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Urban sentiment mapping using language and vision models in spatial analysis

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Introduction: Understanding how urban environments shape public sentiment is crucial for urban planning. Traditional methods, such as surveys, often fail to capture evolving sentiment dynamics. This study leverages language and vision models to assess the influence of urban features on public emotions across spatial contexts and timeframes.

Methods: A two-phase computational framework was developed. First, sentiment inference used a BERT-based model to extract sentiment from geotagged social media posts. Second, urban context inference applied PSPNet and Mask R-CNN to street view imagery to quantify urban design features, including visual enclosure, human scale, and streetscape complexity. The study integrates publicly available data and spatial simulation techniques to examine sentiment-urban form relationships over time.

Results: The analysis reveals that greenery and pedestrian-friendly infrastructure positively influence sentiment, while excessive openness and fenced-off areas correlate with negative sentiment. A hotspot analysis highlights shifting sentiment patterns, particularly during societal disruptions like the COVID-19 pandemic.

Discussion: Findings emphasize the need to incorporate public sentiment into urban simulations to create inclusive, safe, and resilient environments. The study provides data-driven insights for planners, supporting human-centered design interventions that enhance urban livability.

KEYWORDS

geospatial intelligence, ai-driven sentiment analysis, computer vision in urban studies, computational urban design, street view analysis, public perception mapping, urban morphology modeling

1 Introduction

Urban areas are complex, dynamic environments that can significantly shape human perceptions and emotions. With the global trend toward increasing urbanization, understanding the interplay between urban spaces and public sentiment has become increasingly crucial. In today's digital age, these interactions are not only influenced by physical spaces but are also documented and shared through digital platforms (Luo et al., 2011; Sadiq et al., 2020; United States Geospatial Intelligence Foundation, 2021). However, despite the critical role of qualities of urban design (e.g., visual enclosure, human scale, and streetscape complexity) traditional research methodologies have notable limitations. For example, methods such as field surveys, interviews, and direct observations, often fail to capture the full scope of human experiences across diverse urban settings or over extended periods (Ben-Akiva and Bierlaire, 1999; Choudhry et al., 2015; Ewing et al., 2006; Hadavi et al., 2015; Montello et al., 2003; Steen Jacobsen, 2007; Tveit et al., 2018).

To address these gaps, a two-phase computational framework is proposed. The first phase, "sentiment inference," leverages location-based social media (LSM) data combined with natural language processing (NLP) techniques to extract characterizations of public sentiment from social media content, to construct a robust dataset that captures diverse human experiences and emotional responses to urban environments. The second phase, "urban context inference," applies computer vision techniques (e.g., PSPNet and Mask R-CNN) to street view imagery to quantify qualities of urban design, such as visual enclosure, human scale, and streetscape complexity.

By examining the intersection of urban spaces and human sentiments through digital lenses, the research contributes to the academic discourse on urban development and design (Ahn et al., 2022). Earlier studies, such as those of Tveit et al. (2018) and Ewing et al. (2006), have focused on pedestrian behavior and urban morphology. Recent advances in digital methodologies such as Ahn et al. (2022); Choudhry et al. (2015) provide the foundation for this study's two-phase approach, offering a comprehensive understanding of the urban-human sentiment dynamic.

This research makes three key contributions: First, it integrates NLP techniques with urban studies to infer public sentiment from LSM data, providing a scalable and efficient alternative to traditional sentiment analysis methods. Second, it connects the inferred sentiments to features representing qualities of urban design so that their relationships can be explored. Finally, it offers actionable insights for urban planners and policymakers, emphasizing specific design elements that can enhance public well-being and satisfaction in urban environments.

The paper is organized as follows: the next section reviews relevant literature to situate the research within existing academic discourse. Following this, the proposed two-phase computational framework is described in detail, including an example application. The results are then presented, with a discussion of their broader implications for urban planning and design. Finally, the conclusion highlights the study's contributions and outlines directions for future research.

2 Background

To position this study within the context of existing research, it is crucial to outline how previous studies have examined the relationship between urban design and human sentiments. To this end, this section synthesizes key contributions from urban design, environmental psychology, and sentiment analysis, highlighting the multidisciplinary efforts to understand the intricate connections between urban environments and public sentiment. Recent advancements in machine learning models, including language and vision models, have revolutionized how researchers analyze both textual and visual data, providing deeper insights into how people emotionally respond to their urban surroundings. These developments offer new avenues for capturing the dynamic and nuanced interplay between urban spaces and public sentiment, moving beyond the limitations of traditional research methodologies.

2.1 Impact of urban design on public sentiment

The urban design profoundly influences the emotional experiences of its inhabitants, shaping how people perceive, interact with, and feel about their surroundings. Urban design goes beyond aesthetics; it reflects an ongoing dialog between space and sentiment, where the built environment can evoke a wide range of emotional responses (Ewing et al., 2006; Gehl, 2013). Works by prominent researchers such as Jacobs (1961) and Lynch (1964) have significantly contributed to this understanding, emphasizing the importance of vibrant, mixed-use neighborhoods and pedestrian-centric designs. Jacobs (1961) highlights how human-centered urban design promote social interaction, safety, and a sense of community, while Lynch (1964) focuses on the psychological and cognitive dimensions of cityscapes, stressing the importance of landmarks, paths, and nodes in creating a city's "imageability."

Building on these early ideas, Talen (2006) argues for the need to create compact, pedestrian-friendly urban environments, underscoring their role in enhancing social cohesion and emotional well-being. Carmona (2010) and Talen and Ellis (2002) further integrate sensory and aesthetic considerations into urban planning, advocating for designs that prioritize human experience and emotional responses. These perspectives move beyond mere infrastructure to consider the intangible feelings that urban spaces evoke.

Lynch (1964)'s framework, emphasizing identity, structure, and meaning, continues to be influential in explaining the deep connections individuals form with their surroundings. These connections extend beyond simple recognition of space to more profound emotional and cognitive associations. Environmental psychology, particularly through the works of Kaplan and Kaplan (1989) and Ulrich (1983), has further explored these connections, examining the therapeutic and restorative effects of natural elements within urban environments. Their research demonstrates that natural features like trees and green spaces can significantly enhance emotional well-being, reduce stress, and improve overall mental health.

Duan et al. (2022) expand upon this understanding by focusing specifically on urban youth sentiments and the built environment. Their study in Shanghai reveals that sentiment intensity is significantly associated with built environment elements at smaller scales, with youth expressing a mix of emotions that reflect both positive and negative associations with urban features. This work underscores the importance of spatial scale in understanding sentiment dynamics and emphasizes the unique emotional geographies of younger populations.

Ewing and Handy's (2009) contributions are particularly notable for their efforts to quantify these abstract constructs. By developing measurable metrics related to visual enclosure, human scale, and streetscape complexity, they shifted the discourse from theoretical to empirical. Whereas challenges remain in operationalizing these metrics, their work marks a new era in urban planning where human sentiment is recognized as a critical factor in evaluating urban spaces. Similarly, He et al. (2024) explore the nonlinear and synergistic relationships between macro- and micro-scale urban built environmental factors and public sentiment, emphasizing the need to consider street-level features that directly shape human perceptions. Their findings suggest that recreation facilities, mixed land use, and a rich street view environment are key contributors to positive sentiment, reinforcing the importance of context-sensitive urban design strategies.

2.2 Measuring sentiment

Measuring sentiment in urban landscapes presents its own set of challenges and has driven numerous innovations in recent years. Goodchild (2007)'s concept of "Citizens as Sensors" revolutionized the field by recognizing that citizens themselves can serve as valuable sources of experiential data. This approach harnesses the power of everyday urban dwellers to provide rich, ground-level insights into the qualitative aspects of urban spaces.

Research inspired by this concept spans a wide range of domains, from sentiments about infrastructure (such as walkability and bikeability) to more abstract notions like safety, aesthetics, and the presence of nature (Baobeid et al., 2021; Motieyan et al., 2022). Traditional tools, such as on-ground evaluations and Likert-scale surveys, laid the foundation for measuring public sentiment but have limitations in scale, scope, and temporal coverage (Hartig and Staats, 2006; Nasar, 1990). These methods often fail to capture the dynamic and rapidly changing nature of urban environments.

The advent of the digital revolution has fundamentally transformed sentiment analysis in urban studies. Technological innovations, particularly crowdsourcing platforms and advanced deep learning (DL) algorithms have enabled more extensive and nuanced sentiment assessments. Tools like Google Street View have democratized data collection, providing accessible and detailed visual information about urban environments. Meanwhile, DL techniques have enhanced the ability to interpret complex visual data, as demonstrated by projects like the MIT Media Lab's Place Pulse, which combines crowdsourced data with computational methods to measure urban sentiments with unprecedented detail (Dubey et al., 2016).

Li et al. (2024) leverage big textual data from social media to evaluate public space usage and perception in Xiamen, China. Their study demonstrates how social media data can uncover dynamic citizen experiences, such as social sentiment, leisure activities, and preferred visual elements, offering urban planners critical insights into placemaking practices. This underscores the growing importance of big data as a tool for understanding urban vibrancy and public interaction. Textual data from social media platforms has further expanded the capabilities of sentiment analysis. These platforms serve as repositories of spontaneous reflections and reactions, providing raw, unfiltered insights into how people feel about their urban surroundings. As Batty (2013) notes, social media data captures intimate personal narratives that reveal the public's perceptions and interactions with their environments. When analyzed effectively, these narratives may offer a deeper understanding of urban sentiments and interactions (Guerrero et al., 2016; Martí et al., 2017).

Despite these advancements, the precise relationship between specific urban features—such as greenery, visual enclosure, and pedestrian-friendly infrastructure—and public sentiment remains underexplored. Prior studies have indicated potential links but lack the comprehensive framework required to evaluate these interactions systematically over time within an urban context. This study addresses this gap by exploring the extent to which qualities of urban design may impact sentiment.

