

Review

GeoAI and Multimodal Geospatial Data Fusion for Inclusive Urban Mobility: Methods, Applications, and Future Directions

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Abstract

Urban mobility is a central challenge for sustainable and inclusive cities, as climate change, congestion, and spatial inequality increasingly reveal mobility patterns as expressions of deeper social and spatial structures. Inclusive urban mobility examines whether transport systems equitably support the everyday movements and accessibility needs of historically marginalized and underserved populations. The integration of artificial intelligence with geographic information science, combined with multimodal geospatial data fusion, provides powerful tools to diagnose and address these disparities by integrating heterogeneous data sources such as satellite imagery, GPS trajectories, transit records, volunteered geographic information, and social sensing data into scalable, high-resolution urban mobility analytics. This paper presents a systematic survey of recent GeoAI studies that fuse multiple geospatial data modalities for key urban mobility tasks, including accessibility mapping, demand forecasting, and origin–destination flow prediction, with particular emphasis on inclusive and equity-oriented applications. The review examines 18 multimodal GeoAI studies identified through a PRISMA-ScR screening process from 57 candidate publications between 2019 and 2025. The survey synthesizes methodological trends across data-, feature-, and decision-level fusion strategies, highlights the growing use of deep learning architectures, and examines emerging techniques such as knowledge graphs, federated learning, and explainable AI that support equity-relevant insights across diverse urban contexts. Building on this synthesis, the review identifies persistent gaps in population coverage, multimodal integration, equity optimization, explainability, validation, and governance, which currently constrain the inclusiveness and robustness of GeoAI applications in urban mobility research. To address these challenges, the paper proposes a structured research roadmap linking these gaps to concrete methodological and governance directions including equity-aware loss functions, adaptive multimodal fusion pipelines, participatory and human-in-the-loop workflows, and urban data trusts to better align multimodal GeoAI with the goals of inclusive, just, and sustainable urban mobility systems.



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Keywords: GeoAI; multimodal data fusion; urban mobility; spatial equity; explainable AI; participatory analytics; federated learning; urban policy

1. Introduction

Urban mobility fundamentally shapes development, influencing the distribution of economic opportunities, access to essential services, and overall societal participation. [1,2]. However, significant inequities persist, particularly among marginalized groups that face structural barriers to reliable and accessible transportation [3,4]. Research demonstrates

significant disparities in transit and micro-mobility access for minority and disadvantaged neighborhoods. For example, a spatial analysis in Austin, Texas found that nearly 80% of residents, especially those in transit-dependent and Black-majority areas, have no access to bikes and scooters, highlighting extreme inequity in micro-mobility services [5]. Similarly, studies in cities like San Antonio reveal that low-income and minority communities often face limited access to public transit and bike-sharing systems, which exacerbate existing divisions along lines of income, race, and class [6,7]. Comparable patterns of inequity are observed globally. In Europe, Malmö, Manchester, and Utrecht show low-income populations experience nearly twice lower access to shared micromobility services, even in areas where infrastructure appears spatially available [8]. In Bogotá, Colombia, the TransMilenio BRT serves around 2.4 million passengers daily, yet low-income users experience 20–30% longer travel times due to crowding and peripheral station locations [9]. Together, these cases demonstrate how structural barriers in mobility systems operate across geography, income groups, and transport modes [10].

Such inequalities in transit and micromobility access reinforce social segregation and limit opportunities for disadvantaged populations. Mobility patterns and technological barriers can further restrict access for groups differentiated by gender, age, and disability status [5–7,11]. These exclusions produce layered disadvantages, including constrained access to employment, education, and healthcare, as well as disproportionate exposure to environmental risks such as traffic pollution and unsafe street conditions [12]. Consequently, urban mobility is increasingly understood not only as a transportation challenge but also as a critical issue of spatial justice and social equity.

