of older adults	Physical activity-related studies in elders	– Functionality – Safety – Aesthetics – Destinations and facilities
Virtual-STEPS	Auditing instruments that can be used for widespread surveillance at local, provincial, and national levels	Auditing infrastructure	– Pedestrian infrastructure – Traffic calming and streets – Building characteristics – Bicycling infrastructure – Transit – Aesthetics/disorder

ANC: active neighborhood checklist; CANVAS: computer assisted neighborhood visual assessment system; EGA-Cycling: environmental Google street view-based audit-cycling to school; MAPS: Microscale Audit of Pedestrian Streetscapes; PEDS: pedestrian environmental data scan; S-VAT: SPOTLIGHT-Virtual Audit Tool; SPACES: systematic pedestrian and cycling environment scan; SSO: systematic science observation; SWEAT-R: Seniors' Walking Environmental Assessment Tool—Revised; Virtual-STEPS: Virtual Systematic Tool for Evaluating Pedestrian Streetscapes.

validated tools included the Computer Assisted Neighborhood Visual Assessment System (CANVAS, $n = 9$), Active Neighborhood Checklist (ANC, $n = 8$), Microscale Audit of Pedestrians Streetscapes (MAPS, $n = 8$), SPOTLIGHT virtual audit tool (S-VAT, $n = 7$) and Social Science Observation (SSO, $n = 4$). Less frequently used tools, those with usage counts of 2 or less, encompassed the Neighborhood Environment Walkability Scale (NEWS), Pedestrian Environmental Data Scan (PEDS), QUALITY neighborhood obesogenic potential diagnosis (QUALITY-NHOOD), Senior's Walking Environmental Assessment Tool-Revised (SWEAT-R), Systematic Pedestrian And Cycling Environment Scan (SPACES), Virtual Systematic Tool for Evaluating Pedestrian Streetscapes (Virtual-STEPS), Combination of CANVAS, Irivine-Minnisota inventory (Irivine), PEDS, and Project on Human Development Chicago Neighborhoods (PHDCN). In parallel, 28 studies employed unvalidated tools, which were typically developed by investigators themselves to meet the specific needs of their research.

Among single studies, only S-VAT and MAPS were used in multiple countries: six studies harnessed S-VAT, deploying it across five European cities: Belgium, France, Hungary, the Netherlands, and the United Kingdom. Meanwhile, two studies tapped into MAPS, employing it within a broader international context that encompassed five cities spanning Australia, Belgium, Brazil, China, and Spain. The remaining studies were conducted in single countries and used various BEA tools (as depicted in Figure 3(a)). For example, six studies used MAPS across four countries (Belgium, Brazil, Japan, and the United States), while one study employee S-VAT (the Netherlands). In contrast, ANC, CANVAS, and PEDS were primarily used within the United States, while SSO, SWEAT-R, and Virtual-STEPS were used in both Canada and the United States. In Europe, the Environmental Google Street View-Based Audit-Cycling to School (EGA-Cycling) tool found utility specifically in Belgium. Besides, SPACES made appearances in both New Zealand and Spain. Among those studies, S-VAT and Virtual-STEPS were used only by the research groups who developed them, while other auditing tools were utilized by at least two or more research groups (Figure 3(b)).

In terms of scale, tools, such as PEDS, S-VAT, SPACES, SSO, SWEAT-R, and Virtual-STEP have been used at city scales, including single-city ($n = 12$) and multi-city ($n = 7$) studies (as depicted in Figure 4). The rest tools (ANC, EGA-Cycling, MAPS) have been conducted at varying scales, spanning county ($n = 1$), state ($n = 4$), and city ($n = 13$). It is noteworthy that CANVAS stands out as the sole tool applied at the national scale ($n = 1$), although it is worth highlighting that the majority of studies using CANVAS were still primarily conducted at the city ($n = 7$) and county scale ($n = 1$).

Audited built environment attributes and their types

Frequently audited built environment attributes included street-related features (e.g. street lights, street parking, and streetscape aesthetics) ($n = 52$), sidewalk-related features (e.g. width, buffers, and continuity) ($n = 49$), and traffic-related features (e.g. signals, volume, public transit stops, and environment) ($n = 47$). Other notable attributes include land use ($n = 33$), facility-related features ($n = 28$), visual perceptions (e.g. aesthetics) ($n = 25$), and social environment (e.g. safety) ($n = 16$) (as detailed in Figure 5, see Supplementary Appendix Table S1). The selection of these attributes often aligned

