Computers, Environment and Urban Systems 122 (2025) 102329

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

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

Toward satisfactory public accessibility: A crowdsourcing approach through online reviews to inclusive urban design

Lingyao Li [a,*,1], Songhua Hu [b,1], Yinpei Dai [c], Min Deng [d], Parisa Momeni [a], Gabriel Laverghetta [a], Lizhou Fan [c], Zihui Ma [e], Xi Wang [f], Siyuan Ma [g], Jay Ligatti [a], Libby Hemphill [c]

[a] University of South Florida, Tampa, FL, United States
[b] Massachusetts Institute of Technology, Cambridge, MA, United States
[c] University of Michigan, Ann Arbor, MI, United States
[d] Texas Tech University, Lubbock, TX, United States
[e] University of Maryland, College Park, MD, United States
[f] Texas A&M University, College Station, TX, United States
[g] Vanderbilt University, Nashville, TN, United States

ARTICLE INFO

Keywords:
Accessibility
Crowdsourcing
Text mining
Inclusive urban design
Large language models

ABSTRACT

As urban populations grow, the need for accessible urban design has become urgent. Traditional methods for assessing public perceptions of accessibility, such as surveys and interviews, are often resource-intensive and geographically limited in scope. Crowdsourcing via online reviews offers a valuable alternative to understanding public perceptions, and advancements in large language models (LLMs) can facilitate their use. In this study, we examine over one million Google Maps reviews from points of interests (POIs) across the United States and fine-tune the Llama 3 model using the Low-Rank Adaptation (LoRA) technique to identify public sentiment toward accessibility. At the POI level, most categories – restaurants, retail, hotels, and healthcare – show negative sentiments, indicating persistent barriers across key sectors. Socio-spatial regression analysis reveals that more positive sentiment is associated with areas that have higher proportions of white residents and greater socioeconomic advantage. Conversely, more negative sentiment is expressed in areas with higher concentrations of elderly and highly-educated populations. Interestingly, no clear link is found between the presence of disabilities and public sentiments, but a significant positive relationship does exist between disability-friendly scores and public perception. Overall, our findings demonstrate the value of crowdsourcing with LLM-enhanced analysis in identifying accessibility challenges and informing inclusive urban design, offering actionable insights for planners, policymakers, and advocates striving toward more equitable cities.

1. Introduction

As urban populations continue to grow, the importance of creating inclusive cities that cater to all citizens has become increasingly urgent. Despite significant advances in urban planning and development, urban accessibility – defined in this study as the ease with which individuals, especially those with disabilities, can reach and effectively utilize urban infrastructure and services – remains inconsistent within cities (Nicoletti, Sirenko, & Verma, 2023; Spadon, Gimenes, & Rodrigues-Jr, 2017). For instance, while public transportation systems are designed to include elevators and audio–visual aids, some regions still have steep stairs and narrow doorways that limit access (Tatano, Guidolin, Peltrera, et al., 2017). Similarly, although many newer buildings comply with modern accessibility standards by incorporating ramps, wide doorways, and accessible restrooms, older structures often lack these essential features (Andani, Rostron, & Sertyesilisik, 2013; Froehlich-Grobe, Regan, Reese-Smith, Heinrich, & Lee, 2008). This inconsistency in accessibility significantly impacts the daily

* Corresponding author.
E-mail addresses: lingyaol@usf.edu (L. Li), hsonghua@mit.edu (S. Hu), daiyp@umich.edu (Y. Dai), mindeng@ttu.edu (M. Deng), parisamomeni@usf.edu (P. Momeni), glaverghetta@usf.edu (G. Laverghetta), lizhouf@umich.edu (L. Fan), zma88@umd.edu (Z. Ma), xiwang@tamu.edu (X. Wang), siyuan.ma@vumc.org (S. Ma), ligatti@usf.edu (J. Ligatti), libbyh@umich.edu (L. Hemphill).
[1] These authors contributed equally to this work.

https://doi.org/10.1016/j.compenvurbsys.2025.102329
Received 18 January 2025; Received in revised form 15 July 2025; Accepted 16 July 2025
Available online 23 August 2025

lives of individuals, especially those with disabilities (Aini, Marlina, & Nikmatullah, 2019; Bromley, Matthews, & Thomas, 2007). Therefore, it is essential to investigate and improve accessibility in urban environments to ensure that cities become truly inclusive for citizens.

Accessibility research has experienced substantial growth in recent decades, with an increasing number of related papers being presented at human–computer interaction (HCI) venues (Mack et al., 2021). The investigation of accessibility within urban environments has often relied on approaches such as surveys (Bekci & Sipahi, 2023; Lau & Chiu, 2004; Ziemke, Joubert, & Nagel, 2018) and field studies (Wang, Pei, Zhang, & Tang, 2023). While these approaches offer valuable insights into public perceptions of accessibility and its related service, they are often time-consuming and costly. In addition, they may be limited in scope and participant diversity (Pinna, Garau, & Annunziata, 2021). For example, surveys often struggle to capture a broad range of perspectives and require extra effort to include individuals with disabilities (Wilson et al., 2013). Field studies, while thorough, can be resource-intensive and may not adequately represent the diverse experiences of users across various areas of a city (Wang et al., 2023). As a result, these traditional methods may fail to provide a comprehensive understanding of the accessibility challenges across large urban areas.

Recently, crowdsourcing through social media or online reviews has shown potential for gathering insights from broad and diverse populations (Blohm, Leimeister, & Krcmar, 2013; Neto & Santos, 2018). It also highlights the critical role of HCI in today's digital landscape and serves as an interface through which users actively contribute their experiences and perceptions (Liao, Zhou, & Zhou, 2020). Crowdsourcing from social media or reviews can facilitate data collection and dissemination, making it possible to harness collective intelligence to understand public perceptions of urban environments (Saha et al., 2019; Salomoni, Prandi, Roccetti, Nisi, & Nunes, 2015). Therefore, this approach is particularly valuable for gathering wide experiences from citizens. In the context of accessibility, crowdsourcing approaches – such as using online reviews – may risk underrepresenting individuals with disabilities who are less likely to contribute such content. However, compared to traditional methods, this approach is significantly more cost-effective, reducing the need for surveys, on-site inspections, or fieldwork, and can complement insights from those survey studies (Hossain & Kauranen, 2015).

Previous research has highlighted the value of crowdsourced data for investigating traffic flow (Hu et al., 2024), infrastructure management (Li, Mao, Wang, & Ma, 2022), and urban environment (Li, Hu, Shaw & Hemphill, 2024) but rarely focused on inclusive urban design. In addition, while social media data are often unstructured and contain various information, there has been limited exploration of how large language models (LLMs) can be leveraged to understand public perceptions of urban-related issues. Existing studies on using crowdsourcing to evaluate urban accessibility concentrate on specific aspects of the built environment such as walkability (Gong, 2023; Wang, Haworth, Chen, Liu, & Shi, 2024) or they investigate small-scale geographic areas, such as individual streets or neighborhoods (Hara, Le, & Froehlich, 2013a; Saha et al., 2019). While these studies provide valuable insights, they are limited in scope and do not explain how public perceptions relate to factors such as geography and socioeconomic factors. To build on this literature, we studied two specific research questions:

- **RQ1 (POI analysis).** (1) What patterns exist in public sentiments of accessibility across Point of Interest (POI) types; and (2) What are the key aspects that can explain the sentiments?
- **RQ2 (Socio-spatial analysis).** (1) What patterns exist in public sentiments of accessibility across different geospatial areas; and (2) How are these geospatial patterns associated with local socio-spatial factors?

This study explores how user-generated reviews from Google Maps can illuminate public perceptions of accessibility across different POI types and geospatial areas. The first question examines how reviews mentioning accessibility features differ across various POI types and identifies semantic patterns in reviews to discern practical issues that shape public attitudes toward accessibility as positive or negative. The second question explores how accessibility sentiment relates to local socio-spatial factors. The goal is to identify the socioeconomic, demographic, and land development elements that influence public views on accessibility. Meanwhile, it is important to note that the findings from this study are intended to complement, not replace, traditional survey methods. Individuals with disabilities may be less likely to visit certain public spaces or contribute online reviews, which could bias the data toward those concerned about accessibility but not necessarily living with disabilities themselves. As such, equity-related conclusions should be drawn with caution. Overall, this research provides valuable insights for urban planners, policymakers, and accessibility advocates seeking to promote inclusive urban design and improve accessibility for all – especially for people with disabilities.

2. Related work

2.1. Accessibility in urban planning

Urban environments consist of infrastructure and facilities, such as sidewalks and public transportation, which serve individuals from diverse socioeconomic backgrounds. To ensure equitable access, these environments must cater to people of all abilities (Saha et al., 2022). Urban accessibility can be studied from both macroscopic and microscopic perspectives (Pereira & Herzenhut, 2023). At the macro level, accessibility focuses on large-scale urban planning issues, such as transportation systems and city infrastructure, which affect entire populations (Pereira & Herzenhut, 2023). In contrast, microaccessibility examines the accessibility of individual services and facilities (Grisé, Boisjoly, Maguire, & El-Geneidy, 2019). Prior studies in this area have examined physical barriers in urban infrastructure, such as technical malfunctions in bus entrance/exit ramps (Velho, 2019) and obstructed sidewalks (Hara, Le, & Froehlich, 2013b). Our study addresses the microaccessibility of urban environments by investigating accessibility challenges at POIs.

As microaccessibility studies frequently highlight, people with disabilities are disproportionately affected by environmental hazards, making them particularly vulnerable to accessibility issues in urban environments (Jampel, 2018). For example, a prior study found that when hurricanes struck, households with disabled residents were significantly less likely to evacuate (Brodie, Weltzien, Altman, Blendon, & Benson, 2006). This underscores the urgency of inclusive urban design. In the United States, the Americans with Disabilities Act (ADA) Accessibility Standards regulate urban infrastructure to ensure that accessibility requirements are met (Board, 2014). Additionally, the framework of universal design offers principles for creating environments that accommodate individuals of varying abilities (Imrie & Luck, 2014). Taught in academic settings (Sirel & Sirel, 2018), these principles have shaped key urban design factors like walkability, legibility, and overall accessibility (Duman & Asilsoy, 2022).

However, there are still significant gaps in accessibility for disabled people, resulting in decreased quality of life (III, 2020). For example, poor sidewalk quality has been shown to severely restrict urban mobility for disabled individuals (Clarke, Ailshire, Bader, Morenoff, & House, 2008). Physical barriers often cause anger, anxiety, and frustration for those affected (Velho, 2019). Despite the successful passage of ADA legislation, new deployments of public infrastructure may still be inaccessible. For example, newer designs of Bay Area Rapid Transit train cars lacked space for wheelchair users compared to older versions, prompting backlash from disabled communities (Editorial Staff of C.B.S. S.F., 2014). Emerging technologies such as micromobility devices and autonomous delivery robots have created additional obstacles on urban pathways (Bennett et al., 2021).

To effectively address these challenges, it is crucial to understand public attitudes toward accessibility. Researchers have employed various methods to assess these attitudes. For example, a typical work conducted interviews with 33 disabled participants to investigate their perceptions of public facilities (Fänge, Iwarsson, & Persson, 2002). Surveys are also popular tools to assess people's attitudes toward urban vitality (Paköz & k, 2022) and accessible transportation (Ceccato, Deflorio, Diana, & Pirra, 2020). Through surveys, prior work found that people, politics, and budget were intrinsically tied to underfunded accessibility improvement projects (Saha et al., 2021). However, these traditional methods, based on either surveys or interviews, are hindered by their limited geographic scope and lack of scalability. New approaches using crowdsourcing may offer an additional solution to these issues of limited data (Ilieva & McPhearson, 2018).

2.2. Crowdsourcing to investigate accessibility

2.2.1. Crowdsourcing to study urban environments

Crowdsourced data, such as social media data, collaborative websites, generated by the public, have become fine-grained proxy data of urban activity (Niu & Silva, 2020). Crowdsourcing approaches have become increasingly prevalent in studying urban environments, providing researchers with innovative tools for real-time, large-scale, decentralized data collection and analysis (Certoma, Corsini, & Rizzi, 2015). This trend reflects a growing recognition of the potential for crowdsourcing to address complex urban challenges (Velázquez, Faka, & Kounadi, 2024). Typical applications include examining the "sense of place" along the Las Vegas Strip using Tripadvisor reviews (Song, Wang, Fernandez, & Li, 2021), investigating public satisfaction of parking using Google Maps reviews (Li, Hu, Dinh, & Hemphill, 2024), and analyzing the urban vibrancy in Hong Kong with Facebook data (Chen, Hui, Wu, Lang, & Li, 2019). A more recent study utilizes Google reviews to investigate users' sentiments regarding Cairo's urban parks. Using topic modeling and sentiment analysis, the study identifies four key themes, including quality and maintenance, family and activities, costs and affordability, and natural environment, and finds that most of reviews expressed positive sentiments (Mohamed & Kronenberg, 2025).

In the context of urban accessibility, crowdsourcing has demonstrated its value as well. Most crowdsourcing-based studies take a macroscopic perspective, focusing on city-level accessibility features (Mirri, Prandi, Salomoni, Callegati, & Campi, 2014; Zhu & Diao, 2020)—for example, using crowdsourcing to improve the identification of temporary obstacles in accessibility mapping systems (Rice et al., 2013). In terms of the microascessibility perspective, there are also multiple studies. For instance, previous research has leveraged crowdsourcing to improve accessibility for mobility-impaired individuals in smart cities, illustrating how these efforts are driving the development of more inclusive urban spaces (Panta et al., 2019). Another typical study introduces a web-based tool that allows crowdworkers to remotely label pedestrian-related accessibility problems by virtually walking through streets through Google Street View (Saha et al., 2019). However, when leveraging crowdsourcing, there is a need to differentiate between two primary types of crowdsourcing approaches: (1) active crowdsourcing, and (2) passive crowdsourcing, both of which offer unique contributions to urban planning, accessibility, and sustainability (Kamaldin et al., 2019).

2.2.2. Active crowdsourcing

Active crowdsourcing relies on direct participation from individuals, where users consciously contribute data or feedback (Mobasheri, Deister, & Dieterich, 2017). For example, public webcams and citizen science initiatives have played a pivotal role in enhancing flood models and early warning systems through real-time data collection (Helmrich et al., 2021). In the context of urban accessibility, active crowdsourcing is also effective. A typical example is Project Sidewalk, which allows users to annotate street-level images from Google Street View (GSV) to identify accessibility barriers. Using a gamified interface on Amazon Mechanical Turk, Project Sidewalk efficiently scales up accessibility audits, demonstrating the advantages of active crowdsourcing for urban accessibility audits (Hara et al., 2013b; Saha et al., 2019). Another typical application is The EasyGo platform, which exemplifies active crowdsourcing by involving users to report and map barriers and facilities across cities. This platform offers custom routing for mobility-impaired individuals (Panta et al., 2019). However, these active crowdsourcing approaches often face challenges related to data sparsity and user fatigue (Ding, Wald, & Wills, 2014).