2.3 Language and vision models in urban analysis

2.3.1 Language models for sentiment analysis

Recent advancements in Large Language Models (LLMs) have significantly enhanced the capacity to analyze complex textual data from social media, enabling a more sophisticated understanding of public sentiment toward urban environments. Among the most notable LLMs is BERT (Bidirectional Encoder Representations from Transformers), developed by Devlin et al. (2019). BERT involves a bidirectional approach to processing text, allowing for context to be understood in both forward and backward directions. This innovation has proven highly effective for sentiment analysis tasks, especially for understanding nuanced expressions of public sentiment found in social media data. BERT has been employed in numerous studies for urban analysis, such as assessing the emotional responses to different urban spaces in cities like New York and London (Ho et al., 2024). The model's ability to capture context from both directions allows it to accurately interpret sentiment even in short, informal, or ambiguous social media posts.

Building upon BERT, Liu et al. (2019) propose RoBERTa (Robustly optimized BERT approach) in which the pre-training method is refined by using more extensive data and dynamic masking techniques. This model has been shown to outperform BERT in various sentiment analysis tasks. XLNet (Yang et al., 2020), another influential LLM, integrates autoregressive and autoencoding techniques to capture word dependencies, improving upon BERT by removing the independence assumption of masked words. Research by Sharma et al. (2024) used RoBERTa and XLNet to analyze positive or negative opinions or attitudes toward public transportation such as electric vehicle.

Moreover, models like T5 (Text-to-Text Transfer Transformer) (Raffel et al., 2023) and GPT-3 (Generative Pre-trained Transformer 3) by OpenAI (Brown et al., 2020) extend the capabilities of LLMs to generate and classify text, providing robust tools for sentiment analysis. T5's ability to convert all text-based problems into a text-to-text format has been useful in creating sentiment scores from raw text data, as demonstrated in a study on the sentiment of residents toward green spaces in urban areas. Meanwhile, GPT-3's natural language generation capabilities have been used to analyze public discourse on urban policy changes by generating potential sentiment interpretations from vast social media datasets (Kheiri and Karimi, 2023). Additionally, ALBERT (A Lite BERT) (Lan et al., 2020) reduces model size while maintaining performance, making it ideal for sentiment analysis in resource-constrained environments. ALBERT has been utilized in studies focusing on smaller cities or specific neighborhoods, such as research into local sentiments around urban renewal projects in Toronto Canada, where computational resources were a constraint.

2.3.2 Vision models for sentiment analysis

Alongside advancements in language models, computer vision models have greatly improved the analysis of visual data in urban studies. The Pyramid Scene Parsing Network (PSPNet) (Zhao et al., 2017) is highly regarded for its ability to perform semantic segmentation by capturing global contextual information from images through a multi-level feature pyramid. PSPNet has been extensively used to analyze complex urban scenes, such as detecting green spaces, sidewalks, and buildings from high-resolution street view images in cities of various scales (Aman et al., 2022; Biljecki and Ito, 2021). The model's pixel-wise accuracy makes it particularly effective for differentiating fine details in dense urban environments. Mask R-CNN (He et al., 2017), another state-of-the-art model, extends Faster R-CNN by adding a branch for predicting segmentation masks, which enables precise object detection. This model has been employed in a variety of urban studies to identify and classify urban features like trees, vehicles, pedestrians, and street furniture. For instance, several studies used Mask R-CNN to evaluate street-level greenery's impact on pedestrian satisfaction, finding a significant correlation between greenery and positive pedestrian experiences (Lu et al., 2023).

YOLO (You Only Look Once) models (Jocher, 2022; Redmon et al., 2016), are recognized for their object detection capabilities, which make them ideal for applications requiring rapid analysis of visual data. In urban contexts, YOLO has been applied to monitor traffic patterns and pedestrian density, providing insights into urban mobility and safety (Kunekar et al., 2024). U-Net (Ronneberger et al., 2015), initially designed for biomedical image segmentation, has also been adapted for urban analysis tasks such as segmenting building footprints from satellite imagery. U-Net's symmetrical architecture allows for the capture of fine spatial details, making it suitable for urban morphology studies. It has been used to assess the impact of building density and form on urban heat islands (Lee and Kim, 2022). Additionally, the DeepLab family of models (Chen et al., 2018) employs an Atrous convolution and a fully connected Conditional Random Field (CRF) to improve segmentation accuracy at multiple scales, which has been applied in studies aiming to map urban vegetation and assess the walkability of neighborhoods (Zhang et al., 2022). Though these models have different strengths, all have proven to be valuable tools in extracting features relevant to urban planning, such as green spaces, pedestrian pathways, and building characteristics, from high-resolution images.

3 Framework

This section outlines the framework developed to investigate the connection between urban design and public sentiment. The framework integrates sentiment data from social media with features representing qualities of urban design derived from street view imagery, providing a structured approach to analyzing how different urban features may influence public sentiment over time. The methodology is designed to capture temporal dynamics within a single urban context, reflecting the complex nature of urban environments.

The framework focuses on two key hypotheses: (1) specific urban features, such as greenery, streetscape complexity, and pedestrian infrastructure, are significantly associated with public sentiment, and (2) other events, such as societal disruptions, can jointly influence sentiment. By combining sentiment data and urban features, this framework provides a computational approach for examining these relationships.

The analytical framework is divided into two primary components: (a) sentiment inference and (b) urban context inference, which are subsequently integrated to assess their relationship. Figure 1 illustrates the overall workflow of the framework.

3.1 Sentiment inference

The sentiment inference component extracts public sentiment data from social media platforms using advanced natural language processing (NLP) techniques. Models such as BERT, RoBERTa, and GPT-3 are applied to analyze text, emojis, and other expressive elements within social media posts. These models generate sentiment scores that reflect public emotional responses to specific geotagged urban locations. The resulting dataset is mapped with precise spatial and temporal markers, enabling visualization of sentiment patterns across different urban contexts and timeframes.

3.2 Urban context inference

The urban context inference component quantifies characteristics of the built environment surrounding the geotagged social media posts. Points of interest (POIs) are selected based on streets near social media posting sites, spaced at regular intervals to ensure comprehensive coverage. Street view imagery databases, such as Google Street View, are queried for images of these locations, often from multiple vantage points.

Advanced computer vision techniques, including the Pyramid Scene Parsing Network (PSPNet) and Mask R-CNN, are applied to these images to extract features representative of qualities of urban design such as visual enclosure, human scale, and streetscape complexity. These models segment and classify urban features, such as sky, greenery, roads, and buildings, providing a detailed representation of the built environment. The results are then integrated with sentiment scores from the sentiment inference component to evaluate how urban features correlate with public emotional responses over time.

3.3 Relationship assessment

The final step integrates sentiment metrics with features representing qualities of urban design to analyze their connections. Hot spot analysis is performed to identify significant spatial clusters of sentiment and visualize emotional patterns across the urban landscape. Statistical methods, including correlation and regression analyses, evaluate relationships between specific urban features and public sentiment, accounting for temporal variations. These analyses provide insights into how the association between urban environments and sentiment evolves over time.

4 Case study

To demonstrate the application of the analytical framework, a case study was conducted for a region of interest (ROI) within the city of Columbia, MO, USA. The city of Columbia is of moderate size, host to a population of 126,254 and is a notable hub for higher education. The ROI (Figure 2) is a 1.57 sq. km. area within the city's central business district, one that is frequently visited by residents and tourists.

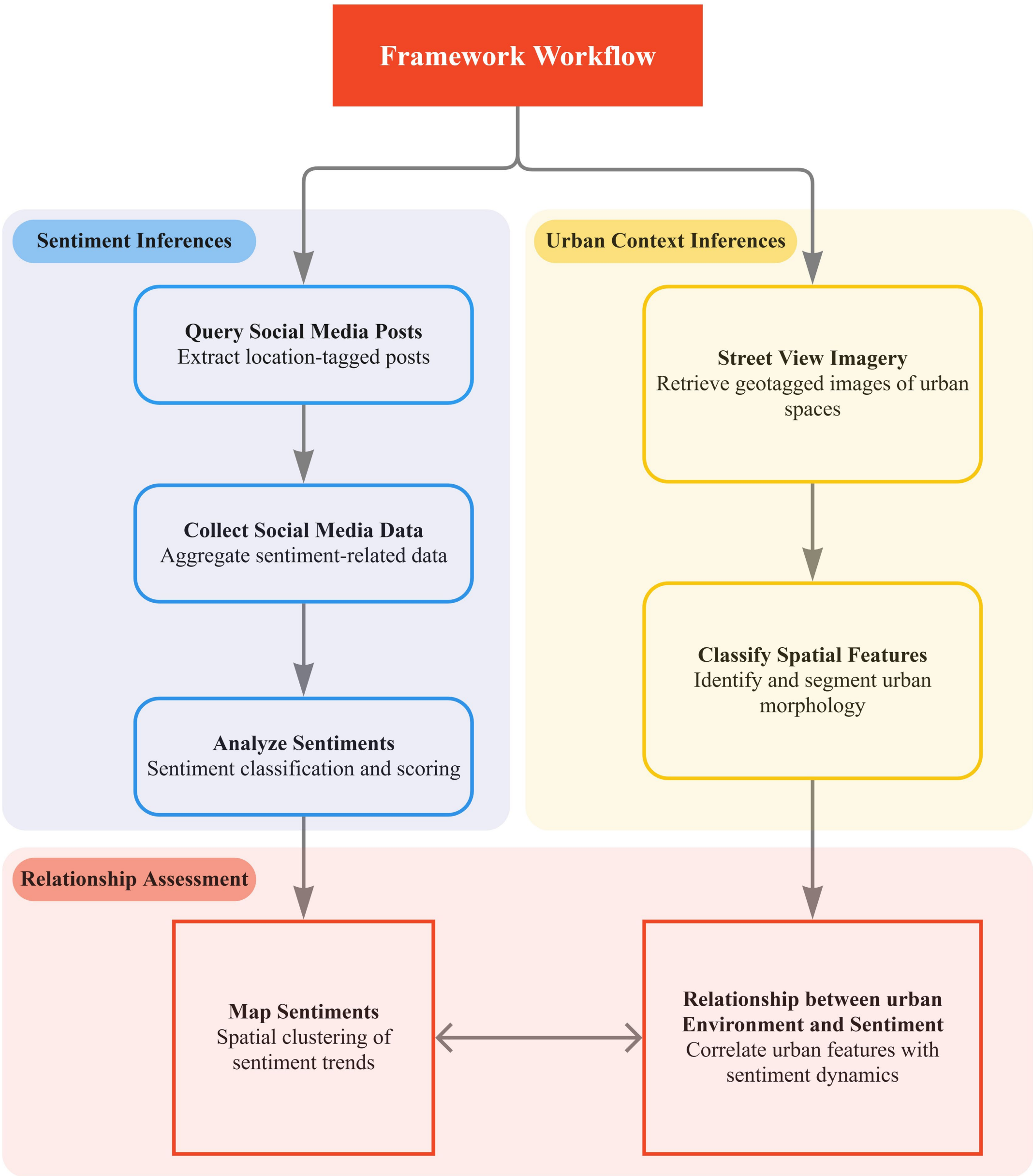

FIGURE 1
Analysis framework.

