

The Influence of Urban Environment on Sentiments: A Systematic Review

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The Influence of Urban Environment on Sentiments: A Systematic Review

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Abstract: Rapid urbanization and population growth have intensified interest in understanding how urban environments relate to people's sentiments and emotions. In recent years, social media data have increasingly been used to investigate these relationships, while a wide range of analytical approaches has been employed to identify and quantify sentiment. This study presents a systematic review of the associations between characteristics of the urban environment and human sentiments and emotions, while also examining the methodological approaches used to assess these relationships. The review was reported in accordance with the PRISMA 2020 guidelines. From an initial set of 655 records, 59 studies met the inclusion criteria. These were published between 2018 and 2025, with most case studies conducted in China (64%), followed by North America (12%), with additional studies in Europe and other Asian contexts. Weibo, a Chinese microblog comparable to Twitter (now X), was the most frequently used data source. Machine-learning and deep-learning (ML/DL) approaches were the most frequently used for sentiment analysis, followed by lexicon-based, hybrid, and manual approaches. Findings reveal generally positive associations between green and blue spaces and positive sentiments, as well as with scenic landscapes, urban features that facilitate social interaction, and social activities, while industrial and transport environments tend to be associated with more negative sentiments. On

the other hand, several spatial and density-related indicators show heterogeneous relationships with sentiments, with the association types varying across studies and urban contexts. External stressors are generally associated with negative sentiment, including air pollution, heat-related conditions, extreme precipitation, and signs of environmental degradation. However, some indicators, such as air temperature and noise, show mixed relationships. Higher levels of walkability and perceived safety are also associated with more positive sentiments. Overall, several recurring findings across the reviewed studies can guide urban planning, including improving access to green and blue spaces, enhancing spatial configuration and public infrastructure, ensuring adequate maintenance and accessibility, , reducing exposure to environmental stressors, and improving conditions around transport hubs and stations.

Keywords: sentiment analysis. urban environment. systematic review.

1. Introduction

Urbanization represents a major global trend in the twenty-first century, significantly influencing health and well-being. Currently, over 55% of the global population resides in urban areas, with estimates indicating an increase to 68% by 2050 (United Nations, 2020). Cities provide jobs and are centres of innovation and wealth creation (Nieuwenhuijsen, 2020). Nevertheless, rapid urbanization and poor urban planning are associated with several environmental and public health challenges, including irrational land use, inadequate transport facilities, high levels of air pollution and noise, environmental degradation, urban heat island effects, and lack of green space (H. He et al., 2023; Nieuwenhuijsen, 2020). These urban conditions can affect environmental exposures and lifestyle factors and, consequently, morbidity and mortality (Nieuwenhuijsen, 2020), while rapid urbanization has also been associated with poor resident sentiments (He et al., 2023). In addition, climate change can further

intensify some of these environmental and health pressures, particularly those related to heat and air pollution (Watts et al., 2019). Understanding the potential impact of the urban environment on health is complex because numerous factors influence personal health and well-being. Although healthcare and genetics are often seen as the main determinants of health, social and environmental factors also have a vital role. Around 23% of deaths worldwide in 2012 were linked to the physical environment, including air and noise pollution, housing, transport, and other factors (Prüss-Üstün et al., 2016).

The significance of physical attributes in landscape perception has been debated for a long time (Kaplan et al., 1989). However, landscape quality is not determined solely by the physical characteristics of the environment, but also by how these characteristics are perceived and interpreted by individuals (Lothian, 1999). It is therefore important to understand how people perceive and evaluate different environmental features (He et al., 2023). These evaluations of the urban environment may be reflected in the sentiments expressed by individuals.

Research on the relationships between well-being and the urban environment has received considerable attention (Krefis et al., 2018), using methods such as surveys and wearable sensors (Benita et al., 2019; Kestens et al., 2016; Osborne et al., 2023). However, social media data can also be utilized to examine residents' sentiments in relation to the urban environment. One advantage over questionnaires and interviews is the large amount of user-generated data available for sentiment analysis, as these platforms allow individuals to respond to current events and share their opinions voluntarily, without intermediaries (Babaikina et al., 2024; Fan et al., 2023).

New technologies have opened the door to addressing this complex issue, with advances in Information and Communication Technologies (ICT), the Internet of Things (IoT), and cloud computing (Sundmaecker et al., 2010). Georeferenced data from social networks such as Twitter (now X), Instagram, Flickr, and Weibo can support urban sustainability research and decision-making by providing large-scale and near-real-time information about human behavior in cities. For example, in the context of

urban parks, these data can provide information on visitation patterns and equitable access (Ilieva & McPhearson, 2018). More recently, deep-learning-based NLP approaches have been used to assess sentiments related to park accessibility, safety, aesthetics, attractiveness, maintenance, and usability, providing information that can support urban management and policymaking(W. Huang et al., 2025).

Given the importance of data obtained from social media, research using sentiment analysis to examine the connection between sentiments shared on social networks and the urban environment has increased (H. He et al., 2023; Yang et al., 2022). Techniques such as sentiment analysis, topic modelling, and deep learning are frequently used to extract sentiments from social media data (Ghahramani et al., 2021; X. Zhang et al., 2023). However, understanding the spatial-temporal changes and the factors driving these sentiments, based on big data, remains limited (He et al., 2023)Moreover, relatively few studies have examined the relationship between sentiments and the broader urban environment (Yang et al., 2022).

In addition, the associations between specific characteristics of the urban environment and sentiments are not always consistent. For example, the relationships between density-related indicators and sentiments can vary according to spatial scale: lower plot ratio and population density were associated with more positive sentiments at the neighbourhood level, whereas higher building and road densities were associated with more positive sentiments at the subdistrict level(Fan et al., 2023). These findings illustrate the complexity of the relationship between urban characteristics and sentiments and the importance of considering multiple urban variables and spatial scales.

This systematic review aims to synthesize current knowledge on how the urban environment is associated with human sentiments and emotions, with particular attention to data sources, sentiment analysis techniques, and statistical methods. It also aims to identify the urban environment variables examined in the reviewed studies, including morphological, environmental stressor, and social factors,

and to summarize the direction of the reported associations with sentiment and emotions as positive (+), negative (-), or contradictory ($\times$).

In this review, sentiments and emotions are treated as related but distinct concepts. Sentiment refers to a positive or negative evaluative orientation, whereas emotion refers to more specific affective states. However, for the purpose of this review, only the positive or negative valence reported by the original studies was considered. When studies analysed specific emotions in greater detail, these individual emotion categories were not included in the synthesis. The terminology adopted by the original studies was preserved.

2. Systematic Review Methodology

Despite procedural differences among various types of literature review, all can be carried out through eight common stages (Xiao & Watson, 2019): (1) formulation of the research problem; (2) development and validation of the review protocol; (3) literature search; (4) selection for inclusion; (5) quality assessment; (6) data extraction; (7) data analysis and synthesis; and (8) reporting of results (Figure 1).

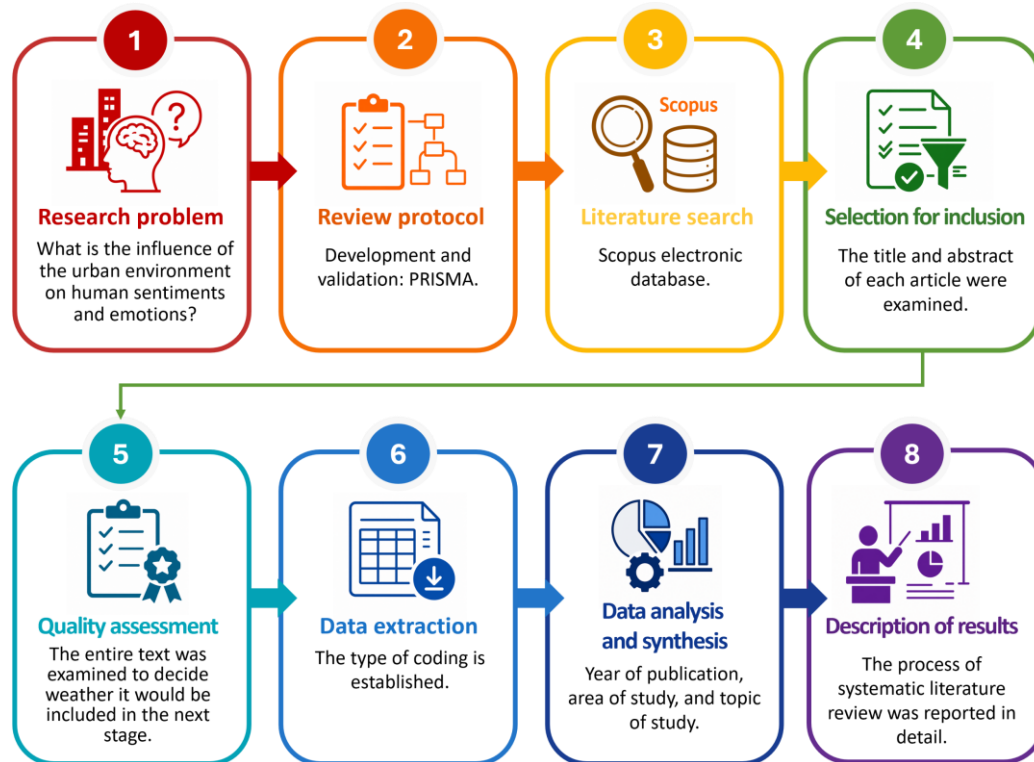


Figure 1 – Systematic revision process. Adapted from (Koutsos et al., 2019).