2.2.3. Passive crowdsourcing

In contrast, passive crowdsourcing does not require direct user involvement (Loukis & Charalabidis, 2015). Instead, it leverages data generated from everyday activities and passive systems. Compared to active crowdsourcing, passive crowdsourcing has several typical advantages. First, passive crowdsourcing does not require direct user involvement and allows for continuous data collection without the need for participant recruitment, which can be resource-intensive and limiting in scale (Ding et al., 2014; Ghermandi & Sinclair, 2019). More importantly, passive crowdsourcing can help gather vast amounts of data from a broad set of populations, providing richer and more representative datasets. This broader data collection also enables deeper and more nuanced analysis, revealing insights that might be missed with smaller, actively gathered datasets from conventional methods like surveys or interviews in urban studies (Chuang, Benita, & Tunçer, 2022; Li, Hu, Dinh, & Hemphill, 2024).

Previous research has shown the remarkable potential of passive crowdsourcing via GPS tracking or social media to decipher public sentiments and attitudes across domains in urban environments (Basak, Bhaumik, Roy, & Bandyopadhyay, 2020). For instance, Williams, Xu, Tan, Foster, and Chen (2019) gathered data from several Chinese social media platforms, such as Baidu Map, and created a computational model using residential visit patterns to identify "Ghost cities" in China—areas with significant housing vacancies due to excessive development relative to their population size. Chen et al. (2019) analyzed Facebook data to study urban vibrancy in Hong Kong, focusing on residents' visits to POIs to understand spatial structures and leverage social media insights for enriched urban planning. Similarly, Chuang et al. (2022) collected over 20 million geolocated tweets from July 2012 to October 2016 to analyze park visits in Singapore. Their statistical analysis showed that high surrounding population density and family-oriented facilities, such as playgrounds, could lead to greater visitor density in parks.

Passive crowdsourcing has also illustrated its potential in addressing urban environmental issues or emergent events, including disaster damage estimation (Li, Bensi, & Baecher, 2023), community resilience (Ma, Li, Hemphill, Baecher, & Yuan, 2024), and evacuation efforts (Li, Ma, & Cao, 2021). For example, air pollution monitoring has been transformed by mobile sensors on vehicles and smartphones, enabling the collection of detailed air quality data at a city-wide scale (Huang et al., 2018). Another typical study utilized the passively collected location data from mobile devices to examine the impact of floods, winter storms, and fog on road traffic (Hu et al., 2024). It found that the patterns that emerged from crowdsourced data could provide meaningful insights into disaster response and recovery in road transportation systems.

Existing efforts to use passive crowdsourcing for urban accessibility have been limited. One typical application is the SmartBFA system (Kamaldin et al., 2019), which gathers data through Internet of Things (IoT) devices attached to wheelchairs. Another key initiative is AccessMap (Aly, Youssef, & Agrawala, 2021), which enhances road maps by passively crowdsourcing accessibility data from smartphone sensors to detect features like ramps and curb cuts. Additionally, previous research on automated road accessibility assessments like mPass has utilized wheelchair-mounted sensors for passive crowdsourcing (Iwasawa, Nagamine, Yairi, & Matsuo, 2015; Prandi, Salomoni, & Mirri, 2014). These sensors collect accelerometer data to evaluate ground surface conditions and identify obstacles such as steps and slopes. However, these efforts often remain limited to small-scale experiments or require the installation of specialized sensor equipment.

Prior studies have demonstrated the significant potential of crowdsourcing to enhance urban studies. However, several challenges remain. First, many previous studies focus primarily on the number of social media visits to infer urban environment or accessibility, often overlooking the rich textual content shared by users that could reveal deeper insights into their sentiments and opinions. Second, there is a noticeable gap in research specifically addressing public perceptions of accessibility for disabled individuals. This area is complex and requires nuanced understanding to decode opinions that go beyond simple visitation metrics. Third, given that social media posts and online reviews are unstructured, there has been limited exploration into using LLMs to improve the interpretation of these opinions. To address these challenges and harness the potential of passive crowdsourcing, we propose the two research questions outlined in the introduction.

2.3. Factors potentially affecting accessibility-related sentiment

Understanding public perception of accessibility or related aspects requires examining a range of demographic, socioeconomic, and environmental factors. First, prior research highlights demographic conditions as significant determinants shaping the lived experiences of individuals with disabilities (Iezzoni, 2011). Specifically, demographic characteristics such as age, gender, ethnicity, educational attainment, marital status, and the nature and severity of disability substantially are associated with individuals' perceptions of their health and well-being (Botticello, Rohrbach, & Cobbold, 2015). These demographic factors can exacerbate existing disadvantages caused by disability (Krahn, Walker, & Correa-De-Araujo, 2015). Regression-based analyses have also linked life satisfaction among disabled persons to demographic factors such as age, marital status, family structure (number of children, household size) (Pagán, 2015).

In addition, research consistently shows that the socioeconomic factors shapes accessibility experiences. For example, the census nationwide survey implies that the urban–rural context could impact accessibility experiences. In the United States, disability prevalence is actually higher in rural areas (14.7% of residents) than in urban areas (Bureau, 2023). However, rural residents with disabilities in focus groups reported that their communities were "generally less sensitive to disability access issues" compared to urban areas (Iezzoni, Killeen, & O'Day, 2006). Next, communities of low-income areas tend to have older public facilities and fewer accommodations. A 2017 survey of Americans with disabilities finds that 20% encountered an accessibility barrier (in a building, service, or transit) at least once per day, and 12% faced multiple daily barriers (Center for Disability Issues and the Health Professions, 2017). In addition, an early study examining public attitudes to people with intellectual disability in Hong Kong shows that lower education levels are associated with more negative attitudes toward people with disabilities, whereas higher education correlates with more positive, understanding views (Lau & Cheung, 1999).

In addition to socioeconomic and demographic influences on general perceptions, prior research has explored specific factors affecting satisfaction with accessibility features. For example. Previous surveys examining satisfaction among disabled individuals have identified accessibility features – including public spaces, room accommodations, recreational areas, bathrooms, and dining facilities – as critical factors influencing hotel satisfaction (Tutuncu, 2017). Similarly, community participation for individuals with disabilities varies according to demographic attributes and aspects of the built environment, such as land usage patterns and residential density (Botticello, Rohrbach, & Cobbold, 2014). These findings from prior research justify incorporating demographic, socioeconomic, and urban environmental factors when modeling satisfaction with the accessibility of public facilities, which further support the factor selection in subsequent regression modeling.

3. Data and methods

Fig. 1 illustrates a framework for conducting research collected from Google Maps reviews, specifically focusing on accessibility-related sentiment analysis. Fig. 1a shows the distribution of POIs with 5 or more related reviews in the United States, which are then used for subsequent POI analysis. Fig. 1b displays the Google Maps reviews for the Smithsonian National Museum. It includes two example user reviews – one negative and one positive – related to accessibility for wheelchair users. After we collect those reviews, we build models for classifying the opinions from Google Map reviews (Fig. 1c). The classification process involves using both LLMs like BERT and Llama 3, as well as baseline models such as RoBERTa sentiment analysis and various TF-IDF-based models.

3.1. Data preparation

Google Maps reviews serve as our primary source for gauging residents' attitudes toward accessible facilities. Google Maps allows users to freely rate and review POIs, including businesses, attractions, and public spaces. We select Google Maps reviews as our primary data resource due to two major reasons (see example in Fig. 1b). First, it has seen substantial growth in user reviews, outperforming competitors like Yelp and TripAdvisor (Munawir, Koerniawan, & Dewancker, 2019). Second, unlike social media platforms such as Facebook or Twitter (now called X), Google Maps reviews specifically focus on customer experiences with businesses and locations, making them particularly suitable for our crowdsourcing approach. The online reviews collected from Google Maps can provide a reliable and relevant dataset for our study on attitudes toward accessible facilities (Lee & Yu, 2018).

To implement the study, we utilize the dataset published by UC San Diego (Li, Shang, & McAuley, 2022; Yan, He, Li, Zhang, & McAuley, 2023), which encompasses Google Maps reviews up to September 2021 across the United States. The dataset consists of 666,324,103 reviews with 4,963,111 POIs covered. For each POI, this data repository includes:

- User-generated review data: Usernames, ratings, comments, and images.
- Business metadata: Addresses, geolocation data, descriptions, categories, pricing, operating hours, links to the business, and other related information.

To systematically identify Google Maps reviews that reflect residents' attitudes toward accessible facilities, we adopt a hybrid top-down and bottom-up method, grounded in both regulatory standards and empirical review patterns. For the top-down method, we begin by referencing the ADA Accessibility Guidelines (ADAAG) (Board, 2002), which define a set of core elements and spaces relevant to accessibility compliance, such as access aisles, accessible routes, curb ramps, marked crossings, and transfer devices. These definitions from ADAAG serve as a base for an initial dictionary of terms expected to indicate accessibility concerns within user reviews.

Next, we apply a bottom-up method by recognizing that public users often use informal or non-technical language in online reviews. Specifically, we conduct a frequency analysis on the top 10,000 most common unigrams and bigrams in the Google Maps review corpus. Through this, we notice that not all ADAAG-listed terms appear in user reviews, and some frequently occurring terms do not necessarily indicate accessibility concerns within their specific contexts. Consequently, we refine our term list by selecting only those ADAAG terms and frequently occurring unigrams and bigrams from the reviews that clearly referenced accessibility. This bottom-up method ensures relevance and accuracy in capturing accessibility-related terms in reviews.

To ensure both coverage and contextual relevance, three authors conduct three interactive rounds of word collection by reviewing both

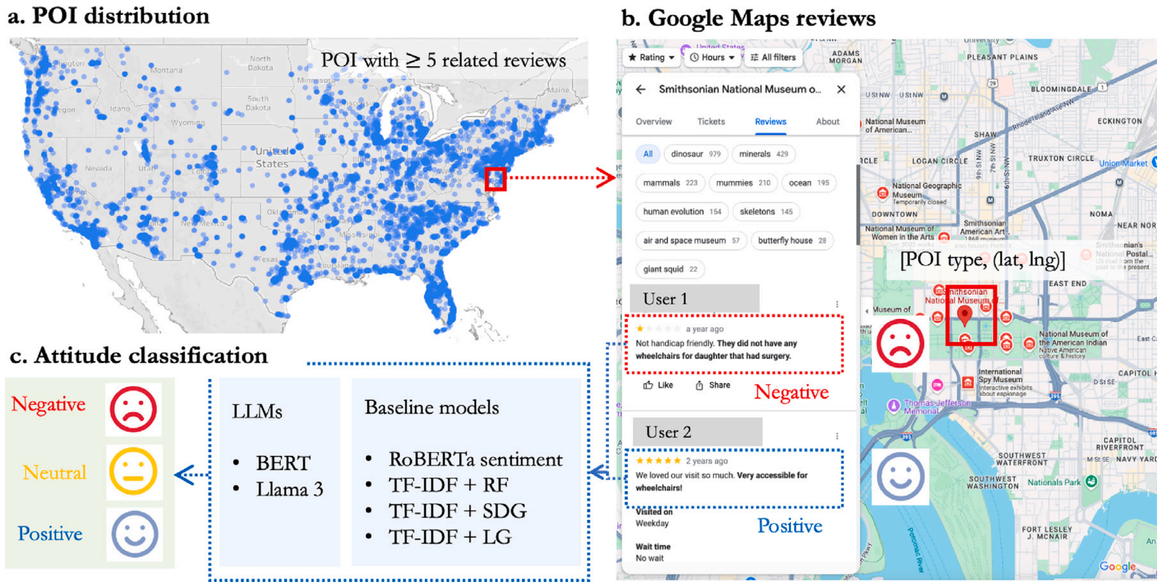


Fig. 1. An illustrative framework to conduct the data analysis.

ADAAG guidelines and the top 10,000 frequent unigrams and bigrams collected from Google Maps reviews. After systematically combining ADAAG definitions with a frequency-based analysis of review text, we establish a final dictionary tailored specifically to extracting accessibility-focused comments. The finalized search terms used in our analysis are listed below.

Search list: "accessible," "accessibility," "ada compliance," "ada compliant," "blind," "braille," "curb cut," "curb ramp," "deaf," "disabilities," "disability," "disabled," "grab rail," "hand splint," "handicap," "handrail," "hearing loss," "induction loop," "mobility aid," "service animal," "service cat," "service dog," "tactile map," "tactile paving," "tactile warning," "tgsi," "vision impairment," "visual impairment," and "wheelchair."

Several points need to be highlighted given this search list. First, it should be noted that some elements mentioned in the ADA Accessibility Guidelines, such as "elevator", "open area", and "play area", do not return any relevant Google Maps reviews in this context. Including such elements could introduce a significant amount of noise into our analysis, and therefore, we exclude them from our search list. As a result, we filter in 1,013,771 reviews that potentially reflect attitudes toward accessible facilities. While it is important to note that online reviews may contain typographical errors, this study does not account for these typos due to the challenges in comprehensively addressing all possible misspellings for each term. Last, it is worthwhile noting that our search strategy captures different forms of words. For instance, both "handicap" and "handicapped" are included in our results, as our filtering process identifies reviews containing the root word, thus encompassing various grammatical forms.

3.2. Data annotation

Identifying users' perspectives on accessibility from Google Maps reviews can be approached as a text classification problem in natural language processing (NLP). Initially, we explore the possibility of using pre-existing sentiment analysis tools, such as RoBERTa sentiment model. However, phrases such as "handicap accessible" or "Not ADA accessible" are frequently categorized as neutral by these models. This likely occurs since general sentiment analysis tools fail to capture the subtle nuances related to attitudes toward accessible facilities. As a result, it becomes necessary to create specialized text classification models tailored to this specific research context.