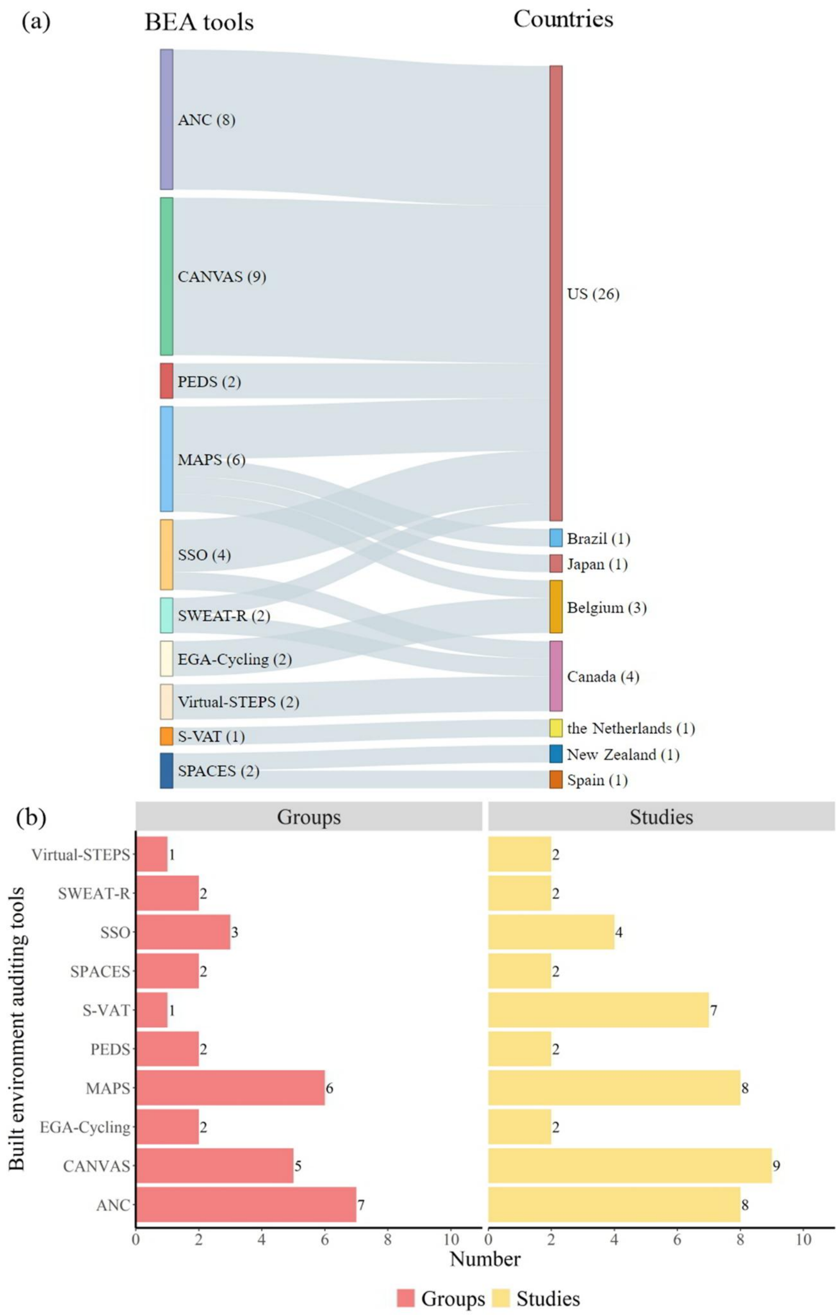

Figure 3. An overview of the studies using different built environment auditing tools in different countries, (a) represents the number of these tools within different countries (in parentheses), (b) represents the number of these tools that have been applied by different groups and in various studies. ANC: active neighborhood checklist; BEA tools: built environment auditing tools; CANVAS: computer assisted neighborhood visual assessment system; EGA-Cycling: environmental Google street view-based audit-cycling to school; MAPS: Microscale Audit of Pedestrian Streetscapes; PEDS: pedestrian environmental data scan; S-VAT: SPOTLIGHT-Virtual Audit Tool; SPACES: systematic pedestrian and cycling environment scan; SSO: systematic science observation; SWEAT-R: Seniors' Walking Environmental Assessment Tool—Revised; Virtual-STEPS: Virtual Systematic Tool for Evaluating Pedestrian Streetscapes.