4.1 Location-based social media data acquisition

This study utilized public Instagram posts as proxies for sentiment expression related to the city's streetscapes. Previous research has used hashtag-based approaches (e.g., #Columbiamissouri, #Southboston, #cambridge) to analyze urban emotions (Kim et al., 2020) and explore identity-related interpretations in urban identity comprehension (Jang and Kim, 2019). However, these methods have limitations. For example, many posts lack location data, complicating their linkage to specific geographic sites and not all posts express personal sentiments—some are merely advertisements.

To address these limitations, this study instead focused on retrieving posts from known Instagram posting sites (i.e., Facebook locations). Given the absence of a straightforward method to query Instagram posting sites by city at the time of this research, the study utilized the *instagraphi* Python package (https://github.com/adw0rd/instagrapi) to search for Instagram posting sites. This was done by inputting geographic coordinates, representing specific POIs within the study area, into the *instagrapi*. These coordinates were selected to cover key locations within the city's central business district, ensuring comprehensive spatial representation of Instagram posting sites for sentiment analysis.

Through this method, 135 unique Instagram posting sites were identified within the region (Figure 3a). The names of these sites were categorized into one of eight land use types using OpenStreetMap (OSM) tags (Figure 3b). Of the initial 135 sites, some were discarded due to their broad representation of locales

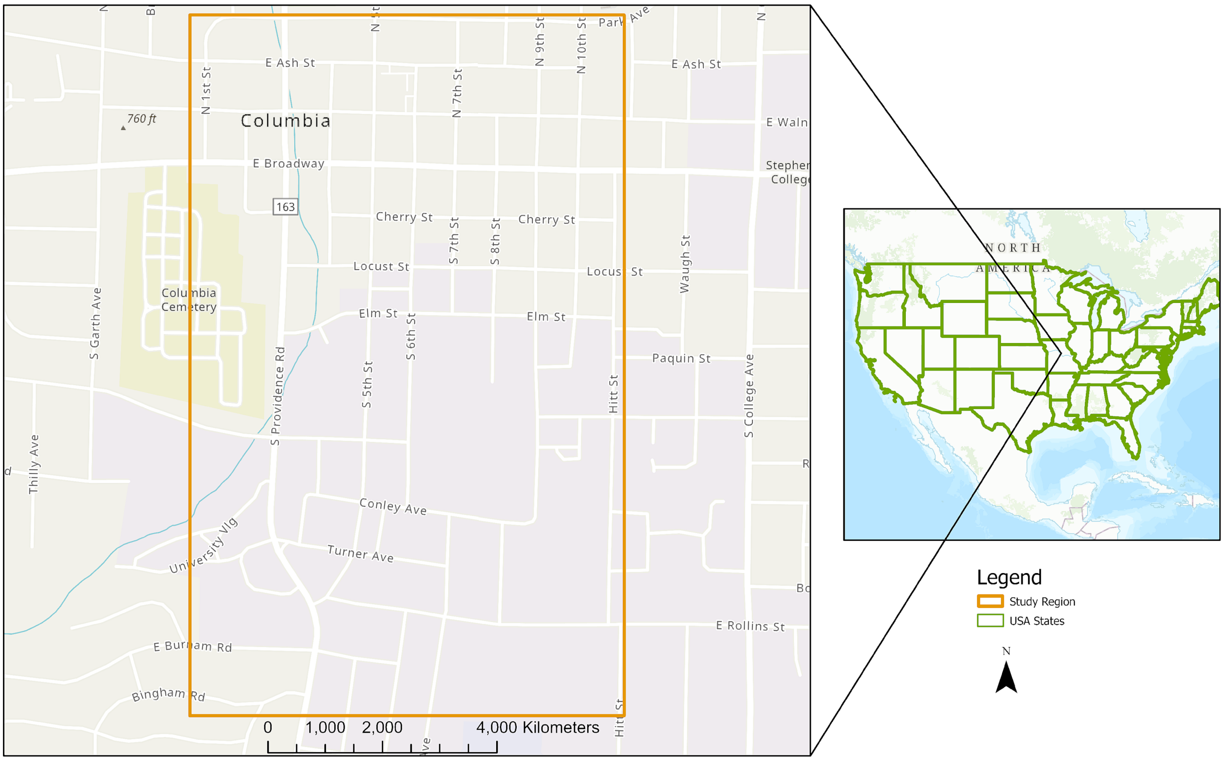

FIGURE 2
Region of interest.

like "Columbia, MO." Ultimately, 111 posting sites were retained. At the time of this research, access to Instagram posts was restricted to a small set of data providers. Partnering with InstaLoadGram, a third-party data provider, public posts associated with these sites were retrieved. Each post is attributed with its latitude, longitude, date, and caption. A total of 63,861 posts made between January 1, 2015, and October 20, 2021, were retrieved. Posts without captions, containing advertisements or promotional material were excluded, yielding 47,107 eligible posts for analysis. Figure 4 shows the distribution of posts over the years, with notable fluctuations. The number of posts steadily increased from 2015 to 2018, peaking in 2017 with 8,776 posts. A noticeable decline is observed in 2020, with 5,372 posts, likely reflecting the impact of COVID-19, followed by a recovery in 2021, reaching 6,871 posts. These variations reflect changing posting behaviors over the analyzed period.

4.2 Sentiment analysis

To categorize posts based on sentiment, an LLM was used to process geotagged posts using a normalized rating system. Among several deep learning (DL) models reviewed, the Hugging Face API's BERT-based pre-trained Transformer model, a type of LLM particularly effective for social media data was selected (Devlin et al., 2019). BERT (Bidirectional Encoder Representations from Transformers) read text bidirectionally, unlike traditional left-to-right or right-to-left methods, capturing a richer understanding of language (Sanh et al., 2019). To quantify and interpret the sentiment associated with each social media posting, computational analyses were performed using the Google Colab Pro platform, configured with an Nvidia Tesla P100-PCIE GPU and supported by 16GB of RAM. The sentiment analysis covered 47,107 postings, requiring a computational time of approximately 26,375 s. In this application, the BERT model effectively deciphered the nuanced human sentiments expressed in Instagram posts, classifying them into a standardized binary rating system of 'Negative = 0' or 'Positive = 1'. This transformation provided a clear, straightforward method to analyze overall sentiment trends in the dataset (Colón-Ruiz and Segura-Bedmar, 2020). Figure 5 illustrates the BERT-based NLP model in action, demonstrating how the model processes input text and arrives at a sentiment score. Thus, in addition to the latitude, longitude, date, and caption of each posting, the sentiment analysis adds the inferred sentiment score and its likelihood. It is only this information that is considered in subsequent analyses.

4.3 Retrieval of street view images (SVIs)

Street View Images (SVIs) of georeferenced street segments provide a rich dataset for spatial feature classification, capturing street-level perspectives. Among available sources, Google Street View (GSV) is a prominent public repository, with over 220 billion images from more than 100 countries worldwide, collected through diverse methods (e.g., driving, pedaling, sailing, walking) using specialized cameras (Google Street View, 2022). Access to this vast database is enabled through the Google API, which requires specific parameters, including location coordinates (latitude and longitude), camera pitch, and heading, to ensure the retrieval of relevant SVIs.