Developing classification models requires training and testing datasets. Typically, attitude classification encompasses three categories: positive, neutral, and negative. However, we observe that certain reviews, despite containing pertinent keywords, do not express any specific attitudes toward accessible facilities or services. For instance, statements like "The restaurant is in a good location and very accessible to the freeway" or "It is well located and accessible" are not related to accessible facilities in the intended context. This is because keywords such as "accessible" can have different meanings depending on the context. To address this, we introduce an additional class, "unrelated", to the existing categories. Generally, comments that mention the availability or satisfaction of accessible facilities are categorized as positive. Comments that highlight the lack of accessible facilities, poor quality of such facilities, or inadequate service are classified as negative.

Specific examples of each category are provided in Table 1. We chunk the reviews into sentences and then focus on the part that contains the targeted aspects for attitude classification. This is because some online reviews are long and may cover aspects unrelated to attitudes toward accessible facilities or services. This handling can be useful when a review expresses conflicting sentiments about various aspects (see the fourth example in Table 1).

Following this way, two authors are involved in the data annotation process. Both authors have read the ADA Accessibility Guidelines and acknowledged the criteria to classify the attitude based on Google Maps reviews. We further select a randomly sampled set of 200 reviews to verify the agreement between two annotators. These sampled reviews are labeled independently by each annotator. We use Krippendorff's $alpha$ (Krippendorff, 2018) to measure the inter-coder agreement, as described by the following equation.

$$\alpha = 1 - \frac{D_o}{D_e} \quad (1)$$

Where:

- D_o is the observed disagreement between annotators
- D_e is the expected disagreement by chance

The inter-coder agreement for our annotation, measured by Krippendorff's $alpha$, is 0.87, indicating a strong level of agreement. Following this, two annotators label a total of 2840 randomly sampled reviews, dividing them into 2272 for training and 568 for testing, based on the 80/20 split principle. Consequently, the training set comprises 531 negative, 103 neutral, 458 positive, and 1180 unrelated reviews, while the testing set consists of 127 negative, 23 neutral, 129 positive, and 289 unrelated reviews.

Table 1
Representative Google Maps reviews for public attitudes toward accessibility.

Google Maps review [sic]	Targeted text [sic]	Attitude
UNBELIEVABLE! So many cool Great Danes! And what a valuable service for people with disabilities! Thank you for helping others!	And what a valuable service for people with disabilities!	Positive
Such a great clean park. Not much for kids to do but it has a very nice walking trail around the park. Good level parking lot with handicap space. Would probably be a great place to walk your dog or just hang out with loved ones. Benches available for sitting but no covered areas if its raining.	Good level parking lot with handicap space.	Positive
So I am reading the reviews and the elevator is still out. Maybe I should call the American's with Disabilities. The elevator must be working for people with disabilities. And to say the less, the key card took forever to get activated	Maybe I should call the American's with Disabilities. The elevator must be working for people with disabilities.	Negative
Handicap spots are not accessible during lunch, they say call but the line is busy or rings and rings. Other than that great food.	Handicap spots are not accessible during lunch, they say call but the line is busy or rings and rings.	Negative
Closet was very small and difficult to close once you hung clothes on hangers in it. Seems like we might have had a handicap room and that could be the reason for the unusual setup of the closet and the bathroom.	Seems like we might have had a handicap room and that could be the reason for the unusual setup of the closet and the bathroom.	Neutral
Very nice place to taste good oriental food. At prices very accessible to all people ...	At prices very accessible to all people ...	Unrelated
I always had my morning coffee here in this very coffee shop near the mall. It was very accessible and near my workplace. I love their coffee compared to other coffee shops in the city. I love pairing my coffee with their muffins. It was like salt and pepper, a perfect match. I recommend this coffee shop to the coffee lovers out there!	It was very accessible and near my workplace.	Unrelated

3.3. Attitude classification

3.3.1. Sentiment models

As prior studies have used sentiment analysis to gauge public attitudes, we start by testing a sentiment analysis model called RoBERTa Sentiment (Barbieri, Camacho-Collados, Espinosa Anke, & Neves, 2020; Loureiro, Barbieri, Neves, Espinosa Anke, & Camacho-collados, 2022). It is trained based on RoBERTa framework, which is a robustly BERT pre-training approach. The RoBERTa sentiment model used in this study is trained on a corpus of 123.86 million tweets collected up to the end of 2021 and fine-tuned for sentiment analysis based on the TweetEval benchmark.

3.3.2. TF-IDF baseline models

With the training and testing datasets prepared, the subsequent phase involves constructing and assessing classification models (Fig. 1c). We incorporate three conventional NLP text classification models utilizing Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF is a measure that assesses the significance of a word within a document in relation to a set of documents (corpus). The formula for calculating TF-IDF is as follows:

$$\text{TF-IDF}(t,d) = \text{TF}(t,d) \times \text{IDF}(t) \tag{2}$$

Where:

- $\text{TF}(t,d)$ is the frequency of term t in review d divided by the total number of terms in d.
- $\text{IDF}(t)$ is the inverse document frequency of term t, calculated as:

  $$\text{IDF}(t) = \log\left(\frac{N}{1+\text{DF}(t)}\right)$$

  Where N is the total number of Google Maps reviews in the corpus, and $\text{DF}(t)$ is the number of reviews containing the term t.

It is important to note that TF-IDF does not capture the semantic meaning of terms and therefore cannot consider the context in which a word appears in a review. Next, we integrate TF-IDF with three machine learning classifiers: random forest (RF), stochastic gradient descent (SGD), and logistic regression (LR). This results in three baseline models: TF-IDF+RF, TF-IDF+SGD, and TF-IDF+LR.

We conduct hyperparameter tuning on the training dataset using K-fold cross-validation with $K = 10$ for each of the three TF-IDF baseline models. Table 2 displays the hyperparameters and their corresponding grid search values for each model. During the training iteration, the model is trained on nine subsets and validated on the remaining subset. By employing 10-fold cross-validation, we evaluate the listed hyperparameter values and choose the optimal one for each model.

3.3.3. Large language models (LLMs) implementation

Additionally, we utilize two LLMs for the classification task: BERT (Devlin, Chang, Lee, & Toutanova, 2019) and Llama 3 (Dubey et al., 2024). For BERT, we use the bert-base-uncased model with 110M parameters. Then, we fine-tune the BERT model to enhance its performance on accessibility-related sentiment classification. The fine-tuning process involves K-fold cross-validation with $K = 5$. We also perform a grid search to optimize key hyperparameters including the batch size and number of epochs. The grid search is listed in Table 2.

For Llama 3, we select the Llama-3-8B-Instruct as the backbone model, taking into account the available computational resources. We fine-tune the Llama 3 model to generate the labels using the LoRA (Hu, Shen, et al., 2022) technique for 10 epochs. LoRA is an efficient fine-tuning method that introduces low-rank updates to model parameters, reducing the memory and computational overhead during training (Hu, Shen, et al., 2022). The LoRA rank is set to 32, with a scaling factor α of 16, leading to a total of 83.89M training parameters. To stabilize training, we use a learning rate of 3e-5 and a batch size of 64. To retain the instruction-following capabilities of Llama-3-8B-Instruct on our sentiment analysis task, we also design a specific system prompt (shown in the box below) and pre-process it with data samples following the standard OpenAI chat format.

Table 2
Grid search values for candidate models.

Model	Hyperparameter	Grid search
TF-IDF+RF	min_samples_leaf	1, 2, 4
	n_estimators	100, 200, 300, 400
	max_depth	10, 20, 40, 80, 100, 120
TF-IDF+SGD	clf_alpha	1e−4, 1e−3, 1e−2, 1e−1, 1, 10
	clf_max_iter	500, 800, 1000, 2000, 3000
	clf_penalty	l2, l1, elasticnet
TF-IDF+LR	clf_C	0.1, 0.5, 1, 2, 5, 10, 20
	clf_max_iter	10, 20, 50, 100, 200
	clf_solver	sag, saga, lbfgs, newton-cg
BERT	num_epochs	1, 2, 3, 4, 5
	batch_size	16, 32, 64
Llama 3	num_epochs	5, 6, 7, 8, 9, 10
	learning_rate	1e−5, 2e−5, 3e−5
	batch_size	32, 64

You are a language model trained to identify the sentiment for the accessibility from reviews. Your task is to analyze the text of each review and assign an appropriate label based on the sentiment or relevance of the content. The possible labels are:

- *Negative: The review expresses a negative sentiment or criticism about the accessibility of disabilities.*
- *Positive: The review expresses a positive sentiment or praise about the accessibility for disabilities.*
- *Neutral: The review provides a factual or mixed description without strong positive or negative sentiment.*
- *Unrelated: The review does not pertain to accessibility or describe any attitude toward accessibility. Reviews that discuss personal experiences or talk about something or somewhere accessible but not for disabilities, even have positive or negative words, should be labeled as unrelated.*

For each input, respond with the label that best describes the sentiment or relevance of the review.

3.3.4. Performance measures

After fine-tuning the hyperparameters of baseline models and the two LLMs, we evaluate the performance of these six candidate models: RoBERTa Sentiment, TF-IDF + RF, TF-IDF + SGD, TF-IDF + LR, BERT, and Llama 3. Given that the number of samples in each category is imbalanced, the performance of these candidate models is assessed using four key metrics: Precision, Recall, F1-score, and Accuracy. Precision indicates the percentage of TP cases among all reviews predicted correctly by a respective model. Recall reflects the percentage of TP cases out of all actual positive cases. The F1-score provides a harmonic mean of precision and recall, balancing both metrics. Accuracy measures the proportion of correctly classified reviews out of all reviews. The evaluation is performed on the testing dataset, and the performance results of each model are shown in Fig. 2.

Several key observations can be drawn from Fig. 2. The sentiment analysis tool is not valid for our task, due to its inability to identify unrelated comments or refer to our specific contexts. TF-IDF-based models, while potentially useful for differentiating terms in reviews, struggle to interpret semantic meanings in this context, which could significantly limit their performance. The BERT model shows improvement and obtains an overall accuracy of 81%. However, due to the imbalanced nature of the training samples, its performance in the neutral class remains limited. Last, fine-tuned Llama 3, possibly due to its large-scale pre-training process and robust text understanding capabilities, achieves the highest testing accuracy and a more balanced and higher F1-score across all classes. Based on the performance results, we select the fine-tuned Llama 3 as the best-performing model and apply it to the entire dataset for subsequent analysis.

3.4. Semantic analysis

With sentiment classified for each review, we then explore how individual words influence overall sentiment for different POI types. We use a tool called lexical salience-valence analysis (LSVA) (Taecharungroj & Mathayomchan, 2019) to examine the words within reviews. LSVA performs text mining and evaluates the relationships between words and the sentiments expressed in the reviews by defining salience and valence. Unlike simple word frequency counts in positive or negative reviews, the LSVA method provides a visualization of word frequency across the document corpus and its impacts on overall sentiment. LSVA defines a word's salience and valence in the following way:

$$\text{salience}|_{\text{word}_i} = \log_{10}(N_{\text{total}})|_{\text{word}_i} \tag{3}$$

$$\text{valence}|_{\text{word}_i} = \frac{N(\text{positive}) - N(\text{negative})}{N_{\text{total}}}|_{\text{word}_i} \tag{4}$$

Where:

- N_{total} represents the number of reviews in which the term $word_i$ appears.
- $N(\text{positive})$ represents the number of positive reviews in which $word_i$ appears.
- $N(\text{negative})$ represents the number of negative reviews in which $word_i$ appears.
- The salience of a term is computed by the logarithm with a base 10 function of the frequency of each term.
- The valence of a term is computed as $N(\text{positive}) - N(\text{negative})$ divided by its total count N_{total}, which measures how positive a particular term appears in a corpus.

3.5. Regression modeling

To assess whether public perceptions of accessibility vary across regions with different socioeconomic statuses, we construct a regression model correlating accessibility sentiment with nearby socio-spatial features. We calculate the average sentiment from all accessibility-related reviews within each region, selecting regions with more than 10 reviews as our regression samples. Counties with insufficient reviews are excluded because the limited number of reviews cannot reliably represent the overall sentiment of the entire county. Sensitivity analysis is then performed by adjusting the minimum review threshold from 0 to 50. Results show that regression results stabilize after a threshold of 10. To address the modifiable area unit problem (MAUP) (Hu, Chen, Jiang, Sun, & Xiong, 2022), which suggests that outcomes can vary based on spatial aggregation levels, we fit the regression at both county and census block group (CBG) levels. The regression is fitted under the generalized additive model (GAM) framework. The GAM is a semi-parametric framework that combines parametric linear predictors with a suite of additive, non-parametric nonlinear predictors. These nonlinear components are fitted using various types of smooth splines, enhancing the model's flexibility and adaptability. In our specification, the effects of main covariates of interest are modeled with linear terms, whereas the geospatial correlation between counties/CBGs that are located closer to each other is modeled with a smoother function. We additionally allow for state-specific random effects. Therefore, our regression model is formulated as:

$$g(E(Y)) = \beta_0 + \sum_{k=1}^{N_l} \beta_k X_k + ti(\text{SR}) + s(\text{RE}) + \epsilon \tag{5}$$

Where:

- Y is CBG- or county-level sentiment, assuming that both follow the Gaussian distribution.
- $g(\cdot)$ refers to the link function, which is the identity function in this case.
- β_0 is the overall linear intercept.

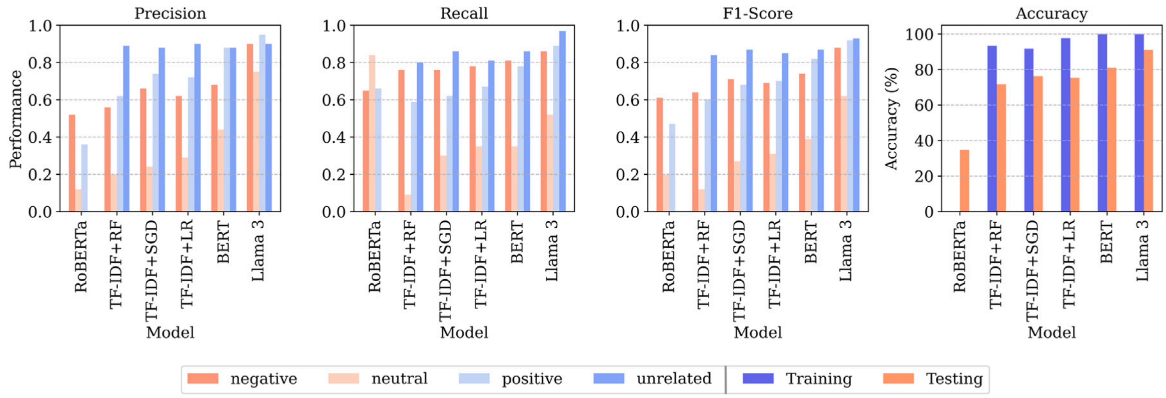


Fig. 2. Classification performance of candidate models measured by Precision, Recall, F1-score, and Accuracy.

