Cities 156 (2025) 105535

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Understanding the user perspective on urban public spaces: A systematic review and opportunities for machine learning

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ARTICLE INFO

Keywords:
Urban public spaces
Users
Computer Vision
GeoAI
Natural Language Processing
Street

ABSTRACT

With people-centered approaches gaining prominence in urban development, studying urban public spaces from the user's perspective has become crucial for effective urban design, planning, and policy-making. The rapid advancement of Machine Learning (ML) techniques has enhanced the ability to analyze and understand user data in urban public spaces, such as usage patterns, activities, and public opinions. However, limited efforts have been made on a structured understanding of urban public spaces from the user's perspective. These knowledge gaps have also hindered the full realization of ML's potential in describing and analyzing urban public spaces. After systematically reviewing 319 relevant papers, this study analyzes ten dimensions of the user's perspective on urban public spaces and identifies three unaddressed issues: (1) interpretation of user's perception, (2) overlooked user demographics, and (3) data acquisition. In addition, this review also examines the applications of ML to these dimensions and their potential to tackle the three issues, and highlights two main opportunities to integrate ML for more rigorous and data-driven public spaces studies: (1) combining Computer Vision and Natural Language Processing in public spaces quality measurement and (2) investing in high-quality user data.

1. Introduction

Urban public spaces is a core concept and an essential physical element in cities and crucial for improving the quality of life and well-being of society (Carmona, 2010; Carr et al., 1992; Gehl & Svarre, 2013; Talen, 2008). Based on this value, the primary qualities of urban public spaces have been regarded as publicness (Varna, 2014) and sociability (Mehta, 2014), embodying a strong connection between the spaces and their users. A widely accepted argument suggests that urban designers and authorities should prioritize the public's needs during the space-shaping process, acknowledging people's right to inspect the quality of urban public spaces (Banerjee, 2001; Carmona & Sieh, 2004; Mehta, 2014). Consequently, the exploration towards a more profound comprehension of space quality from the lens of users has become a noticeable subject in urban studies. Importantly, the user's perspective is crucial for informing urban policy and management decisions. For instance, incorporating user feedback on the accessibility and safety of public parks can guide policymakers in allocating resources for infrastructure improvements or security measures, ensuring these spaces meet the public needs and expectations. Despite its significance, the examination of the user's perspective on urban public spaces has yet to be systematically sorted out.

Meanwhile, Machine Learning (ML) has increasingly been employed in urban public spaces research (Barreda Luna et al., 2022; D'Autilia & Hetman, 2018; Song et al., 2021; Wilczynska et al., 2021), primarily to address quantitative aspects, such as spatial data mining and pattern recognition of daily lives in public spaces (Ojha et al., 2019). Thanks to the capability of dealing with complex and nonlinear urban public spaces data, ML is gaining attention in this field, supporting the trend of a more scientific and quantitative evolution (Ibrahim et al., 2020). While a few literature reviews have examined ML applications in urban design and planning (Chaturvedi & de Vries, 2021; Ibrahim et al., 2020; Wang & Biljecki, 2022), their focus or starting point has primarily focused on the technical aspects of ML. In contrast, this review will approach the discussion of ML from the specific lens of the user's perspective in urban public spaces. By thoroughly reviewing the existing research on this topic, the discussion of ML will be centered on exploring its potential solutions to address the remaining issues and challenges identified.

Therefore, this article systematically reviews the existing literature

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https://doi.org/10.1016/j.cities.2024.105535
Received 9 January 2024; Received in revised form 7 May 2024; Accepted 16 October 2024
Available online 6 November 2024

to derive a clear understanding of the user's perspective on urban public spaces, and then assesses the extent to which ML has been applied to this topic for suggesting new opportunities for future studies. With a dual objective, this review aims to:

(1) Delineate the key dimensions of the user's perspective on urban public spaces and highlight the remaining challenges that need to be addressed.
(2) Provide an overview of the role of ML in this topic, outlining a future research agenda that can leverage the full potential of ML techniques to advance the understanding of user's perspective in urban public spaces.

Through a systematic examination of the user's perspective and the applications of ML, this review seeks to contribute a holistic understanding of this crucial aspect of urban studies. It will also uncover gaps and opportunities for integrating ML approaches in further research.

The structure of this review is as follows. First, in Section 2, the background of relevant urban public spaces studies and ML applications in this field are introduced. Section 3 describes the review approach. Then, the dimensions and challenges of the user's perspective on urban public spaces and the ML applications are presented in Sections 4 and 5, respectively. Finally, research opportunities and potentials are discussed in Section 6.

2. Background

How to define urban public spaces is a longstanding debate among scholars in this field. While there are various perspectives on this matter, it is widely accepted that "publicness" is the key quality of urban public spaces (Varna, 2014) and "sociability" is a primary role of it (Mehta, 2014). One fundamental function of urban public spaces is to fulfill the general public's needs and requirements (Alwah et al., 2021; Carmona & Tiesdell, 2007; Carr et al., 1992; Francis, 2003). However, opinions or perspectives from the public are often neglected in both academia and practice. This oversight highlights a critical gap in the understanding and evaluation of urban public spaces, where the user's perspective remains underexplored (Alwah et al., 2021; Carmona & Tiesdell, 2007; Carr et al., 1992; Lynch, 1984; Zamanifard et al., 2019).

In recent years, scholars have made significant progress in addressing this gap by developing indexes, tools, or methods for urban public spaces quality measurements and assessments that prioritize the user's perspective (Alwah et al., 2021; Cho et al., 2015; Ewing & Clemente, 2013; Mehta, 2014; Varna, 2014). These tools can help identify specific areas for improvement in urban design and management, and to enhance the overall user experience and satisfaction (Mehta, 2014). Moreover, quantitative data generated from these tools can facilitate evidence-based decision-making, enabling policymakers and designers to prioritize resources based on more objective assessments of space quality (Ewing & Clemente, 2013).

Among these studies, Mehta's (2014) Public Space Index (PSI) could be a significant milestone. By summarizing the influential works such as Carr et al.'s (1992) and Gehl's (1971) studies, Mehta developed the PSI consisting of five dimensions: inclusiveness, meaningful activities, safety, comfort, and pleasurability. This framework has a profound influence on later studies. Zamanifard extended PSI into the Public Space Experiential Quality Index (PSEQI), notably emphasizing the user's perspective (Zamanifard et al., 2019). PSEQI integrates insights from diverse studies, forming a comprehensive framework for evaluating urban public spaces. This holistic approach enables policymakers, designers, and stakeholders to understand the needs and preferences of users. Unlike previous tools that may have focused primarily on physical attributes, PSEQI acknowledges the multifaceted nature of user experience. It considers factors like perceived accessibility or sense of safety, recognizing them collectively contribute to the overall quality of public spaces. As a result, it provides one of the most comprehensive discussions of the user's perspective on urban public spaces.

Starting from concluding the essential functions of urban public space, Zamanifard et al. (2019) reorganizes the key elements of urban public spaces qualities in previous studies from the user's perspective and sorted them into four dimensions and 15 variables. These dimensions are as follows, along with their respective variables indicated in brackets: *comfort (perceived accessibility, sense of safety, climate comfortability, walking convenience, seating convenience), inclusiveness (perceived university, sense of exclusion, feeling towards regulation and control, managerial activities, commerciality), diversity & vitality (use and activity, events and programs attendance, potential of meaningful social interactions), image & likeability (feelings towards place, likes and dislikes)*. The PSEQI is "the user-centered approach to the characteristics that urban scholars associate with good (responsive) public spaces". It also argues that users' evaluation of urban public spaces' quality is as important as expert observation (Zamanifard et al., 2019). Therefore, this research, particularly the 15 variables, provides a significant reference for discussing urban public spaces from the user's perspective.

However, it is important to note that while PSEQI offers one of the most comprehensive discussions of the user's perspective on urban public spaces, its initial intent for these 15 variables was primarily to measure the spaces quality. Therefore, it is necessary to rethink these variables when exploring the relationship between users and urban public spaces. To achieve this, a review of existing studies is needed to understand what dimensions of the user's perspective are relevant to urban public spaces and what still requires further study. This review will utilize these 15 variables as the starting point and reorganize them into different dimensions of the user's perspective during the review process, as outlined in Section 3.

At the same time, the above quantitative tools also face criticism, some argue that use of standardized metrics may fail to capture the unique context and nuanced qualities, potentially leading to oversimplified or misleading assessments (Ewing & Clemente, 2013). Quantitative data collection and analysis can also be resource-intensive, and the data availability and quality could be questionable (Alwah et al., 2021). Encouragingly, the emergence of new data environments and ML methods suggests opportunities to ameliorate many problems associated with these quantitative tools. This, in turn, heightens the potential for these tools to more accurately and comprehensively inform urban design and policy-making.

Compared to the frequently used research methods that are usually limited to sporadic observations and laborious data collection (Noyman et al., 2019), the ML approach can save time and cost (Chaturvedi & de Vries, 2021; Rossetti et al., 2019), and deal with the "loose", "noisy", and "scattered" social media data and self-motivated content (Yang & Liu, 2022). For instance, Song et al. (2021) performed topic modeling tasks based on TripAdvisor review data for a sense of place study. Currently, reviews have been done on computer vision (Biljecki & Ito, 2021; Ibrahim et al., 2020) and ML in urban land use planning (Chaturvedi & de Vries, 2021) or urban geography (Liu & Biljecki, 2022). More scholars intend to unlock the potential of ML to study urban public space, especially its power to investigate public spaces through users.

However, the integration of ML in urban public spaces research is still at an early stage and needs coherence. This leads to a fragmented understanding of its potential applications. Furthermore, there are still several questions that require clarification to fully comprehend the user's perspective on urban public space, which makes the potentials of ML in this topic more ambiguous in future studies. Thus, it is imperative to conduct a more thorough investigation into existing studies of user's perspective on urban public spaces and review the integration of ML in these studies. Through this approach, it will be possible to gain a more comprehensive understanding of the value of ML in advancing the knowledge of urban public spaces from the user's perspective and optimizing the future research agenda.