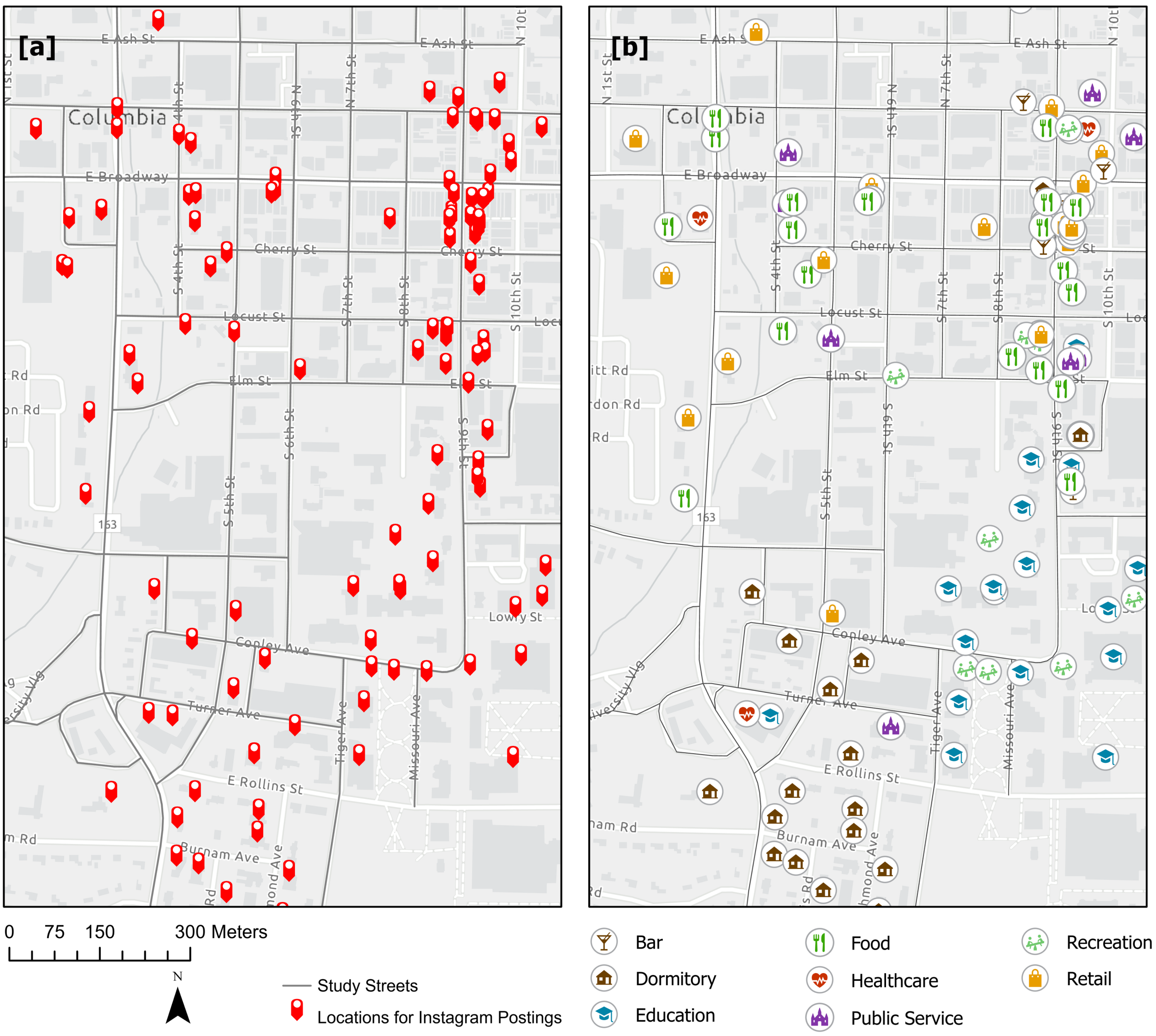

FIGURE 3
(a) Instagram posting locations, **(b)** Categories of posting locations.

In this application, 341 points of interest (POIs) were created at 30 m intervals along the roads within the ROI. These POIs, representing specific locations and their respective headings along the roads, were used to query the GSV images via the Google API (Figure 6 - left panel). Four different viewing perspectives were considered for each POI: (a) forward movement, (b) 90 degrees, (c) 180 degrees, and (d) 270 degrees from the POI (Figure 6 - right panel). To maintain consistent visual parameters, the horizontal field of view was set to 90 degrees, and the pitch of the 800×400 pixel images was fixed at 0 degrees. This approach resulted in the retrieval of 1,364 images, four for each POI.

4.4 Spatial feature classification

Two deep learning models for urban space analysis, the PSPNet and Mask R-CNN, were utilized in this application. PSPNet is renowned for its semantic segmentation capabilities, effectively capturing and analyzing global contextual information within images. Conversely, Mask R-CNN excels in object detection by generating precise bounding boxes and segmentation masks for every identifiable object in an image. Using a pre-trained PSPNet on the 150-category ADE20k dataset, the images were segmented into 12 categories of urban features thought to contribute to three qualities of urban design - visual enclosure, human scale, and streetscape complexity. The segmented features in each image were either summarized by computing the proportion of the image area occupied by features of a category or by computing the number of features in the image of a category as detailed in Table 1. For example, the 'Sky' category represents the proportion of pixels classified as 'Sky' out of the total image pixels. The 'Bicycle' category represents the number of features in an image that were classified as a bicycle.

The presence of features such as sky, walls, fences, vegetation, and buildings were used to represent visual enclosure as they indicate the openness or confinement of an urban space. Such features help explain the spatial configuration and its impact on public sentiment, where open spaces might evoke feelings of freedom, and confined spaces may induce a sense of restriction. The human scale was represented by the presence

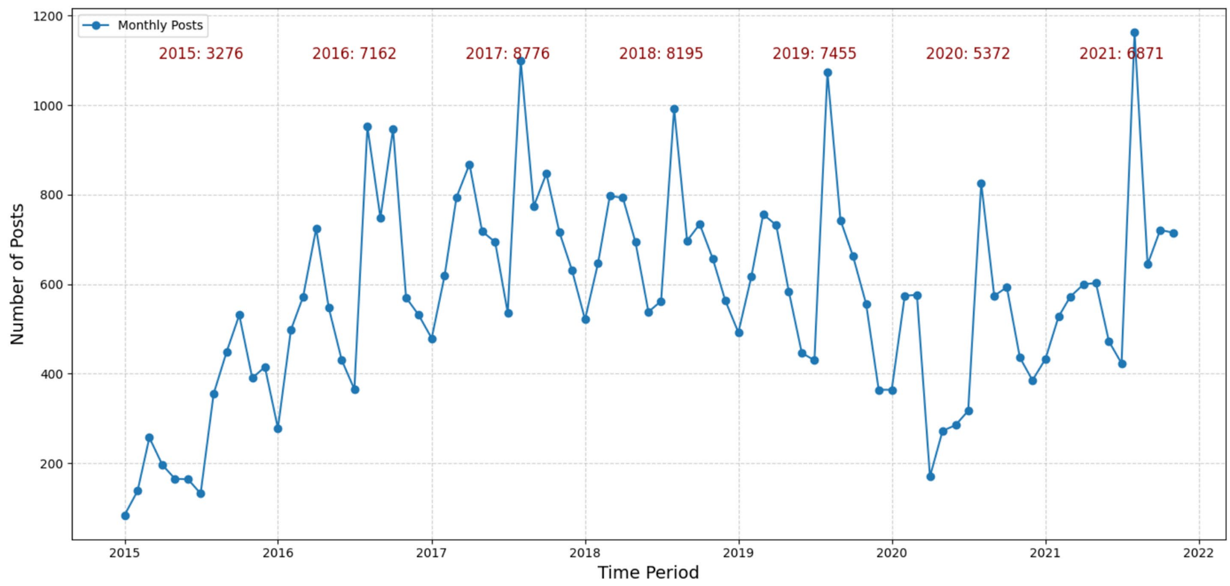

FIGURE 4
Monthly Instagram posting frequency over the years 2015–2021 (n = 47,107).

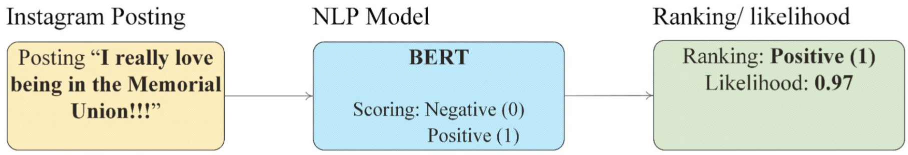

FIGURE 5
BERT-based NLP model.

of features such as roads and sidewalks, which are indicators of potential for movement and human interaction. Pedestrian-friendly environments have been historically linked to positive urban experiences, fostering social interactions and enhancing public sentiment. Finally, streetscape complexity was represented by the quantity of people, bicycles, motor vehicles, streetlights, and signboards present in each image.

To approximate the factors representing the qualities of urban design (visual enclosure, human scale, and complexity), the following steps were conducted. First, for each of the 1,364 street view images corresponding to 341 Points of Interest (POIs), the proportion of area (for visual enclosure and human scale) or the count (for streetscape complexity) was computed across all 12 urban feature categories. Figure 7 illustrates a representative street view image (Figure 7a) processed using PSPNet for pixel segmentation (Figure 7b) and Mask R-CNN for object detection (Figure 7c). These models facilitated the extraction and quantification of urban features present in each image, enabling a detailed breakdown of their spatial attributes. Next, to summarize the surrounding urban characteristics at each POI, the proportions/counts computed for the four images (from the directional perspective 0°, 90°, 180°, and 270°) were combined. For each feature category, proportions (e.g., "Tree") were summed across the four directional images and then divided by four to calculate the mean proportion for that category at the POI. Conversely, count-based features (e.g., pedestrians, vehicles) were summed across the four directional images to represent the total feature counts for that POI. Finally, for each of the 47,107 geotagged social media posts, the proportions/counts of the feature categories surrounding POIs within a 100 m of the post's location were averaged. This step allowed urban feature characteristics surrounding each posting site to be incorporated into the sentiment analysis. For instance, if a posting location is within 100 m of three POIs, the mean value of their feature proportions (e.g., % "Tree") or total feature counts (e.g., number of pedestrians, vehicles, etc.) is attributed to that post.

5 Results

The results of the analyses are summarized at several temporal levels: (a) all years (2015–2021), (b) pre-COVID (2019), (c) during COVID (2020), and (d) post-COVID (2021), focusing on the relationships observed between urban design and public sentiment. First, the spatial distribution of public sentiment across different locations in the ROI is examined, identifying hotspots of positive and negative sentiment. The temporal analysis highlights changes in the spatial clustering of sentiment over these time periods. Second, the associations between urban design and public sentiment are analyzed over the same set of time periods. This analysis explores how urban features, such as greenery, streetscape complexity, and pedestrian infrastructure, contribute to positive or negative sentiment and how these relationships changed over the pre-COVID, during COVID, and post-COVID periods.