- β_k is the coefficient of the *kth* variable X_k, where X_k is the variable set with linear effects. Here it includes all socio-spatial factors outlined in Table 3.
- SR denotes the spatial autocorrelation term. Here spatial autocorrelation is fitted by $ti(\cdot)$, which is a marginal nonlinear smoother that excludes main effects.
- RE denotes the state-level random effects captured by the penalized spline function $s(\cdot)$.
- ϵ is the error term.

The data sources for the independent variables are listed below: Socioeconomics and demographics are from the 2018–2022 5-year American Community Survey (ACS) (Bureau, 2022a); POI variables are from Google Maps; Road density is collected from OpenStreetMap; Partisanship is from the 2020 presidential election result from the MIT election lab. The Disability-Friendly Score is sourced from AAA State of Play (of Play, 2025) and is derived from 12 key factors that reflect the quality of life, inclusion, and overall success of individuals with disabilities, with higher scores indicating greater disability-friendliness. These factors include: the existence of digital accessibility laws, the number of wheelchair-friendly trails, the median wage for disabled workers aged 18–64, the employment rate of disabled individuals living in the community, the rate of health insurance coverage among disabled individuals, the percentage living in poverty, the percentage with a four-year college degree, the percentage of individuals with ambulatory disabilities who can self-care, the proportion living in poor or overcrowded housing conditions, the National Center for Access to Justice's Disability Access Index, Forbes Advisor's Access to Healthcare Index, and the average number of annual sunny days by state.

Comprehensive details and descriptive statistics for all independent variables (CBG-level) are presented in Table 3. Variables in *italic* are excluded from the models due to high multicollinearity, indicated by a variance inflation factor (VIF) greater than 5. Additionally, to mitigate the effects of outliers, influential observations are removed if their Cook's distance exceeds $4/(n-k-1)$, where n is the regression sample size and k is the total number of independent variables in the regression (Belsley, Kuh, & Welsch, 2005).

4. Results

The result analysis explores two research questions. For the first research question, we examine whether the public perception of accessibility varies across different POI types. Specifically, we investigate two aspects: whether different POI types exhibit variation in public sentiment, and what factors or aspects extracted from reviews contribute to the sentiment for different POI types. For the second research question, we explore the variation in public perception of accessibility from the geospatial perspective. Again, we divide this into two parts: identifying the patterns in public perception across different geographic areas, and examining the important social, demographic, and economic factors associated with the public sentiments.

Each POI in Google Maps is associated with a category. This category can be mapped onto the North American Industry Classification System (NAICS) codes (Bureau, 2022b). For example, a POI labeled as "restaurant" by Google Maps corresponds to the 3-digit NAICS code "722-Food Services and Drinking Places", while a "Grocery store" corresponds to "445-Food and Beverage Stores". However, with 102 3-digit NAICS codes, interpretation can present challenges. To address this, we manually group frequently mentioned Google Maps categories into several major POI types that are often associated with high-volume daily activities. Other POI types such as manufacturing facilities, production plants, or construction companies are not included in subsequent analysis as they are not closely related to the public's daily activities. For the subsequent analysis, the POI types we focus on are:

- Restaurant: Food and drink providers, e.g., restaurants, bars, drinking places.
- Retail Trade: Merchandise sellers, e.g., grocery stores, convenience stores, home goods stores.
- Recreation: Leisure and entertainment facilities, e.g., recreation centers, stadiums, gyms, playgrounds.
- Hotel: Short-term lodging providers, e.g., hotels, motels.
- Personal Service: Consumer-oriented service businesses, e.g., spas, salons, massage therapists.
- Health Care: Medical facilities and services, e.g., medical centers, urgent cares, dentists, hospitals.
- Transportation: People and goods movement services, e.g., bus stops, bus stations, shipping services.
- Public Service: Government and community services, e.g., business centers, mailbox, security services, locksmiths.
- Apartment: Multi-unit residential buildings, e.g., apartments.
- Education: Learning and instruction institutions, e.g., schools, universities, colleges.

4.1. POI analysis

4.1.1. What are the sentiment patterns among POI types?

To address RQ1(1), we begin by presenting the descriptive results categorized by POI types, as illustrated in Fig. 3. When considering all reviews for analysis (the blue bar in Fig. 3(a)), the most commonly mentioned POI types include Restaurant, Retail Trade, Recreation, Hotel, Personal Service, and Health Care. However, when applying a threshold of five reviews or more (the red bar in Fig. 3(a)), the order changes slightly, with Retail Trade, Recreation, Hotel, Personal Service, Restaurant, and Health Care being the most mentioned, in which Restaurants show a significantly smaller proportion of POIs with five or more reviews. This suggests that while restaurants and drinking

Table 3
Summary of independent variables in the regression model.

Variable	Description	Mean	Std.
Socioeconomic			
Population Density	Population density (people per acre)	4.822	9.577
Employment Density	Employment density (jobs per acre)	11.015	26.342
Poverty	households below poverty	14.179	11.888
Rural Population	rural population	8.399	22.887
Urban Population	% urbanized population	83.162	35.362
Median Income	Median household income (Inflation-Adjusted), in \$ 10^3/household	6.419	3.065
Highly-Educated	% residents with at least a Bachelor's degree	35.146	19.993
Demographics			
Male	% males	49.332	6.812
Age 18–44	% residents aged 18 to 44 years	39.167	15.004
Age 45–64	% residents aged 45 to 64 years	24.721	8.249
Age over 65	% residents aged 65 and older	17.475	11.907
White	% Non-Hispanic Whites	62.597	25.470
Asian	% Asians	5.904	9.557
African American	% African Americans	11.252	16.244
Hispanic	% Hispanics/Latinos	16.497	19.160
Others	% Other minorities	0.936	4.093
Disability	% residents with a disability	11.623	11.434
Review			
Avg. POI Score	Average POI score for all POIs collected from Google Maps, regardless of POI types or review contents	4.250	0.182
Review Density	Total accessibility-related review density	0.393	1.111
Disability Friendliness			
Disability-Friendly Score	Disability-Friendly score calculated by AAA State of Play	114.562	16.700
Partisanship			
Republican	% Republicans in 2020 presidential candidate vote totals	64.013	17.134

places are the most commonly reviewed POIs, most of them receive a very small number of comments that mention accessibility.

We select six major POI types for subsequent analysis given the following two reasons. First, they are closely associated with daily activities that produce high visit volumes, accounting for over 90% of total reviews across all POIs. Second, local businesses such as restaurants, retail trades, and recreation centers often experience high turnover rates and busy demand periods, indicating that accessibility issues could be more pronounced at these POIs. In addition, to avoid small sample bias from POIs with only one or two comments, we select those POIs with at least five reviews mentioning accessibility to plot the sentiment distribution. The sentiment distribution for each of these POI types is illustrated in Fig. 3(b).

The sentiment analysis across different POI types reveals diverse patterns and insights (Fig. 3(b)). Most POI categories exhibit negative average sentiments, with Retail Trade showing the most negative outlook with all three quartiles being negative (Q1: −0.67, Q2: −0.35, and Q3: −0.11). Recreation is the only POI type with a positive average sentiment (Q2: 0.12). Restaurant presents the highest negative first quartile (Q1: −0.78).

In addition, the distribution patterns offer further insights into sector-specific experiences. Retail Trade and Restaurant display right-skewed distributions indicating a tendency toward negative experiences with accessibility. Personal Service and Hotel show approximately normal distributions. In particular, Personal Service shows a relatively normal distribution centered near neutral, implying balanced experiences. Moreover, Recreation's left-skewed distribution aligns with its overall positive sentiment. Health Care exhibits a unique "U-shaped" distribution, with higher frequencies at both extremes (−1 and 1), suggesting polarized opinions about healthcare accessibility.

4.1.2. What are the aspects explaining the sentiments among POI types?

In response to RQ1(2), we delve into the aspects that explain the sentiments across the six major POI types, including Restaurant, Retail, Recreation, Hotel, Personal Service, and Health Care. We follow Eqs. (3) and (4) to calculate the salience and valence of each term in the corpus of reviews in terms of each POI type. Fig. 4 shows the unique accessibility-related sentiments for each POI type, facilitating better understanding by exploring the aspects contributing to positive and negative experiences, respectively marked in red and blue circles.

For Restaurant, negative sentiments are predominantly associated with staff interactions, service, the presence of service animals, particularly service dogs, and barriers such as steps and ramps. Accessibility-related terms such as "wheelchair", "entrance", and "parking" appear with neutral or slightly positive sentiments. This indicates that while structural accessibility features may be in place, social factors such as service and staff interactions contribute to negative sentiment.

In the Retail sector, accessible features such as "parking", "entrance", and "wheelchair" appear on the positive side of the valence axis, indicating appreciation for outdoor physical accommodations. However, negative sentiments stem from issues like "door", "employee", "line", "aisle", and "cart", which suggest challenges with the indoor environment in stores, such as handling accessibility for customers who require physical accommodations as well as customer service issues.

For Recreation, more positive sentiments appear. Those positive aspects are mainly associated with terms such as "accessible", "park", "ramp", "facility","trail", and "family", highlighting the positive impact of inclusive environments, particularly for family-friendly spaces. On the negative side, aspects such as "service", "staff", and "entrance" appear, showing that despite the availability of accessible features, other operational issues such as poor service or design negatively impact individuals' experiences.

The Hotel category presents a more imbalanced sentiment distribution, with only a few positive aspects shown in the figure, including "pool" and "staff". Negative sentiments dominate the terms, arising from infrastructure issues related to "room", "elevator", and "bathroom", to service issues related to "guest", "book", and "reservation". This highlight areas where accommodation for accessibility needs may fall short, particularly in terms of room features and staff assistance.

In the Personal Service sector, the positive aspects include "comfortable", "staff", and "process", reflecting satisfaction with the ease of service and assistance provided. However, terms like "seat", "space", "spot", "handicap", and "bathroom" reflect negative experiences, suggesting challenges related to accessibility facilities.

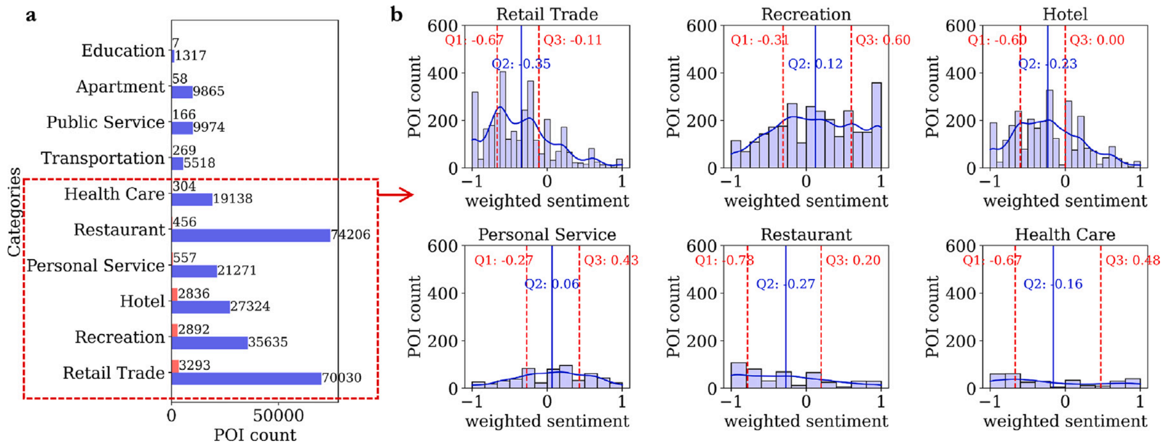


Fig. 3. Descriptive results for sentiment by POI. (a) Number of POIs by types. (b) Distribution of sentiment. The x-axis represents the weighted sentiment by averaging all sentiments associated with a POI, while the y-axis shows the POI count.

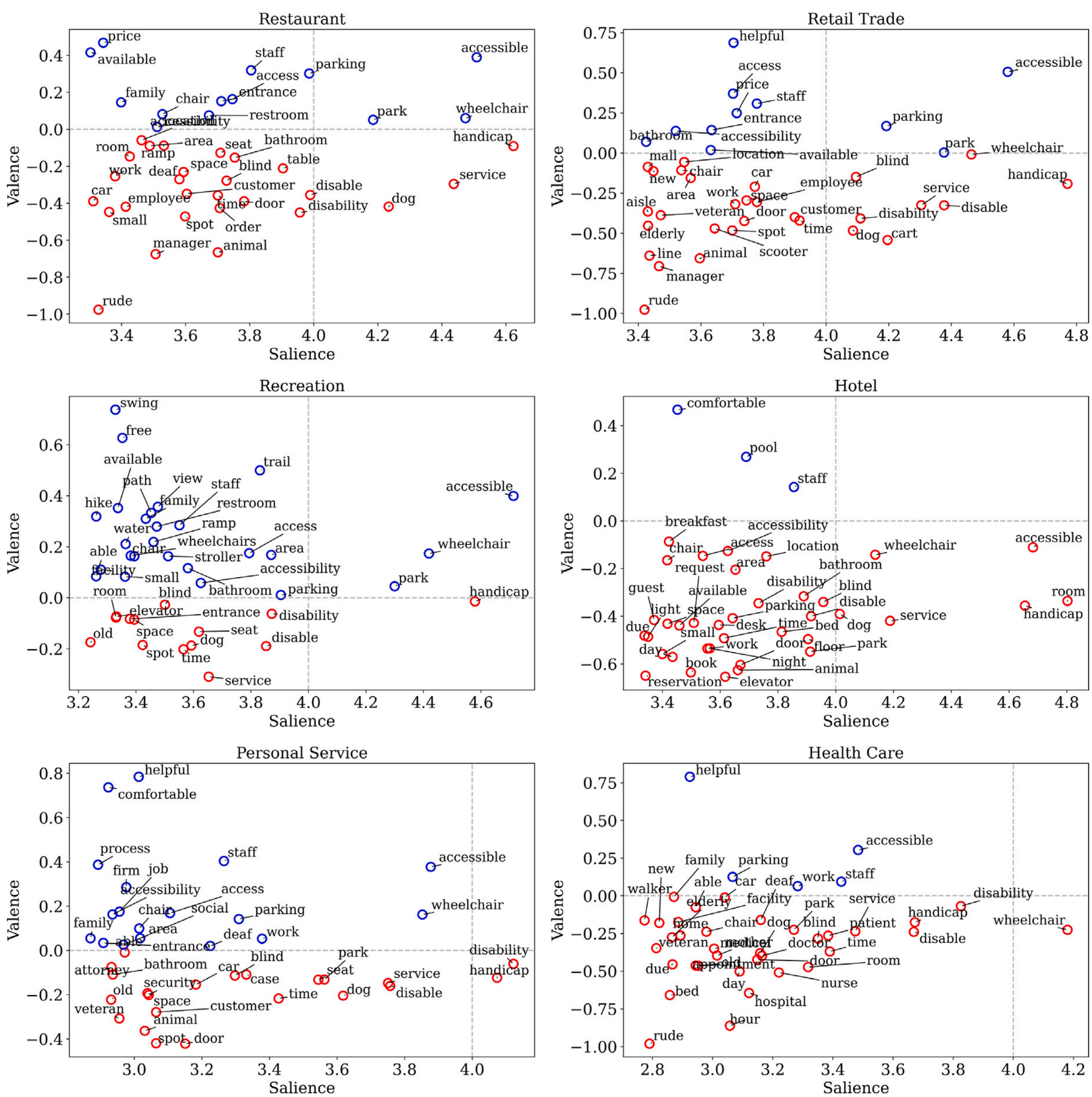


Fig. 4. Semantic analysis using LSVA based on POI types. The x-axis represents the salience using Eq. (3), while the y-axis represents the valence using Eq. (4).