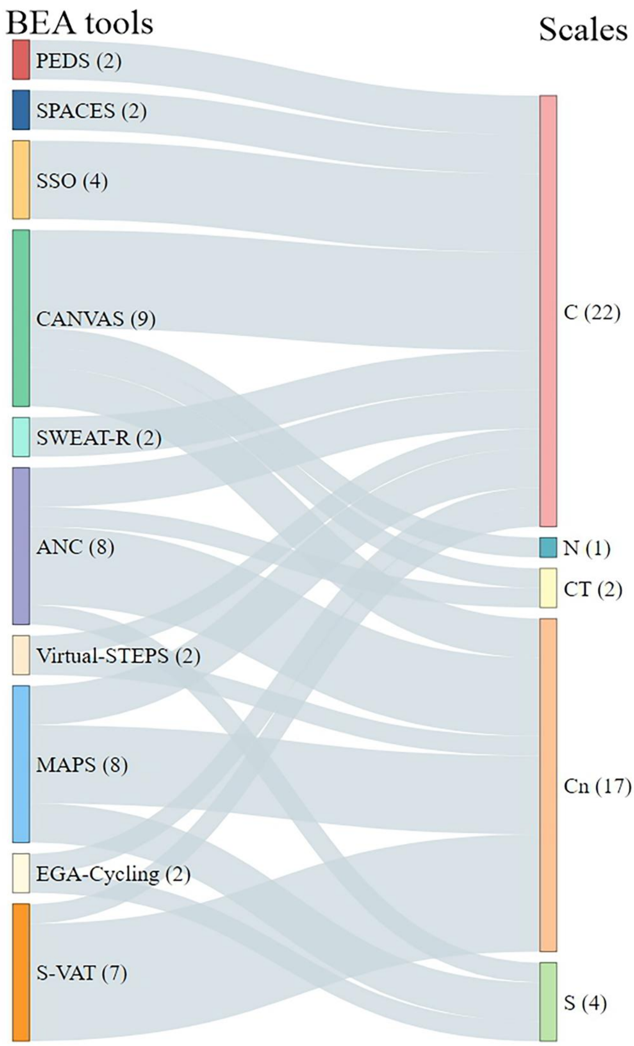

Figure 4. The number of the included studies using different built environment auditing tools at different scales (in parentheses). *Note:* N—National; S—State (e.g. in the US) or equivalent unit; C—City; Cn—multicity; County—County or equivalent unit. ANC: active neighborhood checklist; BEA tools: built environment auditing tools; CANVAS: computer assisted neighborhood visual assessment system; EGA-Cycling: environmental Google Street view-based audit-cycling to school; MAPS: Microscale Audit of Pedestrian Streetscapes; PEDS: pedestrian environmental data scan; S-VAT: SPOTLIGHT-Virtual Audit Tool; SPACES: systematic pedestrian and cycling environment scan; SSO: systematic science observation; SWEAT-R: Seniors' Walking Environmental Assessment Tool—Revised; Virtual-STEPS: Virtual Systematic Tool for Evaluating Pedestrian Streetscapes.

with the specific aims of the auditing, reflecting the distinct classifications within the field. For example, urban morphology studies focused on auditing land use, while transportation and mobility studies typically zeroed in on sidewalk-related features. Studies on health and well-being, socio-economic, and tool validation or development typically audit multiple built environmental variables to capture the comprehensive characteristics of the built environment. These audited attributes manifested as either

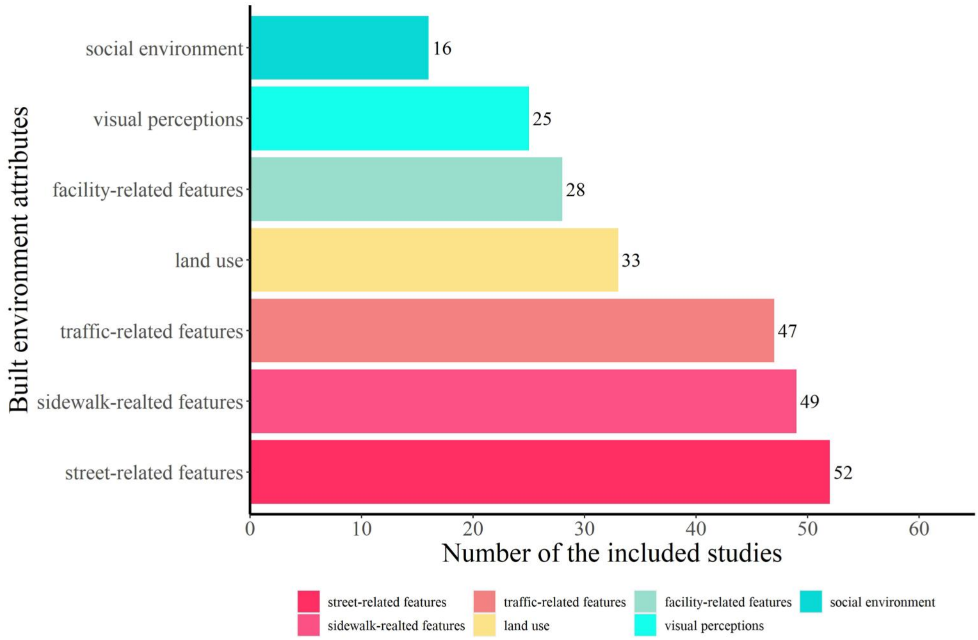

Figure 5. The count of studies auditing different built environment attributes.