Stage 1: The research problem is defined as: “What is the influence of the urban environment on human sentiments and emotions?”. The research question guides the selection of studies, data extraction, synthesis, and reporting of results, and should be sufficiently specific to define the scope of the review (Xiao & Watson, 2019).

Stage 2: For the review protocol, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement was selected (Moher et al., 2010) because it ensures scientific rigor (Brereton et al., 2007; Okoli & Schabram, 2010) and effectively supports evidence-based conclusions (Moher et al., 2010). PRISMA provides a set of guidelines for reporting systematic reviews and meta-analyses. The PRISMA 2020 statement replaces the 2009 version and offers updated guidance (Page et al., 2021).

Stage 3: For the literature search, the Scopus electronic database was used. Scopus provides access to an extensive array of peer-reviewed literature, encompassing journals, conference proceedings, and additional sources pertinent to the social sciences. As a result, it constitutes a significant resource for conducting research on topics such as sentiment and emotion analysis (Ballew, 2009).

In recent years, particularly over the past decade, research on sentiment analysis indexed in Scopus has exhibited a marked upward trend, underscoring the increasing relevance and breadth of the field (Ahmad et al., 2023). Comprehensive reviews utilizing Scopus data have linked sentiment analysis to foundational studies of public opinion and have highlighted its interdisciplinary character, notably its integration of social and cultural perspectives (Mäntylä et al., 2018). Furthermore, bibliometric analyses based on Scopus reveal a considerable volume of publications addressing topics such as emotional intelligence and social interaction, thereby confirming the database's robust coverage of the social and cultural dimensions of emotion research ((Farajy et al., 2025; Ida & Prabakar, 2024).

The comprehensive scope of Scopus in indexing research related to sentiment, emotion, and social interaction surpasses that of Web of Science (WoS), as it includes all journals covered by WoS in addition to a broader selection of titles ((Ahmad et al., 2023; Ida & Prabakar, 2024; Mäntylä et al., 2018), This expanded coverage is particularly notable within the social sciences, where Scopus provides access to a wider range of relevant literature (Harzing & Alakangas, 2016; López-Illescas et al., 2008; Mongeon & Paul-Hus, 2016).

Since the topic of sentiment analysis is broad, we combined different keywords related to the study objective using Boolean operators, performing the search by title, abstract, and keywords: TITLE-ABS-KEY ("sentiment analysis" AND urban). The study focuses on sentiments, classified as positive or negative. Specific emotions (e.g., joy, sadness, anger, or fear) were not analyzed individually. In studies that use the term "emotions," they were only considered when the authors themselves presented them in aggregate as positive or negative. Thus, although feelings and emotions are distinct concepts,

the review does not intend to treat them as equivalent, but only to consider the positive/negative dimension reported by the included studies. The search conducted up to December 2025 yielded a total of 655 documents. The results were then restricted to documents published in English, resulting in 508 papers.

Stage 4: After compiling the reference list, the selection of studies was performed manually by IB, and the references were organized both in Microsoft Excel and Mendeley. Each article was examined to determine whether it would proceed to the next stage of selection. The database records were filtered according to the following predefined inclusion criteria: document type (journal article or book chapter); English language; and relevance to sentiment analysis in an urban environment. Therefore, after screening titles and abstracts, 310 articles were excluded because, although these studies used sentiment analysis to explore people's opinions, they did not aligned with the scope of this review because the sentiment analysed referred primarily to a specific event, service, activity, or issue rather than to characteristics of the broader urban environment. This includes studies focusing on COVID-19-related contexts, such as reopening measures during lockdowns, mobility restrictions, or urban sentiment influenced by the pandemic (Y. Chen et al., 2023; B. Jia et al., 2025; Jung, 2025; W. Sun et al., 2023; S. Wang et al., 2024; Yiğit Uzunali & Uzunali, 2025), where sentiments were analysed under the exceptional conditions of the pandemic; studies primarily focused on tourist satisfaction, tourist perceptions, or tourism-oriented destination management (W. Chen et al., 2025; Chu & Yang, 2025; Gou et al., 2025; M. Jia et al., 2024; Kashyap & Hong, 2025; Saoualih et al., 2024; H. Yuan et al., 2025); studies regarding citizens' concerns in public transport (Henriquez-Jara et al., 2025; Shukla et al., 2024; Tran et al., 2023); comments specifically about pollution (Khusna Amalia et al., 2024; Nuryana et al., 2025); and sentiments specifically related to urban traffic (Cao et al., 2018; S. Wang et al., 2018). Although public transport, pollution, and traffic can represent characteristics of the urban environment, these studies focused specifically on opinions about these topics rather than on their relationship with

the broader urban environment. Also, studies relying solely on self-reported sentiments without applying a sentiment analysis tools to textual data (Covato & Jeawak, 2023), and studies that aggregated all urban variables into composite indices without analyzing their individual contributions to sentiment (X. He et al., 2024), were excluded because the individual associations between urban-environment variables and sentiment could not be identified.

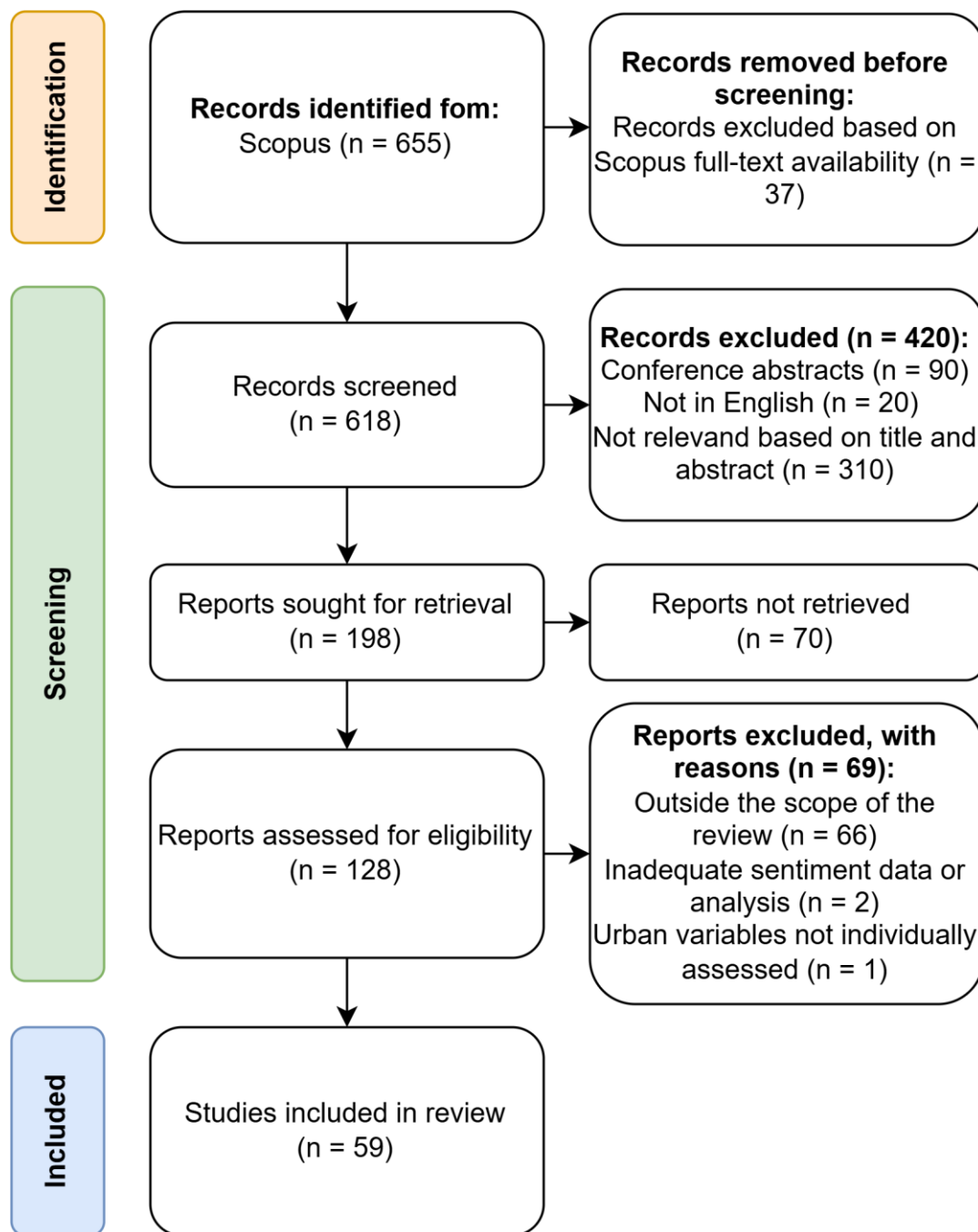
Stage 5: The full texts of the remaining articles were assessed according to the predefined inclusion and exclusion criteria. Articles were excluded when they did not provide relevant data on the relationship between sentiment and identifiable characteristics of the urban environment. A total of 59 articles (Table 1) met the eligibility criteria and were included for data extraction and analysis.