Recent advances in Geospatial Artificial Intelligence (GeoAI) offer powerful new tools to diagnose and potentially mitigate systemic mobility inequities that traditional analytical approaches have struggled to capture. Emerging at the intersection of machine learning, geographic information science, and urban analytics, GeoAI integrates advanced AI techniques with geospatial datasets to move beyond descriptive mapping toward predictive and prescriptive modeling of complex urban phenomena [1]. Unlike conventional transportation planning approaches, which often rely on periodic surveys and aggregated statistics, GeoAI integrates large-scale heterogeneous datasets—including satellite imagery, street-level imagery, GPS mobility trajectories, sensor networks, and volunteered geographic information [13–15]. This capability allows researchers and planners to analyze urban mobility systems at unprecedented spatial and temporal resolution.

Contemporary GeoAI techniques, such as convolutional neural networks (CNNs) for feature extraction from imagery, graph neural networks (GNNs) for spatial network analysis, transformer architectures for multimodal data fusion, and federated learning frameworks for privacy-preserving collaborative analytics, enable the characterization of urban environments, detection of accessibility barriers, and joint model training across distributed agencies or cities [16–20]. These methods address specific challenges that impede equitable urban mobility analytics:

- data heterogeneity—integrating diverse modalities with mismatched resolutions and formats [17].
- algorithmic bias—detecting and correcting systematic under-representation of marginalized communities in training data [18].
- scalability—processing large-volume geospatial big data across cities and regions [19]; and
- interpretability—using explainable AI techniques to ensure that model decisions can be audited and trusted by stakeholders [20].

Despite these advances, several limitations remain. Challenges related to data quality, representational bias, computational resource constraints, privacy governance, and the

limited transferability of models across urban contexts continue to constrain the application of GeoAI in urban mobility research [21–23]. Recent studies therefore emphasize the importance of integrating transfer learning, multimodal data fusion, federated learning, explainable AI (XAI), and human-in-the-loop approaches to develop GeoAI systems that are both technically robust and socially responsible [21–23].

Several recent reviews have examined geospatial analytics, GIS-T methods, and intelligent transportation systems. However, these reviews typically focus on transportation modeling techniques, geospatial data infrastructures, or smart mobility technologies without systematically examining multimodal geospatial data fusion within GeoAI frameworks or its implications for equity-oriented urban mobility analysis.

This study addresses that gap by synthesizing empirical GeoAI studies that integrate multiple geospatial modalities for urban mobility tasks and by evaluating how current approaches incorporate equity, interpretability, and participatory design considerations.

The remainder of this paper is organized as follows. Section 2 presents the PRISMA-ScR systematic survey methodology. Section 3 introduces the theoretical foundations of inclusive urban mobility and spatial equity. Section 4 reviews multimodal GeoAI techniques and data fusion strategies. Section 5 provides a comparative analysis of the reviewed studies. Sections 6–8 synthesize applications, technical challenges, and evaluation approaches. Section 9 discusses key research gaps and future directions, and Section 10 concludes the paper.

2. Methods: Systematic Survey

This study adopts a PRISMA-ScR-guided systematic review to synthesize recent advances in GeoAI and multimodal geospatial data fusion for urban mobility. The review combines a transparent literature search strategy, explicit inclusion and exclusion criteria, structured data extraction, and qualitative comparative synthesis. This approach is appropriate for a rapidly evolving interdisciplinary field where terminology, datasets, and modeling practices vary across geographic information science, transportation research, and artificial intelligence.

2.1. Review Design and Scope

This study adopts a PRISMA-ScR-guided systematic review protocol to synthesize recent advances in GeoAI and multimodal geospatial data fusion for urban mobility. The review conducts a transparent literature search procedures, explicit inclusion criteria, and comparative quality synthesis. The scope of the review focuses on empirical studies addressing urban mobility problems using multimodal geospatial data and machine learning methods, with particular attention to accessibility analysis, demand forecasting, origin–destination (OD) flows, and equity-relevant mobility outcomes.

2.2. Literature Search Strategy

A semantic literature search was conducted using the Elicit platform, which aggregates publications indexed in Semantic Scholar and OpenAlex, covering more than 138 million academic records. Semantic research was selected to capture conceptually related studies across disciplines where similar methods may be described using different terminology. The search targeted peer-reviewed journal articles and high-quality conference papers published approximately between 2019 and 2025, reflecting the period during which GeoAI and multimodal data fusion techniques have matured in urban analytics.