continuous or categorical variables. The continuous variables included the number ($n = 12$) and percentage ($n = 13$) of the attributes, such as the number of bicycles and the green area-to-street ratio. Conversely, the categorical variables signified the presence or absence of attributes ($n = 75$), such as the presence of sidewalks, traffic signals, and litter. Other studies considered categorical attributes that spanned various levels ($n = 38$), such as different speed limits. To further assess the quality of these built environment attributes, researchers employed Likert scales ($n = 27$) or scoring values ($n = 9$). These metrics offered quantifiable assessments, spanning criteria, such as the cleanliness of streets and properties or conditions of streets, thus contributing to a nuanced evaluation of the built environment.

Most studies ($n = 64$), undertook an evaluation of the reliability associated with the assessed built environment attributes. This evaluation commonly employed established metrics, including the percentage of agreement ($n = 28$), Cohen's Kappa ($n = 19$), intra-classes coefficients ($n = 14$), Cronbach's α ($n = 3$), and other less frequently used indexes ($n < 3$). The choice of reliability assessment metrics was contingent upon the nature of the audited variable. When the audited variables were continuous, the correlation coefficients were the favored option, while when variables audited were categorical, the percentage of agreement, Cohen's Kappa, intra-classes coefficients (ICC), and Cronbach's α were preferable choices, serving as robust indicators for testing the reliability.

The choice of indicators for audited built environment attributes differs among studies. Due to the ambiguity in some auditing characteristic definitions, the reliability and validity of gathered audit measures tend to be higher for objective attributes