Stage 6: In data extraction, which was performed manually by IB, coding is established, either inductive or deductive, depending on whether the analytical categories emerge from the data or are based on pre-existing concepts (Suri & Clarke, 2009). Inductive coding develops categories from patterns identified during the examination of the included studies, whereas deductive coding applies categories established before the analysis. This review adopted a combined deductive–inductive approach: predefined general categories were complemented by variables identified from the included studies, while the direction of their reported associations with sentiment was coded deductively using predefined categories (Hajrasoulih et al., 2018).

Stage 7: For data analysis and synthesis, the content of each article was examined, including study topic, year of publication, and study area. A meta-analysis was not conducted due to the heterogeneity among the included studies in terms of the urban variables examined, data sources, sentiment analysis methods, spatial scales, and statistical approaches; instead, the results were synthesized according to the direction of the reported associations (Koutsos et al., 2019). The studies were then grouped into three categories: (1) data source (i.e., the social media or other digital data sources used in the included studies), (2) sentiment classification method or tool (i.e., manual, lexicon-based,

machine-learning, deep-learning, and hybrid approaches), and (3) methods to assess associations (i.e., procedures used to examine the relationship between sentiment and independent variables). Finally, the urban environment variables reported in the reviewed studies were organized into broader groups and themes (e.g., physical, stressors, and social factors), and the direction of their reported association with sentiment was synthesized as positive (+), negative (−), or contradictory (><), indicating that both positive and negative associations were reported across the reviewed studies.

Stage 8: In reporting the results, the process of the systematic literature review was described in detail (Okoli & Schabram, 2010), with the study selection process reported using the PRISMA 2020 flow diagram (Figure 2).



211 **Figure 2** - PRISMA 2020 flow diagram of the study selection process.

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3. Results

3.1. Publication year and study area

The number of articles published each year indicates growing interest in sentiment analysis in urban environments (Figure 3). Between 2018 and 2021, one study was published per year, followed by seven studies in 2022, six in 2023, 16 in 2024, and 26 in 2025. Accordingly, 71.2% of the reviewed studies were published in 2024 and 2025, indicating a significant increase in recent research on this topic.

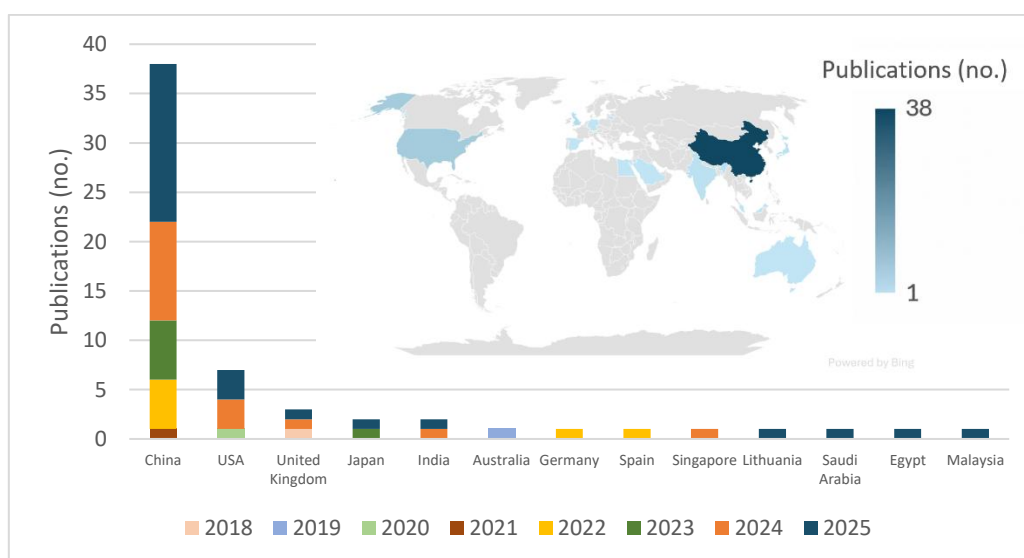


Figure 3 – Publication year and study area.

From a geographical perspective, the literature is strongly concentrated in Asia, particularly in China, which is represented in 38 of the reviewed studies ($n = 38$), followed by the USA ($n = 7$), the United Kingdom ($n = 3$), Japan and India ($n = 2$ each). In contrast, the remaining countries are represented by one study each ($n = 1$) (Figure 3). According to this distribution, the research remains uneven, with limited representation from other regions.

Regarding the findings reported in the main geographical contexts represented in the review, studies in Chinese metropolitan areas and megacities mainly examined the relationships between the urban environment and public sentiment, particularly regarding air pollution, urban density, heat, and green spaces (Ge et al., 2025; H. He et al., 2023; P. Sun et al., 2024; Y. Sun et al., 2021). In Chinese cities, positive sentiment is usually associated with urban parks, scenic spots, business districts, and cultural areas, while negative responses are more often found around transport hubs, healthcare facilities, and industrial areas (Y. Gao et al., 2022; Y. Yuan et al., 2024; Zhu et al., 2024).

Among the studies conducted in the United States, positive sentiment is associated with greenery, pedestrian-friendly and visually attractive environments, as well as well-maintained spaces that support recreation and interaction with nature, while negative responses are associated with congestion, limited amenities, maintenance and safety concerns, and socioeconomic and environmental stressors (Aman & Matisziw, 2025; L. Li et al., 2025; Nwanaji-enwerem et al., 2025).

Furthermore, in Europe, the studies analyzed cover a variety of urban contexts, including Barcelona, Berlin, Kaunas, and London. Positive responses are associated with pedestrian and recreational spaces (Grazuleviciute-vileniske et al., 2025), storefronts, historical and cultural environments, beaches (Yang et al., 2022), vegetation (Ke et al., 2024), parks (Kovács-Györi et al., 2018), blue spaces (M. Gao & Fang, 2025), and features such as interesting plants and swimming infrastructure (S. Chen et al., 2022). In contrast, some transport-related environments, particularly railway areas, are associated with more negative sentiment (M. Gao & Fang, 2025; Yang et al., 2022).

Studies from other Asian contexts indicate that the relationship between urban characteristics and sentiment varies across geographical and cultural contexts. Green-space design, cultural elements, and the distribution of public facilities are related to sentiment, but their relevance differs between locations (Kikutani & Yoshida, 2025; S. Liu et al., 2023; W. Zhang & Su, 2024). For example, differences were found in the China–Japan comparison of urban green spaces, while in Singapore,

perceptions of urban green spaces were generally positive, but no consistent relationship was found between individual land-cover types and satisfaction (S. Liu et al., 2023; W. Zhang & Su, 2024).

3.2. Data, sentiment analysis and statistical methods

After a comprehensive analysis, each study was categorized according to three topics: data source, sentiment analysis method or tool, and relation or analytical method (Figure 4). The results highlight two primary data sources: the Weibo/Chinese ecosystem and Twitter/X together accounting for 32 of the 59 studies (54.2%), 21 studies used Weibo and 11 used Twitter/X. Overall, most studies linking the urban environment to sentiment use textual data from social networks and other digital platforms, such as Weibo, Twitter/X, Ctrip, Google Maps, and DianPing, although images from social media such as Flickr are also used.