Search queries combined thematic concepts related to: GeoAI and geospatial artificial intelligence; Multimodal or multi-source data fusion; Urban mobility, transportation,

accessibility and equity; Traffic prediction, demand forecasting, and origin–destination modeling; Participation and ethics.

Example query structure:

- (i) *“GeoAI” AND (“multimodal” OR “data fusion”) AND (“urban mobility” OR “transport equity”)*
- (ii) *“graph neural network” AND (“OD flow” OR “accessibility”) AND “multimodal”*
- (iii) *“deep learning” AND (“transport demand” OR “walkability”) AND “geospatial fusion”*
- (iv) *“explainable AI” AND “urban mobility” AND (“equity” OR “fairness”)*
- (v) *“federated learning” AND “transport” AND “multimodal”*

The initial semantic search returned to 2847 records. Semantic ranking and relevance filtering reduced this set to 57 candidate studies, which were then screened through title, abstract, and full-text review.

2.3. Study Screening and Selection

Study selection was performed using a two-stage screening process.

2.3.1. Titles and Abstracts Screening

Titles and abstracts were reviewed to exclude papers that: addressed non-urban or non-mobility domains; relied on a single data modality; or focused on purely conceptual or methodological topics without empirical application.

2.3.2. Full-Text Screening

Full-text articles were evaluated according to predefined inclusion criteria. Studies were retained if they:

- integrated two or more geospatial data modalities (e.g., GPS traces, mobile phone data, satellite imagery, transit records, crowdsourced maps) were employed;
- apply data-, feature-, or decision-level fusion techniques;
- addressed urban mobility tasks such as accessibility mapping, traffic or demand forecasting, travel behavior modeling, and OD analysis were addressed;
- reported quantitative evaluation metrics or comparative performance against the baselines.

Following this screening process, 18 studies were included in the final synthesis. The study selection process followed the PRISMA-ScR framework and is illustrated in the PRISMA flow diagram (Figure 1).

2.4. Data Extraction and Analytical Framework

A structured data extraction protocol was applied to each included study, capturing a common set of attributes. For every paper, the extracted information covered the urban mobility task and application domain, the geographic context and spatial scale, and the geospatial data modalities that were combined. Details on the fusion strategy (data-, feature-, or decision-level) and core modeling approaches for example, CNNs, RNNs/LSTMs, GNNs, transformers, or knowledge-graph models were also recorded, together with the evaluation metrics reported (such as RMSE, MAE, MAPE, accuracy, or F1-score) and any explicit considerations related to equity, explainability, or fairness. To support comparative synthesis, studies were then grouped according to fusion strategy and application domain, enabling cross-study comparison of methodological effectiveness, scalability, and interpretability. The extracted attributes were used to construct a structured comparative summary of the reviewed studies, which is presented in the Results section.