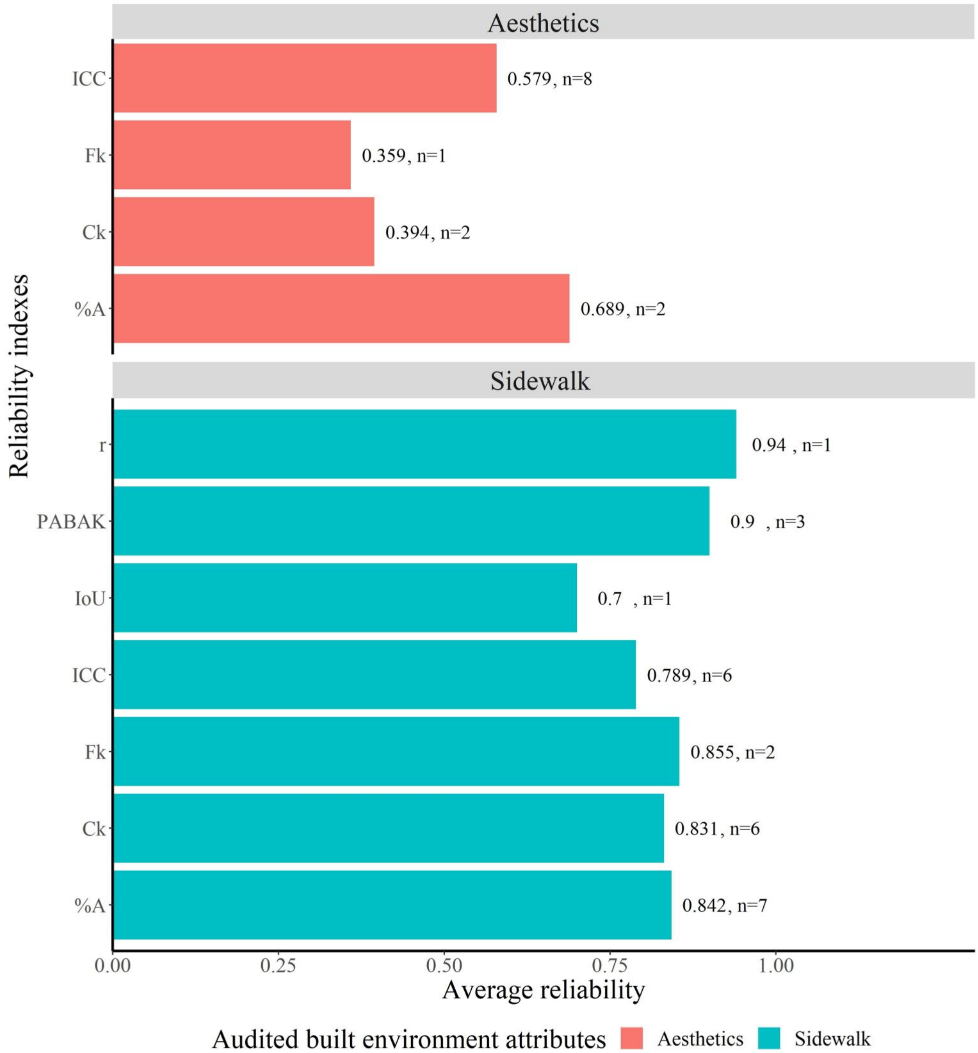

Figure 6. The average reliability indexes among different built environment attributes. Ck: Cohen's kappa statistics; Fk: Fliess' kappa statistic; ICC: intra-class coefficient; IoU: intersection-over-union metric; PABAK: prevalence-adjusted bias-adjusted kappa coefficient; *r*: correlation coefficients; %A: % of agreement.

than subjective assessments. Among audited attributes, the presence of a sidewalk, a typical objective attribute, has the highest average reliability (0.837) across the majority of studies, exceeding the noteworthy threshold of 0.7 (as illustrated in Figure 6). In contrast, subjective measurements, such as the quality of the environment, exhibited lower reliability due to the potential influence of different auditors, as exemplified by aesthetics, which scored an average reliability of 0.505 in Figure 6.

Comparisons of the reliability of built environment attributes across different countries posed challenges due to the diversity of auditing tools, reliability indices, and measurement scales employed. Direct comparisons of unvalidated auditing tools proved intricate, given the inherent variations in auditing items they exhibited. In contrast, validated auditing tools demonstrated their utility in facilitating cross-regional comparisons, including ANC, CANVAS, EGA-Cycling, PEDS, and Virtual-STEPS, which were predominantly applied within specific countries, as illustrated in Figure 4. Among these tools, MAPS stood out as the sole suitable tool for facilitating cross-country reliability comparisons. Upon our analysis, a clear pattern emerged: MAPS, when conducted in the US, exhibited notably higher reliability, with an average Cohen's Kappa coefficient of 0.55. In comparison, MAPS implementations in five global cities (Australia, Belgium, Brazil, China, and Spain) demonstrated slightly lower reliability, with an average intraclass correlation coefficient (ICC) of 0.48.

Several studies using the same auditing tool (S-VAT) were conducted in five European cities across different countries. Notably, safety and aesthetics showed the lowest reliability, as evidenced by Cohen's kappa statistics and Cronbach's $\alpha < 0.5$. In contrast, land use and food outlets consistently demonstrated higher reliability with Cohen's kappa statistics and Cronbach's α surpassing 0.7. Furthermore, when it came to auditing walking and cycling infrastructure, two studies presented divergent reliability results. The reliability of auditing walking infrastructure was reflected in Cohen's kappa statistics exceeding 0.82, whereas for the cycling infrastructure, Cohen's kappa statistics fell below 0.3.

Purpose and application scenarios of validated auditing tools

Most of the validated auditing tools included in this study were designed to investigate the associations between the built environment and health-related behaviors and outcomes, such as cycling, environmental exposure, obesity, physical activity, and walkability (as detailed in Table 1, $n = 8$). Virtual-STEPS is the only tool designed to audit infrastructure across various levels. Specifically, SSO is a more generalized social science methodology to examine phenomena or aspects of behavior beyond health-related concerns. Therefore, these validated auditing tools have diverse application scenarios and audited attributes due to their intended purposes (Table 1). It is important to underscore that the choice of auditing tools should be thoughtfully guided by the specific research objectives, ensuring alignment with the desired outcomes.

The strengths and weakness of the validated auditing tools varied among the different studies. In terms of weakness, some tools lacked certain built environment attributes related to physical activity (ANC) and complex micro-scale elements (MAPS), while others did not have a uniform, standard checklist for BEA (SSO). Moreover, some tools audited the built environment according to observation locations through the internet, potentially raising concerns about the confidentiality of human subjects (CANVAS). The remaining tools may be affected by system errors in the sampling process, for example, audited street segments generated by self-reported cycling routes to schools instead of actual routes (EGA-Cycling). On the flip side, these tools exhibited notable strengths. MAPS, for instance, offers a more comprehensive assessment as it provides scores at four levels, routes, crossings, segments, and cul-de-sacs. CANVAS, as a web application program, has the great potential to integrate longitudinal data. Other tools contribute to specific health-related studies, such as EGC-Cycling for assessing the physical environment along cycling routes, PEDS for assessing the walking environment, S-VAT for assessing the subjective obesogenic environment (obesogenic environment, a fundamental concept in public health, pertains to an environment or context that actively fosters and facilitates the onset of obesity in individuals), SPACES for assessing the walking and cycling environment, and SWEAT-R for physical activity-related aging studies among elders.