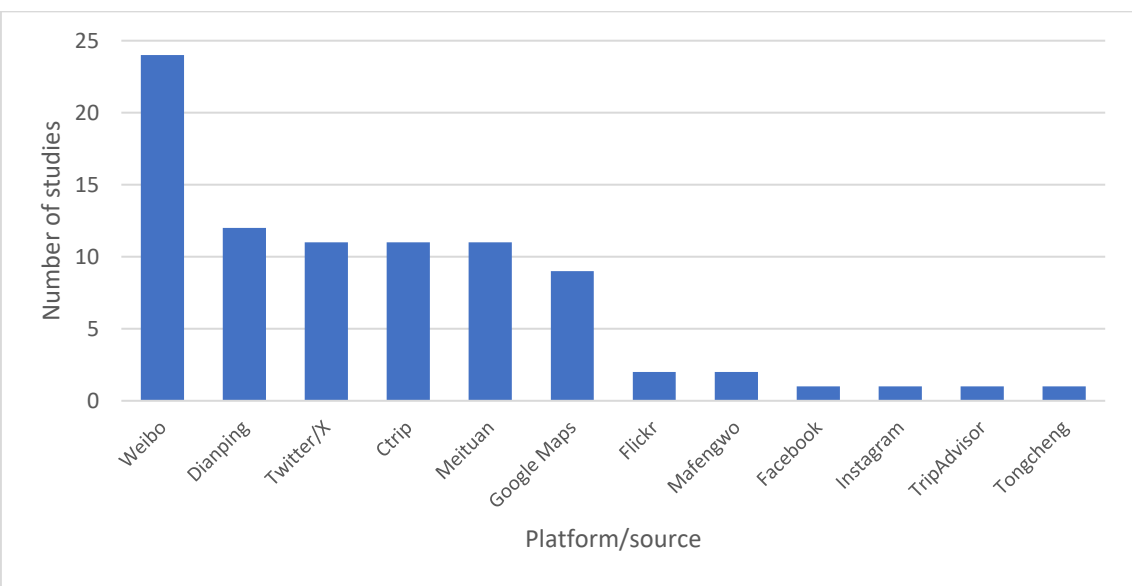


Figure 4 – Sentiment analysis data sources.

The results show that sentiment classification techniques used in the reviewed studies fall into five categories: 1) manual; 2) machine-learning approach; 3) deep-learning; 4) lexicon-based approach;

and 5) hybrid approach. The manual approach involves the classification of sentiment by human coders rather than through an automated computational method; the machine-learning approach uses ML algorithms and linguistic features to identify sentiment patterns from training data; the deep-learning approach uses deep neural network architectures, including transformer-based models, and large language models; the lexicon-based approach relies on a sentiment lexicon (i.e., a pre-compiled collection of known sentiment terms); and the hybrid approach combines lexical resources with machine-learning methods (Duwairi & Ahmed, 2015; Mao et al., 2024; Maynard & Funk, 2012; Medhat et al., 2014).

As shown in Table 1, the authors employed a heterogeneous set of sentiment-analysis methods and tools, including lexicon-based methods (e.g., EmoLex and VADER), software libraries (e.g., TextBlob and SnowNLP), emotion-recognition software (e.g., FireFACE), and external NLP services (e.g., Tencent, Baidu, Alibaba, YuyiData, Google). Studies focusing on Chinese metropolitan areas and megacities frequently employed Chinese-language cloud-based NLP services provided by Baidu, Tencent, and Alibaba, as well as deep learning models (e.g., BERT, RoBERTa, SKEP, ERNIE, and RNN-LSTM). In contrast, studies based on Twitter/X relied mainly on lexicon-based methods (e.g., VADER and EmoLex), although some combined these resources with machine-learning models, thereby adopting a hybrid approach (e.g., VADER with RoBERTa).

Table 1 -Data sources, sentiment-analysis methods, and analytical methods used in the included studies

Study	Data source	Sentiment-analysis method	Relation / analytical method	Authors
1	Weibo	YuyiData	Support Vector Regression (SVR)	(Y. Gao et al., 2022)
2		FireFACE	Split-plot ANOVA; Multivariate linear regression (MLR)	(S. Huang et al., 2022)

3		Tencent, Baidu and Alibaba NLP	Spearman correlation; Random Forest (RF) + Permutation Feature Importance (PFI)	(Kong et al., 2022)
4		Dictionary	Curve estimation; Correlation matrix; Coupling coordination modelling	(Tao et al., 2022)
5		Baidu NLP	Fixed-effects quadratic regression model	(Y. Cheng et al., 2023)
6		SKEP ERNIE	Multilevel regression model; Gradient boosting decision tree	(Fan et al., 2023)
7		BERT	Fixed-effects panel regression model	(H. He et al., 2023)
8		DL RNN-LSTM	Structural equation modeling (SEM)	(Lai & Deal, 2023)
9		Dictionary	Pearson correlation; Exploratory Factor Analysis (EFA)	(R. Zhang, 2023)
10		Naive Bayes SnowNLP	Correlation analysis	(P. Sun et al., 2024)
11		Baidu NLP	Regression model; Likelihood Ratio Test	(Y. Cheng et al., 2024)
12		BERT	ANOVA; Fixed-effects panel regression model	(H. He & Sun, 2024)
13		BERT	Structural equation modeling (SEM)	(Y. Yuan et al., 2024)
14		RoBERTa	Association rule mining using the Apriori algorithm	(Zhu et al., 2024)
15		JioNLP	XGBoost + SHapley Additive exPlanations (SHAP)	(Y. Cheng et al., 2025)
16		BERT	XGBoost; SHAP	(Ge et al., 2025)
17		SnowNLP	ANOVA; Tukey post-hoc tests; Pearson correlation	(T. Huang et al., 2025)
18		ML-Ask	Multivariate linear regression (MLR)	(Kikutani & Yoshida, 2025)
19		Dictionary	Stepwise multiple linear regression	(Y. Li et al., 2025)
20		ERNIE	XGBoost + SHAP; GeoSHAPLEY	(Lu et al., 2025)
21		Dictionary	—	(Qin et al., 2025)
22	Twitter/X	EmoLex	—	(Kovács-Györi et al., 2018)
23		EmoLex	Pearson correlation	(Lim et al., 2019)
24		TextBlob	Spearman correlation	(S. Chen et al., 2022)

25		VADER SentiStrength	Pearson correlation	(Yang et al., 2022)
26		VADER RoBERTa	Pearson correlation	(S. Cheng & van Ameijde, 2024)
27		VADER	Random Forest (RF) + SHAP	(P. He et al., 2024)
28		Microsoft Azure	Spatial regression	(Khare & Chatterjee, 2024)
29		VADER	Spatial regression	(Lee, 2024)
30		Natural Language Toolkit (NLTK) Google Cloud NLP	Ordinary Least Squares (OLS)	(M. Wang et al., 2024)
31		GPT-3.5 using Chain-of-Thought (CoT)	Pearson correlation	(W. Zhang & Su, 2024)
32		BERT	Spearman correlation; Multiple linear regression; one-way ANOVA	(M. Gao & Fang, 2025)
33	Flickr	ConvNet	—	(Oliveira et al., 2020)
34		TextBlob	—	(Ke et al., 2024)
35	Facebook	VADER	—	(Grazuleviciute-vileniske et al., 2025)
36	Instagram	BERT	Ordinary Least Squares (OLS)	(Aman & Matisziw, 2025)
37	Google Maps	ChatGPT 4.0	—	(Karban, 2025)
38		Llama 3	Generalized Additive Model (GAM)	(L. Li et al., 2025)
39		EmoLex	Robust multiple regression; Random Forest + SHAP	(Mohamed & Kronenberg, 2025)
40		EmoLex	ANOVA; Welch's t-tests	(Nwanaji-enwerem et al., 2025)
41		VADER	—	(Rusli et al., 2025)
42		VADER	—	(Saha et al., 2025)
43	Dianping	Manual	Multiple linear regression	(R. Liu & Xiao, 2021)
44		LSTM	Spearman correlation; Principal Component Analysis (PCA)	(W. Ren et al., 2024)
45		ROST EA1.9.04	—	(Pan et al., 2024)
46		ERNIE	—	(W. Huang et al., 2025)
47		Baidu AI Cloud	Multiple linear regression	(L. Li & Wang, 2025)

48		SnowNLP	Pearson correlation	(W. Li et al., 2025)
49		SnowNLP	Pearson correlation and structural equation modeling (SEM)	(Z. Li & Dong, 2025)
50		VADER	—	(Rezaeimalek et al., 2024)
51	Ctrip	ROST CM6	One-way ANOVA; Pearson correlation	(Z. Zhang et al., 2025)
52	Resident complaint data from an official open platform	LSTM-CNN ERNIE	XGBoost + SHAP	(Z. Chen et al., 2024)
53	Ctrip & Google Maps	Baidu & Google NLP	Beta regression	(Huai & de Voorde, 2022)
54	Weibo & Google Maps	Baidu & Google NLP	Pearson correlation	(S. Liu et al., 2023)
55	Meituan, Dianping, Mafengwo & Ctrip	ROST CM6	—	(J. Chen & Han, 2025)
56	Dianping & Ctrip	Baidu & Google	Multiple linear regression	(J. Li et al., 2025)
57	Google Maps & TripAdvisor	Baidu AI Cloud	Multiple linear regression	(K. Liu et al., 2025)
58	Weibo, Dianping, Meituan, Ctrip & Tongcheng	Dictionary	—	(S. Ren & Chen, 2025)
59	Ctrip, Dianping & Weibo	ERNIE	—	(Yan et al., 2025)

