Mind the Gap: Urban-Rural Disparities in Wheelchair Accessibility for POI Recommendations

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Abstract. Point-of-Interest recommendation systems (POI-RS) play a central role in how people discover and visit places. However, these systems often overlook accessibility needs of users, particularly individuals with ambulatory disabilities. Using Google Maps data enriched with U.S. population statistics, we quantify geographic disparities in how POIs are labeled with wheelchair accessibility information. We find that (i) the likelihood that a POI is labeled as wheelchair-accessible increases with population size and (ii) rural areas contain disproportionally more venues with *unknown* accessibility status. We conduct an analysis on six recommendation models, containing baseline, Matrix Factorization, and POI models, to quantify the bias in performance between places with accessibility metadata and no metadata, and find evidence that this bias propagates through these systems, resulting in further disparities in recommendations for users with mobility-related needs. We conclude by discussing implications for POI-RS design, including the systematic collection of accessibility metadata and the development of fairness-aware models to support more inclusive and equitable recommendations.

Keywords: Recommender Systems (RS) · Point-of-Interest (POI) Urban-Rural Digital Divide · Inclusion · Wheelchair Accessibility

1 Introduction

According to WHO, an estimated 1.3 billion people live with a disability [49], a number that is steadily increasing in Western countries, partly due to an aging population, as evident in the U.S. census data [45]. In the United States (US), 6.3% of people with disabilities have mobility limitations, such as difficulty walking or climbing stairs [13]. Ensuring equitable access to physical spaces is both a matter of human rights and a core requirement for sustainable societal development. This goal aligns with the United Nations (UN) Sustainable Development Goals (SDG) on Reduced Inequalities [43] and Sustainable Cities and Communities [44], which advocate for inclusive and sustainable human settlements.

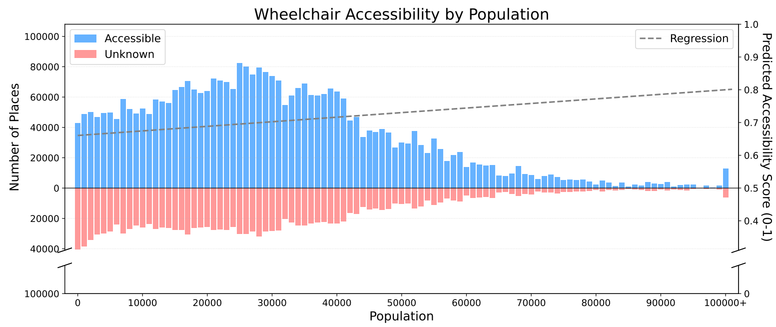

Fig. 1: Wheelchair-accessibilty coverage in Google Maps is uneven across population levels, disproportionately affecting people in rural areas. As population increases, both the number of accessible POIs and those with unknown accessibility increases; rural areas have more POIs with unknown accessibility.

Point-of-Interest recommendation systems (POI-RS) guide users in discovering and choosing places for dining, recreation, social activities, and essential services, shaping their daily experiences and access to community life, while also influencing the local economy [19] and tourism [15].

Despite this impact, accessibility features relevant to wheelchair users (e.g., accessible entrances, restrooms, or parking), are rarely represented in the data POI-RS utilize or in the objectives they optimize. While a large body of research for accessibility-aware routing for people with disabilities exists [3,6,17,20,21,22, 35,39,42,57], POI-RS that explicitly model accessibility remain scarce, with only a few notable exceptions [33,34]. This omission creates digital barriers that compound the already existing physical ones people with disabilities experience [5].

In this paper, we investigate how urban-rural disparities in wheelchair accessibility and in accessibility *metadata* affect POI-RS. We link Google Maps data with U.S. population statistics and show that accessibility labels are more common in areas with higher population size, whereas rural areas contain disproportionately many POIs with *unknown accessibility*. Because POI-RS depend on such metadata, this gap negatively affects recommendation performance for wheelchair users outside dense areas. To illustrate this effect, we (i) analyze coverage disparities (see Figure 1) and (ii) evaluate prediction bias across six standard recommendation models, including two-specific POI-RS models.