3. Review approach

A systematic review approach (Biljecki & Ito, 2021; Chaturvedi & de Vries, 2021) was adopted to identify papers relevant to the user's perspective on urban public spaces. The process involved five key steps (Fig. 1):

(1) An initial pool of papers was acquired through keyword searches.
(2) Irrelevant papers were manually screened out based on pre-defined criteria.
(3) Spider backward searches were performed to obtain additional relevant papers to form the final review corpus.
(4) The full texts of the final review corpus were assessed to summarize each paper's key ideas, research intentions, and problems addressed.
(5) An in-depth analysis was conducted with a specific focus on the research methods employed, especially those utilizing ML approaches.

Before the initial search, it is crucial to define "urban public spaces". This review adopts Zamanifard's summary of relevant studies: "An urban public space refers to a built environment within a city or downtown area that is freely accessible to the general public and serves multiple purposes." This definition aligns with Carr et al.'s (1992) description of public spaces as "the stage upon which the drama of communal life unfolds", emphasizing their role in facilitating movement, communication, play, and relaxation. Both definitions highlight the essential characteristics of urban public spaces as accessible, multifunctional areas that support various aspects of urban life. This understanding is widely recognized by researchers in urban design and planning fields (Alwah et al., 2021; Carmona, 2010; Mehta, 2014; Varna, 2014). According to this definition, categories of urban public spaces included in this review are urban parks, squares, plazas, sheltered activity spaces, playgrounds, streets, and so on. Spaces with pre-assigned specified functions like food courts, sports courts, car parks, and public transportation spaces are also not under discussion here (Carmona, 2010). The term "user" refers to "the general public who use the space and are not involved in the design or management of that space (Zamanifard et al., 2019)".

Therefore, in step one, the keywords "public", "space*", "user*" were used to search the "Topic" (title, abstract, and keyword) in the *Web of Science Core Collection* for the relevant literature. By using the combination of "public" and "space*", space categories in most of the search results were in line with the urban public spaces definition above, such as "public space", "urban open space", "urban parks", and so on. However, papers focusing on spaces like "public transportation space" or "public stadiums" were also covered. These would be screened out manually in step two. The keyword "user*" was used to ensure the papers included perspective from space user, some important terms like "residents" or "citizens" could also be covered by this keyword as "user" was a widely used term in urban public spaces research. Categories of search results are limited to "urban studies" and "regional urban planning" to focus more on urban space issues. The last query was performed on 31 August 2023, and there were 563 search results in total.

In step two, the above papers were assessed according to the following screening criteria: (1) Only the full text written in English was considered. (2) The public spaces should be consistent with the above definition of urban public space. For example, those papers focusing on

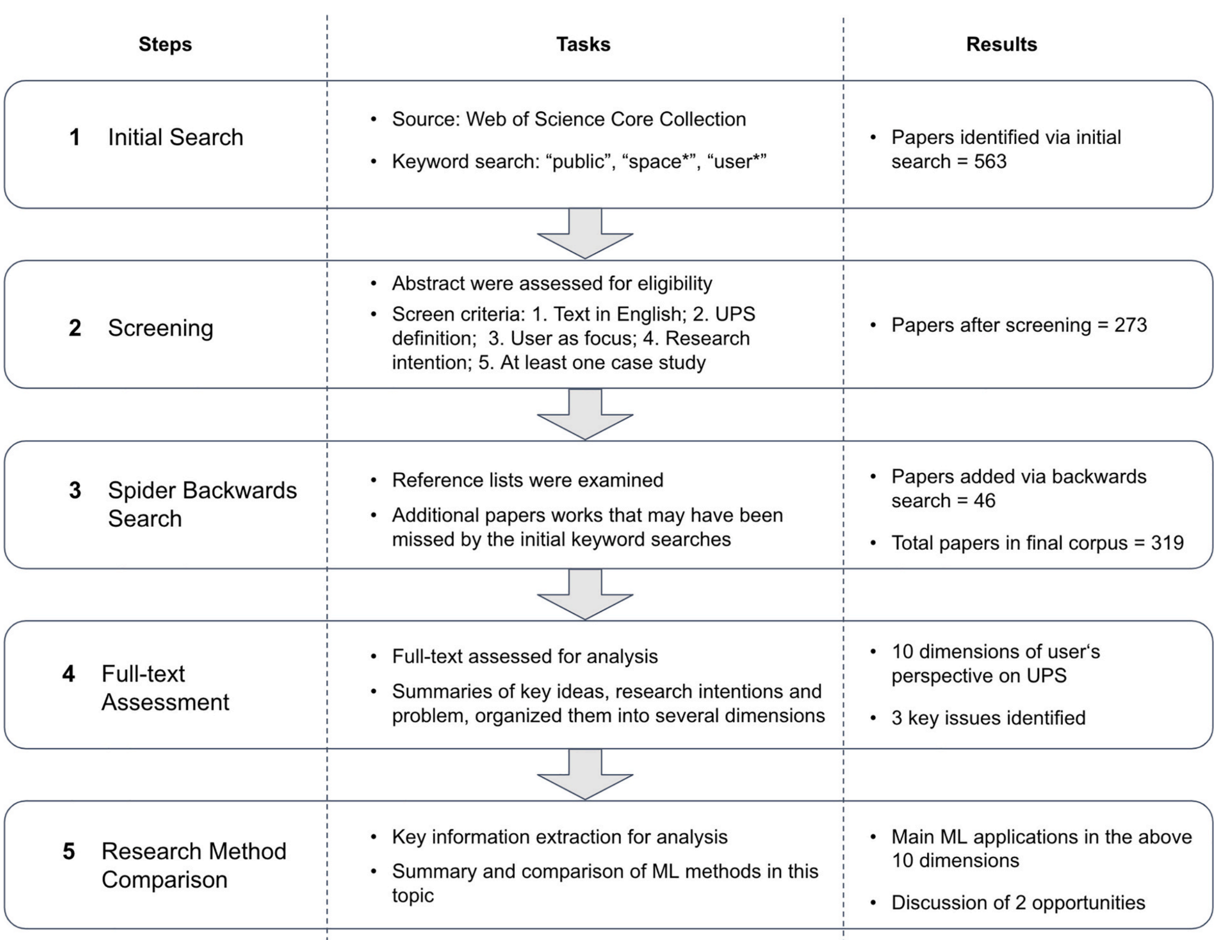

Fig. 1. Flowchart of review approach.

the transportation space or those in remote suburban or rural areas were excluded. (3) Users should be one of the main subjects when studying the space; (4) The research intention should improve urban public space quality. Some papers were deducted as their focuses were human health, medical research, infrastructure planning, etc. (5) The research should contain solid research methods and at least one case study to ensure the research depth and quality. Eventually, 273 papers were selected after the screening process.

In step three, spider backward searches were conducted because it was found that some critical papers mentioned in Section 1 were missing in the initial search results. As a result, another 46 papers were added to the corpus. They are not shown in the search results because one of the search keywords was not mentioned in their paper titles or abstracts. For example, the paper studying the user's perspective on street quality (Zhang et al., 2019) was not shown in search results in step one because it did not mention the keyword "public spaces". Due to the generic nature of the urban public spaces topic and the exploratory intention, this review does not claim to cover all the existing papers relating to user's perspective on urban public spaces. Nevertheless, most literature, especially research trends in recent years, would have been captured by this corpus of 319 papers.

In step four, the full texts of the 319 papers were analyzed, focusing on the research intentions, dimensions of the user's perspective, methods, contributions, and limitations. The results were then organized into several dimensions using the variables in PSEQI as a reference. During the review process, the initial 15 variables were recalibrated in two manners:

First, some variables were combined to avoid repetition, as the variables were initially designed for measuring space quality, and overly detailed for organizing literature. Four variables were combined into the *use & activity* dimension for integrated discussion. *Potential of meaningful social interactions* and *events & programs attendance* variables are included due to their shared definition as the *use & activity* dimension: Research in this dimension investigates the reason and pattern of people using a place and participating in activities, people's behavior and social interactions in public spaces. *Seating convenience* and *walking convenience* variables are two critical indicators for public spaces. In the reviewed studies, they were always discussed with user's (walking) behaviors, and they contribute to the foundation for social interaction and activities in public spaces (Frank, 2020), therefore, they are also included in this dimension. Moreover, *sense of exclusion* and *perceived university* variables were lumped into *universality* dimension. Universality shares the same meaning as inclusiveness, which "signifies that space design and managing policies reassure accessibility and useability of the space for all members of the society". This definition inherently encompasses the meaning of *sense of exclusion* and *perceived university* variables, which are two measuring indicators for *universality* (Cheliotis, 2020; Thombre & Kapshe, 2021). Similarly, *feeling towards regulation and control*, *managerial activities* and *commerciality* were lumped into *feeling towards management* dimension. Second, two new dimensions, *sensory experience* and *health*, were added.

Because PSEQI was based on a particular research purpose, the 15 variables could not cover all the topics when discussing the review results. In addition to the variables in PSEQI, some papers investigated the user's visual experience (Ma et al., 2021) or sound quality (Engel et al., 2018) in urban public spaces, they were included into the *sensory experience* dimension, which means user's sense towards the surrounding environments, such as the sight, hearing and smell. Furthermore, there were also studies about the relations between public spaces and user's physical or mental health (Campagnaro et al., 2020; Grilli et al., 2020; Peschardt & Stigsdotter, 2013), so the *health* dimension was added. Eventually, this review presents ten dimensions describing the user's perspective on urban public spaces.