Specifically, machine-learning approaches use algorithms to classify sentiment in textual data based on syntactic and/or linguistic features (e.g., Medhat et al., 2014). In the reviewed studies, sentiment classification was performed using probabilistic classifiers, such as Naive Bayes; neural-network and deep-learning architectures (e.g., ConvNet, RNN-LSTM, LSTM, and LSTM-CNN); transformer-based models (e.g., BERT, RoBERTa, SKEP, and ERNIE); and, in more recent studies, large language models (e.g., GPT-3.5, ChatGPT 4.0, and Llama 3). However, no unsupervised clustering method was identified as a sentiment-classification technique in the reviewed sample; these methods are usually used to identify sentiment patterns in data without pre-defined labels and are based on computing similarity between data points, as illustrated by clustering algorithms such as K-means (Shayaa et al., 2018).

The reviewed studies frequently used external NLP services and pre-trained models. Among lexicon-based resources, VADER was the most frequently used method in the reviewed sample (Grazuleviciute-vileniske et al., 2025; P. He et al., 2024; Lee, 2024; Rezaeimalek et al., 2024; Rusli et al., 2025; Saha et al., 2025). It combines a sentiment lexicon with linguistic and heuristic rules (Hutto & Gilbert, 2014). EmoLex was also frequently used (Kovács-Györi et al., 2018; Lim et al., 2019; Mohamed & Kronenberg, 2025; Nwanaji-enwerem et al., 2025) and provides associations not only with the two sentiments but also with the eight basic emotions (Mohammad & Turney, 2013). Recent applications also illustrate the use of EmoLex with georeferenced Twitter/X data to map the spatial distribution of positive and negative sentiment in urban environments (Betco et al., 2025).

Finally, to examine relationships and patterns between sentiment and urban-environment variables, a variety of analytical methods were employed, including: (a) correlation analyses (e.g., Pearson correlation and Spearman's rank correlation); (b) regression and curve-fitting models (e.g., multiple linear regression, panel-data regression, fixed-effects regression, fixed-effects quadratic regression, beta regression, multilevel regression, spatial regression, and curve estimation); (c) group-comparison and association tests (e.g., ANOVA, split-plot ANOVA, Welch's t-test, and chi-square tests); (d) structural and dimensionality-reduction methods (e.g., structural equation modelling, exploratory factor analysis, and principal component analysis); and (e) predictive machine-learning models (e.g., gradient-boosting decision trees, Random Forest, Support Vector Regression, and XGBoost). Some studies also employed model-interpretation methods, such as Permutation Feature Importance, SHAP, and GeoSHAPLEY, to assess the contribution of individual urban-environment variables to model predictions. When no formal statistical test was applied, the relationship between sentiment and urban variables was generally explored through exploratory spatial interpretation (e.g., comparing sentiment hotspots with urban features), and/or textual interpretation (e.g., identifying

recurring keywords, topics, or themes in reviews and comments) (Grazuleviciute-vileniske et al., 2025; Karban, 2025; Pan et al., 2024).

3.3. Relationship to the urban environment

Variables related to the urban environment were organized into three groups (physical factors, external stressors, and society) and categorized based on their association with positive sentiment (+), negative sentiment (−), or contradictory evidence (><) (Table 2). Only the relationships identified by the studies themselves as relevant/significant were considered in the synthesis. Comparing the magnitude of the associations would be debatable, since the studies use very different methods and present the results through metrics that are not directly comparable to each other. When examining the indicators collectively, physical factors (e.g., green and blue spaces, land use, density, transportation, spatial layout, and public infrastructure) showed 38 positive, 9 negative, and 13 contradictory relationships. External stressors, represented by environmental conditions, showed 3 positive, 8 negative, and 2 contradictory relationships. Society-related factors (e.g., security, mobility, economic stressors, and social context) showed 9 positive and 8 negative relationships, with no contradictory relationships identified.

Table 2 - Relationship between urban environment and positive sentiment/emotional responses; + positive relationship, - negative relationship, >< conflicting evidence.

Groups	Theme	Urban feature	References
Physical	Green print	+ Vegetation density >< Presence of vegetation + Presence of green spaces + Proximity to green spaces + Density of green spaces + Plant diversity + Trees + Urban park (presence, proximity and accessibility) + Urban forest + Natural elements / nature-related elements >< NDVI >< Informal green spaces	(Aman & Matisziw, 2025; Chae et al., 2023; S. Chen et al., 2022; Z. Chen et al., 2024; Y. Cheng et al., 2024; Fan et al., 2023; H. He et al., 2023; H. He & Sun, 2024; S. Huang et al., 2022; W. Huang et al., 2025; Karban, 2025; Ke et al., 2024; Khare & Chatterjee, 2024; Kong et al., 2022; Kovács-Györi et al., 2018; Lai & Deal, 2023; L. Li & Wang, 2025; W. Li et al., 2025; Y. Li et al., 2025; Lim et al., 2019; R. Liu & Xiao, 2021; S. Liu et al., 2023; Lu et al., 2025; W. Ren et al., 2024; Rusli et al., 2025; P. Sun et al., 2024; M. Wang et al., 2024; Y. Yuan et al., 2024; R.

			Zhang, 2023; W. Zhang & Su, 2024; Zhu et al., 2024)
	Blue print	+ Proximity to blue spaces + Density of water bodies + Presence of water + Beach / coastal blue space + Lakefront landscape + Urban rivers + Artificial water features	(S. Chen et al., 2022; Fan et al., 2023; M. Gao & Fang, 2025; P. He et al., 2024; Huai, Songyao and Van de Voorde, 2022; W. Huang et al., 2025; Khare & Chatterjee, 2024; Kong et al., 2022; Lai & Deal, 2023; W. Li et al., 2025; Z. Li & Dong, 2025; S. Liu et al., 2023; Rusli et al., 2025; Tao et al., 2022; Yang et al., 2022; R. Zhang, 2023; Z. Zhang et al., 2025)
	Land use Land cover	+ Commercial land - Industrial land - Impervious surfaces >< Land use mix	(Fan et al., 2023; M. Gao & Fang, 2025; Kong et al., 2022; Y. Li et al., 2025; Lu et al., 2025; P. Sun et al., 2024)
	Densities	>< Road density >< Building density + Store density	(Aman & Matisziw, 2025; Fan et al., 2023; M. Gao & Fang, 2025; Ge et al., 2025; H. He et al., 2023; W. Li et al., 2025; Y. Li et al., 2025; Lu et al., 2025; P. Sun et al., 2024; Yang et al., 2022)
	Transport	- Railway areas - Transport hubs and stations + Public transport accessibility	(Y. Gao et al., 2022; Y. Li et al., 2025; Z. Li & Dong, 2025; Lim et al., 2019; Saha et al., 2025; Yang et al., 2022; Y. Yuan et al., 2024)
	Spatial configuration	+ Open / wide space - Excessive enclosure + Park size + Water feature size >< Sky visibility + Green visibility >< Water visibility >< Imageability>< Colour complexity >< Perception of crowding - Intersections/crossroads + Spatial connectivity / permeability + Scenic landscapes + Cultural landscapes + Landscape element diversity + Architectural quality - Loss of authenticity / homogenization	(Aman & Matisziw, 2025; J. Chen & Han, 2025; S. Chen et al., 2022; Z. Chen et al., 2024; S. Cheng & van Ameijde, 2024; Y. Cheng et al., 2024; M. Gao & Fang, 2025; Y. Gao et al., 2022; Ge et al., 2025; Huai & de Voorde, 2022; S. Huang et al., 2022; Karban, 2025; Khare & Chatterjee, 2024; Kong et al., 2022; W. Li et al., 2025; Y. Li et al., 2025; Lim et al., 2019; K. Liu et al., 2025; R. Liu & Xiao, 2021; S. Liu et al., 2023; Lu et al., 2025; Pan et al., 2024; S. Ren & Chen, 2025; W. Ren et al., 2024; Rusli et al., 2025; P. Sun et al., 2024; Tao et al., 2022; M. Wang et al., 2024; Yan et al., 2025; R. Zhang, 2023; Z. Zhang et al., 2025)
External stressors	Public infrastructures	+ Historic areas >< Commercial areas - Industrial areas >< Traffic areas + Artistic and cultural areas + Pathways, sidewalks and squares + Religious facilities - Healthcare and welfare facilities >< Educational facilities + Recreational facilities + Framework and service facilities + Sports infrastructure + Facility maintenance + Pet-friendly spaces + Family-friendly spaces	(Aman & Matisziw, 2025; J. Chen & Han, 2025; S. Chen et al., 2022; Fernandez et al., 2022; Y. Gao et al., 2022; Grazuleviciute-vileniske et al., 2025; Karban, 2025; Kikutani & Yoshida, 2025; Lee, 2024; J. Li et al., 2025; L. Li et al., 2025; L. Li & Wang, 2025; Z. Li & Dong, 2025; Lim et al., 2019; K. Liu et al., 2025; R. Liu & Xiao, 2021; S. Liu et al., 2023; Pan et al., 2024; Qin et al., 2025; S. Ren & Chen, 2025; Rezaeimalek et al., 2024; Rusli et al., 2025; M. Wang et al., 2024; Y. Yuan et al., 2024; R. Zhang, 2023; Zhu et al., 2024)
	Environment	- Air pollution + Urban Cool Islands	(Y. Cheng et al., 2023, 2025; H. He et al., 2023; H. He & Sun, 2024; P. He et al.,