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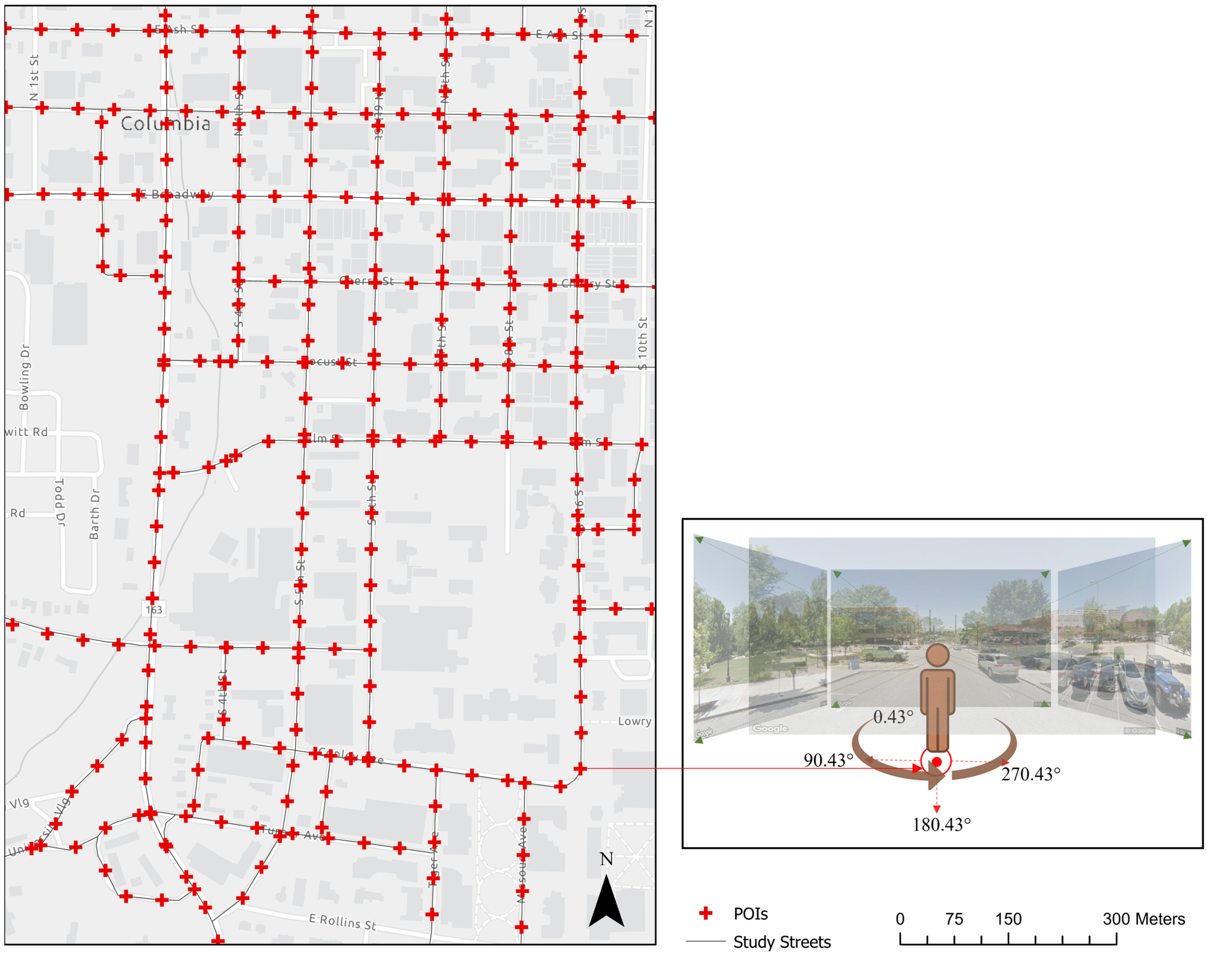

FIGURE 6
POIs along the street segments and SVIs per POI.

5.1 Spatial distribution of sentiment

A Getis-Ord Gi* hotspot analysis (Getis and Ord, 1992) was applied to the sentiment of postings from the years 2015–2021 at locations in the ROI. The analysis utilized a fixed Euclidean distance of 300 m and incorporated False Discovery Rate (FDR) correction to account for multiple hypothesis testing. The results (Figure 8a) revealed distinct spatial autocorrelation, identifying statistically significant clusters of positive sentiment (hotspots) and negative sentiment (cold spots).

Positive sentiment hotspots were predominantly concentrated in the Southern region, with 25 sites statistically significant at the 90% confidence level or higher. Of these, 24 sites were significant at the 99% level, collectively representing 11,396 posts. These hotspots align with areas characterized by favorable urban features such as greenery, pedestrian infrastructure, and aesthetically pleasing environments. In contrast, negative sentiment cold spots were primarily located in the Northwest sector, where 26 sites were significant at the 99% level, collectively representing 23,119 posts. These cold spots may correspond to areas with less favorable urban attributes, such as inadequate infrastructure, higher traffic congestion, or limited public amenities.

As illustrated in Figure 3b, the Instagram posting locations vary by land use type, which may provide insight into the spatial distribution of activities. For instance, the Southern hotspots in Figure 8a correspond to locations with high recreational activity and visually appealing features, including parks and pedestrian spaces. Additionally, the clustering near educational institutions and dormitories suggests a relationship between these spaces and positive sentiment, perhaps influenced by community dynamics and student-centric activities. Conversely, cold spots in the Northwest are concentrated near areas of dense commercial and transportation activity, which may evoke negative perceptions due to congestion, noise, or limited pedestrian infrastructure.

Next, the relationship between urban design and sentiment is examined across three distinct periods [pre-COVID (2019), during COVID (2020), and post-COVID (2021)] in an attempt to understand the extent to which societal disruption may impact their relationship.

5.1.1 Pre-COVID

The spatial distribution of positive sentiment hotspots in 2019 (Figure 8b) is more diffuse compared to the pattern observed over the observed years. Twelve sites were significant at the 90%

TABLE 1 Categories of urban features analyzed and corresponding qualities.

Qualities of urban design	Urban feature categories	Description
Visual enclosure	Sky	Proportion of image area classified as sky
	Wall	Proportion of image area classified as wall
	Fence	Proportion of image area classified as fence
	Tree	Proportion of image area classified as tree, grass, or other vegetation
	Building	Proportion of image area classified as building or other structure
Human scale	Road	Proportion of image area classified as road surface
	Sidewalk	Proportion of image area classified as sidewalk, steps, or pathway
Streetscape complexity	Person	Count of pedestrians detected in the image
	Bicycle	Count of bicycles detected in the image
	Motor vehicle	Count of motor vehicles detected in the image
	Streetlight	Count of streetlights detected in the image
	Signboard	Count of signboards detected in the image

confidence level, with 9 sites reaching the 99% level, collectively representing 576 posts. Negative sentiment cold spots are more concentrated, with 3 sites at the 95% significance level and 3 sites at the 99% level, collectively accounting for 503 posts. During this period, public sentiment appears to reflect typical urban interactions, with hotspots in areas characterized by favorable features like greenery and pedestrian-friendly infrastructure. On the other hand, cold spots in areas associated with challenges such as congestion, lack of public amenities, or limited pedestrian accessibility.

5.1.2 During COVID

During the pandemic, the spatial distribution of sentiment is significantly different (Figure 8c). There are a greater number of negative sentiment cold spots, with 11 sites significant at the 90% level and 11 sites at the 99% level, collectively linked to 1,372 posts. The number of positive sentiment hotspots is significantly diminished, with only 6 sites significant at the 90% level and 2 sites at the 95% level, representing 852 posts. These changes may reflect restricted access to urban spaces and increased stressors, such as health concerns and reduced social interaction during the pandemic. Such stressors perhaps contributed to the expansion of negative cold spots and the contraction of positive hotspots.

5.1.3 Post-COVID

In 2021, as restrictions eased, the spatial clustering of positive sentiment also increases (Figure 8d). The number of positive hotspots increases to 6 sites significant at the 90% significance level, 2 sites at 95%, and 17 sites at the 99% level, representing 1,347 posts. However, the number of negative sentiment cold spots also increases, with 29 sites significant at the 99% level, collectively associated with 3,352 posts. The small increase in clustering of positive sentiment may reflect increased mobility and interactions with favorable urban spaces, though the persistence of negative cold spots could stem from unresolved infrastructure issues, limited access to amenities, or other lingering effects unrelated to the pandemic. Also, the observed trends may reflect the influence of other factors acting on sentiment other than the pandemic.

5.2 Dynamics of urban context-sentiment relationships

5.2.1 General relationship 2015–2021

The relationship between urban features and public sentiment over the period 2015–2021 was evaluated using ordinary least squares (OLS) regression. Table 2 summarizes the results, showcasing significant associations between various urban features and sentiment rankings. The variables representing the presence of urban features (e.g., 'Sky', 'Wall', etc.) indicate the proportion of the visual area covered by these features in the analyzed images.

Features representing enclosure reveal contrasting relationships. The negative coefficient for the proportion of the area classified as 'Sky' ($b = -1.00$, $p < 0.001$) suggests that excessive openness is perceived unfavorably, potentially evoking discomfort or a lack of shelter. In contrast, the proportion of area classified as 'Fence' ($b = -0.47$, $p < 0.001$) and 'Wall' ($b = -0.10$, $p < 0.001$) represents physical barriers that are often associated with reduced visibility or restricted movement, which may contribute to negative sentiment. Conversely, the positive association for the proportion of area classified as 'Tree' ($b = 0.16$, $p < 0.001$) perhaps indicating the value of greenery in enhancing public perceptions of urban environments.

Features tied to human scale also exhibit distinct sentiment associations. 'Sidewalk' ($b = 0.44$, $p < 0.001$) emerges as a strong positive contributor, possibly reflecting the public's preference for pedestrian-friendly infrastructure. 'Road' ($b = -0.23$, $p < 0.001$) suggests negative perceptions tied to vehicular dominance, possibly due to noise, pollution, or safety concerns in car-centric areas. Features representing urban complexity reveal the importance of active and visual elements. 'Person' ($b = 0.35$, $p < 0.001$) and 'Bicycle' ($b = 0.26$, $p < 0.001$) display positive sentiment associations, perhaps indicating the value of vibrant, active streetscapes that support human interaction and sustainable transportation. In contrast, 'Streetlight' ($b = -0.33$, $p < 0.001$) and 'Signboard' ($b = -0.60$, $p < 0.001$) suggest that excessive artificial lighting or visual clutter may detract from perceived urban quality.