In the final step, particular attention was paid to how the ML techniques were employed across the studies in relation to the previously identified ten dimensions and issues of the user's perspective on urban public spaces. Ultimately, based on this comprehensive assessment of the literature, two significant opportunities for future studies in this field were identified and discussed.

4. User's perspective and its dimensions

This section presents the review result of the ten dimensions of the user's perspective on urban public spaces and the research gaps. First, the state of the art of the literature in ten dimensions is discussed respectively. Second, three unresolved issues of the user's perspectives on urban public spaces research are identified based on synthesizing the above ten dimensions.

4.1. The ten dimensions of user's perspective

The user's perspective on urban public spaces includes the following ten dimensions: *Feeling towards place*, *Satisfaction*, *Sensory experience*, *Use & activity*, *Sense of safety*, *Health*, *Climate comfortability*, *Perceived accessibility*, *Universality*, and *Feeling towards management*. The number of papers included in each dimension is shown in Fig. 2. A single research paper may address more than one dimension but not more than two. For example, in an article examining the role of aesthetics in the conviviality of public open spaces, both *Sensory experience* and *Universality* dimensions were discussed (Thombre & Kapshe, 2021).

For each dimension, the definitions and scope are first clarified, the significant discoveries are summarized, and then the limitations or unsolved problems are discussed in the end. Table 1 provides a summary of the key focus of each dimension.

4.1.1. Feeling towards place

The definition of *feeling towards place* dimension is quoted from the same variable in PSEQI, which is "used in a broader sense and reflects the feelings and opinions, both negative and positive, that people hold towards a place (Zamanifard et al., 2019)." This definition is developed from the concepts of imageability by Lynch (1960) and likeability by Nasar (1990). According to this definition, some other terms could be categorized into this dimension, including user's perspective (Abbasi et al., 2016; He et al., 2020; Rossetti et al., 2019), preference (Loures, 2015; Naghibi et al., 2020; Rahnema et al., 2019), and the sense of place (Song et al., 2021). There are 135 papers focusing on this dimension. The papers that specifically study the user's satisfaction were discussed in the later *satisfaction* dimension.

Research of this dimension mainly focuses on three issues: (1) Framework for urban public spaces quality measurement. (2) Perceptions of particular user groups. (3) Relationships with other factors.

The urban public spaces quality measurement frameworks usually employ literature review, focus group, and case study supported by structured or semi-structured interviews and questionnaires (Muleya & Campbell, 2020; Dŏgan, 2021; Alwah et al., 2021). These proposed frameworks had some convergence, such as the sensory public space quality framework (Muleya & Campbell, 2020) adapting the PSEQI for more specific scenarios. The quantitative tool proposed by Alwah et al. (2021) breaks down the variable measurement into a finer resolution to provide a more specific interpretation of the user's preference for urban parks and urban squares.

Studies also frequently examine perceptions of specific user groups like teenagers and the elderly (Lesan & Gjerde, 2021; Manyani et al., 2021; Subramanian & Jana, 2018; Wickramaarachchi et al., 2022), providing evidence for specific urban improvement strategies. For example, by studying 51 recreational open spaces across three cities in India, Subramanian and Jana (2018) collected the elders' feelings to identify the deficits in essential convenience and provided a more specific elder-friendly urban design guideline in Indian cities.

Another issue is the relationships between users' feelings and other factors like human health (Grilli et al., 2020; Knoell et al., 2018), air qualities (Engel et al., 2018), activities (Stigsdotter & Grahn, 2011).

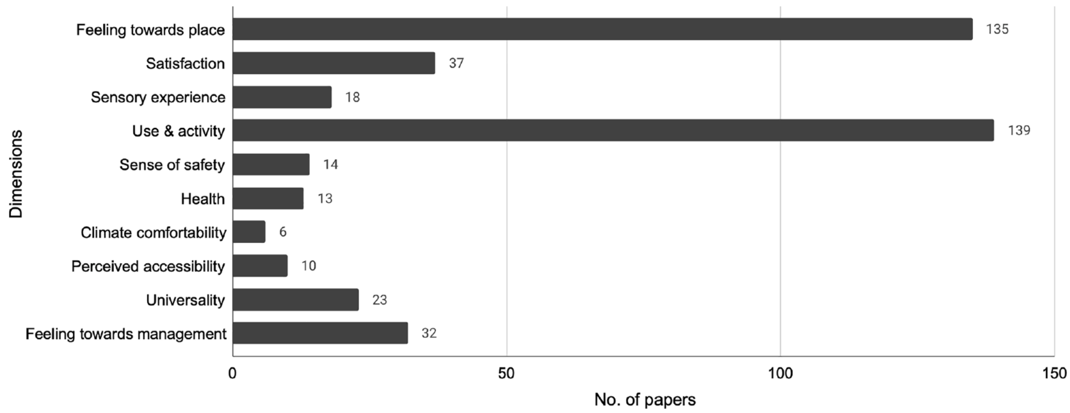

Fig. 2. Amount of papers included in each dimension.

Table 1
Summary of the main focus of the 10 dimensions.

Dimensions	Main topics	Limitations or problems
Feeling towards place	• Framework for urban public spaces quality measurement. • Perceptions of particular user groups. • Relationships with other factors.	Systematic interpretation approaches are needed for the measurements.
Satisfaction	• Using user's subjective feedback. • Capturing user's behavior and activity pattern data. • Comparing the user's needs and the performance of space.	The balance between the needs of different user groups in urban public spaces deserves more consideration.
Sensory experience	• Visual factors' influence on user's feeling • Soundscape.	To what extent that the SVI could represent the actual visual perceptions.
Use & activity	• The relationships between activities and spatial characteristics. • Public life and diversity of the users. • User's behavior patterns and social interactions.	The uncertain representativeness of using the activity pattern as a proxy of the user's perception of places.
Sense of safety	• Safety evaluation. • Relationship with other factors.	Limitation of subjective opinions in collected data and context-sensitive nature of the study.
Health	• Mental health. • Physical health.	Lack of long-term measurement and trace of the human physical health condition.
Climate comfortability	• Air quality. • Thermal comfort.	To what extent the climate-sensitive design is needed for urban public space.
Perceived accessibility	• Spatial factors that affect accessibility. • Accessibility assessment framework.	The uncertain role of legal regulation and management on accessibility of various user groups.
Universality	• Significance of universality. • Publicness and the right to place. • Conviviality	Cross-contextual comparisons are needed to analyze the differences in perceptions of the universality of public spaces in different regions.
Feeling towards management	• Balance between urban management and universality. • Management activities. • Physical installations' impact.	Inadequate quantitative research in this dimension.

These papers usually pay more attention to the associated dimensions, so they are discussed in the later dimensions.

Systematic interpretation approaches are needed for the *feelings towards place* dimension. Although some researchers advocated for more universal criteria to conduct the user feeling measurement (Alwah et al., 2021), the more considerable enhancement should be on how to perform the measurement and how to interpret the collected data. There would not be universal measuring criteria, and variables of the measurements should remain flexible because adaptation to local conditions is always an overarching principle in urban studies (Subramanian & Jana, 2018).

4.1.2. Satisfaction

The definition of *satisfaction* is derived from the *Likes and dislikes* variable in PSEQI. It discusses how and why the users are satisfied with a place and to what extent it meets the user's demands. Different from the *feeling towards place* dimension that focuses on the user's overall perspective of the spaces, the *satisfaction* dimension includes the papers that explicitly stress the consideration of user satisfaction and user needs in urban public spaces. 37 papers focus on this dimension.

Research of this dimension mainly focuses on three types of user satisfaction evaluation approaches: (1) Using user's subjective feedback. (2) Capturing user's behavior and activity pattern data. (3) Comparing the user's needs and the performance of space.

The first is accessing user satisfaction via subjective feedback from users. Data collecting methods are the questionnaire survey (Abbasi et al., 2016; Ho et al., 2021; Potts et al., 2017) or crowdsourcing data acquisition (Ramirez et al., 2021; Sun & Shao, 2020). These researchers concluded that user satisfaction with the urban environment depends on two main factors, the physical environment and space management. In addition, different social contexts showed different priorities. Sun and Shao (2020) developed a useful artificial intelligence-based satisfaction analysis approach for open green spaces and found that the management and policy factor was a more critical influencer on user satisfaction under the local context.

The second is capturing user's behavior and activity pattern data and using these objective data as metrics for satisfaction (Smaniotto Costa et al., 2017). By comparing the different spatial characters and user choices, the more popular places and their spatial characters were identified, which could be used to guide future design.

The third is examining the gap between the user's needs and the performance of space. The quantification tool of Alwah et al. (2021) provided a solution for quantifying the extent of the user needs to be met by urban public space, and it was explicable to provide feedback to the space management and decision-makers.

The existing literature has answered how to identify the most significant aspect to satisfy user needs and how to measure the satisfaction level. However, the user groups themselves required more attention

(Potts et al., 2017; Sun & Shao, 2020). Though some research had particular attention to some special groups (Yung et al., 2016), the balance between the needs of different user groups in urban public spaces deserves more consideration.

4.1.3. Sensory experience

Sensory experience dimension is different from the above *feeling towards place* dimension, and it emphasizes a more direct sense towards the surrounding environments rather than the subjective judgment of the users. There are 18 papers focusing on this dimension.

Research of this dimension mainly focuses on two issues: (1) Visual factors' influence on user's feeling. (2) Soundscape.

The impact of visual factors on the user's feeling (Law et al., 2020; Nia et al., 2017; Tang & Long, 2019; Ye et al., 2019) is a trending topic. The results of those studies confirm that visual quality is one of the decisive factors of user preference (Tang & Long, 2019; Ye et al., 2019). It also positively correlated with the housing price (Law et al., 2020). Visual perception of the environment could be changed according to the changes in urban morphology (Nia et al., 2017).