2 Accessibility Gaps in POI Recommenders

We argue that the development of accessibility-aware POI-RS is limited by two factors: (i) the lack of accessibility data and (ii) the limited integration of accessibility in model design.

Point-of-Interest recommender systems (POI-RS) aim to predict locations a user is likely to visit, typically based on past check-in history. To improve prediction accuracy, models often incorporate contextual metadata such as coordinates, social relationships, POI categories, or temporal information [29]. Approaches range from traditional matrix and Poisson factorization or link-based models [10, 14, 24, 26, 27, 28, 32, 47] to hybrid approaches [52, 55, 56] and deep learning techniques [12,31,37] that capture complex user-POI interactions [38]. Despite these advances, accessibility is rarely modeled. A major reason for this lies in the lack of accessibility information in the datasets used to train POI-RS. Without such data, accessibility cannot be incorporated as an optimization target.

Widely used benchmark datasets for training and evaluating POI-RS models, such as Gowalla [11], Foursquare [51], and Yelp [54], provide social, geographical, and categorical metadata, but little or no accessibility information. Yelp recently added attributes for ambulatory, visual and hearing accessibility. However, such data is not available in other commonly used and older datasets [53].

Beyond research benchmarks, major commercial map providers such as Google and Apple Maps include accessibility information for POIs, though it is typically self-reported by businesses and therefore inconsistent. Non-commercial providers such as OpenStreetMap rely entirely on crowd-sourced contributions, which vary widely across regions. Community-driven initiatives like Wheelmap.org [48], AccessNow [1], and the PIUMA project on FirstLife [4, 7, 9] help expand coverage. However, such efforts are still limited in scope, with rural areas particularly underserved due to smaller populations and fewer contributions.

Given these gaps, in our work, we leverage Google Maps data enriched with U.S. census statistics to analyze disparities in accessibility coverage across urban and rural places and their effects on recommender systems performance.

3 Data and Operationalization

For our analysis, we utilize a dataset from Google Maps comprising 666 million reviews from over 113 million users of more than 5 million businesses in 50 US states, collected in 2021 [25, 50]. The dataset includes multiple attributes, among them features related to wheelchair accessibility. These may be provided by business owners, suggested by users, or retroactively added by the platform. In our work, to contextualize accessibility with demographic information, we enrich the dataset with US census data [46]. Business addresses are linked to county populations using their ZIP codes, enabling us to stratify accessibility information by population size.

We define accessibility of POIs as follows:

- **Accessible**: a POI explicitly annotated as having a wheelchair-accessible entrance. Note that we focus on wheelchair-accessible entrances, as it is the most common accessibility attribute, whereas other attributes (e.g., restrooms, parking) are inconsistently available in the dataset.
- **Unknown accessibility**: a POI without any accessibility metadata. Also, 1.8% of places with some accessibility features but no entrance details were

categorized as "unknown", as this omission carries a high risk of inaccessibility.

We exclude non-active businesses, resulting in a total of 4.6 million POIs, of which 3.3 million are wheelchair accessible. For stratification, we bin counties into five population ranges, i.e., $< 1k$, $1k - 5k$, $5k - 10k$, $10k - 50k$, and $> 50k$.

4 Empirical Findings

Figure 1 visualizes the distribution of accessible POIs and POIs with unknown accessibility across county population ranges. A fitted linear regression line ($\beta_1 = 1.6 \times 10^{-3}, R^2 = 6.9 \times 10^{-2}$) indicates a positive association between population size and the likelihood of a POI being labeled as accessible. We observe a clear disparity: rural counties with lower populations have a higher proportion of POIs with unknown accessibility status. From the perspective of users with mobility impairments, such missing information functions as a barrier equivalent to inaccessibility [2]. In practice, people with disabilities have to make decisions under uncertainty; withholding accessibility metadata therefore contributes to exclusion.