Discussion

Enhancing accuracy in quantifying built environment features

Existing SVI-based auditing methods struggle to accurately assess certain built environment attributes that are less quantifiable than dichotomous attributes, such as the presence of sidewalks and traffic lights, etc. For example, even the lowest reliability observed in accessing dichotomous transport environment attributes surpassed that of evaluating the social environment (Ben-Joseph *et al.* 2013). Auditing results for those attributes often differ between auditors and across time periods (Cândido *et al.* 2018). Such attributes typically lack well-defined criteria, systematic schemes of assessment, and accurate geometric information—such as the width of the sidewalk—and may be influenced by subjective factors including individuals' perceptions related to neighborhood aesthetics and safety. We believe addressing these challenges is more complex than image classification and semantic segmentation through computer vision techniques alone (Jia *et al.* 2019a, 2020).

Integrating artificial intelligence (AI) with computer vision holds great potential for overcoming these technical barriers. AI and computer vision can collaboratively create a standardized dataset of commonly built environmental features with consistent or relatively stable geometric information, such as cars. By using these features as references within the SVI, geometric information for other features can be inferred from the degrees of distortion, as determined by computer vision. Nguyen and colleagues have made substantial contributions to the field of environmental auditing through the application of AI and computer vision. They leveraged deep learning models to construct a comprehensive neighborhood characteristic database derived from Google SVI data, covering regions across the United States. Their research endeavors, spanning multiple publications (Nguyen *et al.* 2018, 2019, 2020, 2021, 2022, Yue *et al.* 2022), have centered on investigating the intricate relationships between the built environment and various health outcomes. Of particular significance is their pioneering work in providing practical examples of auditing items, which encompass elements, such as buildings, crosswalks, and greenery. This exemplifies the utilization of AI and computer vision techniques in conducting audits, thereby advancing the methodology in this domain. For instance, one study conducted in China utilized Tencent SVI and a deep learning model to assess the quality of the street space (Tang and Long 2019). However, it is worth noting that the number of audited attributes is still much lower than auditing by labor efforts. Also, the development of end-to-end deep learning models, spanning from initial input to final output variables, may be particularly suited for the Likert-scale variables like neighborhood safety. This serves to minimize subjectivity bias and inconsistencies among auditors. For example, Google SVI has been used to infer the perceived safety (safety scores ranging from 0 to 10) (Zhang *et al.* 2021), while Tencent SVI has been employed to measure physical disorder (a scoring value ranging from 0.16 to 0.48) in China (Chen *et al.* 2022). In addition, despite the rapid development of methodologies, we found that most studies still heavily relied on human labor rather than fully harnessing the capabilities of computer vision techniques. In fact, the number of audited streets in existing studies has been <1,000 and has been limited to a single city or a small number of cities. The integration of AI has the potential to scale up SVI-based built environmental auditing to encompass a large study area, which is often necessary for large-sample health datasets, such as epidemiological cohort studies. For instance, a study conducted in China examined the associations between SVI-derived urban neighborhood disorder and the long-term recurrence risk of patients with acute myocardial infarction (Zhang *et al.* 2023).

Choosing a suitable SVI-based BEA method and enhancing robustness

Our study showed that SVI-based BEA is comprised of virtual audits by labors (VL) and computer-assisted audits (CA) (81.3 *vs.* 18.7%, Supplementary Appendix Table S1). VL is labor-intensive, which hinders large-scale BEA. Typically, the number of audited units is <1,000, and the scope is limited to a single city. However, the strength of VL lies in the customization of audited built environment attributes to cater to specific research objectives. For example, a series of studies used S-VAT but they audited different attributes based on their research needs (Bethlehem *et al.* 2014, Compernolle *et al.* 2016). In contrast, CA faces challenges in expanding the spectrum of audited attributes, particularly subjective ones. CA relies on extracting the required attributes from semantic segments of deep learning models, which were fixed and depended on the labeled training datasets. For example, while CA could audit the green space and crosswalk, it may not be able to access subjective built environmental conditions that are not labeled in the training dataset, such as the availability of dedicated places for walking or cycling (Keralis *et al.* 2020). Despite this limitation, CA can be applied to a wider geographical extent, e.g. covering national or regional scales, while efficiently obtaining objective attributes and avoiding the need for labor-intensive work. Researchers should choose the best method according to the strength of SVI-based BEA methods and their research goals.