Soundscape is also a specialized field, and when it is studied with the urban public spaces quality (Engel et al., 2018), it becomes an essential part of the user's perspective. The research found that urban green spaces could effectively reduce the perceived noise level (Irvine et al., 2009). The sound quality had a weak positive correlation with the air quality in busy street areas (Engel et al., 2018). There was no literature on the senses of smell or touch as far as this review explored.

As recommended in the reviewed papers, the next step of the visual experience research could look at how the visual qualities affect the overall perceptions of users on urban public spaces and the extent that the SVI could represent the actual visual perceptions of users (Tang & Long, 2019). Law et al. (2020) also suggests studying the extent to which the generated 3D images like CityEngine images can replace authentic images in the training data used by the CNN, and this offers a new area for research. As for sound, ML had not been applied to the study of the sound experience, and some methods could be borrowed from visual research to enhance the analysis of the sound experience in urban public spaces.

4.1.4. Use & activity

The definition of *use & activities* dimension includes investigating the reason and pattern of people using a place, people's behavior in public spaces, and participating in activities, and if meaningful social interactions happen in the activities (Zamanifard et al., 2019). There are 139 papers focusing on this dimension.

Research of this dimension mainly focuses on three issues: (1) The relationships between activities and spatial characteristics. (2) Public life and diversity of the users. (3) User's behavior patterns and social interactions.

The most concerned issue is the relationships between certain activities and the spatial characteristics, such as the street vending (Barreda Luna et al., 2022), recreational activities (Carraz & Merry, 2022; Lindberg & Schipperijn, 2015), and exercise (Mora, 2012; Sreetheran, 2017). A System for Observing Play and Recreation in Communities (SOPARC) is widely used in this type of research. The activities in urban public spaces were also investigated for reactivating and promoting a place (Ganji & Rishbeth, 2020; Potts et al., 2017) or improving the design (Chen et al., 2016; Ekizoglu & Mortamais, 2018; Heikinheimo et al., 2020; Lau et al., 2021).

Public life and the diversity of the users are also studied. It is proved that the activity could serve as a metric for diversity measurement of the diversity (Denoon-Stevens & Ramaila, 2018; Harun et al., 2013; Hegetschweiler et al., 2017; Urrutia del Campo et al., 2021; Yeo et al., 2016) and the approaches to measure public life powered by sensors and ML is proposed by Williams et al. (2019), which has the potential to make the data collection process in this dimension more efficient.

User behavior patterns and social interactions are often studied together, and by qualitatively analyzing the human behaviors, the physical and land use characteristics were proved to be important in supporting the social interaction in urban public spaces (Mehta, 2009). Aelbrecht (2017) introduced a body-language method to qualitatively identify the potential of social interaction. Cheliotis (2020) highlights recent achievements in the computational simulation study of human spatial behavior by developing an agent-based model and proves its applicability in predicting human movement.

The main limitation of *use & activity* dimension is the uncertain representativeness of using the activity pattern as a proxy of the user's perception of places (Noyman et al., 2019), such as using the geolocated telecom data to represent the popularity of a place. This uncertainty needs to be substantiated by more practical case studies. The other limitation lies in the data collection methods. For example, Lau et al. (2021) suggested improving the data collection process and avoiding the drawback of the self-reporting questionnaires by incorporating multi-source data.

4.1.5. Sense of safety

The *sense of safety* dimension discussed here emphasizes the subjective feelings of people rather than the objective measurement of the physical configurations in the spaces (Navarrete Escobedo, 2020). Examples are feelings during dark hours, the necessity for more police, and the emergency to repair the infrastructure. The sense of safety has been proved to significantly impact a person's decision-making, behavior, and mental status during their presence in a place (Leslie & Cerin, 2008; Saelens & Handy, 2008; Wilcox & Keselman, 2003). There are 14 papers focusing on this dimension.

Research of this dimension mainly focuses on two issues: (1) Safety evaluation. (2) Relationship with other factors.

The *sense of safety* towards urban public spaces could be evaluated from the aspect of crime prevention (Telep & Weisburd, 2012; Zavadskas et al., 2019), disaster prevention (Yang, 2019), and infrastructure maintenance (Groff & McCord, 2012; Zavadskas et al., 2019). Zavadskas et al. (2019) proposed a holistic safety evaluation methodology by multi-criteria decision-making and verified the effectiveness of this approach. The safety sense of females was given special attention, Evensen et al. (2021) proposed a place-sensitive tool called SAFE for assessing perceived safety in urban parks for management intention. Gargiulo et al. (2020) found that it was critical to monitor green spaces by developing a safety map with the help of GIS.

Another is the correlation between the *sense of safety* with other factors, such as perception, management, and thermal comfort. Sense of safety served as one focused indicator to analyze the heterogeneous perceptions of urban public spaces (Ramirez et al., 2021). The positive correlation between the sense of safety and management was examined by investigating the use of closed-circuit television (Brands et al., 2016) and the security zone strategy (Nemeth & Hollander, 2010). The safety and thermal comfort were studied together by Olsen et al. (2019) and resulted in an improved protective spatial design strategy for playground space.

There are two main limitations in this dimension. First, the *sense of safety* data collected are all through self-reporting (Evensen et al., 2021). Therefore, the subjectiveness in that dataset might affect the result. The other is that the safety evaluation process is rather context-sensitive (Brands et al., 2021), people from different cultural backgrounds have very different recognition of safety, so it is hard to achieve universal safety evaluation criteria.

4.1.6. Health

Health dimension studies the impact of a place on users' health conditions, including both physical and mental health (Campagnaro et al., 2020; Grilli et al., 2020; Peschardt & Stigsdotter, 2013). This dimension focuses more on the long-term impact of urban public spaces on users, and the research interest saw more considerable growth after the outbreak of COVID19 (Reyes-Riveros et al., 2021). There are 13 papers focusing on this dimension. Research on this dimension mainly focuses on the relationship of urban public spaces with health from two aspects: (1) Mental health. (2) Physical health.

One is the correlation between mental health and the urban public spaces. Agusti and Guerrero Llados (2022) identified the proportion of green space, building aesthetics, and building density as the key factors influencing user emotion by measuring the emotion changes of participants in different spaces. The other is the correlation between physical health conditions and the urban public spaces. Plunz et al. (2019) made use of Twitter sentiment analysis to measure the health condition by comparing tweets inside or outside the park in New York and confirmed the restorativeness of urban green spaces. Similar results were also obtained by Peschardt and Stigsdotter (2013), Grilli et al. (2020) and Campagnaro et al. (2020) regarding human body health improvement and stress relief.

The research on this dimension still needs some improvement. As suggested by Reyes-Riveros et al. (2021) and Noel et al. (2021), long-term measurement and trace of the human physical health condition could provide more solid analysis than the questionnaire survey data, though the costs might be higher. Moreover, the existing research mainly concentrated on the wellness value of urban green spaces. Therefore, the research on this dimension could expand to other types of urban public spaces like streets and urban squares.

4.1.7. Climate comfortability

The *Climate comfortability* dimension indicates the subjective evaluation of the body comfort expressed by the users, which includes thermal comfort and air quality. There are six papers on thermal comfort and one on air quality.

Research of this dimension mainly focuses on two issues: (1) Air quality. (2) Thermal comfort.

First is the correlation between the user's perception and air quality. Air quality perceptions were collected by a structured questionnaire survey and a positive correlation between the sound quality and overall perceived quality in both urban parks and busy streets (Engel et al., 2018).

Second is the correlation between thermal comfort and spatial factors. The relationship between the thermal profile and spatial use was identified by Urrutia del Campo et al. (2021), field measurements of climatic data, materials thermal properties, human activities and locations, as well as urban design factors were collated, and visualized by mapping. In addition, Wilson et al. (2008) did an on-site experiment and survey to test user's responses to the micro-climate. The user adaptability of thermal condition change was considerable, and the impact of urban design and planning intervention on the micro-climate was limited. Therefore, more attention should be paid to the bigger socio-economic context. In contrast to this argument, Boumaraf and Amireche (2021) highlighted the climate-sensitive urban design by comparing the recorded human activities and monitored micro-climate data.

The question in the above contradictory arguments remains unsolved. It could be described as how much or to what extent the climate-sensitive design is needed for urban public spaces improvement and what is the weight of the thermal comfort in the perceived public spaces quality (Boumaraf & Amireche, 2021). As for the air quality, Engel et al. (2018) suggested that the on-site measurement could be performed to strengthen the research methodology. The more mutual methodologies in thermal comfort research could be a reference for air quality studies (Peng et al., 2019; Urrutia del Campo et al., 2021).

4.1.8. Perceived accessibility

The *Perceived accessibility* dimension indicates how urban public spaces could be accessed. It also emphasizes the accessibility that users could perceive, which significantly influences the perceived quality of a place (Stauskis, 2018; Zamanifard et al., 2019). There are ten papers focusing on this dimension.

Research of this dimension mainly focuses on two issues: (1) Spatial factors that affect accessibility. (2) Accessibility assessment framework.

Spatial factors affecting accessibility are continuing to be researched over time (Lavadinho, 2006; Moore, 2021; Pasaogullari & Doratli, 2004; Stauskis, 2018). Plot size, road network connectivity, and segmentation degree were identified as significant factors influencing the accessibility of the place. By applying the house of quality matrix combined with the analytic network process, Wey and Chiu (2013) found the relation between the technical requirements and the pedestrian needs of accessibility issues under the transitoriented development. Jian et al. (2020) recognized accessibility as one of the critical indicators of the spatial justice framework.

Accessibility assessment framework or tools is another aspect. Pearsall and Eller (2020) used exploratory spatial data analysis to examine local patterns of gentrification and qualitative analysis to examine the public accessibility of the public green spaces and the experiences of residents and community leaders during the park development process. Barreda Luna et al. (2022) developed a public spaces accessibility tool to provide location profiles using socioeconomic data and achieved spatial categorization for street vending activities.