		>< Air temperature - Heatwave intensity - Extreme precipitation - Extreme temperature - Thermal discomfort >< Noise + Peaceful and tranquil environment - Presence of trash - Odor / smell - Signs of urban decay + Cleanliness	2024; Huai & de Voorde, 2022; T. Huang et al., 2025; W. Huang et al., 2025; Karban, 2025; R. Liu & Xiao, 2021; Mohamed & Kronenberg, 2025; Nwanaji-enwerem et al., 2025; Oliveira et al., 2020; W. Ren et al., 2024; Rusli et al., 2025; Y. Sun et al., 2021; Yang et al., 2022; Z. Zhang et al., 2025)
Society	Security	+ Perception of security - Crime	(W. Huang et al., 2025; Karban, 2025; Khare & Chatterjee, 2024)
	Mobility	+ Ease and comfort in mobility + Walkability - Congestion / Traffic + Universal accessibility	(Grazuleviciute-vileniske et al., 2025; Karban, 2025; L. Li et al., 2025; L. Li & Wang, 2025; Rusli et al., 2025; Saha et al., 2025; K. Zhang et al., 2023)
	Economic stressors	+ High land value - High poverty rate - House prices - Income inequality + Distance to slums - Expensive paid amenities - Low-income areas - Over-commercialization	(Fan et al., 2023; P. He et al., 2024; Khare & Chatterjee, 2024; L. Li et al., 2025; Mohamed & Kronenberg, 2025; Pan et al., 2024; Yang et al., 2022; X. Zhang & Chen, 2023)
	Social context	+ Social interaction + Social characteristics + Social activities	(J. Chen & Han, 2025; Y. Gao et al., 2022; Karban, 2025; Lee, 2024; K. Liu et al., 2025; R. Zhang, 2023)

For instance, the results show that green and blue infrastructure were generally associated with more positive sentiment: higher vegetation density and the presence or proximity of water bodies (S. Chen et al., 2022; Fan et al., 2023; H. He et al., 2023; Lai & Deal, 2023; Lim et al., 2019; R. Liu & Xiao, 2021; Yang et al., 2022; W. Zhang & Su, 2024). However, this relationship was neither necessarily linear nor universally positive. Evidence suggests that the emotional effects of green and blue elements depend on design and maintenance; when these elements are improperly managed, they may be associated with negative complaints or weaker positive sentiment (Z. Chen et al., 2024; S. Liu et al., 2023). Indeed, we observed a positive relationship between the presence, proximity, density, and visibility of green infrastructure (e.g., green spaces, vegetation, urban forests, and plants) and blue infrastructure (e.g., water bodies, water, and beaches). More specific nature-related elements, such as

trees, lawns, rocks, valleys, trails, and natural sounds, were also linked to positive emotional and restorative experiences (Chae et al., 2023; R. Zhang, 2023).

Regarding land use, positive relationships are found for commercial areas, while negative relationships are reported for industrial land and impervious surfaces (Fan et al., 2023; Kong et al., 2022). More specifically, Fan et al. (2023) found that, at the subdistrict level, commercial land and less industrial land are more likely to foster positive sentiment. Similarly, in Barcelona, Yang et al. (2022) found that historic areas, shopfront density, and beach areas are positively linked with sentiment.

Regarding urban density, the results are more complex: road density and shop density tend to be positively associated with sentiment, while building density shows mixed results (Fan et al., 2023; H. He et al., 2023; P. Sun et al., 2024; Yang et al., 2022). Fan et al. (2023) found that higher densities of buildings and roads were more likely to foster positive sentiment at the subdistrict level, whereas at the neighborhood level, a lower plot ratio (i.e., lower building density/intensity) was preferred.

Finally, transport-related features tend to show more negative relationships with sentiment. Transport nodes such as railway stations are generally linked to negative sentiment (Y. Gao et al., 2022; Lim et al., 2019). In Barcelona, Yang et al. (2022) found that the percentage of railway areas was negatively linked with sentiment, which the authors attributed to the greater prevalence of large, empty railway zones in suburban districts.

External stressors have varied effects: air pollution usually impacts negatively, but noise and “contamination” can sometimes be positively correlated with public sentiment because these two indicators are mainly concentrated in the city centre, where various services, intense street activities, and amenities are located (Yang et al., 2022). Y. Sun et al. (2021) found that the public primarily complained about exhaust emissions from companies and factories, and that there is a significant link between negative sentiment and PM2.5 levels. Findings by Oliveira et al. (2020), using Flickr images, also demonstrate that pollution features among the common urban problems represented in negative user-

posted images. Also, extreme heat and extreme precipitation tend to reduce sentiment, while moderate greenness and comfortable temperatures are associated with more positive sentiment (Y. Cheng et al., 2023; H. He et al., 2023).

3.4. How methods align with urban factors

Table 1 and Table 2 highlight different methodological matchings. For instance, studies using the Chinese platform and NLP ecosystem (such as Weibo, Baidu, Tencent, and Alibaba NLP services) frequently rely on machine-learning or deep-learning approaches (e.g., SKEP, ERNIE, BERT, RNN/LSTM, vendor NLP services) (e.g., Fan et al., 2023; Gao et al., 2022; Kong et al., 2022; Lai & Deal, 2023). This pattern is particularly evident among Weibo-based studies, where 15 of the 21 studies use ML/DL approaches (Table 1). Figure 5 shows that ML/DL is the most frequently used sentiment-analysis approach across the reviewed literature (34 studies), followed by lexicon-based methods (21 studies), hybrid approaches (3 studies), and manual analysis (1 study).

Although ML/DL predominates in sentiment classification, the sentiment-analysis approach should be distinguished from the analytical methods subsequently used to examine relationships between sentiment and urban environment variables. Several studies combine sentiment classification with statistical or machine-learning techniques such as Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting Decision Trees (GBDT), XGBoost/SHAP, panel regression, and structural equation modelling (Y. Cheng et al., 2025; Fan et al., 2023; Y. Gao et al., 2022; P. He et al., 2024; Z. Li & Dong, 2025). These analytical methods enable the examination of linear, nonlinear, and context-dependent relationships between sentiment and urban characteristics.

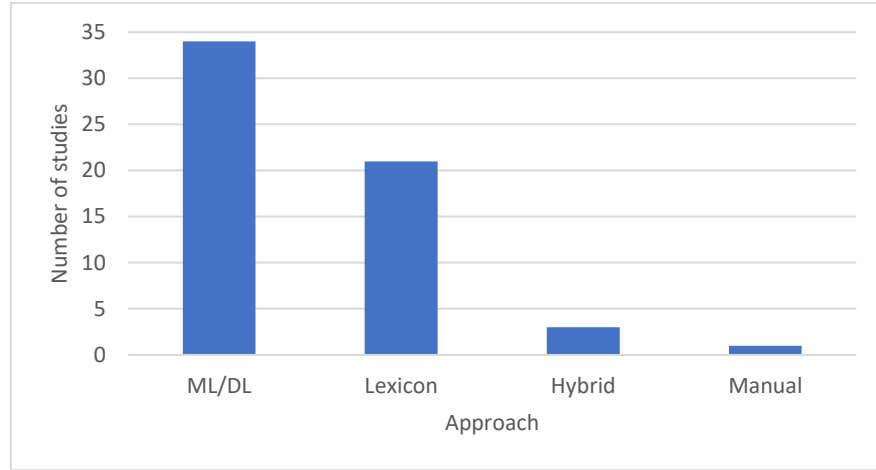


Figure 5 – Sentiment analysis methods.