Figure 9 visualizes the distribution of urban feature values across positive and negative sentiment categories. Features such as 'Tree' and 'Sidewalk' display higher values under positive sentiment, reinforcing their association with favorable public perceptions of livable urban spaces. In contrast, features like 'Fence', 'Streetlight', and 'Road' are more strongly associated with negative sentiment,

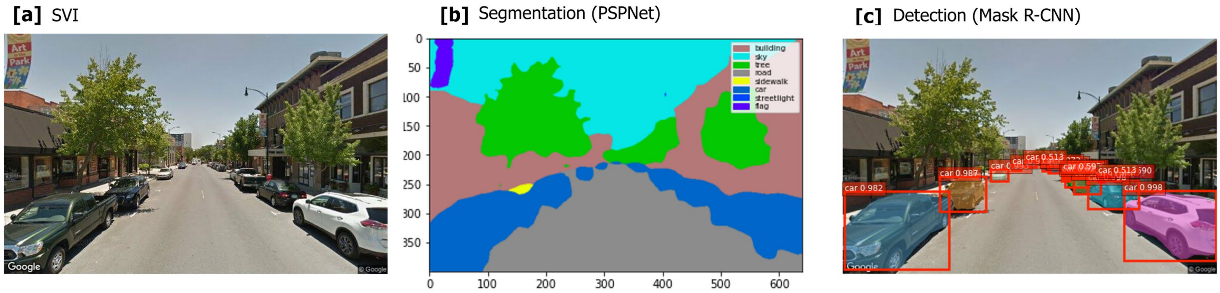

FIGURE 7
Spatial feature classification. **(a)** representative Google Street View image; **(b)** PSPNet segmentation map; **(c)** Mask R-CNN object detection with bounding boxes.

possibly reflecting potential discomfort or dissatisfaction tied to these elements. Interestingly, features like 'Wall' and 'Building' exhibit overlapping distributions for positive and negative sentiment. This suggests their impact on public sentiment may be highly context dependent. For example, greater presence of walls might enhance safety or structure in some scenarios, fostering positive sentiment, but may also evoke a sense of restriction or enclosure in other contexts, leading to negative sentiment. Similarly, a greater presence of buildings can enhance functionality and aesthetics in well-designed settings but may be associated with overcrowding or reduced openness in denser urban environments. These results highlight the roles of specific urban features and the need to consider broader contextual factors when interpreting their impact.

5.2.2 Relationship: pre-COVID

For the pre-COVID period (January to December 2019), an eigenvector spatial filter was applied to the OLS analysis, adding four eigenvectors to mitigate autocorrelation in the residuals. The analysis reveals distinct patterns in how various urban features influenced public sentiment. Table 3 summarizes the regression results, highlighting the associations between urban features and sentiment. The analysis highlights significant sentiment associations for features like 'Sky' ($b = -1.05$, $p < 0.001$), which exhibits a strong negative association with public sentiment. This is suggestive of a discomfort with open spaces during the pre-COVID period, possibly due to perceptions of exposure or lack of shelter. 'Fence' ($b = -0.47$, $p < 0.001$) also indicates a significant negative association, conceivably reflecting concerns related to restricted movement or visibility.

Conversely, 'Tree' ($b = 0.14$, $p < 0.001$) exhibits a positive association with public sentiment, which aligns with research on the importance of greenery in promoting positive emotional responses. 'Sidewalk' ($b = 0.42$, $p < 0.001$) strongly correlates with positive sentiment, possibly reflecting the public's appreciation for pedestrian-friendly infrastructure. 'Road' ($b = -0.19$, $p < 0.001$) shows a negative association, perhaps reflecting dissatisfaction with vehicular dominance and related urban challenges like noise and pollution. 'Person' ($b = 0.31$, $p < 0.001$) and 'Bicycle' ($b = 0.31$, $p < 0.001$) are positively associated with public sentiment, which may reflect the value of active and human-centered spaces. 'Streetlight' ($b = -0.37$, $p < 0.001$) and 'Signboard' ($b = -1.59$, $p < 0.001$) show strong negative associations, suggesting that excessive artificial lighting and visual clutter may be negatively perceived.

Figure 10 visualizes sentiment distributions for various urban features during the pre-COVID period. Features like 'Tree' and 'Sidewalk' display higher densities under positive sentiment, conceivably reflecting their alignment with public preferences for greenery and walkable spaces. In contrast, 'Fence' and 'Sky' are strongly associated with negative sentiment, potentially indicating discomfort with physical barriers and open spaces. 'Wall' and 'Building' have overlapping distributions, perhaps indicating their context-dependent impact on public sentiment.

5.2.3 Relationship: during COVID

For the COVID-19 period (January to December 2020), an eigenvector spatial filter was applied to the OLS analysis, adding six eigenvectors to mitigate autocorrelation in the residuals The results in Table 4 show significant changes in sentiment associations compared to the pre-COVID period.

'Sky' ($b = -1.30$, $p < 0.001$) exhibited a stronger negative association compared to the pre-COVID period, possibly reflecting increased discomfort with open spaces during the pandemic. Fence ($b = -0.45$, $p < 0.001$) and 'Building' ($b = -0.17$, $p < 0.001$) continued to have a negative relationship with sentiment, while 'Tree' ($b = 0.08$, $p = 0.004$) maintained a modest positive relationship.

'Sidewalk' ($b = 0.44$, $p < 0.001$) remained a significant positive contributor, perhaps indicating its importance for pedestrian mobility during lockdowns. 'Road' ($b = -0.12$, $p < 0.001$) maintained a negative association, perhaps reflecting dissatisfaction with vehicular dominance even during reduced traffic periods. 'Person' ($b = 0.23$, $p < 0.001$) and 'Bicycle' ($b = 0.23$, $p < 0.001$) sustained positive sentiment associations, suggestive of a preference for active and human-centered spaces. Interestingly, 'Signboard' ($b = 0.74$, $p < 0.001$) shifted to a positive association, perhaps reflecting an appreciation for localized commercial activity during restricted times.

Figure 11 demonstrates the distribution of urban features for positive and negative sentiment. Whereas 'Tree' and 'Sidewalk' continue to dominate positive sentiment distributions, 'Sky' and 'Fence' align more strongly with negative sentiment, perhaps reflecting increased public concern for open and enclosed spaces during the pandemic.

5.2.4 Relationship: post-COVID

For the post-COVID analysis (January to December 2021), an eigenvector spatial filter was applied to the OLS analysis, adding four eigenvectors to mitigate autocorrelation in the residuals. The analysis

FIGURE 8
Hotspot analysis **(a)** all years (2015–2021), **(b)** pre-COVID (2019), **(c)** during COVID (2020), **(d)** post-COVID (2021).

TABLE 2 General relationship between urban features and sentiment ranking 2015–2021.

Qualities of urban design	Urban feature categories	Estimate	Std. Error	t-value	p-value$^+$	Lower bound	Upper bound
Enclosure	Sky	−1.00	0.01	−97.38	< 0.001 ***	−1.02	−0.98
	Wall	−0.10	0.02	−5.93	< 0.001 ***	−0.13	−0.06
	Building	−0.12	0.01	−13.18	< 0.001 ***	−0.14	−0.11
	Fence	−0.47	0.02	−23.69	< 0.001 ***	−0.51	−0.43
	Tree	0.16	0.01	16.16	< 0.001 ***	0.14	0.18
Human scale	Road	−0.23	0.01	−24.16	< 0.001 ***	−0.25	−0.21
	Sidewalk	0.44	0.01	53.21	< 0.001 ***	0.43	0.46
Complexity	Streetlight	−0.33	0.01	−37.04	< 0.001 ***	−0.34	−0.31
	Signboard	−0.60	0.10	−6.24	< 0.001 ***	−0.79	−0.41
	Person	0.35	0.01	46.06	< 0.001 ***	0.33	0.36
	Bicycle	0.26	0.01	34.44	< 0.001 ***	0.25	0.28
	Motor Vehicle	−0.13	0.02	−8.15	< 0.001 ***	−0.16	−0.10

$^+$FDR adjustment applied.
Dependent variable: Negative (0) or Positive (1) Sentiment.
Model fit metrics: Residual standard error: 0.33 on 47,094 degrees of freedom.
Adjusted R^2: 0.53, F-statistic: 4370 on 12 and 47,094 DF (p-value < 0.001).

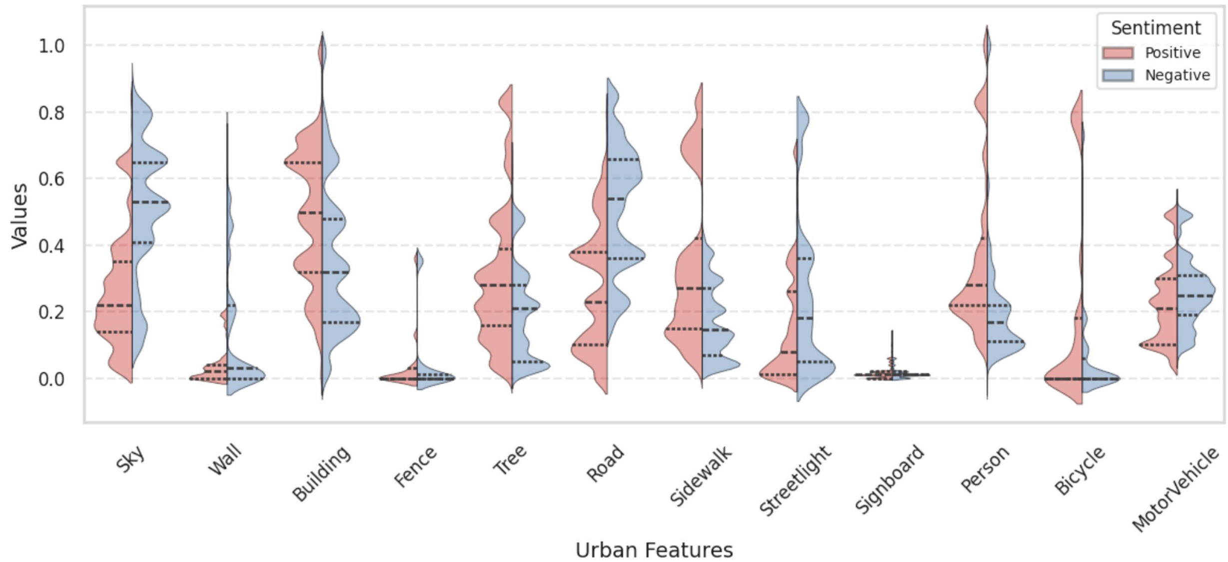

FIGURE 9
General distribution of urban features by sentiment 2015–2021.

summary in Table 5 highlights the stability and shifts in sentiment toward various urban features.

Post-COVID sentiment remained influenced by features representing enclosure, with ‘Sky’ ($b = -1.35$, $p < 0.001$) continuing to show a strong negative association. This indicates a persistent public preference for enclosed spaces, possibly tied to lingering concerns over safety or comfort in open areas. ‘Fence’ ($b = -0.39$, $p < 0.001$) and ‘Building’ ($b = -0.14$, $p < 0.001$) also retained negative associations, reflecting continued apprehension about restricted visibility or overly urbanized environments. Conversely, ‘Tree’ ($b = 0.19$, $p < 0.001$) maintained a strong positive relationship, underscoring the enduring value of greenery in urban spaces.