The reviewed papers have given suggestions for future perceived accessibility research. For example, other than the known essential infrastructure of perceived accessibility like wheelchair ramps, the function played by legal regulation and management on various user groups should be constantly studied (Stauskis, 2018). In addition, how privatization shapes public accessibility and how this process unfolds in different urban contexts at different times needs more research (Pearsall & Eller, 2020).

4.1.9. Universality

Universality means the quality of involving or shared by all people or things in the world or a particular group (Stevenson, 2022). Under the discussion of urban public spaces, it signifies the capabilities of designing and managing policies to strengthen user's feeling of space accessibility and usability for all members of the society (Zamanifard et al., 2019). Diversity, right to place, conviviality, and inclusiveness belong to this dimension. There are 23 papers discussing this dimension.

Research of this dimension mainly focuses on three issues: (1) Significance of universality. (2) Publicness and the right to place. (3) Conviviality.

Many researchers have proved the significance of universality in urban public spaces. Jian et al. (2020) proposed the public spaces spatial justice evaluation framework and argued that the relational interactions among the five key aspects could offer better guidance for public spaces development: access and management, sociability and diversity, demand and provision, social stratum and information, and social inclusion.

Publicness and the right to place are other critical issues. Basu and Nagendra (2021) found that the higher public investment in urban parks might lead to the uneven right to public spaces for users of different genders and incomes. Similarly, it was found that the privatization of public spaces may cause a loss of diversity and sociability, according to the interview survey in Philadelphia. However, Adams et al. (2021) reported a different finding that the privatized urban public spaces might offer opportunities for social interactions in the context of segregated cities like Johannesburg and Nairobi. Last but not least, conviviality has also been proved to have a positive correlation with visual aesthetics in built environment (Thombre & Kapshe, 2021) and events provision (Cheliotis, 2020).

The limitation of this dimension is that the context of case studies greatly influences the analysis result. Future studies could make cross-contextual comparisons to analyze the differences in people's perceptions of the universality of public spaces in different regions. At the same time, variables controlling and the objectivity of data sampling need to be concerned (Ho et al., 2021). Moreover, Adams et al. (2021) reported the research challenges after the COVID-19 outbreak, such as the impact of the pandemic on the equity of the right to use public spaces, especially for different income groups.

4.1.10. Feeling towards management

Management of urban public spaces is always a critical part of the quality of urban public spaces (Varna, 2014) or in the urban planning process (Carmona & Tiesdell, 2007). Research of the *feeling towards management* dimension studies how urban public spaces management approaches affect users' feelings and preferences. There are 32 papers focusing on this dimension.

Research of this dimension mainly focuses on three issues: (1) Balance between urban management and universality. (2) Management activities. (3) Physical installations' impact.

Achieving the balance between urban management and universality of urban public spaces is always discussed concerning urban policy. The contradiction between the two factors was revealed by case studies in Scotland (Atkinson, 2003). Innovative management strategies were proposed to meet the requirements of various users and adapted to changing times (De Magalhaes & Carmona, 2006; Helms, 2007; Nemeth & Hollander, 2010). The impact of the COVID-19 pandemic on public spaces management was also discussed. Policy and controls were proved to help citizens adapt to the crisis (Bakir & Attia, 2021). However, the over-controlling or over-strict pandemic measures would prevent public spaces from contributing to ease the negative effect of the pandemic on human psychological health (Erdonmez & Atmis, 2021).

Management activities also influence this dimension. Nikolaidou et al. (2016) explored the possibilities of participatory planning with the help of efficient management and policies. Facility maintenance and staff management, openness, community and education events, reactions to users' complaints, smartness, and security were identified as the critical indicators for urban parks management in Hong Kong (Chan et al., 2018).

Verifying the capability of physical installations on users' feelings to management is another issue. The effectiveness of closed-circuit television in enhancing safety (Brands et al., 2016) or activeness (Klauser, 2007) in urban public spaces was assessed in a different context.

The limitation of this dimension is inadequate quantitative research (Silva-Sanchez & Jacobi, 2016). For example, researchers can use the follow-up data collection to record the change in the users' behavior patterns after implementing the new management policies. In particular, crowdsourcing data could also be utilized to complete the existing survey data.

4.2. The three unresolved issues of user's perspective on urban public spaces

These ten dimensions together provide a comprehensive framework for urban public spaces research from the user's perspective. Moreover, a consolidated analysis of these ten dimensions assists in identifying remaining issues in existing research. Through retrieving the research limitations in these ten dimensions, three main issues emerge eventually: interpretation of user's perception, overlooked user demographics, and data acquisition. Addressing these issues will contribute to a more in-depth understanding of the user's perspective on urban public spaces.

4.2.1. Interpretation of user's perception

The relationship between factors in some dimensions and the overall user's perspective still needs to be investigated. In the *sensory experience* dimension, one remaining question is how the visual qualities affect user's overall perceptions (Tang & Long, 2019). Similarly, the relation between the thermal comfort (Boumaraf & Amireche, 2021) or perceived accessibility (Pearsall & Eller, 2020) and the user's overall perception, and the representativeness of using the activity pattern as a proxy of user's perception is also unaddressed in *climate comfortability*, *perceived accessibility* and *use & activity* dimensions, respectively.

These limitations also result in the lack of substantial evidence for developing the urban public spaces quality frameworks that aim to represent the overall user's perspective in *feeling towards place* dimension (Alwah et al., 2021; Zamanifard et al., 2019). It is significant to determine the extent to which each dimension contributes to the holistic experience and how to interpret indicators in quality measurement tools accurately. The weak interpretation of these measurements might be a barrier to bringing these tools into practical use. For example, Tang and Long (2019) suggests that the next step of visual perception research is to look at how the visual qualities affect the overall perceptions of users.

Moreover, the discrepancy between the user perceptions and actual activities requires deeper investigation. For example, studies have revealed the "perception bias" issue by identifying differences between the sense of safety based on visual assessments of the urban environment and actual behavioral indicators like crime rates (Zhang et al., 2021) or the choice of transportation modes (Ramirez et al., 2021). Moreover, the activity patterns of users could vary from the physical environments of places as captured in street-level images (Zhang et al., 2020). Deciphering this discrepancy between perception and reality is essential for accurately interpreting user perceptions.

4.2.2. Overlooked user demographics

The focus on the user needs to be increased from two aspects. First, demographic information can help to identify different user groups, which is important to research in *satisfaction, use & activity* dimensions. For instance, the satisfaction benchmark might vary between different age or gender groups (Potts et al., 2017; Sun & Shao, 2020), and based on which, more detailed public spaces satisfaction measurements will facilitate better design strategies. Similarly, data on different income groups is also important to studies in both *perceived accessibility* and *universality* dimensions. Second, the geographic information could be extracted from the user demographics, which is meaningful to the context-sensitive studies in *sense of safety, perceived accessibility*, and *universality* dimensions. For example, Pearsall and Eller (2020) suggested more cross-contextual comparisons of factors influencing the outcomes of park creation and its implications for policy and practice to realize equitable green urban neighborhoods.

4.2.3. Data acquisition

Many studies have mentioned the data acquisition issue, which has two aspects, the shortcoming of self-reporting data and the need for continuous and consistent data acquisition processes. In *Use & activity*, *Sense of safety* and *Feeling towards management* dimensions, researchers acknowledged the potential bias in the self-reporting data collected by surveys. Therefore, they have made efforts to overcome this drawback by using multisourced data-set and increasing the data volume (Evensen et al., 2021; Lau et al., 2021; Nikolaidou et al., 2016). In *Health* and *Feeling towards management* dimensions, researchers suggest performing long-term data acquisition as the current data sampling is always done in a relatively short period, the reliability is uncertain (Brands et al., 2016; Noel et al., 2021; Reyes-Riveros et al., 2021).

5. Application of machine learning in the user's perspective on urban public spaces

As briefly described in Section 1, in the last decade, big data and machine learning developments have allowed increasing scalability of methodologies to understand the effects of urban public spaces attributes on the way they are perceived (Ramirez et al., 2021). There are 32 papers involving ML among the 319 papers, around 10 %. The number of papers started to increase in 2019 (Fig. 3), mirroring the surge of ML across urban studies and other fields. The percentage and number of papers using ML in the *feeling towards place* and *use & activity* dimensions are the most prominent (Fig. 4). This section discusses the application of ML in the user's perspectives on urban public spaces. Different ML methods and their applications in this topic are introduced, followed by an analysis of their advantages and disadvantages.

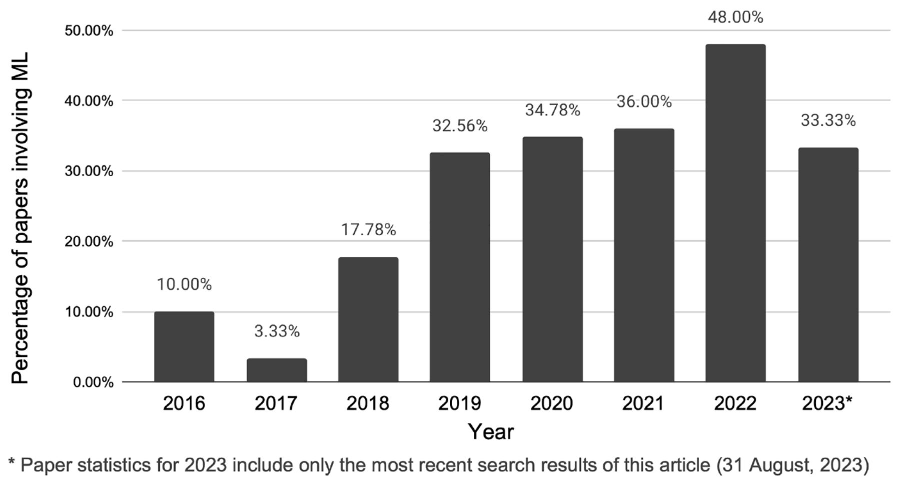

Fig. 3. Number of papers involving ML in this topic in recent years.