Validating SVI-based BEA results demands caution, and further practical studies are needed, especially in developing countries. Validation of VL requires multiple auditors whose results can be compared to enhance validation effectiveness under a uniform training process. If possible, the field auditing results can complement the validation process. Additionally, when it comes to VL-based audit tools, particularly those validated ones, our findings indicate that they tend to exhibit higher reliability in the country where they were originally developed as compared to their application in other countries (Millstein *et al.* 2013, Fox *et al.* 2021, Koo *et al.* 2022). This discrepancy can likely be attributed to the differences between auditing attributes initially formulated to suit the specific built environment of the country in which the tool was created, and those in different countries. For CA, the validation mostly relied on the validation datasets of the deep learning model, which are scarce in developing countries. Tencent SVI was leveraged to assess physical disorder within a large urban area in China (Chen *et al.* 2022, Li *et al.* 2022a). A developed virtual audit platform encompassed 16 attributes that evaluate the quality of street spaces across five dimensions (Li *et al.* 2022a). These studies, as the practical case studies in the realm of BEA, offer valuable insight and a blueprint that can be adapted for other developing countries. Thus, there is room for improvement in the validation of the SVI-based BEA, with particular attention to the reliability measurements of built environment attributes during validation.

Reliability measurements in SVI-based built environment audits are contingent on the specific attributes being audited and the auditing methods employed. They vary depending on whether the audited environment attributes are subjective or objective in nature. For example, Cohen's Kappa should be used in categorical attributes, such as the presence of sidewalks, and relative correlation coefficients for continuous attributes, such as car counts, while different auditing methods employ distinctive assessment indicators: VL primarily uses consistent assessment indicators, such as the agreement of prevalence and CA relies on traditional machine learning model performance evaluation metrics, such as the F1 score, R^2, and AUC.

Considering existing validation and reliability measurements, auditing built environment attributes still faces challenges. Objective attributes may focus on obtaining more accurate geometric information, while subjective attributes need the establishment of a scoring standard for assessing built environment conditions, thereby making the auditing results more robust. For example, the Place Pulse dataset was an effective solution for assessing built environment conditions, aiming to map urban areas perceived as safer, livelier, wealthier, more active, beautiful, and friendly (Salesses *et al.* 2013, Naik *et al.* 2014, 2016, 2017). We believe that AI-powered BEA tools may be available in the future based on this summarized characteristic of existing tools in this study.

Addressing time lag and spatial limitations of SVI

Current SVI-based auditing grapples with issues related to time lag and spatial limitations, potentially affecting the accuracy of BEA. The data update cycle of SVI for certain locations has been observed to be relatively lengthy, particularly in rapidly expanding urban areas. Moreover, images were updated progressively and independently across space, which means that some adjacent locations' SVIs may not be captured simultaneously. For example, the newly taken SVI had the highest correlation coefficient with field auditing (Wilson *et al.* 2012). Additionally, the capturing method of SVI only records views from the street, this shortcoming was especially evident in developing countries where images are primarily available only along major roads.

SVI taken in field surveys and generated from other sources (e.g. commercial providers of panoramic images, Giga Pan®, and Lancers) could supplement Google SVI. For instance, Giga Pan® has demonstrated a high sensitivity of up to 80%, making it a viable alternative when Google SVI is unavailable (Twardzik *et al.* 2018). The increasing availability of other SVIs in developing countries also provides opportunities for carrying out BEA and designing corresponding auditing tools. Both Baidu and Tencent SVI have expanded their coverage to include more than 297 cities in China. Nevertheless, SVIs from other sources may be insufficiently accurate. In a comparison study of auditing results, Google SVI showed higher reliability in measuring small features (e.g. levelness and condition of sidewalks, obstructions, and presence of bike racks) than field surveys, Google Maps, and Bing Maps (Ben-Joseph *et al.* 2013). Consequently, when combining SVI data from various sources, it is essential to exercise caution and conduct reliability and consistency testing before utilization.