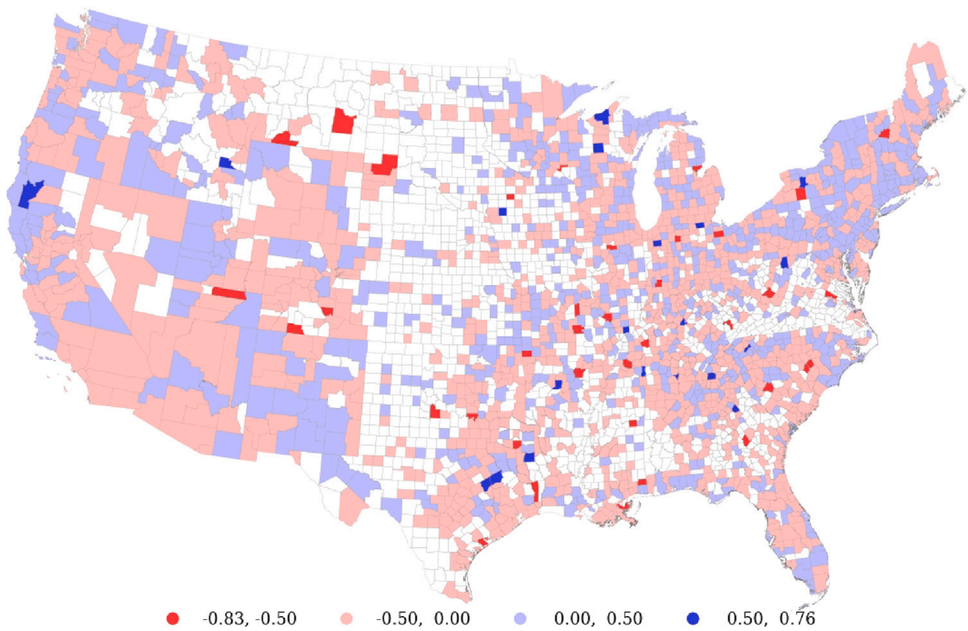


Fig. 5. Spatial distribution of accessibility sentiment.

For Health Care, the highly negative terms associated with sentiments include "doctor", "nurse", "service", "appointment", and "time" reflecting frustrations with service received. Other negative terms such as "room" and "door" reflect negative experiences with medical environments. However, positive aspects such as "staff", "helpful", and "family" indicate appreciation for supportive staff and accessible infrastructure in healthcare facilities.

Across all POI types, accessible physical infrastructure (e.g., parking, wheelchair access, entrance, ramp) tends to receive positive feedback, while issues with staff (e.g., employee, manager, doctor, nurse), service (e.g., service animal, reservation, book), and accommodations for individuals with disabilities (e.g., space, spot, bathroom, seat) lead to more negative sentiments. This highlights the multifaceted nature of accessibility, where both physical infrastructure and human or social factors play crucial roles in shaping accessibility experiences.

4.2. Socio-spatial analysis

4.2.1. What are the sentiment patterns across geographic regions?

We plot the variation in accessibility sentiment across all counties in the contiguous United States in Fig. 5. Counties with negative sentiment are depicted in blue, those with positive sentiment in red, and counties with fewer than 10 reviews are left uncolored. The choropleth map underscores a high dispersion in accessibility sentiment, with positive and negative reviews appearing sporadically, lacking a clear spatial clustering pattern. This is further evidenced by the insignificant spatial interaction term in Table 4. However, a notable pattern is observed in the distribution of absent reviews: counties in the Midwest regions tend to have fewer accessibility-related reviews, whereas counties in the Northeast, South Atlantic, and West are more likely to leave reviews that mention accessibility. This may be attributed to the lower population densities and public service availability in these regions.

We further explore the socio-spatial differences between counties based on the presence of more than 10 accessibility-related reviews. Of the total, 1976 counties have more than 10 reviews, while 1080 counties do not. As shown in Fig. 6, counties with higher population densities, greater employment densities, and higher levels of urbanization are more likely to accumulate a substantial number of accessibility reviews. Notable racial disparities also emerge, particularly among Asians, African Americans, and other racial minorities, which may reflect the location preferences associated with these groups' activities. This comparison highlights a potential limitation of the sentiment regression analysis: the counties included in regression are not randomly selected but rather show selection biases. These biases are influenced by the tendencies of individuals who post reviews on Google Maps, as well as by the more densely developed regions where reviews are more frequently collected.

4.2.2. How are sentiment patterns associated with local socio-spatial factors?

We first perform a univariate correlation analysis at the county level, identifying the top three positively correlated features as: Avg. POI Score (0.169), White (0.139), and Disability-Friendly score (0.102). Conversely, the top three negatively correlated features were: African American (−0.119), Hispanic (−0.077), and Poverty (−0.071). Similar patterns were observed at the CBG level, where the positive leaders were: Avg. POI Score (0.282), White (0.120), and Median Income (0.079), and the negative leaders were: Hispanic (−0.085), Poverty (−0.080), and African American (−0.077). This analysis suggests that areas with higher socioeconomic status and a larger percentage of White residents tend to have a more favorable public perception of urban accessibility.

We do not find a significant correlation between accessibility sentiment and % residents with disabilities. As detailed in Fig. 7 (a–c), the Pearson correlation at the county level between disability and accessibility sentiment is only −0.021. Interestingly, this correlation slightly increases to −0.044 when considering only those with disabilities below poverty, and decreases to −0.007 for those above poverty. These findings highlight the underlying socioeconomic disparities in accessibility sentiment, although the links between disability and accessibility sentiment are not statistically significant. However, we find a significant positive correlation (Pearson = 0.357 at the state level) between the Disability-Friendly Score from the AAA State of Play (of Play, 2025) and sentiment derived from Google Maps reviews, as shown in Fig. 7(d). This strong alignment supports the validity of our approach, suggesting that Google Maps review sentiment can serve as a reliable proxy for assessing disability friendliness.

We then fit the GAM and report the regression results in Table 4. Model goodness-of-fit, the adjusted R^2, is 0.126 for CBG-level modeling and 0.099 for county-level modeling. While these values are moderate,

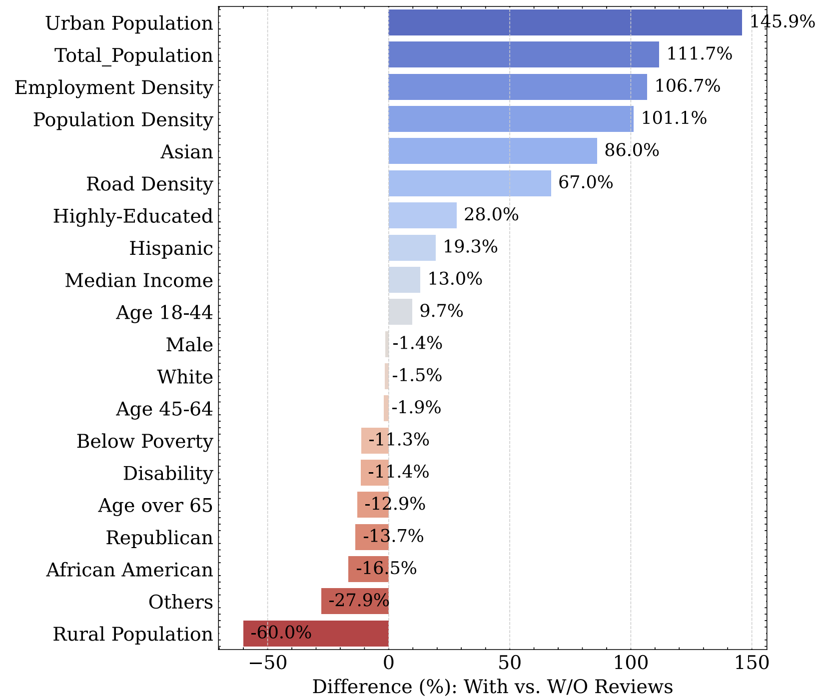


Fig. 6. Socio-spatial difference in accessibility review engagement: Counties with and w/o > 10 accessibility reviews.

they are considered reasonable given the numerous immeasurable factors that could influence public perception. Regarding nonlinear effects, the spatial interaction terms are not statistically significant, suggesting weak spatial dependence in the spatial distribution of accessibility sentiment. However, the state-level random effects are all statistically significant, with degrees of freedom (e.d.f.) consistently greater than 1, indicating pronounced random effects at the state level. This could be attributed to unobserved effects or influences inherent to the states themselves.

The coefficients of the two models are largely similar, although there are subtle differences in their statistical significance. Demographic factors reveal that elderly populations consistently exhibit a negative relationship with accessibility sentiment. This trend may indicate the high dependence of elderly adults on barrier-free urban facilities, underscoring their unique needs within the community. Additionally, the racial and ethnic composition of a region is significantly associated with accessibility sentiment. Areas with higher proportions of African American and Hispanic populations generally report more negative accessibility experiences compared to predominantly White regions. The percentage of males shows a significantly positive relationship with sentiment at the county level, but the significance disappears at the CBG level. Similar to the univariate correlation analysis, no clear relationship is evident between the percentage of people with disabilities and accessibility sentiment.

Among socioeconomic factors, high employment density exhibits a strong negative correlation with accessibility sentiment but only at the CBG level. The rural population exhibits a significant negative relationship but only at the county level. Household poverty rates consistently show negative relationships with accessibility sentiment, suggesting that economically disadvantaged areas are more likely to experience subpar accessibility facilities. Interestingly, regions with more highly educated residents tend to exhibit more negative sentiments toward accessibility. This may be because these individuals are more attuned to the design and functionality of accessibility facilities and are also more likely to express their opinions through online reviews. Lastly, a strong (also the strongest among all variables) positive relationship is found between averaged POI scores and accessibility sentiment, which is plausible as the average POI score represents the overall user experience with local services in the region.

We document a significant negative relationship between the percentage of Republicans and accessibility sentiment. Republican-majority regions typically emphasize limited government involvement, reduced public spending, and reliance on market solutions, potentially resulting in fewer investments in accessibility infrastructure beyond minimal ADA compliance (Law, 2025). Consequently, residents in Republican-majority areas might perceive less support for accessibility, contributing to lower accessibility sentiment. Finally, we document a significant positive relationship between Disability-Friendly scores and accessibility sentiment, which is intuitive and highlights the consistency between external accessibility conditions and public perceptions.

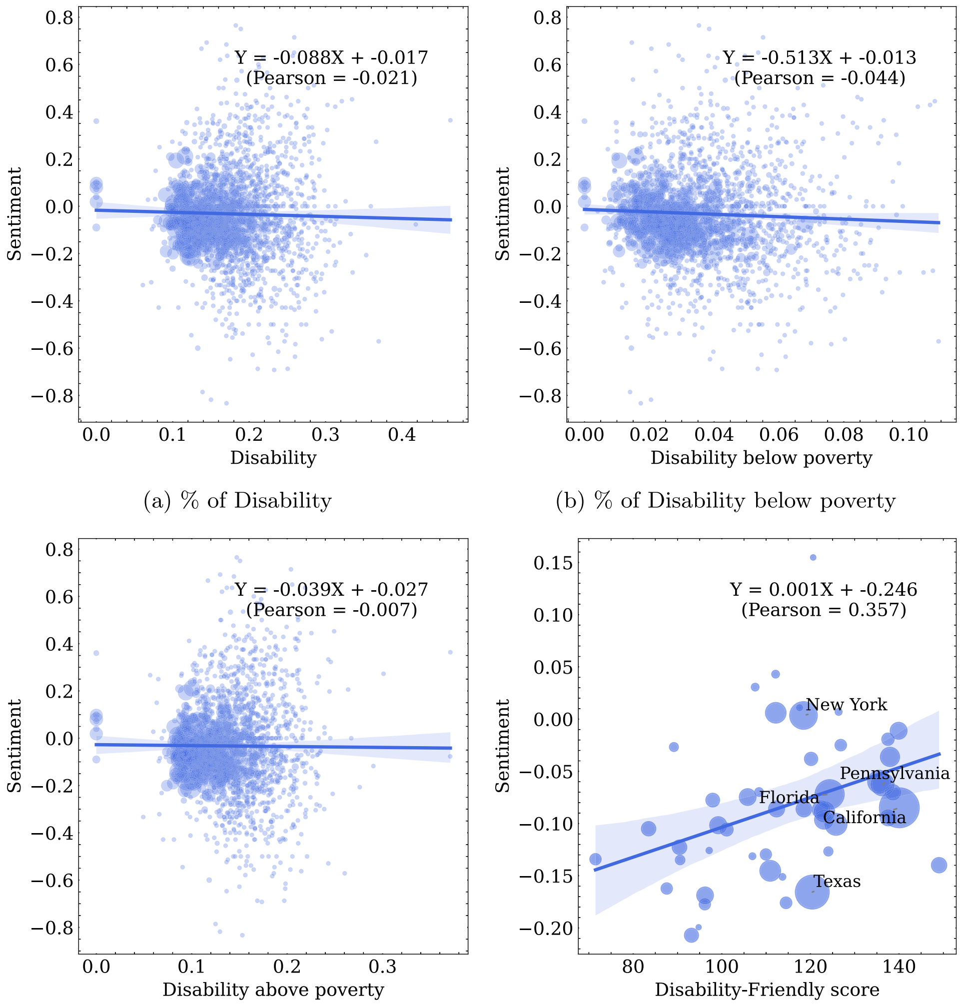
5. Discussion

5.1. Key findings

In this study, we collect Google Maps reviews across the United States and use fine-tuned LLMs to analyze public sentiment on accessibility, exploring the relationship between these sentiments and socio-spatial factors. The key findings are outlined below.