The alignment between methodological approach and urban-factor group also shows that Physical variables dominate across the reviewed literature. Among the 34 ML/DL studies, 31 examine Physical variables, compared with 10 addressing External stressors and 7 addressing Society-related factors. Similarly, 18 of the 21 lexicon-based studies examine Physical variables, while 7 address External stressors and 10 Society-related factors. All three hybrid studies examine Physical variables, whereas the single manual study considers both Physical factors and External stressors. These results indicate that no methodological approach is exclusively associated with a specific urban-factor group, although Physical variables clearly predominate across approaches.

Lexicon-based approaches are distributed across several data sources, including Weibo, Twitter/X, Google Maps, Dianping, and Ctrip, using methods such as dictionaries, VADER, EmoLex, JioNLP, ML-Ask, and ROST. Hybrid approaches are comparatively uncommon, accounting for only three of the 59 studies, all of which examine Physical variables in the current classification. Image-focused studies in the sample rely on ML/DL techniques, including ConvNet (Oliveira et al., 2020) and FireFACE (S. Huang et al., 2022). Manual sentiment analysis is represented by only one study (R. Liu & Xiao, 2021), which examines both Physical variables and External stressors.

Figure 6 further disaggregates these relationships by showing the number of studies using each sentiment-analysis method that examines variables belonging to the Physical, External stressors, and Society macro-categories. The heatmap confirms the predominance of Physical variables across most sentiment-analysis methods and reveals differences in methodological coverage among the three macro-categories. Cloud NLP services show the broadest distribution, with 9 studies addressing Physical variables, 8 External stressors, and 9 Society-related variables. VADER also extends over the three groups (8, 3, and 6 studies, respectively). BERT is strongly concentrated on Physical variables (8 studies), with fewer applications to External stressors (2) and none to Society, whereas ERNIE is represented across all three groups (5 Physical, 2 External stressors, and 1 Society). Dictionary-based methods are predominantly associated with Physical variables (5 studies), while ROST is distributed across Physical (3), External stressors (1), and Society (2). Overall, these patterns reinforce the dominance of Physical variables but also show that some sentiment-analysis methods are applied across a broader range of urban-factor groups than others.

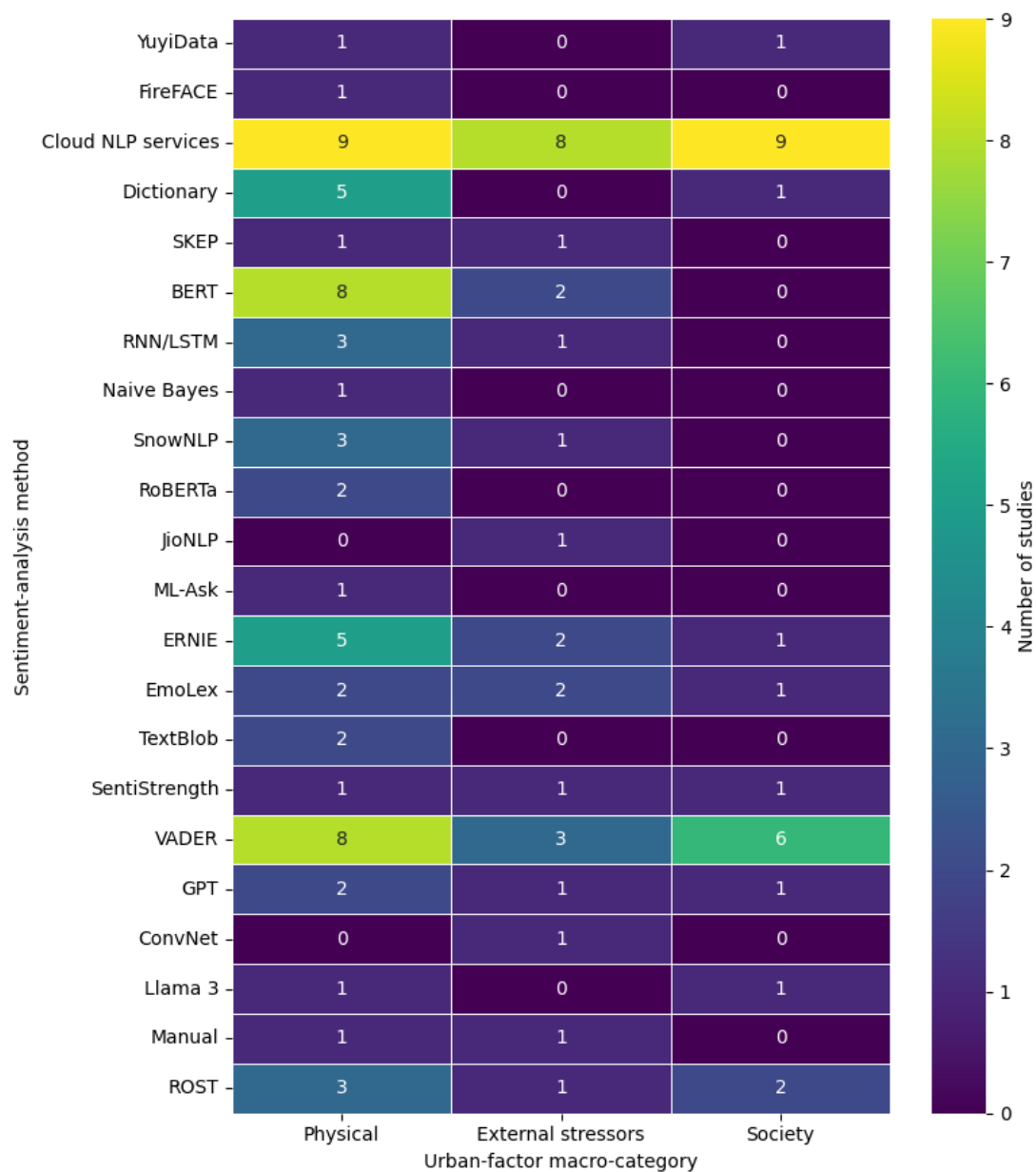


Figure 6 – Cross-table analytical narrative.

4. Discussion

4.1. Geographical and methodological patterns

The results indicate a rapid and recent growth of research on sentiment analysis in urban environments, a pattern consistent with the broader bibliometric evolution of the field reported by Betco et al. (2026), who identified a marked increase in scientific production and a peak in publications in

2025. This growth coincides with increased discussion of sustainable cities and the growing availability of georeferenced data from social networks (Ilieva & McPhearson, 2018). However, the strong geographical concentration of the reviewed literature, particularly in China, indicates that current knowledge is based disproportionately on a relatively restricted set of geographical and cultural contexts. Overall, the studies show that some relationships recur across different geographical settings, while others remain context-dependent, consistent with evidence that urban perception can vary with local and cultural context (Quintana et al., 2025).

This geographical concentration is also associated with methodological patterns. The frequent use of external NLP services and pre-trained models reduces the need for researchers to develop and train a new sentiment classifier for each study. This is particularly relevant because supervised machine-learning methods require sufficiently comprehensive labelled training data to achieve effective and reliable classification of test data (e.g., Shayaa et al., 2018). Lexicon-based resources are also frequently employed because they do not require labelled training data. Nevertheless, the predominance of particular platforms, languages, NLP ecosystems, and geographical contexts should be considered when interpreting the generalizability of the relationships identified between urban characteristics and sentiment.

Recent methodological developments also suggest that model interpretability should be complemented by an explicit assessment of prediction uncertainty. Betco et al. (2026), combining machine-learning models, SHAP explanations and Shannon entropy in a spatial sentiment framework, demonstrated that the factors driving sentiment predictions can be interpreted together with their spatial uncertainty, distinguishing areas where model explanations are more reliable from those requiring greater caution.

4.2. Urban environment and sentiment: consistent and context-dependent relationships

Among the most consistent findings, green and blue infrastructure emerge as important elements associated with positive sentiment and emotional responses. These benefits are widely recognized in the literature as promoting health and well-being through various mechanisms, such as facilitating physical activity (Coombes et al., 2010; Ribeiro et al., 2015; Thompson Coon et al., 2011), reducing stress and depression and encouraging relaxation (Ribeiro et al., 2026; White, Alcock, et al., 2013; White, Pahl, et al., 2013), being associated with lower exposure to noise and air pollution (Hystad et al., 2014), regulating heat (Bowler et al., 2010; Gill et al., 2007), and lower levels of loneliness and higher social interaction and community cohesion (Castro et al., 2026; de Vries et al., 2013; Maas et al., 2009; van den Berg et al., 2017).