‘Sidewalk’ ($b = 0.47$, $p < 0.001$) continued to emerge as a major positive contributor, reflecting public appreciation for walkable, pedestrian-friendly infrastructure as cities reopened. ‘Road’ ($b = -0.03$, $p = 0.258$), however, showed an insignificant relationship, suggesting reduced concern over vehicular dominance during this recovery period. ‘Person’ ($b = 0.25$, $p < 0.001$) and ‘Bicycle’ ($b = 0.29$, $p < 0.001$) sustained positive associations with sentiment, reinforcing the importance of active, human-centered spaces in urban recovery. Notably, ‘Signboard’ ($b = 0.68$, $p < 0.001$) shifted to a positive association, suggesting an increased public interest in commercial and informational elements as urban life resumed normalcy. However, ‘Streetlight’ ($b = -0.34$, $p < 0.001$) continued to exhibit a

TABLE 3 Relationship between urban features and sentiment ranking (pre-COVID period).

Qualities of urban design	Urban feature categories	Estimate	Std. Error	*t*-value	*p*-value⁺	Lower bound	Upper bound
Enclosure	Sky	−1.05	0.02	−43.98	< 0.001 ***	−1.10	−1.00
	Wall	−0.04	0.04	−1.09	0.28	−0.11	0.03
	Building	−0.09	0.02	−3.96	< 0.001 ***	−0.13	−0.05
	Fence	−0.47	0.05	−9.67	< 0.001 ***	−0.57	−0.38
	Tree	0.14	0.02	5.86	< 0.001 ***	0.09	0.19
Human scale	Road	−0.19	0.02	−8.38	< 0.001 ***	−0.24	−0.15
	Sidewalk	0.42	0.02	20.87	< 0.001 ***	0.38	0.45
Complexity	Streetlight	−0.37	0.02	−17.52	< 0.001 ***	−0.41	−0.32
	Signboard	−1.59	0.27	−5.95	< 0.001 ***	−2.12	−1.07
	Person	0.31	0.02	18.07	< 0.001 ***	0.28	0.35
	Bicycle	0.31	0.02	16.19	< 0.001 ***	0.27	0.35
	Motor Vehicle	−0.21	0.04	−5.81	< 0.001 ***	−0.28	−0.14

⁺FDR adjustment applied.
Dependent variable: Negative (0) or Positive (1) Sentiment.
Model fit metrics: Residual standard error: 0.31 on 7,438 degrees of freedom.
Adjusted R^2: 0.57, F-statistic: 616.7 on 16 and 7,438 DF (p-value < 0.001).

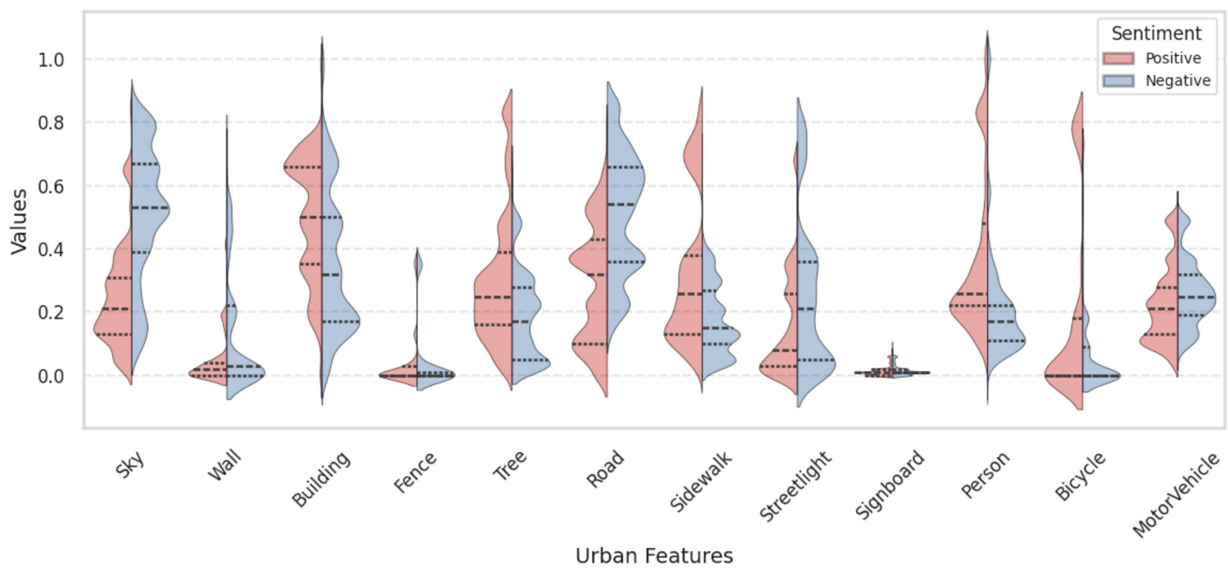

FIGURE 10
Distribution of urban features by sentiment (pre-COVID period).

negative relationship, highlighting concerns over excessive artificial lighting.

Figure 12 shows the distribution of urban features across positive and negative sentiments during the post-COVID period. Features such as 'Tree' and 'Sidewalk' retained higher distributions for positive sentiment, emphasizing their continued importance in fostering favorable perceptions of urban environments. Conversely, 'Sky' and 'Fence' remained dominant in the negative sentiment category, reflecting persistent concerns about open spaces and restricted visibility. The positive association with 'Signboard' stands out as a key shift, indicating renewed public interest in visual and commercial elements as cities recovered from the pandemic.

6 Discussion and conclusion

This study explored the relationship between urban features and public sentiment by integrating sentiment data from geotagged social media posts and urban metrics derived from street view imagery. The research utilized a two-phase computational framework: first, applying NLP techniques with LLMs to analyze public sentiment; and second, using computer vision models to quantify qualities of urban design, including visual enclosure, human scale, and streetscape complexity. This framework sheds light on how urban environments may shape human emotions and perceptions, particularly within the context of other events, such as societal disruptions.

TABLE 4 Relationship between urban features and sentiment ranking (during COVID period).

Qualities of urban design	Urban feature categories	Estimate	Std. Error	t-value	p-value⁺	Lower bound	Upper bound
Enclosure	Sky	−1.30	0.03	−44.76	< 0.001 ***	−1.36	−1.24
	Wall	−0.10	0.05	−2.23	0.026 *	−0.19	−0.01
	Building	−0.17	0.03	−6.47	< 0.001 ***	−0.22	−0.12
	Fence	−0.45	0.05	−8.26	< 0.001 ***	−0.56	−0.34
	Tree	0.08	0.03	2.86	0.004 **	0.03	0.14
Human scale	Road	−0.12	0.03	−4.07	< 0.001 ***	−0.17	−0.06
	Sidewalk	0.44	0.03	17.32	< 0.001 ***	0.39	0.49
Complexity	Streetlight	−0.36	0.03	−12.92	< 0.001 ***	−0.42	−0.31
	Signboard	0.74	0.21	3.53	< 0.001 ***	0.33	1.16
	Person	0.23	0.02	10.5	< 0.001 ***	0.19	0.28
	Bicycle	0.23	0.02	9.47	< 0.001 ***	0.18	0.28
	Motor Vehicle	−0.07	0.04	−1.69	0.091	−0.15	0.01

⁺FDR adjustment applied.
Dependent variable: Negative (0) or Positive (1) Sentiment.
Model fit metrics: Residual standard error: 0.32 on 5,353 degrees of freedom.
Adjusted R^2: 0.54, F-statistic: 348.9 on 18 and 5,353 DF (p-value < 0.001).

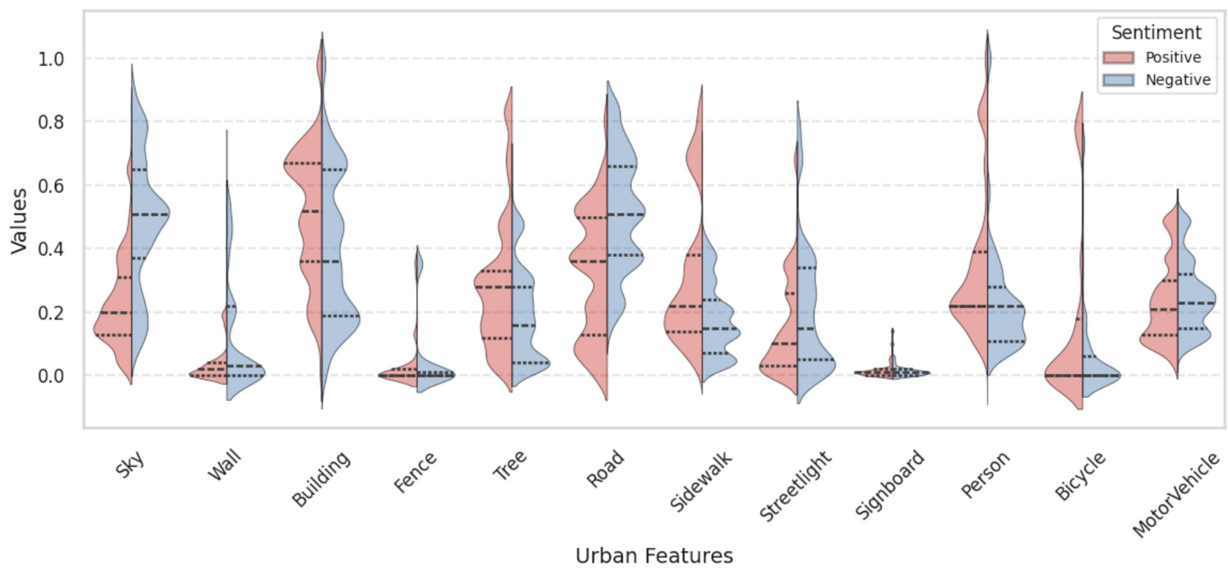

FIGURE 11
Distribution of urban features by sentiment (during COVID period).