First, most POI types show negative sentiments, except for Recreation. This suggests an overall negative attitude from the public toward accessibility features in most POI types. Furthermore, sentiment analysis reveals distinct distribution patterns during the study period. For example, Retail Trade and Restaurants display right-skewed distributions, indicating a need for more attention to accessibility improvements, while Health Care shows a polarized distribution, meaning people have either very positive or very negative experiences, with little middle ground.

Second, public perceptions of positive and negative aspects differ depending on the type of POI. Infrastructure-related aspects like “parking”, “wheelchair”, and “entrance” receive positive feedback, indicating that accessibility design is generally effective in these areas. However, negative sentiments converge to human-related or social factors. Specifically, Hotels and Health Care received extensive negative



(a) % of Disability (b) % of Disability below poverty (c) % of Disability above poverty (d) Disability-Friendly score

Fig. 7. Scatter plot for validation: Disability Percentage (From ACS) & Disability-Friendly score (From AAA State of Play) vs. Sentiment (From Google Map reviews).

feedback on aspects such as “service”, “doctor”, “nurse”, “time”, and “room”, emphasizing issues related to service providers and the quality of service itself. Prior research has also highlighted the challenges staff faces in communicating with guests with disabilities during service encounters in hospitality settings (Kalargyrou, Barber, & Kuo, 2018). Although Recreation and Personal Services receive relatively fewer negative comments, their accommodation for accessibility, such as “spot”, “handicap”, and their inclusive environment for “dog” and “old”, need improvement, as these terms show negative sentiment.

Third, there are significant geographical disparities in sentiment toward accessibility. Areas with higher socioeconomic status and predominantly White populations display more positive perceptions, likely due to better-funded infrastructure and services in these regions. In contrast, regions with higher Hispanic and African American populations, as well as those with higher poverty rates, show more negative sentiments, reflecting systemic neglect and fewer resources available for accessibility improvements. Additionally, areas with larger populations of elderly and highly-educated residents display strong negative sentiments toward urban accessibility, indicating these groups can be more sensitive to the design and functionality of accessibility facilities. Our study also aligns with existing findings regarding barriers to health care for individuals with disabilities who are members of underserved racial and ethnic groups (Peterson-Besse, Walsh, Horner-Johnson, Goode, & Wheeler, 2014). Finally, Republican-leaning regions exhibit more negative sentiment toward accessibility, potentially due to differing political ideologies and policy priorities regarding infrastructure investment and public service provision.

Last, no significant link is found between the presence of people with disabilities and public perceptions. While higher densities of disabled individuals could typically suggest increased feedback, as these communities are most affected by accessibility shortcomings, the lack of a significant correlation implies that public sentiment is not necessarily reflecting their needs. This disconnect suggests that areas with larger disabled populations may not receive the necessary attention or improvements, highlighting a gap in inclusive planning. These results align with existing research, which shows that public agencies address only minimum accessibility standards and overlook the lived experiences of disabled individuals (Levine & Karner, 2023). Moreover, the lack of attention to accessibility issues in transportation planning (Levine & Karner, 2023) and public services (Krahn et al., 2015) reflects a broader disconnect between policy and the actual needs of disabled communities. However, **a significant positive relationship does exist between Disability-Friendly scores and public perception**, suggesting that better external accessibility infrastructure, improved healthcare resources, and a more supportive natural, political, and socioeconomic environment do contribute to more favorable public perceptions of accessibility.

Table 4
Regression outcomes (standardized)

Variables	CBG-level	County-level
(Intercept)	−0.095***	−0.038***
Demographics		
Asian	0.001	0.002
African American	−0.011**	−0.022***
Hispanic	−0.022***	−0.021***
Others	−0.010*	0.000
Male	−0.004	0.014**
Age over 65	−0.011**	−0.015**
Age 45–64	−0.003	−0.005
Disability	0.001	−0.002
Socioeconomics		
Population Density	0.004	0.024
Employment Density	−0.030***	−0.017
Rural Population	−0.001	−0.021**
Poverty	−0.011**	−0.006*
Highly-Educated	−0.020***	−0.014*
Reviews		
Review Density	−0.008	−0.018
Avg. POI Score	0.097***	0.029***
Partisanship		
Republican	−0.007*	−0.010*
Disability Friendliness		
Disability-Friendly Score	0.013**	0.016**
Nonlinear terms (degrees of freedom (e.d.f.))		
ti(Lat,Lng)	2.602	1.705
s(State)	128.347***	16.053***
Model fit		
Adjusted. R2	0.127	0.107
R2	0.141	0.123
Sample size	8702	1901

*** Significance code: 0.001
** Significance code: 0.01
* Significance code: 0.05.

5.2. Theoretical implications

By integrating advanced NLP techniques with socio-spatial analysis, our study contributes methodologically to computational urban science in several ways. First, at the core of our approach is the fine-tuning of the LLaMA 3 model using the LoRA technique and applying it to extract aspect-based sentiment. This enables efficient domain adaptation by introducing trainable low-rank matrices into each transformer layer, significantly reducing the number of trainable parameters. As a result, it lowers computational overhead and mitigates overfitting, as demonstrated by the model's strong performance (Fig. 2). We then apply the fine-tuned model to conduct aspect-based sentiment analysis, allowing us to extract nuanced opinions related to specific accessibility features from user reviews. This combination of LoRA-based adaptation and aspect-level analysis presents a scalable and efficient method for mining large-scale textual data in urban contexts.

Second, leveraging the aspect-level sentiment output, we perform large-scale analysis on Google Maps reviews across the United States to extract public perceptions of accessibility at different geospatial scales. We then integrate this sentiment data with demographic variables from the American Community Survey to conduct a socio-spatial correlation analysis. This allows us to examine how public attitudes toward accessibility relate to underlying socioeconomic and spatial factors. The resulting framework offers a replicable model for future research aimed at understanding how demographic and socioeconomic contexts influence public sentiment in urban environments.

Our study contributes an additional approach leveraging passive crowdsourcing approach to investigate public perceptions of urban infrastructure systems. By leveraging large-scale crowdsourced data from tens of thousands of online reviews, we achieve coverage at a broad geospatial scale. This crowdsourcing approach can also operate at low cost and near real-time, enabling continuous sentiment monitoring without the overhead of survey design or fieldwork. While crowdsourcing has inherent biases, it still remains more demographically representative than typical surveys, which often rely on small or biased panels. Online reviews draw from a broad and diverse user base, and prior studies have widely demonstrated crowdsourcing's effectiveness despite its limitations. Finally, this passive crowdsourcing approach captures genuine user experiences, including staff behavior, signage clarity, and navigability, that physical audits often miss, since it requires no active participation from users.

While our study presents a scalable empirical tool that leverages passive crowdsourcing through online reviews to monitor public sentiment across broad geospatial areas, it is important to emphasize that this approach is best seen as a complement, rather than a replacement for other established methodologies. Each method offers distinct strengths and faces unique limitations. For instance, conventional survey studies (Fänge et al., 2002; Paköz & k, 2022) provide structured, targeted data collection and allow researchers to gather detailed demographic information and perceptions directly from specific populations, but are often limited by smaller sample sizes, higher costs, and geographic or respondent bias. Sensor-based approaches (e.g., wheelchair-mounted (Mobasheri et al., 2017) or mobile sensors (Aly et al., 2021)) offer precise, objective data on physical features like slopes and surface conditions. However, they are often equipment-dependent and could be costly to deploy at large scale. Virtual reality (VR) allows controlled testing of urban designs by simulating environments and capturing user responses (Mott et al., 2019). Yet, virtual settings cannot fully mirror real-world complexity, and high costs and accessibility barriers can still limit participation. Together, these methods form a complementary toolkit; when combined, they offer a more comprehensive view of accessibility for both research and policy.

5.3. Practical implications

5.3.1. Implications for key stakeholders

The findings from this study reveal disparities in public perceptions of accessibility and their correlations with various socio-spatial factors – including race, poverty, age, education, and political leaning – while also identifying which POI-level features and services drive negative or positive feedback. These findings move beyond general perceptions of space to uncover why accessibility fails or succeeds from the perspective of public experience. As such, they carry implications for several key stakeholders, including government agencies, local businesses, and people with disabilities and their caregivers.

Government agencies play a pivotal role in shaping policies and infrastructure to enhance public spaces. Our findings reveal that accessibility issues are not evenly distributed across space or service types, but also are instead tied to social inequities and political geographies. Our findings highlight two critical areas for improvement. First, significant concerns regarding staff behavior and the adequacy of services and accommodations suggest a need for government agencies to offer staff training programs. The training should ensure that staff are adequately prepared to accommodate people with disabilities. Second, the observed geographic disparities – such as the negative association between accessibility sentiment and poverty, minority population percentages, employment density, and Republican representation – underscore the importance of an equitable distribution of public resources. These insights are strengthened by our multilevel spatial modeling (Table 4) and suggest that accessibility is not only a matter of physical infrastructure but also intersects with broader socioeconomic and political factors. Public investments in accessible infrastructure should target underrepresented and underserved areas, particularly those with high concentrations of low-income, minority, and elderly populations. Incentives such as subsidies or training programs should be provided to businesses in these areas to prioritize accessibility improvements.

For local businesses, improving accessibility and customer service for people with physical disabilities can serve as a competitive advantage. While physical accessibility features such as parking and entrances are often positively received, businesses need to move beyond merely complying with physical accessibility requirements and work on providing inclusive customer service. This includes training staff to be more knowledgeable and responsive to the needs of people with physical disabilities. In addition, businesses should consider adopting practices from POI types that are viewed more positively, such as recreation, to their operations.

Furthermore, our findings demonstrate the importance of advocacy by and for people with disabilities. There are critical needs for improvements in underlying services, such as accommodations (e.g., bathroom accessibility or seating) and service staff interactions, beyond the provision of common, public-aware physical accessibility infrastructure. Individuals with disability and their caregivers should actively post on social media and participate in dialogue with businesses and policymakers to ensure that accessibility efforts extend beyond physical infrastructure to include customer service and accommodation of needs. Voices from them are crucial in raising awareness of issues that are often overlooked by the general public but are equally important to create accessible and inclusive urban environments. Meanwhile, the correlation between Disability-Friendly scores and positive sentiment confirms that improvements in infrastructure, healthcare access, and local policies do shape how people experience accessibility. This lends empirical support to efforts that push beyond compliance to emphasize inclusive and human-centered design in cities.

5.3.2. Implications for policy

Our study highlights spatial disparities in accessibility support for facilities, and policies at both the federal and state level have provided support to mitigate such disparities. At the federal level, legislation like the ADA (Board, 2014) and the Architectural Barriers Act (ABA) (U.S. Congress, 1968) mandate accessibility in new or altered public facilities. Recent developments have extended these mandates to emerging infrastructure. For example, the U.S. Access Board is proposing explicit accessibility standards for electric vehicle (EV) charging stations, while Section 508 now ensures that charger-based ICT (e.g., payment kiosks) is accessible to people with disabilities (Architectural and Transportation Barriers Compliance Board (U.S. Access Board), 2024). Additionally, the Infrastructure Investment and Jobs Act (IIJA) allocates $7.5 billion for EV chargers and mandates equitable deployment, calling out underserved and rural communities and tying federal funds to compliance with accessibility and civil rights statutes (of Transportation, 2021). At the state level, policymakers are beginning to fill gaps that federal standards leave unaddressed. States like California and Washington now require a minimum number of ADA compliant EV charging spaces at public and shared facilities (Legislature, 2023; of the State Architect, 2016). These policies acknowledge spatial inequities and lay the groundwork for more inclusive facility design nationwide.

However, our research reveals that the disparities may still exist on the ground, pointing to several potential directions for policy and legislative change. First, given that areas with higher poverty rates and larger minority populations report more negative accessibility sentiments, legislation should mandate that public investments target these underrepresented communities rather than relying on funding models that favor wealthier localities. Second, since the accessibility of private businesses is crucial, state and local governments can legislate financial incentives, such as subsidies or tax credits, to encourage businesses in these areas to improve accessibility beyond minimum compliance. Finally, our analysis consistently shows that negative sentiment is driven by human and social factors, not just physical infrastructure. Government agencies could therefore legislate standardized accessibility training for service employees, particularly in the healthcare, hospitality, and retail sectors where our findings show significant issues. The analytical methods used in this study could even be adopted by agencies to monitor public sentiment and proactively identify regions or business types that require these targeted interventions.

5.4. Limitations and future work

Given that the crowdsourcing approach relies on user-generated reviews, it is important to acknowledge potential biases related to the characteristics and behaviors of users who choose to leave online reviews. This reflects in multiple aspects. First, previous studies have demonstrated that social media, including online review platforms, could overrepresent certain demographics, such as male, educated, and urban populations (Mellon & Prosser, 2017; Wang et al., 2019). The recent report reveals that the largest user segment falls within the 25 to 34 age group, accounting for approximately 26% of users. This is followed by the 35 to 44 age group at 21%, and the 18 to 24 cohort at 16% (Dey, 2025). As a result, policy recommendations based solely on these data should be interpreted cautiously, while actively sourced data collection methods may offer more reliable insights for accessibility-focused urban planning. We also observe a clear geographic bias, with data heavily concentrated in populated urban are-as. As illustrated in Fig. 1(a) of our paper, POIs with a high volume of accessibility-related reviews are predominantly located on the East and West Coasts, while regions like the Midwest are sparsely represented.

The crowdsourcing approach may also introduce biases related to user behavior, particularly in how and why individuals choose to leave reviews on platforms like Google Maps. For example, people with extremely positive or negative experiences are more inclined to post online reviews (Filieri, 2016), which can impact the representation of the analysis. In our annotated dataset, of the 2840 manually annotated reviews, only 126 are classified as neutral, indicating that users with strong positive or negative opinions are more likely to post reviews on Google Maps. In addition, individuals with disabilities may not equally participate in posting online reviews due to potential accessibility barriers to digital platforms. The perceptions represented in the data might disproportionately reflect views of individuals without disabilities who advocate for accessibility. We also observe that users' posts focus on high-traffic commercial categories, such as restaurants, retail, hotels, and healthcare. These factors underscore that our findings are most reflective of perceptions in dense, urbanized environments and may not capture the full spectrum of experiences in other contexts or POI types.