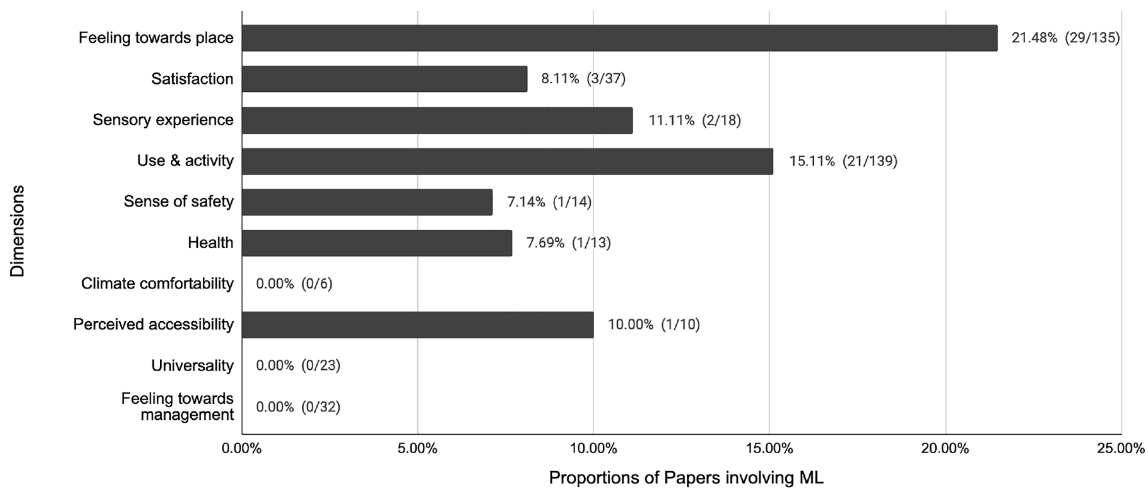

Fig. 4. Proportions of papers involving ML in each dimension.

5.1. *Machine learning methods and their applications*

There are mainly two ML tasks in studying the user's perspective on urban public spaces (Table 2): Computer Vision (CV) and Natural Language Processing (NLP), and both serve several tasks and are used for data processing in different dimensions.

5.1.1. *Computer vision*

CV is highly supportive in the processing of urban image data. It is widely used in *feeling towards place*, *sensory experience*, and *use & activity* dimensions, and is beneficial for handling issues of data acquisition and interpretation of user's perception.

In *use & activity* dimension, object detection and classification is used for processing data collected from the urban environment. For example, a faster R-CNN algorithm was adopted by Williams et al. (2019), Rossetti et al. (2019), and Ramirez et al. (2021) for identifying the moving objects (pedestrians and cars) in videos or pictures. Williams et al. (2019) also used YOLO (You Only Look Once) algorithm for the more effective identification of stationary objects, such as people sitting on a bench. This study also demonstrated that automating the urban public spaces measurement could simplify the data collection process. Leveraging tag labeling services offered by online platforms, such as Google Cloud Vision, they allow for the analysis of a vast number of social media images to study the interaction between humans and the environment (Ghermandi et al., 2022; Song, Richards, & Tan, 2020). With the rapid improvement in computing power, action detection is increasingly used for detecting movement or activities rather than static features. Zhang et al. (2022) detected people's recreational activities from the video clips using the action detection model ACAM (Actor-Conditioned Attention Maps) trained on the AVA dataset (Gu et al., 2018). They demonstrated that the model could detect human figures and effectively identify specific activities like walking or jogging.

In *feeling towards place* and *sensory experience* dimension, the visual quality of the built environment is often studied by semantic segmentation with SVI data. Semantic segmentation is partitioning a digital image into multiple image segments (Ramirez et al., 2021), its reliability and efficiency have been proven in studies. Ye et al. (2019) used the Google Street View and SegNet decoder to measure the human-scale street greenery and proved this method is more accurate than the urban green cover measured by remotely sensed Normalized Difference Vegetation Index (NDVI). Tang and Long (2019) developed a new visual quality and variation evaluation method by capturing a multi-year Tencent Street View covering all the Hutongs in Beijing. Other effective techniques like PSPNet (Pyramid Scene Parsing Network) (He et al., 2020), SegFormer (Huang et al., 2023), and DeepLabV3+ (Ji et al., 2021) have also been employed in existing research. Furthermore,

Table 2
Machine learning methods used in the reviewed papers.

Tasks	Sub-categories	Methods	Discussed in	Dimensions
Computer vision	Semantic segmentation	SegNet	Ramirez et al. (2021), Rossetti et al. (2019), Zhang et al. (2019), Ye et al. (2019), Tang and Long (2019), Qiu et al. (2022), Ma et al. (2021)	Feeling towards place, satisfaction, sensory experience, sense of safety
		PSPNet (Pyramid Scene Parsing Network)	He et al. (2020), Zhang et al. (2022)	Feeling towards place, use & activity
		SegFormer	Huang et al. (2023)	Feeling towards place
		DeepLabV3+	Ji et al. (2021)	Feeling towards place
	Image classification	Tag labeling by Google Cloud Vision	Song, Richards, and Tan (2020), Ghermandi et al. (2022), Wilkins et al. (2022)	Feeling towards place, use & activity
	Object detection	Faster R-CNN	Ramirez et al. (2021), Williams et al. (2019)	Feeling towards place, sensory experience, sense of safety, use & activity
		VGG16 neural network architecture	Law et al. (2020)	Feeling towards place, sensory experience
		YOLO (You Only Look Once) algorithm	Williams et al. (2019)	Use & activity
	Action detection	ACAM (Actor-Conditioned Attention Maps)	Zhang et al. (2022), Wei et al. (2022)	Use & activity
	Emotion detection	Face++ cognition service	Zhu et al. (2021), Huang et al. (2020)	Feeling towards place
		EmoDetect algorithm	Ashkezari-Toussi et al. (2019)	Feeling towards place
	Low-level features extraction (color and edge)	Canny Edge algorithm	Ramirez et al. (2021), Rossetti et al. (2019)	Feeling towards place, sensory experience, sense of safety
Natural language processing	Topic modeling	LDA (Latent Dirichlet Allocation)	Song et al. (2021), Kim et al. (2018), Lansley and Longley (2016)	Feeling towards place
	Sentiment analysis	LSTMM (Long Short-Term Memory Model)	Sun and Shao (2020), Huang et al. (2021), Pistola et al. (2022)	Feeling towards place, satisfaction, sensory experience
		NBLR+POSwemb model	Plunz et al. (2019)	Feeling towards place, health
		Sentiment analysis online platform (e.g. Baidu, Tencent, Alibaba)	Guo et al. (2022), Kong et al. (2022)	Feeling towards place
	Demographic inference	M3Inferenc	Niu and Silva (2023)	Feeling towards place, use & activity
		TFIDF algorithm (term frequency inverse document frequency)	Chen et al. (2021)	Feeling towards place, use & activity
	Text vectorization	Word2Vec	Santos et al. (2020), Sun and Shao (2020), Chen et al. (2021)	Feeling towards place, satisfaction, use & activity
Others	Relationship analysis and classification	ANN (Artificial Neural Network)	Zhang et al. (2019)	Feeling towards place
		Random forest model	D'Autilia and Hetman (2018), Qiu et al. (2022), Qiu et al. (2021), Ji et al. (2021)	Feeling towards place, use & activity
		SVM (support vector machine)	Ye et al. (2019), Qiu et al. (2021)	Feeling towards place, sensory experience
		Boosted gradient tree	Barreda Luna et al. (2022)	Perceived accessibility, use & activity
	Clustering	t-SNE (t-distributed Stochastic Neighbor Embedding)	Barreda Luna et al. (2022), Chen et al. (2021)	Perceived accessibility, use & activity
		PCA (principal component analysis)	Wilczynska et al. (2021)	Use & activity
		k means cluster algorithm	Wilczynska et al. (2021), Huang et al. (2021)	Use & activity

emotion detection is also an important aspect of *feeling towards place* dimension. Researchers have used facial expression detection to study user emotions in urban parks and public spaces (Ashkezari-Toussi et al., 2019; Huang et al., 2020; Zhu et al., 2021). Besides, low-level feature extractions help describe general image characteristics, such as HLS color statistics (mean and standard deviation for the hue, saturation, and lightness channels) and image edges (the percentage of pixels of each image that are determined to be an edge)extracted by Canny Edge algorithm (Ramirez et al., 2021; Rossetti et al., 2019).

The accuracy and volume of the data have been improved with the help of CV and, at the same time, researchers have attempted to measure or explain user's perception with the data processed by ML. For example, to investigate whether social media analytics can provide a reliable measure of perceived city images, Huang et al. (2021) compared the images of the city measured by the social media data and survey data, and the *tf.keras.Sequential* model was used to sort and label Instagram photos and videos related to urban environments. Zhang et al. (2019) introduced the novel systematic, multifactor quantitative approach for measuring street quality with the support of multi-sourced urban data. This measure was based on 5Ds dimensions: Density, Diversity, Design, Destination accessibility, and Distance to transit (Ewing & Cervero, 2010). Among the 5Ds, the Design was evaluated by the SegNet with the SVI data from Baidu Maps API (Fig. 5). In addition to SVI, specifically organized data sets like Place Pulse 2.0 data-set (MIT, 2022) could also be a significant source of user perception studies (Ji et al., 2021; Qiu et al., 2021, 2022; Ramirez et al., 2021; Rossetti et al., 2019).

5.1.2. Natural Language Processing

NLP is concerned with the interactions between computers and human language, mainly how to program computers to process and analyze large amounts of human language data. These methods usually study user-generated text information on social media platforms. It is widely used in *feeling towards place*, *satisfaction*, and *use & activity* dimensions. Studies using social media text data such as Twitter posts or TripAdvisor reviews need NLP to organize the raw data. Text vectorization, or word embedding, is usually a preparation of vectorized data for subsequent analysis. Word2Vec algorithm has been tested as an efficient tool for this task (Chen et al., 2021; Sun & Shao, 2020).