The results indicate that certain urban features, such as greenery (trees) and pedestrian infrastructure (sidewalks), consistently elicit positive public sentiment over time, pointing toward their potential importance in fostering livable urban environments. These findings align with theories of biophilia (Kaplan and Kaplan, 1989; Ulrich, 1983) and human-centered urban design, which highlight the psychological and restorative benefits of natural and pedestrian-friendly spaces. Conversely, features such as visible sky and fences are linked to negative sentiment, reflecting a preference for balanced and enclosed environments that provide a sense of comfort and safety (Alexander et al., 1977; Jacobs, 1961). This study also contributes to the growing body of research on urban morphology and public sentiment by providing empirical evidence for the role of urban form in shaping emotional responses. The findings support existing theories on the importance of greenery and pedestrian-friendly infrastructure (Ewing and Handy, 2009; Gehl and Rogers, 2010), while also revealing context-dependent variations that challenge simplistic assumptions about urban preferences.

The spatial clustering of hotspots and cold spots suggests potential implications for urban design and planning. Positive sentiment associated with parks, pedestrian-friendly zones, and areas near educational institutions indicates the potential importance of spaces that encourage social interaction, community engagement, and a sense of belonging. Conversely, the clustering of cold spots in

TABLE 5 Relationship between urban features and sentiment ranking (post-COVID period).

Qualities of urban design	Urban feature categories	Estimate	Std. Error	t-value	p-value^{+}	Lower bound	Upper bound
Enclosure	Sky	−1.35	0.03	−53.29	< 0.001 ***	−1.4	−1.3
	Wall	−0.06	0.04	−1.74	0.082	−0.13	0.01
	Building	−0.14	0.02	−6.23	< 0.001 ***	−0.18	−0.09
	Fence	−0.39	0.04	−8.93	< 0.001 ***	−0.47	−0.3
	Tree	0.19	0.02	8	< 0.001 ***	0.14	0.24
Human scale	Road	−0.03	0.02	−1.13	0.258	−0.07	0.02
	Sidewalk	0.47	0.02	24.97	< 0.001 ***	0.44	0.51
Complexity	Streetlight	−0.34	0.02	−13.74	< 0.001 ***	−0.38	−0.29
	Signboard	0.68	0.18	3.75	< 0.001 ***	0.33	1.04
	Person	0.25	0.02	12.5	< 0.001 ***	0.21	0.29
	Bicycle	0.29	0.02	16.18	< 0.001 ***	0.25	0.32
	Motor Vehicle	0.04	0.03	1.15	0.251	−0.03	0.1

$^{+}$FDR adjustment applied.
Dependent variable: Negative (0) or Positive (1) Sentiment.
Model fit metrics: Residual standard error: 0.30 on 6,857 degrees of freedom.
Adjusted R^2: 0.61, F-statistic: 663.5 on 16 and 6,857 DF (p-value < 0.001).

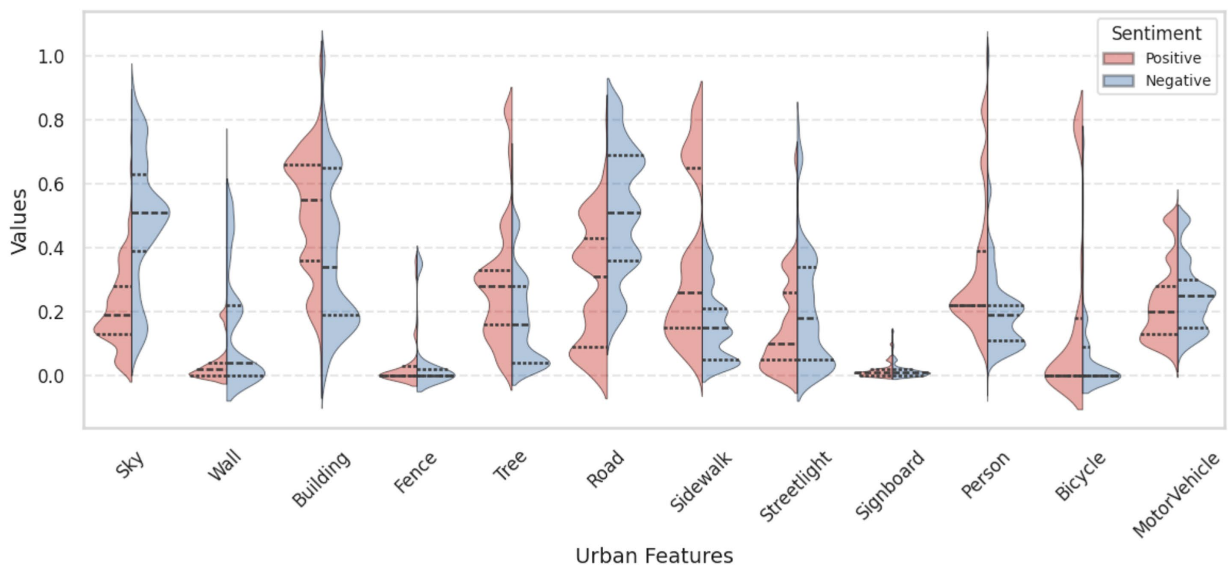

FIGURE 12
Distribution of urban features by sentiment (post-COVID period).

vehicular-dominated areas likely indicate challenges related to noise, congestion, and limited pedestrian accessibility. These findings imply that balanced land-use planning, and human-centered design approaches could help mitigate disparities in sentiment across different urban zones, potentially contributing to more inclusive and adaptable urban environments.

Temporal variations in sentiment are likely due to factors other than qualities of urban design, such as disruptive events. Analysis of sentiment over time periods spanning one such societal disruption, the COVID-19 pandemic provided some insight into this. During the COVID-19 pandemic, the expansion of cold spots in vehicular and commercial zones might reflect heightened public concern for safety and accessibility in urban spaces. In contrast, hotspots near localized commercial areas (e.g., signboards) may suggest a shift in public appreciation for accessible services during periods of restricted mobility. Post-COVID, the reemergence of sentiment hotspots in recreational and pedestrian-friendly spaces could provide evidence of the importance of resilience in urban environments that prioritize inclusivity and adaptability. However, the temporal changes observed in this study could also be interpreted as indicative of broader trends rather than definitively linked to specific disruptions or urban features. This highlights the need for more granular investigations to isolate the relative contributions of land-use patterns, infrastructure changes, and societal disruptions to sentiment dynamics over time. By doing so, future research can build a deeper understanding of how urban design interventions influence public sentiment under varying contexts.

While the proposed framework and example application can provide valuable insights into the relationship between urban features and public sentiment, limitations do exist. The reliance on social media data primarily reflects the perspectives of individuals active on these platforms, which may not fully capture the diversity of public sentiment. Likewise, whereas street view imagery is widely publicly available, it may not be available for all locations and/or dates of interest. As such, other data sources may need to be incorporated to augment the analysis. Additionally, while sentiment analysis enhanced by LLMs is a powerful tool, it may not account for the full spectrum of emotions or contextual nuances. Similarly, the computer vision models used to quantify urban features are subject to potential errors in feature classification, which could influence the accuracy of derived metrics. Misclassification errors in NLP and computer vision models could introduce uncertainties into the results, potentially influencing the observed associations.

The proposed analysis framework was applied to evaluate the relationship between sentiment and features representing qualities of urban design for a single city over a period of years. While the findings are in line with existing theory, more work is certainly needed to assess the extent to which the findings are generalizable to other locations and times. Expanding the analysis to include other urban environments perhaps representing a range of urban layouts, geographic, and socioeconomic contexts might further shed light on factors influencing sentiment. Also, there are a variety of other facets of the urban environment that could be included in this type of analysis, such as non-visual factors like noise, air quality, and cultural significance, which may also shape public perceptions. Further, in the example application of the analysis framework, the sentiment of all social media posts was analyzed together. However, future research could investigate the extent to which the sentiment of various categories (e.g., topic) of posts may be influenced differentially by qualities of urban design. Such an effort though would require a data collection plan that would ensure adequate numbers of posts from categories of interest exist and/or could be collected for a region of interest.

Finally, in this application, sentiment was assessed for each posting and analyzed by time period, but without tracking specific objects or topics across time. Posts at the same location may refer to different objects or experiences, such as a building in one period and a newly opened park or restaurant in another. Consequently, temporal changes in sentiment at specific locations might reflect shifts in public attention to different elements of the urban environment, making it challenging to attribute changes to a single factor. While societal disruptions like the COVID-19 pandemic may have significantly influenced public sentiment, they may not be the sole driver of observed changes. Other factors, such as infrastructure development projects (e.g., addition of new parks, sidewalks, roads, or buildings), politics, natural hazards, etc., may have also contributed. As such, the ability to jointly account for the spatial and temporal presence of the diverse set of factors potentially influencing sentiment is needed. By accounting for both societal disruptions and changes in the physical urban landscape, future studies can better evaluate the interplay of these factors in shaping temporal sentiment dynamics.

Despite these limitations, the consistent patterns observed in this study offer meaningful insights into how urban features influence public sentiment. These findings should be interpreted as indicative trends that contribute to a broader understanding of urban design and public perceptions, rather than as definitive causal relationships. To enhance the robustness and applicability of the framework, future research should integrate additional datasets, such as environmental data (e.g., air quality and noise levels) and cultural variables (e.g., landmarks, public art), to provide a more comprehensive understanding of the factors shaping public sentiment Improvements could also include exploring alternative computational models, validating findings across diverse contexts, and incorporating longitudinal studies and sentiment tracking to better capture the dynamic interactions between urban features and public sentiment. Addressing the uncertainties introduced by model misclassification, future research should systematically evaluate the sensitivity and robustness of the approach by testing different models and assessing the consistency of key findings. Additionally, integrating data on urban infrastructure developments would support a more comprehensive evaluation of how physical and societal dynamics jointly influence public sentiment, particularly when considering the interplay of societal disruptions and infrastructure changes.

In conclusion, this study demonstrates the potential of combining NLP-based sentiment analysis with computer vision techniques to evaluate the relationship between urban features and public sentiment. The findings highlight the enduring importance of greenery and pedestrian-friendly infrastructure in promoting positive urban experiences while also revealing the dynamic and context-dependent nature of public preferences. By aligning urban design strategies with these insights, planners and policymakers can create more inclusive, adaptable, and resilient environments that cater to diverse community needs and respond effectively to evolving societal challenges.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

JA: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. TM: Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

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