This study also presents several avenues for future research. The first opportunity lies in model classification, where improvements can be made in two key areas. First, we could engage more annotators with domain expertise to label a larger dataset for both training and testing. This would allow the model to capture a broader variety of textual information from online reviews, which could ultimately enhance the model's robustness. Second, due to computational limitations, we only fine-tune the Llama 3-8B model in this project. Although the fine-tuned Llama model achieves 91% accuracy, using LLMs with more parameters could potentially improve this accuracy. Future research could also explore testing closed-source models like GPT-4 by OpenAI or Gemini by Google.

The second research direction involves data fusion, which could be approached in two ways. First, our findings reveal that many POIs on Google Maps have only one or two comments related to accessibility, leading to potential sampling biases in large-scale analyses. To mitigate this, future work could incorporate reviews from other platforms like Yelp or TripAdvisor, thereby expanding the dataset and offering a more comprehensive perspective. Additionally, these insights could be integrated with data from active crowdsourcing efforts. For example, previous research has developed platforms where participants actively rate accessibility (Hara et al., 2013b; Saha et al., 2019). By combining data from both active and passive crowdsourcing, we can further highlight the strengths of crowdsourcing approaches in studying accessibility in urban environments.

Another avenue worth exploring is the inclusion of image-based data. For example, incorporating Google Maps Street View images and applying computer vision techniques (Kim & Jang, 2023) or multimodal language models could provide richer, more holistic insights into urban accessibility. This approach would allow for the automatic detection of physical barriers, such as stairs or narrow doorways, and the identification of accessible features like ramps or tactile paving. This could also enable us to make more meaningful recommendations for creating inclusive urban environments.

6. Conclusions

This study demonstrates the potential of leveraging crowdsourced data and advanced LLMs to assess public perceptions of urban accessibility. By analyzing Google Maps reviews across the United States using a fine-tuned Llama 3 model, we provide valuable insights into accessibility challenges at both the POI and socio-spatial levels. Our findings reveal that most POI types show negative sentiments, except for Recreation, with negativity mainly focused on service-related aspects. Our socio-spatial analysis shows that areas with higher proportions of white residents and greater socioeconomic status report more positive sentiment, while areas with more elderly and highly-educated residents express more negative views. However, no clear link is found between the presence of people with disabilities and public perception of accessibility. Overall, this approach offers a more comprehensive and nuanced understanding of accessibility issues compared to traditional survey methods, providing urban planners with crucial information to create more inclusive and accessible urban environments.

CRediT authorship contribution statement

Lingyao Li: Conceptualization, Methodology, Data Curation, Validation, Formal Analysis, Investigation, Visualization, Writing - Original Draft, Writing - Review & Editing, Project administration. **Songhua Hu:** Conceptualization, Methodology, Formal Analysis, Investigation, Visualization, Writing - Original Draft, Writing - Review & Editing. **Yinpei Dai:** Methodology, Investigation, Writing - Original Draft, Writing - Review & Editing. **Min Deng:** Writing - Original Draft, Writing - Review & Editing. **Parisa Momeni:** Data Curation, Writing - Original Draft. **Gabriel Laverghetta:** Data Curation, Writing - Original Draft. **Lizhou Fan:** Writing - Original Draft, Writing - Review & Editing. **Zihui Ma:** Writing - Original Draft, Writing - Review & Editing. **Xi Wang:** Writing - Original Draft, Writing - Review & Editing. **Siyuan Ma:** Writing - Review & Editing. **Jay Ligatti:** Writing - Review & Editing. **Libby Hemphill:** Writing - Review & Editing.

Code availability

The code to support this study can be found on Github https://github.com/Lingyao1219/accessible-urban

Declaration of competing interest

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

Data availability

The datasets and processed results are available upon request from the corresponding author.

References

Aini, Q., Marlina, H., & Nikmatullah, A. (2019). Evaluation of accessibility for people with disability in public open space. In *IOP conference series: materials science and engineering*: *Vol. 506*, (1), IOP Publishing, Article 012018.

Aly, H., Youssef, M., & Agrawala, A. (2021). Better off this way!: Ubiquitous accessibility digital maps via smartphone-based crowdsourcing. In *2021 18th annual IEEE international conference on sensing, communication, and networking* (pp. 1–9). IEEE.

Andani, A., Rostron, J., & Sertyesilisik, B. (2013). An investigation into access issues affecting historic built environment. *American Journal of Civil Engineering and Architecture*, *1*(2), 21–31.

Architectural and Transportation Barriers Compliance Board (U. S. Access Board) (2024). Notice of proposed rulemaking: "Americans with disabilities act and architectural barriers act accessibility guidelines for electric vehicle charging stations". https://www.access-board.gov/evse/.

Barbieri, F., Camacho-Collados, J., Espinosa Anke, L., & Neves, L. (2020). TweetEval: Unified benchmark and comparative evaluation for tweet classification. In T. Cohn, Y. He, & Y. Liu (Eds.), *Findings of the association for computational linguistics: EMNLP 2020* (pp. 1644–1650). Online: Association for Computational Linguistics, http://dx.doi.org/10.18653/v1/2020.findings-emnlp.148, URL https://aclanthology.org/2020.findings-emnlp.148.

Basak, J., Bhaumik, P., Roy, S., & Bandyopadhyay, S. (2020). A crowdsourcing based information system framework for coordinated disaster management and building community resilience. In *Proceedings of the 21st international conference on distributed computing and networking* (pp. 1–6).

Bekci, B., & Sipahi, M. (2023). Investigation of spatial accessibility on the scale of pedestrian areas. *Journal of the Faculty of Engineering and Architecture of Gazi University*, *38*(4).

Belsley, D. A., Kuh, E., & Welsch, R. E. (2005). *Regression diagnostics: Identifying influential data and sources of collinearity*. John Wiley & Sons.

Bennett, C., Ackerman, E., Fan, B., Bigham, J., Carrington, P., & Fox, S. (2021). Accessibility and the crowded sidewalk: Micromobility's impact on public space. In *Proceedings of the 2021 ACM designing interactive systems conference* (pp. 365–380). New York, NY, USA: Association for Computing Machinery, http://dx.doi.org/10.1145/3461778.3462065.

Blohm, I., Leimeister, J. M., & Krcmar, H. (2013). Crowdsourcing: How to benefit from (too) many great ideas. *MIS Quarterly Executive*, *12*(4).

Board, U. S. A. (2002). ADA accessibility guidelines (ADAAG). URL https://www.access-board.gov/adaag-1991-2002.html, (Accessed 22 August 2024).

Board, U. A. (2014). Americans with disabilities act accessibility standards.

Botticello, A. L., Rohrbach, T., & Cobbold, N. (2014). Disability and the built environment: an investigation of community and neighborhood land uses and participation for physically impaired adults. *Ann Epidemiol*, *24*(7), 545–550.

Botticello, A. L., Rohrbach, T., & Cobbold, N. (2015). Differences in the community built environment influence poor perceived health among persons with spinal cord injury. *Archives of Physical Medicine and Rehabilitation*, *96*(9), 1583–1590.

Brodie, M., Weltzien, E., Altman, D., Blendon, R. J., & Benson, J. M. (2006). Experiences of hurricane katrina evacuees in houston shelters: Implications for future planning. *American Journal of Public Health*, *96*(8), 1402–1408. http://dx.doi.org/10.2105/AJPH.2005.084475.

Bromley, R. D., Matthews, D. L., & Thomas, C. J. (2007). City centre accessibility for wheelchair users: The consumer perspective and the planning implications. *Cities*, *24*(3), 229–241.

Bureau, U. S. C. (2022a). American community survey (ACS). https://www.census.gov/programs-surveys/acs/, (Accessed 28 June 2024).

Bureau, U. C. (2022b). North American industry classification system. https://www.census.gov/naics/, (Accessed 09 December 2024).

Bureau, U. C. (2023). Disability rates higher in rural areas Than Urban Areas. URL https://www.census.gov/library/stories/2023/06/disability-rates-higher-in-rural-areas-than-urban-areas.html, (Accessed April 11 2025).

Ceccato, R., Deflorio, F., Diana, M., & Pirra, M. (2020). Measure of urban accessibility provided by transport services in Turin: a traveller perspective through a mobility survey. *Transportation Research Procedia*, *45*, 301–308. http://dx.doi.org/10.1016/j.trpro.2020.03.020.

Center for Disability Issues and the Health Professions (2017). American cities' problems for people with disabilities. (Accessed 11 April 2025).

Certoma, C., Corsini, F., & Rizzi, F. (2015). Crowdsourcing urban sustainability. Data, people and technologies in participatory governance. *Futures*, *74*, 93–106.

Chen, T., Hui, E. C., Wu, J., Lang, W., & Li, X. (2019). Identifying urban spatial structure and urban vibrancy in highly dense cities using georeferenced social media data. *Habitat International*, *89*, Article 102005.

Chuang, I.-T., Benita, F., & Tunçer, B. (2022). Effects of urban park spatial characteristics on visitor density and diversity: A geolocated social media approach. *Landscape and Urban Planning*, *226*, Article 104514.

Clarke, P., Ailshire, J. A., Bader, M., Morenoff, J. D., & House, J. S. (2008). Mobility disability and the urban built environment. *American Journal of Epidemiology*, *168*(5), 506–513. http://dx.doi.org/10.1093/aje/kwn185.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers)* (pp. 4171–4186).

Dey, M. (2025). Google maps statistics and facts [2025]. URL https://electroiq.com/stats/google-maps-statistics/, (Accessed 11 April 2025).

Ding, C., Wald, M., & Wills, G. (2014). A survey of open accessibility data. In *Proceedings of the 11th web for all conference* (pp. 1–4).

Dubey, A., Jauhri, A., Pandey, A., Kadian, A., Al-Dahle, A., Letman, A., et al. (2024). The llama 3 herd of models. (p. 2407). ArXiv E-Prints.

Duman, Ü., & Asilsoy, B. (2022). Developing an evidence-based framework of universal design in the context of sustainable urban planning in Northern Nicosia. *Sustainability*, *14*(20), http://dx.doi.org/10.3390/su142013377.

Editorial Staff of C. B. S. S. F. (2014). BART gives public a look at fleet of the future for 1st time.

Fänge, A., Iwarsson, S., & Persson, Å. (2002). Accessibility to the public environment as perceived by teenagers with functional limitations in a south Swedish town centre. *Disability and Rehabilitation*, *24*(6), 318–326.

Filieri, R. (2016). What makes an online consumer review trustworthy? *Annals of Tourism Research*, *58*, 46–64.

Froehlich-Grobe, K., Regan, G., Reese-Smith, J. Y., Heinrich, K. M., & Lee, R. E. (2008). Physical access in urban public housing facilities. *Disability and Health Journal*, *1*(1), 25–29.

Ghermandi, A., & Sinclair, M. (2019). Passive crowdsourcing of social media in environmental research: A systematic map. *Global Environmental Change*, *55*, 36–47.

Gong, F.-Y. (2023). Modeling walking accessibility to urban parks using google maps crowdsourcing database in the high-density urban environments of Hong Kong. *Scientific Reports*, *13*(1), 20798.

Grisé, E., Boisjoly, G., Maguire, M., & El-Geneidy, A. (2019). Elevating access: Comparing accessibility to jobs by public transport for individuals with and without a physical disability. *Transportation Research Part A: Policy and Practice*, *125*, 280–293. http://dx.doi.org/10.1016/j.tra.2018.02.017.

Hara, K., Le, V., & Froehlich, J. (2013a). Combining crowdsourcing and google street view to identify street-level accessibility problems. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 631–640).

Hara, K., Le, V., & Froehlich, J. (2013b). Combining crowdsourcing and google street view to identify street-level accessibility problems. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 631–640). New York, NY, USA: Association for Computing Machinery, http://dx.doi.org/10.1145/2470654.2470744.

Helmrich, A. M., Ruddell, B. L., Bessem, K., Chester, M. V., Chohan, N., Doerry, E., et al. (2021). Opportunities for crowdsourcing in urban flood monitoring. *Environmental Modelling & Software*, *143*, Article 105124.

Hossain, M., & Kauranen, I. (2015). Crowdsourcing: a comprehensive literature review. *Strategic Outsourcing: An International Journal*, *8*(1), 2–22.

Hu, S., Chen, M., Jiang, Y., Sun, W., & Xiong, C. (2022). Examining factors associated with bike-and-ride (BnR) activities around metro stations in large-scale dockless bikesharing systems. *Journal of Transport Geography*, *98*, Article 103271.

Hu, E. J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., et al. (2022). Lora: Low-rank adaptation of large language models. *ICLR*, *1*(2), 3.

Hu, S., Wang, K., Li, L., Zhao, Y., He, Z., & Zhang, Y. (2024). Multi-crowdsourced data fusion for modeling link-level traffic resilience to adverse weather events. *International Journal of Disaster Risk Reduction*, Article 104754.

Huang, J., Duan, N., Ji, P., Ma, C., Ding, Y., Yu, Y., et al. (2018). A crowdsource-based sensing system for monitoring fine-grained air quality in urban environments. *IEEE Internet of Things Journal*, *6*(2), 3240–3247.

Iezzoni, L. I. (2011). Eliminating health and health care disparities among the growing population of people with disabilities. *Health Affairs*, *30*(10), 1947–1954. http://dx.doi.org/10.1377/hlthaff.2011.0613, PMID: 21976339.

Iezzoni, L. I., Killeen, M. B., & O'Day, B. L. (2006). Rural residents with disabilities confront substantial barriers to obtaining primary care. *Health Services Research*, *41*(4p1), 1258–1275.

III, U. H. (2020). The new urban agenda.

Ilieva, R., & McPhearson, T. (2018). Social media data for urban sustainability. *Nature Sustainability*, *1*, 553–565. http://dx.doi.org/10.1038/s41893-018-0153-6.

Imrie, R., & Luck, R. (2014). Designing inclusive environments: rehabilitating the body and the relevance of universal design. *Disability and Rehabilitation*, *36*(16), 1315–1319. http://dx.doi.org/10.3109/09638288.2014.936191, PMID: 24989068.

Iwasawa, Y., Nagamine, K., Yairi, I. E., & Matsuo, Y. (2015). Toward an automatic road accessibility information collecting and sharing based on human behavior sensing technologies of wheelchair users. *Procedia Computer Science*, *63*, 74–81.