To examine how these disparities influence the performance of recommender systems, we evaluated six models: two naive baselines (i.e., BaselineOnly and Random), two standard matrix factorization models (i.e., NMF [30] and SVD [40]), and two dedicated POI-RS models:

- **BaselineOnly, Random, NMF, and SVD:** BaselineOnly estimates ratings from the global mean with user and item biases, Random samples from a fitted normal distribution. NMF and SVD factorize the rating matrix to learn latent user-item representations. Implemented with Surprise [18].
- **MGMPFM:** This hybrid model utilizes a Multi-center Gaussian Model, which captures the probability of a user's check-in at a specific geographical location, and combines it with a probabilistic Factor Model to model the visitation frequency of related users [10].
- **LGLMF:** This POI recommender model leverages the user's main region of activity and the importance of each POI within the same region as a geographical model and combines it with Logistic Matrix Factorization [36].

We compared their prediction errors for accessible versus POIs with unknown accessibility across our five population ranges.

To capture systematic differences in model performance between these two groups, we introduce the wheelchair accessibility bias ΔWA. This metric quantifies whether recommender models tend to under- or overpredict ratings for accessible POIs relative to those with unknown accessibility. It is defined as:

$$\Delta WA = MAE(\hat{R}_U, R_U) - MAE(\hat{R}_A, R_A) \quad (1)$$

where $\hat{R}_U$ correspond to the predicted ratings for POIs with unknown accessibility, $\hat{R}_A$ for accessible POIs, and MAE denotes the mean absolute error relative

Algorithm	Population ΔWA <1k	1k-5k	5k-10k	10k-50k	>50k	ΔWA Total	MAE Unknown	Accessible	Total
BaselineOnly	-0.0004	0.0026	0.0003	0.0003	-0.0010	-0.0327	0.2695	0.3022	0.2978
Random	-0.0500	0.0086	0.0068	0.0128	-0.0034	-0.0046	3.1522	3.1569	3.1562
NMF	-0.0116	-0.0030	-0.0013	0.0042	0.0094	-0.0357	0.2782	0.3140	0.3092
SVD	-0.0122	-0.0041	-0.0122	-0.0005	-0.0016	-0.0342	0.2602	0.2945	0.2899
MGMPFM	-0.3507	-0.1265	-0.2335	-0.0835	-0.0319	-0.0190	1.3394	1.3585	1.3561
LGLMF	-0.1191	-0.2775	-0.4508	-0.8429	-0.4308	0.5845	2.9766	2.3921	2.5159

Table 1: Prediction bias of BaselineOnly, Random, SVD, NMF, LGLMF and MGMPFM models for POIs with accessible vs unknown-accessibility status for different population bins. More negative values indicate larger underprediction of accessible places.

to the true ratings R_U and R_A, respectively. Intuitively, ΔWA is positive when models predict accessible POIs more accurately than unknown ones, and negative when they systematically underpredict the rating of accessible POIs.

Table 1 shows that accessibility bias is most pronounced in low-population counties (i.e., $< 1k$). In particular, SVD, MGMPFM and LGLMF consistently underpredict ratings for accessible POIs, while NMF shows a slight preference for accessible places in higher population ranges.

These results suggest that missing accessibility metadata not only reflects geographic disparities but also propagates into biased recommendation performance, particularly disadvantaging users in less densely populated, rural areas.

5 Conclusion

This preliminary analysis demonstrates that wheelchair accessibility metadata is distributed unevenly across U.S. regions, with rural areas disproportionally affected by missing information. Because POI recommendation systems (POI-RS) rely on such metadata to generate relevant suggestions, these gaps translate into biased model performance, leaving users with mobility-related needs at a disadvantage, especially outside densely populated areas.

Our findings highlight two key challenges: the lack of reliable accessibility data and the limited integration of accessibility in recommendation model design. Addressing these challenges requires both technical and participatory challenges. On the technical side, fairness-aware techniques like re-ranking [8], constrained optimization [16,41], and counterfactual fairness [23] provide promising directions. Equally important, participatory approaches involving people with disabilities are needed to ensure that recommender systems reflect actual user needs and support more inclusive and equitable access to physical spaces.

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