Bridging the BEA and urban exposome observation through SVI

SVI performs exceptionally well in capturing environmental variables, thereby advancing future environmental health research. It enables the measurements of urban exposome surrounding the participants in large cohorts (Jia *et al.* 2019b). The urban exposome comprises a collection of environmental factors representing an individual's real-life exposure to the outdoor urban environment, with potential implications for human health (Jia 2019). These factors include the built environment, air pollution, road traffic-related indicators, weather, and natural space (Jia and Stein,2017 Robinson *et al.* 2018, Nieuwenhuijsen *et al.* 2019, Ohanyan *et al.* 2022). Consequently, the SVI-based BEA could be an effective tool to observe the urban exposome. For instance, frequently audited built environment attributes are regarded as the most important obesogenic urban exposome. These include factors related to traffic (Luo *et al.* 2021, Wang *et al.* 2021), sidewalks (Wei *et al.* 2021), neighborhood aesthetics (Qu *et al.* 2021), walkability (Yang *et al.* 2021), land use (Jia *et al.* 2021), and bike lanes (Pan *et al.* 2021). In most of the previous cross-sectional or cohort studies, data on an individual's surrounding urban exposome were self-reported by the participants (Gubbels *et al.* 2011). Self-reported data, however, can suffer from bias from participants. Using historical SVI and BEA could help extract the built environment attributes, including sidewalks (Hamim *et al.* 2023), traffic-related factors (Dai *et al.* 2023, Hu *et al.* 2023) and socio-economics factors (Fan *et al.* 2023), to mitigate bias. This would also allow for the comparison of self-reported results, validation of datasets to improve the quality of large cohort data, observation of urban exposome during the life course, and investigation of the potential causal associations between the built environment and human health outcomes.

Lessons learned

Through a systematic review of the commonly audited built environment attributes and auditing tools, our findings provide a comprehensive understanding of the state-of-the-art SVI-based auditing approaches and offer insights into future directions for development. The reliability of these audits varies depending on the type of attribute and the assessment tool used. We have learned that objective attributes, such as the presence of a sidewalk, generally yield higher reliability, while subjective assessments may be influenced by auditor biases, resulting in lower reliability. The use of standardized auditing tools, such as S-VAT, across multiple cities demonstrates the potential for improved comparability and generalizability of research findings. Considering the number of research groups that used these tools, ANC and MAPS were identified as the two most widely accepted auditing tools. Furthermore, many standardized auditing tools have been exclusively implemented in specific countries. This is often attributed to auditing of those attributes that are relevant in these particular countries, which may not necessarily align with conditions found in other nations. Consequently, this localization of attributes has resulted in higher reliability when the tools are applied in the country where they were originally developed, as compared to their performance in other countries. The varying levels of reliability for different attributes within the same tool indicate the need for further refinement and standardization of assessment criteria.

The methodology's merits lie in the adoption of a classification of auditing aims and the integration of various built environment features, ultimately allowing researchers to better understand the relationship between urban design and public health. The broader impact of these findings can inform urban planning and policy-making efforts to promote healthier and more sustainable living environments. Achieving higher reliability in built environment audits requires a careful balance between objective and subjective attributes and the adoption of standardized tools and assessment criteria. This can lead to more robust research findings and an improved understanding of urban environments, ultimately contributing to better-informed urban planning and policy decisions.

Conclusions

This systematic review summarizes the characteristics of the 96 relevant studies of BEA, highlights the current challenges in this area, and proposes potential solutions and future research directions. SVI performs well in capturing certain attributes of the built environment, consistently delivering high audit accuracy. Consequently, there is a pressing imperative: Firstly, we should integrate the power of AI with SVI to establish the standard dataset of commonly built environmental features with invariant or stable geometric information. Secondly, we should explore the potential benefits of using multi-source SVI to facilitate the creating of spatially complete and temporally consistent urban scenes. Thirdly, it is vital to concentrate on customizing and validating BEA tools that are tailor-made for the unique contexts of developing countries. SVI holds immense potential to facilitate environmental health-related studies in the big data era, especially in urban exposome observation. Compared to alternative observation methods like remote sensing or field observation, SVI offers a cost-effective and highly efficient means of capturing the urban physical environment at eye level.

This review shows that SVI has so far proved to be a powerful data source that can be used for environmental auditing on many research topics. As SVI continues to gain popularity, and data collection and processing methods become more standardized, along with the potential expansion of the SVI databases in the future, we anticipate to have access to increasingly accurate spatio-temporal SVI data and cross-platform compatibility in the future. SVI will then become a valuable data source in a growing array of research fields. This study underscores that advancements and adaptations in research methodologies will ultimately facilitate the seamless integration of this novel geospatial data type into diverse research disciplines.

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Author contributions

Peng Jia conceived the idea, secured the funding, supervised the study, and revised the manuscript. Shaoqing Dai conducted the study and wrote the manuscript. Yuchen Li critically revised the manuscript. Alfred Stein and Shujuan Yang commented and revised the manuscript.

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