In *feeling towards place* and *satisfaction* dimensions, user's perception

Fig. 5. Example of applying SegNet to extract key spatial elements (Zhang et al., 2019).

was studied by topic modeling, which is a frequently used text-mining tool for discovering hidden semantic structures in a text body (Lansley & Longley, 2016). LDA (Latent Dirichlet Allocation) algorithm is efficient and economical for it (Lansley & Longley, 2016; Song et al., 2021). Song et al. (2021) used LDA with TripAdvisor data to capture the sense of place in Las Vegas (Fig. 6). Kim (2019) explored the user's perception of urban public spaces through Twitter data and concluded that online reviews could help understand user experiences in public parks or streets. However, the reviews could also be biased in reviews of commercial facilities like hotels or restaurants because of business interests. Furthermore, user perceptions or emotions are also studied by sentiment analysis, which can systematically identify and quantify affective states and personal information. Sentiment analysis online platforms (e.g. Baidu, Tencent, Alibaba) are proven to be valuable tools for analyzing user sentiments and investigating their connection to the environment (Guo et al., 2022; Kong et al., 2022).

Sentiment analysis is also useful in *satisfaction* dimension. Sun and Shao (2020) presents a novel approach to measuring visitor satisfaction towards green and open spaces by crawling Sina-Weibo social media data, which were then processed by LSTMM (Long Short-Term Memory Model). In addition, Plunz et al. (2019) compared the Twitter sentiment in-park and out-of-park for studying the human feelings about urban green space with the application of the NBLR + POSwemb model.

In addition to dealing with the issues of data acquisition and interpretation of user's perception, researchers are also trying to address the user demographic issue by NLP, which is helpful for the research in *feeling towards place* and *use & activity* dimensions. For example, Chen et al. (2021) developed a novel social sensing method called KE-CNN by combining keyword extraction by TFIDF (Term Frequency Inverse Document Frequency) algorithm and synonym substitution by CNN (Convolutional Neural Network) algorithm, which could identify the geographic information by extracting the semantic features from text data. (Niu & Silva, 2023) performed user demographics inference from social media metadata using M3Inference model, and demonstrates the application of geotagged social media data in identifying spatial, temporal and demographic patterns of urban activities.

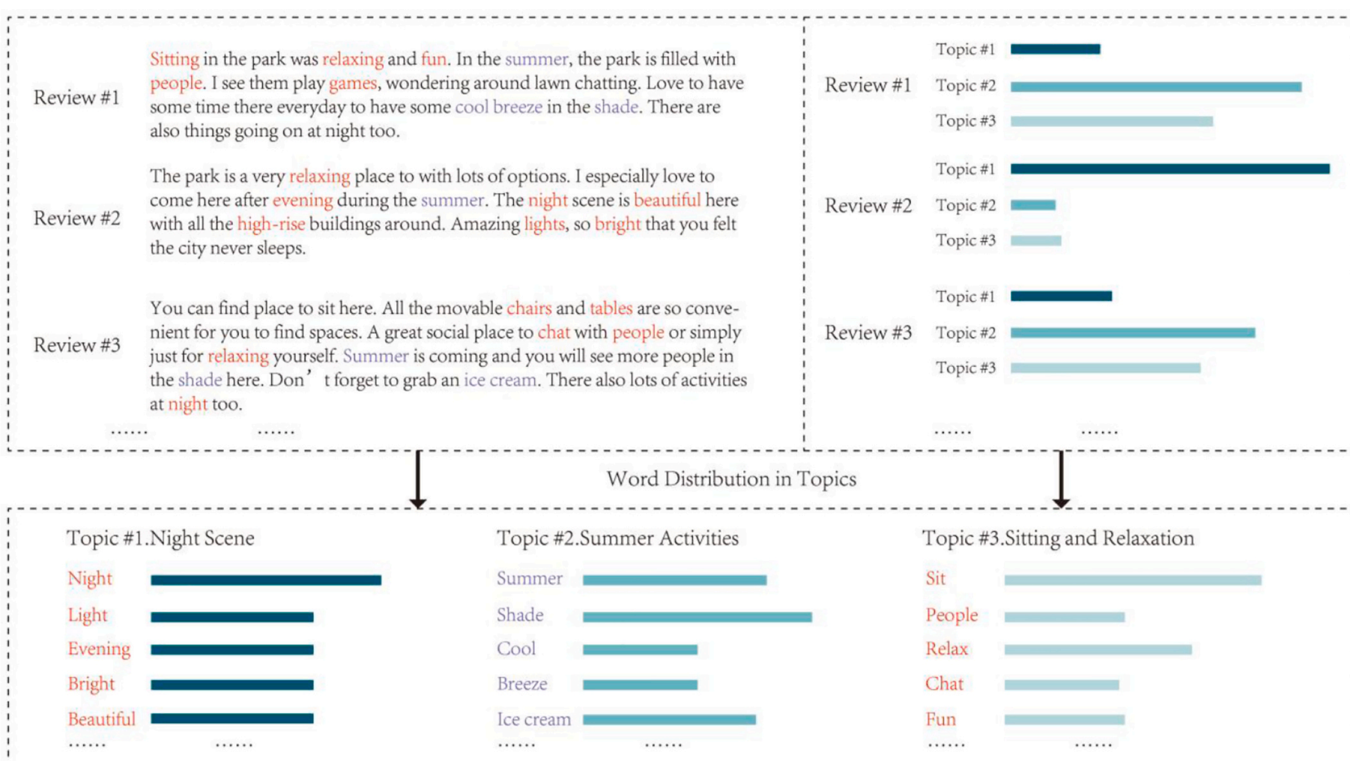

Fig. 6. Example of LDA topic modeling illustration including topic distribution in documents and word distribution in topics (Song, Fernandez, & Wang, 2020).

5.1.3. Others

Besides CV and NLP, studies in *feeling towards place* and *use & activity* dimensions also used ML for correlation analysis and classification, which is a necessary step in the study of user's perception. Ye et al. (2019) argued that training data by SVM (Support Vector Machine) could accurately identify the high, medium, and low values for Google Street View image recognition results. Similarly, in a street quality measurement study, (Zhang et al., 2019) selected ANN (Artificial Neural Network) to train and assess the model with complex non-linear relationships with high accuracy. Boosted gradient tree (Barreda Luna et al., 2022) and random forest model (D'Autilia & Hetman, 2018) are also used for relationship analysis of spatial variables. They show satisfactory results when dealing with large samples of data.

Furthermore, clustering analysis is also useful for research in *use & activity* dimension. Barreda Luna et al. (2022) used t-SNE (t-distributed Stochastic Neighbor Embedding) algorithm to deal with the spatial clustering, which has revealed the hidden relationships between space and activities (Fig. 7). The efficiency of t-SNE has also been proved by Chen et al. (2021). Wilczynska et al. (2021) distinguished three main clusters of urban green spaces by analyzing the connection, interaction, and potential use factors with a combination of PCA (Principal Component Analysis) and k-means cluster algorithm.

6. Discussion

The utilization of ML methods in urban public spaces studies has numerous benefits. Most papers used ML due to its data processing efficiency, as manual data processing could be too costly to be feasible when dealing with a massive amount of data (Plunz et al., 2019; Rossetti et al., 2019). While machine learning has demonstrated potential in addressing the three unresolved issues discussed in Section 4.2, there are still some challenges. These also represent valuable opportunities for future research in the field.

6.1. Machine learning in tackling the three unresolved questions

6.1.1. Increasing objectivity and scientific rigor for measuring user's perception

In the user's perspective study, researchers always need to deal with personal information and subjective biases, prompting the adoption of ML approaches to mitigate these challenges. For example, the widely used SegNet algorithm provides a solution for standardizing image data extraction (Rossetti et al., 2019; Tang & Long, 2019; Ye et al., 2019; Zhang et al., 2019). By consistently analyzing and comparing user-generated images, such as public events photos, SegNet reduces subjectivity compared to manual labeling by assigning categorical labels to individual pixels. Similarly, LDA provides an objective way to understand the text information with less personal bias (Barreda Luna et al., 2022; Kim et al., 2018; Plunz et al., 2019; Song et al., 2021). By identifying the topics present in the corpus, LDA provides a way to understand the underlying meaning and structure of the text information, while minimizing the impact of subjective factors in the analysis.

However, these algorithms still have limitations when increasing objectivity. The main drawback of using unsupervised ML algorithms in urban public spaces studies is their limited explainability. These purely objective algorithms lack contextual relevance, potentially resulting in weak comprehension of the outcomes. Ramirez et al. (2021) argued that the black-box nature of deep networks made it challenging to effectively explain their predictions. This can make it difficult to systematically understand how different factors have influenced the prediction process. In addition, the results generated by ML algorithms often require manual validation to ensure accuracy, as most papers employ human verification to confirm the findings' reliability (Chen et al., 2016; He et al., 2020; Kim et al., 2018; Song et al., 2021; Ye et al., 2019). Addressing this gap is crucial for leveraging the full potential of ML in measuring and interpreting user's perception of urban public spaces with scientific rigor and contextual relevance.

6.1.2. Integrating diverse datasets to enhance data quality

Song et al. (2021) mentioned that the lack of location labels in the TripAdvisor dataset led to a vague spatial resolution. This inadequacy could be improved by the KE-CNN approach (Chen et al., 2021), which has the potential to allow more detailed big data analysis with finer geographical resolutions. Similarly, researchers can also combine data from other sources, such as geo-tagged photos, mobile phone records, and traditional surveys, to create more comprehensive and representative datasets. This integration can help address limitations in individual dataset, such as the tourist-centered perspectives in TripAdvisor data (Song et al., 2021), by incorporating local residents' viewpoints from other sources like local newspapers and Blogs (de Oliveira Capela & Ramirez-Marquez, 2019). Moreover, NLP methods with social media data have the potential to provide more demographic information about users, as Peersman et al. (2011) predicted the user age and gender use chat text data with an accuracy of over 80 %. However, it is noticeable that as user information is a sensitive topic. Therefore, some algorithms could be applied to facilitate fully automated data collection and anonymization, thus reducing privacy issues caused by manual intervention.