Jampel, C. (2018). Intersections of disability justice, racial justice and environmental justice. *Environmental Sociology*, *4*(1), 122–135. http://dx.doi.org/10.1080/23251042.2018.1424497.

Kalargyrou, V., Barber, N. A., & Kuo, P.-J. (2018). The impact of disability on guests' perceptions of service quality delivery in the hospitality industry. *International Journal of Contemporary Hospitality Management*, *30*(12), 3632–3655.

Kamaldin, N., Susan, K., Songwei, K., Chengkai, L., Liang, H., Saini, A., et al. (2019). Smartbfa: A passive crowdsourcing system for point-to-point barrier-free access. In *2019 IEEE 44th conference on local computer networks* (pp. 34–41). IEEE.

Kim, J., & Jang, K. M. (2023). An examination of the spatial coverage and temporal variability of google street view (GSV) images in small-and medium-sized cities: A people-based approach. *Computers, Environment and Urban Systems*, *102*, Article 101956.

Krahn, G. L., Walker, D. K., & Correa-De-Araujo, R. (2015). Persons with disabilities as an unrecognized health disparity population. *American Journal of Public Health*, *105*(S2), S198–S206.

Krippendorff, K. (2018). *Content analysis: An introduction to its methodology*. Sage publications.

Lau, J. T.-f., & Cheung, C.-k. (1999). Discriminatory attitudes to people with intellectual disability or mental health difficulty. *International Social Work*, *42*(4), 431–444.

Lau, J. C., & Chiu, C. C. (2004). Accessibility of workers in a compact city:: the case of Hong Kong. *Habitat International*, *28*(1), 89–102.

Law, B. (2025). State disability discrimination laws. https://pro.bloomberglaw.com/insights/labor-employment/state-disability-discrimination-laws/, (Accessed 22 March 2025).

Lee, K., & Yu, C. (2018). Assessment of airport service quality: A complementary approach to measure perceived service quality based on google reviews. *Journal of Air Transport Management*, *71*, 28–44.

Legislature, W. S. (2023). Washington administrative code 51-50-0429: Electric vehicle charging infrastructure. https://app.leg.wa.gov/WAC/default.aspx?cite=51-50-0429.

Levine, K., & Karner, A. (2023). Approaching accessibility: Four opportunities to address the needs of disabled people in transportation planning in the United States. *Transport Policy*, *131*, 66–74.

Li, L., Bensi, M., & Baecher, G. (2023). Exploring the potential of social media crowdsourcing for post-earthquake damage assessment. *International Journal of Disaster Risk Reduction*, *98*, Article 104062.

Li, L., Hu, S., Dinh, L., & Hemphill, L. (2024). Crowdsourced reviews reveal substantial disparities in public perceptions of parking. arXiv preprint arXiv:2407.05104.

Li, L., Hu, S., Shaw, A., & Hemphill, L. (2024). Crowdsourcing public attitudes toward local services through the lens of google maps reviews: An urban density-based perspective. arXiv preprint arXiv:2404.13156.

Li, L., Ma, Z., & Cao, T. (2021). Data-driven investigations of using social media to aid evacuations amid western United States wildfire season. *Fire Safety Journal*, *126*, Article 103480.

Li, L., Mao, Y., Wang, Y., & Ma, Z. (2022). How has airport service quality changed in the context of COVID-19: A data-driven crowdsourcing approach based on sentiment analysis. *Journal of Air Transport Management*, *105*, Article 102298.

Li, J., Shang, J., & McAuley, J. (2022). Uctopic: Unsupervised contrastive learning for phrase representations and topic mining. arXiv preprint arXiv:2202.13469.

Liao, H.-T., Zhou, Z., & Zhou, Y. (2020). A systematic review of social media for intelligent human-computer interaction research: Why smart social media is not enough. In *International conference on intelligent human computer interaction* (pp. 499–510). Springer.

Loukis, E., & Charalabidis, Y. (2015). Active and passive crowdsourcing in government. *Policy Practice and Digital Science: Integrating Complex Systems, Social Simulation and Public Administration in Policy Research*, 261–289.

Loureiro, D., Barbieri, F., Neves, L., Espinosa Anke, L., & Camacho-collados, J. (2022). TimeLMs: Diachronic language models from Twitter. In *Proceedings of the 60th annual meeting of the association for computational linguistics: system demonstrations* (pp. 251–260). Dublin, Ireland: Association for Computational Linguistics, http://dx.doi.org/10.18653/v1/2022.acl-demo.25.

Ma, Z., Li, L., Hemphill, L., Baecher, G. B., & Yuan, Y. (2024). Investigating disaster response for resilient communities through social media data and the susceptible-infected-recovered (SIR) model: A case study of 2020 western US wildfire season. *Sustainable Cities and Society*, *106*, Article 105362.

Mack, K., McDonnell, E., Jain, D., Lu Wang, L., E. Froehlich, J., & Findlater, L. (2021). What do we mean by "accessibility research"? A literature survey of accessibility papers in chi and ASSETS from 1994 to 2019. In *Proceedings of the 2021 CHI conference on human factors in computing systems* (pp. 1–18).

Mellon, J., & Prosser, C. (2017). Twitter and facebook are not representative of the general population: Political attitudes and demographics of british social media users. *Research & Politics*, *4*(3), Article 2053168017720008.

Mirri, S., Prandi, C., Salomoni, P., Callegati, F., & Campi, A. (2014). On combining crowdsourcing, sensing and open data for an accessible smart city. In *2014 eighth international conference on next generation mobile apps, services and technologies* (pp. 294–299). IEEE.

Mobasheri, A., Deister, J., & Dieterich, H. (2017). Wheelmap: the wheelchair accessibility crowdsourcing platform. *Open Geospatial Data, Software and Standards*, *2*, 1–7.

Mohamed, A. A., & Kronenberg, J. (2025). Users' experiences of park accessibility and attractiveness based on online review analytics. *Scientific Reports*, *15*(1), 1–18.

Mott, M., Cutrell, E., Franco, M. G., Holz, C., Ofek, E., Stoakley, R., et al. (2019). Accessible by design: An opportunity for virtual reality. In *2019 IEEE international symposium on mixed and augmented reality adjunct* ISMAR-adjunct, (pp. 451–454). IEEE.

Munawir, Koerniawan, M. D., & Dewancker, B. J. (2019). Visitor perceptions and effectiveness of place branding strategies in thematic parks in bandung city using text mining based on google maps user reviews. *Sustainability*, *11*(7), 2123.

Neto, F. R. A., & Santos, C. A. (2018). Understanding crowdsourcing projects: A systematic review of tendencies, workflow, and quality management. *Information Processing & Management*, *54*(4), 490–506.

Nicoletti, L., Sirenko, M., & Verma, T. (2023). Disadvantaged communities have lower access to urban infrastructure. *Environment and Planning B: Urban Analytics and City Science*, *50*(3), 831–849.

Niu, H., & Silva, E. A. (2020). Crowdsourced data mining for urban activity: Review of data sources, applications, and methods. *Journal of Urban Planning and Development*, *146*(2), Article 04020007.

Pagán, R. (2015). The contribution of holiday trips to life satisfaction: the case of people with disabilities. *Current Issues in Tourism*, *18*(6), 524–538. http://dx.doi.org/10.1080/13683500.2013.860086.

Paköz, M. Z., & k, M. I. (2022). Rethinking urban density, vitality and healthy environment in the post-pandemic city: The case of Istanbul. *Cities*, *124*, Article 103598. http://dx.doi.org/10.1016/j.cities.2022.103598.

Panta, Y. R., Azam, S., Shanmugam, B., Yeo, K. C., Jonkman, M., De Boer, F., et al. (2019). Improving accessibility for mobility impaired people in smart city using crowdsourcing. In *2019 cybersecurity and cyberforensics conference* (pp. 47–55). IEEE.

Pereira, R. H. M., & Herzenhut, D. (2023). *Introduction to urban accessibility: a practical guide with R*. Institute of Applied Economic Research.

Peterson-Besse, J. J., Walsh, E. S., Horner-Johnson, W., Goode, T. D., & Wheeler, B. (2014). Barriers to health care among people with disabilities who are members of underserved racial/ethnic groups: a scoping review of the literature. *Medical Care*, *52*, S51–S63.

Pinna, F., Garau, C., & Annunziata, A. (2021). A literature review on urban usability and accessibility to investigate the related criteria for equality in the city. In *International conference on computational science and its applications* (pp. 525–541). Springer.

of Play, A. S. (2025). The best and worst U.S. states for people with disabilities. https://www.aaastateofplay.com/the-best-and-worst-us-states-for-people-with-disabilities/, (Accessed 22 March 2025).

Prandi, C., Salomoni, P., & Mirri, S. (2014). mPASS: integrating people sensing and crowdsourcing to map urban accessibility. In *2014 IEEE 11th consumer communications and networking conference* (pp. 591–595). IEEE.

Rice, M. T., Jacobson, R. D., Caldwell, D. R., McDermott, S. D., Paez, F. I., Aburizaiza, A. O., et al. (2013). Crowdsourcing techniques for augmenting traditional accessibility maps with transitory obstacle information. *Cartography and Geographic Information Science*, *40*(3), 210–219.

Saha, M., Chauhan, D., Patil, S., Kangas, R., Heer, J., & Froehlich, J. E. (2021). Urban accessibility as a socio-political problem: a multi-stakeholder analysis. *Proceedings of the ACM on Human-Computer Interaction*, *4*(CSCW3), 1–26.

Saha, M., Patil, S., Cho, E., Cheng, E. Y.-Y., Horng, C., Chauhan, D., et al. (2022). Visualizing urban accessibility: Investigating multi-stakeholder perspectives through a map-based design probe study. In *Proceedings of the 2022 CHI conference on human factors in computing systems*. New York, NY, USA: Association for Computing Machinery, http://dx.doi.org/10.1145/3491102.3517460.

Saha, M., Saugstad, M., Maddali, H. T., Zeng, A., Holland, R., Bower, S., et al. (2019). Project sidewalk: A web-based crowdsourcing tool for collecting sidewalk accessibility data at scale. In *Proceedings of the 2019 CHI conference on human factors in computing systems* (pp. 1–14).

Salomoni, P., Prandi, C., Roccetti, M., Nisi, V., & Nunes, N. J. (2015). Crowdsourcing urban accessibility: Some preliminary experiences with results. In *Proceedings of the 11th biannual conference of the Italian SIGCHI chapter* (pp. 130–133).

Sirel, A., & Sirel, U. (2018). "Universal design" approach for the participation of the disabled in urban life. *Journal of Civil Engineering and Architecture*, *12*, http://dx.doi.org/10.17265/1934-7359/2018.01.002.

Song, Y., Wang, R., Fernandez, J., & Li, D. (2021). Investigating sense of place of the las vegas strip using online reviews and machine learning approaches. *Landscape and Urban Planning*, *205*, Article 103956.

Spadon, G., Gimenes, G., & Rodrigues-Jr, J. F. (2017). Identifying urban inconsistencies via street networks. *Procedia Computer Science*, *108*, 18–27.

of the State Architect, C. D. (2016). California building code, section 11b-812 – electric vehicle charging stations. https://scag.ca.gov/sites/main/files/file-attachments/tt031020_californiaevcsaccessibilityregulations.pdf.

Taecharungroj, V., & Mathayomchan, B. (2019). Analysing TripAdvisor reviews of tourist attractions in Phuket, Thailand. *Tourism Management*, *75*, 550–568.

Tatano, V., Guidolin, F., Peltrera, F., et al. (2017). Urban accessibility of historical cities: the venetian case study. *International Journal of Humanities and Social Sciences*, *11*(5), 1135–1141.

of Transportation, U. D. (2021). Bipartisan infrastructure law: National electric vehicle infrastructure and charging & fueling infrastructure programs. https://www.transportation.gov/rural/ev/toolkit/ev-infrastructure-funding-and-financing/federal-funding-programs.

Tutuncu, O. (2017). Investigating the accessibility factors affecting hotel satisfaction of people with physical disabilities. *International Journal of Hospitality Management*, *65*, 29–36. http://dx.doi.org/10.1016/j.ijhm.2017.06.002.

U. S. Congress (1968). Architectural barriers act of 1968. Public Law 90-480, 42 U.S.C. §4151 et seq.https://www.access-board.gov/law/aba.html.

Velázquez, M. V., Faka, A., & Kounadi, O. (2024). Crowdsourcing applications for monitoring the urban environment. In *Geographical information science* (pp. 397–413). Elsevier.

Velho, R. (2019). Transport accessibility for wheelchair users: A qualitative analysis of inclusion and health. *International Journal of Transportation Science and Technology*, *8*(2), 103–115. http://dx.doi.org/10.1016/j.ijtst.2018.04.005.

Wang, Z., Hale, S., Adelani, D. I., Grabowicz, P., Hartman, T., Flöck, F., et al. (2019). Demographic inference and representative population estimates from multilingual social media data. In *The world wide web conference* (pp. 2056–2067).

Wang, M., Haworth, J., Chen, H., Liu, Y., & Shi, Z. (2024). Investigating the potential of crowdsourced street-level imagery in understanding the spatiotemporal dynamics of cities: A case study of walkability in Inner London. *Cities*, *153*, Article 105243.

Wang, M., Pei, X., Zhang, M., & Tang, Y. (2023). Evaluation and optimization of urban public space accessibility for residents' satisfaction: A case study of nanshan district, Shenzhen city. *Buildings*, *13*(10), 2624.

Williams, S., Xu, W., Tan, S. B., Foster, M. J., & Chen, C. (2019). Ghost cities of China: Identifying urban vacancy through social media data. *Cities*, *94*, 275–285.

Wilson, E., Campain, R., Moore, M., Hagiliassis, N., McGillivray, J., Gottliebson, D., et al. (2013). *An accessible survey method: Increasing the participation of people with a disability in large sample social research*. Deakin University.

Yan, A., He, Z., Li, J., Zhang, T., & McAuley, J. (2023). Personalized showcases: Generating multi-modal explanations for recommendations. In *Proceedings of the 46th international ACM SIGIR conference on research and development in information retrieval* (pp. 2251–2255).

Zhu, Y., & Diao, M. (2020). Crowdsourcing-data-based dynamic measures of accessibility to business establishments and individual destination choices. *Transportation Research Part D: Transport and Environment*, *87*, Article 102382.

Ziemke, D., Joubert, J. W., & Nagel, K. (2018). Accessibility in a post-apartheid city: Comparison of two approaches for accessibility computations. *Networks and Spatial Economics*, *18*, 241–271.