However, the results also demonstrate the importance of local context. Huai and Van de Voorde (2022) noted that, in Shanghai, there is a preference for visually appealing features (e.g., water bodies and colorful elements in urban parks), whereas in Brussels, people favour calm and tranquil environments. Interestingly, perceived crowding had a positive effect on park perceptions in Brussels, indicating that although it might be viewed as negative, crowding can also reflect high visitation and popularity. The authors therefore argue that planners and decision-makers should consider local preferences and seek solutions that balance the needs of different user groups. Also, the study by Lim et al. (2019) on the effects of green spaces on the well-being of urban users in Melbourne reveals a prevalence of positive sentiments in green spaces compared to other urban areas, while negative sentiments were typically associated with major transport infrastructure (e.g., train interchanges, major road junctions and railway tracks). Other studies also indicate that the quality and amount of urban green spaces positively influence sentiment (S. Huang et al., 2022; Y. Zhang et al., 2020).

The context-dependent character of these relationships is particularly evident for urban density. The variation identified in the reviewed studies is consistent with conflicting evidence across different

contexts (D. He et al., 2022; Mouratidis, 2018). In some cases, higher-density environments are associated with greater satisfaction, social well-being and more positive urban perceptions (L. Li & Wang, 2025; Mouratidis, 2018); in others, lower positive sentiment is associated with crowding, excessive commercialization, poor hygiene, outdated infrastructure, weak management or lack of uniqueness (L. Li & Wang, 2025). Thus, density itself may be less relevant than the environmental, functional, and experiential conditions associated with different forms of urban density.

A similar interpretation applies to external stressors. Exposure to air pollution (e.g., particulate matter, nitrogen dioxide, and elemental carbon), typically higher in cities, has been associated with increased mortality and hospital admissions due to cardiovascular and respiratory diseases (Brunekreef & Holgate, 2002) and with overall reduced well-being (Orru et al., 2016). More broadly, the relationship between environmental stressors, expressed sentiment, and their broader socioeconomic consequences varies across climatic, economic, and infrastructural contexts (Y. Cheng et al., 2023; H. He et al., 2023).

Some urban variables therefore show context-dependent associations rather than uniformly positive or negative effects. Fan et al. (2023) found that commercial land was positively associated with residents' sentiment, suggesting that the convenience provided by nearby commercial facilities may help explain positive sentiment in active urban areas, even when these places involve potential externalities such as traffic congestion or noise. Similarly, Y. Gao et al. (2022) found that positive sentiments are more spatially heterogeneous than negative ones, mainly concentrated in tourist sites, commercial areas and cultural districts, whereas negative sentiments are mostly found around transport hubs, hospitals and colleges. This helps explain why commercial areas, traffic-related environments and public facilities should be interpreted as context-dependent urban variables rather than uniformly positive or negative factors (Fan et al., 2023; Y. Gao et al., 2022).

4.3. Planning implications, methodological limitations and future research

Future planning actions should focus on green and blue spaces by increasing their presence, proximity and accessibility, as these features are generally associated with more positive sentiment and happiness across various contexts (S. Chen et al., 2022; Fan et al., 2023; H. He et al., 2023; Lai & Deal, 2023; Lim et al., 2019). Negative transport nodes must be addressed by improving the environmental and experiential conditions (e.g., reducing noise, crowding, and wayfinding stress) around rail hubs (Y. Gao et al., 2022; Lim et al., 2019; Y. Wang et al., 2025; Yang et al., 2022). Differentiating density levels is of significant importance because while road and shop density can be associated with more positive sentiment, building density's impact depends on the context; design should therefore account for local environmental conditions (e.g., thermal comfort, adequate facilities, and greening) (Fan et al., 2023; H. He et al., 2023; Karban, 2025). Managing local stressors like air pollution, heat, and extreme precipitation can involve urban design solutions such as greening, shading, blue-green corridors, and improved drainage (Y. Cheng et al., 2023; H. He et al., 2023; Karban, 2025; Lu et al., 2025). Finally, social comfort, including perceived safety, social characteristics (e.g., sociability, playability, and uniqueness), and ease of mobility, is also crucial for enhancing sentiment (Lee, 2024; Stellacci & Moro, 2022; R. Zhang, 2023).

These directions are consistent with broader bibliometric evidence identifying deep learning, multimodal approaches, and context-aware models among the emerging methodological trajectories in urban sentiment research (Betco, Viana, et al., 2026). Based on these findings, Ataman et al. (2025) and Kikutani and Yoshida (2025) emphasize the importance of integrating citizen-generated data into urban design and planning processes, allowing infrastructure and spatial interventions to better reflect local urban conditions and community needs (Ataman et al., 2025; Kikutani & Yoshida, 2025).

Nevertheless, methodological limitations related to the sources used to infer urban sentiment should also be considered. Recent applications also illustrate the use of EmoLex with georeferenced

Twitter/X data to map the spatial distribution of positive and negative sentiment in urban environments (Betco et al., 2025). Huang and Tu (2024) show that affective reactions inferred from street-view images and social media posts may diverge, suggesting that these sources do not fully capture the multidimensional nature of urban emotions. Complementing these approaches, Dalton et al. (2025) used survey and video-diary responses to examine how building appearance affects perceived wellbeing (Dalton et al., 2025; J. Huang & Tu, 2024). However, these studies still do not directly analyze facial expressions, which remain an important avenue for future research.

5. Conclusion

The growing interest in the relationship between urban environments and public sentiment is reflected in the increasing number of publications, particularly since 2024. Most of the reviewed studies were conducted in China, although research from Europe, North America, and other Asian contexts was also identified. Social media and online platforms have become important sources for examining how people perceive and experience urban environments, with Weibo and Twitter/X among the most frequently used platforms. ML/DL approaches are the most common for sentiment analysis, but the literature includes a broad range of methods, from lexicon-based techniques to hybrid and manual approaches.

The physical environment remains the main focus of this research. Green and blue spaces are generally associated with more positive sentiment, particularly when they are accessible and located close to users. The results also show that the experience of urban space depends on more than the presence of particular land uses or facilities. Spatial configuration, accessibility, maintenance, and the quality of public spaces also matter. Open and connected environments, well-maintained facilities, and recreational and cultural spaces tend to be associated with more positive responses, while industrial areas and major transport environments are more often linked to negative sentiment. At the same time, the

results are not uniform. Variables such as vegetation, density, land-use mix, visibility, and crowding exhibit different relationships across studies, suggesting that their associations with sentiment depend on the characteristics and scale of each context.

External stressors also play an important role in shaping urban sentiment. Air pollution, extreme heat and precipitation, thermal discomfort, and signs of degradation are associated with negative sentiment, whereas cleaner, more tranquil environments are generally associated with positive responses. Some factors, particularly temperature and noise, exhibit less consistent, more context-dependent patterns. Society-related variables are less frequently examined than those related to the physical environment. Still, the reviewed studies indicate that perceived security, ease of mobility, walkability, accessibility, and opportunities for social interaction are generally associated with more positive sentiment. Crime, congestion, and different forms of socioeconomic disadvantage tend to be associated with more negative responses. This imbalance suggests that future research should expand beyond the physical characteristics of urban environments and give greater attention to environmental stressors and social dimensions.

The methodological results also show that there is no direct correspondence between a particular sentiment-analysis approach and a specific group of urban factors. ML/DL, lexicon-based, hybrid, and manual approaches have been applied across different dimensions of the urban environment, although research remains strongly concentrated on physical-environment variables. Environmental stressors and social factors remain less explored and deserve greater attention in future studies. This methodological diversity suggests the value of combining different forms of citizen-generated data and analytical approaches, while recognizing that different data sources and sentiment-analysis methods may capture different dimensions of urban experience.

Overall, this review shows several aspects of the urban environment that may be relevant for urban planning: increasing the presence, proximity, and accessibility of green and blue spaces;

improving urban design and spatial configuration ensuring adequate infrastructure and facility maintenance, and promoting walkability, perceived safety, and sociability; improving the conditions around transport nodes; accounting for context-dependent effects of urban density; and mitigating the impacts of air pollution, heat, and extreme precipitation through appropriate urban-design interventions. However, these findings should be taken thoughtfully, as the predominantly observational and cross-sectional nature of the reviewed studies does not allow causal relationships to be established. At the same time, mixed findings for several variables show that no single urban form can be assumed to produce positive responses in every context. In conclusion, urban policies may benefit from considering residents' perceptions and well-being when seeking to create healthier, more sustainable, and human-centered cities. The use of advanced technologies and sentiment analysis may provide complementary information to support decision-making and the understanding of how people respond to different urban environments.

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