Despite the potential, research has yet to consider integrating and synergizing diverse datasets in urban studies for strengthening the data representativeness and mitigating bias(Song et al., 2021). The application of NLP and social media data to discover hidden information in

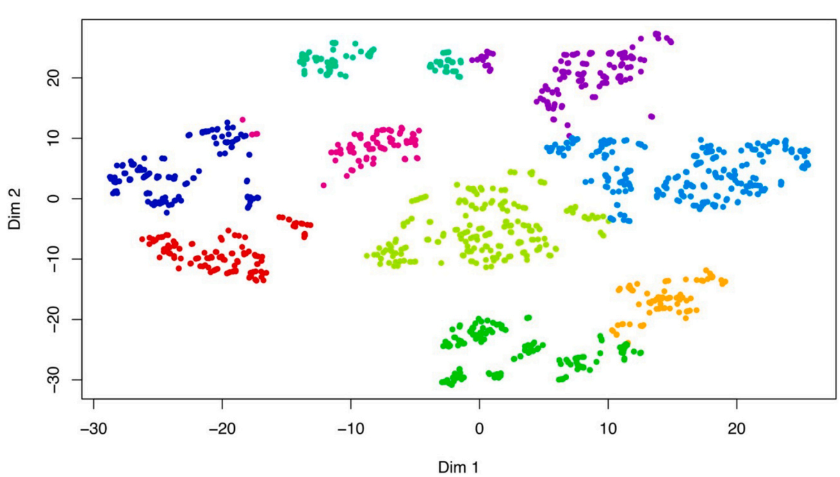

Fig. 7. Example of t-SNE visual identification of groups of spatial characteristics (Barreda Luna et al., 2022).

urban studies remains underexplored. Addressing data scarcity, reliability, and privacy concerns remains crucial. These gaps showed the possibility of ML in dealing with data quality problems in the future.

6.1.3. Improving data acquisition process

Compared to traditional site surveys, methods like topic modeling mitigate the risks of self-reporting biases and oversimplification that can arise from researcher-developed questionnaires (Anton & Lawrence, 2014; Droseltis & Vignoles, 2010). The difficulty in long-term consistent measurement can be solved thanks to ML's power to handle data in real-time. Considering the context-sensitive nature of urban studies, the efficiency of adapting to the local context is crucial. Automated data collection and processing overcome the temporal validity issues faced by manual approaches (Adams et al., 2021; Sun & Shao, 2020), enabling realtime comparisons across different socio-economic contexts. Moreover, the sensor-based public life observation method (Williams et al., 2019), coupled with algorithms like SegNet and YOLO, facilitate privacy-preserving data conversion without storing original images.

However, ML methods alone cannot resolve all data acquisition problems. All mentioned CV algorithms could only partially explain the overall quality due to the ignorance of some factors, such as dilapidation, tidiness, chaos, and human vitality, and the contribution of each factor needed to be clarified (Niu et al., 2022; Tang & Long, 2019). Similarly, in the street greenery assessment research, Ye et al. (2019) claimed that some factors affecting street greening, such as traffic safety, land availability, and socio-economic attributes, were not included in their analysis.

6.2. Opportunities and potentials

6.2.1. Combining CV and NLP in the measurement of user's perception in urban public spaces

CV can be used to automatically extract information from images and analyze the visual aspect of urban spaces or user's human behavior patterns, while NLP can be used to understand user's subjective feelings and opinions about these spaces by analyzing text data such as captions and hashtags (Wan et al., 2021; Yang & Liu, 2022). With the help of data sources such as *Google Places API* (Google, 2022) that contain both image ("Photo") and text ("Review") data, the CV and NLP algorithms could be used together to provide a more valid explanation of urban public spaces quality measurement. This combination can provide a more complete picture of how people use and perceive urban public spaces. In the existing research, Huang et al. (2021) identified city images using images and text from Instagram and Twitter. The five Lynchian elements were identified using image semantic segmentation, keyword extraction, and clustering analysis. After comparing the city image by survey methods, it demonstrates to some extent that the multiplicity of data types positively affects the measurement of city image. In addition, Ramirez et al. (2021) has tested the possibility of explaining the user perception from *sense of safety* dimension by the Place Pulse 2.0 dataset. This dataset could fulfill more potential by combining it with other datasets and methods. For example, Huang et al. (2023) improved the human perception measurement accuracy and explored its correlation with human activities in a real case study.

6.2.2. Investing in high-quality user datasets

Urban public spaces research could target more specific social issues or user groups, while few datasets contain user demographics. To overcome this shortcoming, researchers can make efforts from three aspects. The first is identifying demographic information from the crowdsourcing text dataset, Niu and Silva (2023) summarized existing studies of sociodemographic inference from social media data, and demonstrated an efficient approach of inferring demographics from user profile data. The second is using image data to identify demographic information by computer vision when studying the user's perspective on urban public spaces. Recognizing human gender and age has been proven to be feasible (Ng et al., 2012; Rafique et al., 2019). In addition, developing demographics-embedded training datasets for the ML in this topic is another research direction. The new training dataset should include the demographic information of the users and the socio-economic data, which are essential to the urban public spaces research (Law et al., 2020; Song et al., 2021; Ye et al., 2019).

In the meantime, the ethical concerns of handling users' demographic information are crucial, and the core is privacy protection (Rafique et al., 2019). Social media users may be unaware or have not consented to their data being collected and analyzed for demographic profiling purposes. This raises serious concerns about privacy violations and potential misuse of personal information. Besides, other issues like data reliability and bias also warrant attention (Chen et al., 2021). To mitigate these disadvantages, robust privacy protection measures are highly needed. This includes implementing strict data anonymization techniques and adhering to relevant data protection regulations, such as GDPR and CCPA. These regulations mandate user consent, data anonymization, and data subject rights, helping safeguard privacy. Moreover, leveraging open-source tools can enhance transparency and enable external scrutiny, promoting accountability. Open-source anonymization solutions, like OpenMined's PySyft and differential privacy libraries, can protect user privacy by removing or obfuscating personal identifiers (Ziller et al., 2021). The transparent nature of open-source code allows for independent audits and verification of the anonymization methods, fostering trust in the process. (Chen & Biljecki, 2022).

Besides the above research opportunities for the user's perspective on urban public spaces, research is also needed for the enhancement of the ML methods. For image processing methods, efforts are needed to enhance their ability to deal with more factors in the built environment. As suggested by Tang and Long (2019), tidiness and chaos factors are not recognized by current image processing algorithms, which need to be solved in the future. Moreover, to mitigate the black-box nature, Ramirez et al. (2021) have suggested that unsupervised classification models could be combined with econometric techniques to interpret the influence of different elements.

However, despite the opportunities, it's crucial to acknowledge the limitations associated with employing ML in urban public spaces research. As mentioned in Section 6.1, the quality of ML analysis primarily relies on the data quality (Song et al., 2021). Data accuracy, temporal consistency, and differences between expert and public experiences are additional limitations (Zhang et al., 2019). Privacy protection and language restrictions can also limit data accessibility (Sun & Shao, 2020). Additionally, developing ML algorithms can be difficult despite their efficiency in data processing. As Williams et al. (2019) pointed out in their evaluation of sensors for public life research, expert knowledge is necessary for algorithm development and sensor calibration.

7. Conclusion

This review focuses on the user's perspective on urban public spaces, outlining the ten dimensions to clarify this abstract concept: *Feeling towards place*, *Satisfaction*, *Sensory experience*, *Use & activity*, *Sense of safety*, *Health*, *Climate comfortability*, *Perceived accessibility*, *Universality*, and *Feeling towards management*. Each dimension's primary achievements and limitations are also summarized, providing a road map for future research. For instance, while several frameworks for urban public spaces quality measurement have been developed in *feeling towards place* dimension, there is a need for systematic interpretation approaches to complete these frameworks. After synthesizing the ten dimensions, three unresolved issues in this topic are identified: (1) interpretation of the user's perception, (2) overlooked user demographics, and (3) data acquisition.

Urban public spaces are complex and heterogeneous by nature, especially when considering the user's perspective, which is subjective and has its intricacies. Concurrently, ML exhibits impressive progress in tackling various complex tasks in this domain. This review summarizes ML applications in this topic into two main applications: Computer Vision and Natural Language Processing. The main advantages of ML approaches lie in their ability to reveal hidden insights and process real-time data efficiently and rigorously. However, ML also has shortcomings in its validity. For example, unsupervised algorithms lack robust explainability and image-processing algorithms cannot capture all factors in the built environment comprehensively.

This review has two limitations. It only uses the *Web of Science Core Collection* as the literature source. Thus, the search strategy might not include every single relevant paper. As such, the review results based on the 319 papers, while comprehensive, may provide a limited perspective of the state of the art and future needs in this topic. Moreover, the presentation here is not focused on the specific findings of each paper, but rather emphasizes how they support the comprehension of the ten dimensions of the user's perspective on urban public space.

Further research could explore the interpretation approach of user's perception in urban public spaces by combining the CV and NLP methods and efforts on the high-quality user datasets that contain user demographics. At the same time, improving the current ML algorithms for this topic is also worth exploring.

CRediT authorship contribution statement

Yihan Zhu: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation. **Ye Zhang:** Writing – review & editing, Supervision, Methodology, Investigation. **Filip Biljecki:** Writing – review & editing, Supervision, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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