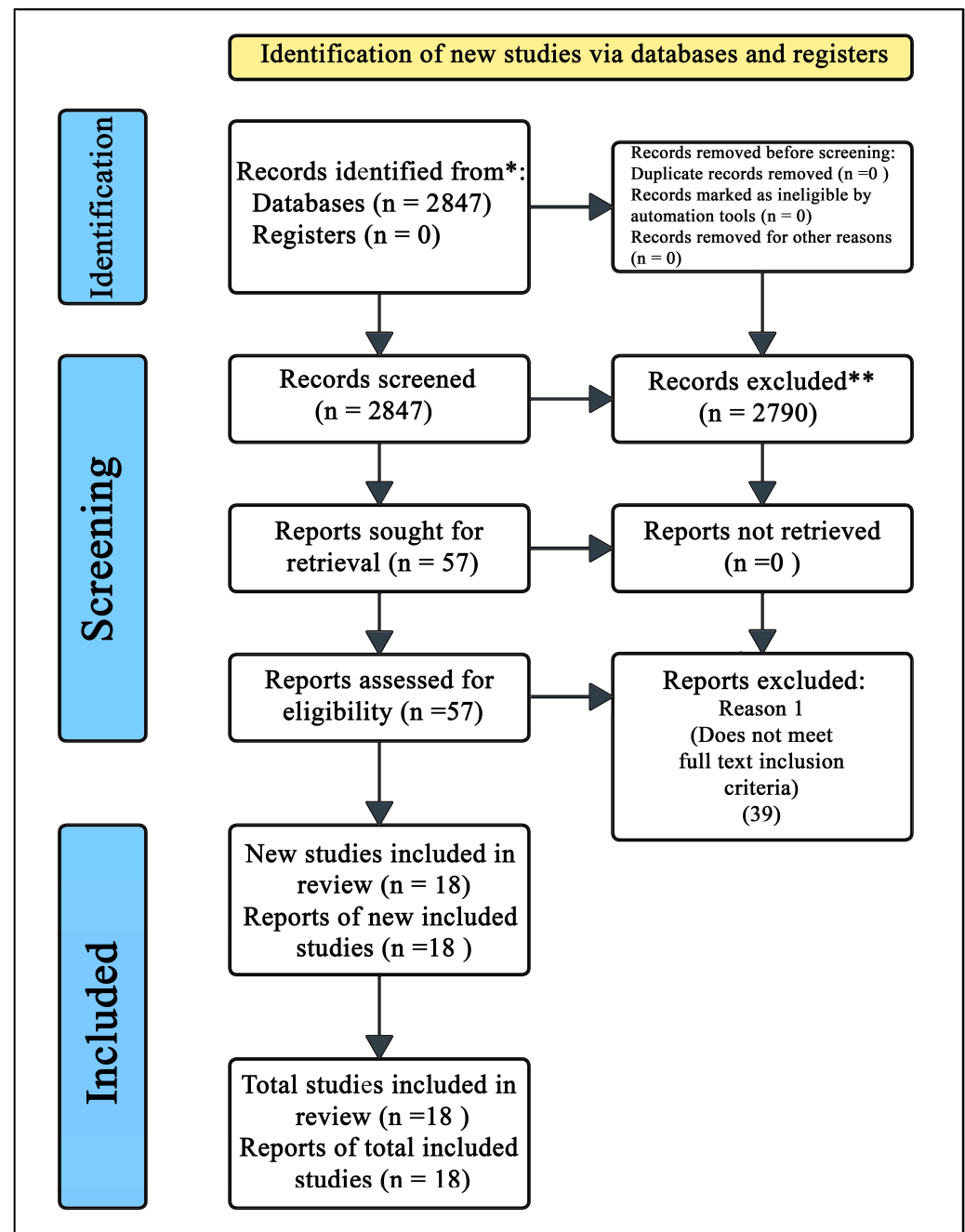


Figure 1. PRISMA-ScR flow diagram illustrating the identification, screening, and inclusion of studies in the systematic survey [24]. * Records identified through semantic search and initial relevance filtering. ** Studies excluded after full-text screening based on predefined inclusion and exclusion criteria.

2.5. Synthesis and Evaluation Approach

Given the heterogeneity of datasets (data sources), modeling architectures, and evaluation metrics across studies, a qualitative comparative synthesis was adopted rather than a meta-analysis. Model effectiveness was assessed relative to reported single-source or non-fusion baselines, with attention to trade-offs between predictive performance, computational complexity, and interpretability.

The comparative synthesis was organized along two main dimensions: Fusion strategy (data-, feature-, or decision-level integration) and Urban mobility application domain (e.g., accessibility analysis, demand forecasting, mode choice modeling) Where available,

subgroup results such as performance different across neighborhoods or time periods were also considered too across potential implications for equity-oriented mobility analysis.

Formal numerical quality scoring was not applied because of the diversity of experimental designs and validation protocols across studies. Instead, methodological robustness was assessed qualitatively based on transparency of model design, use of baseline comparisons, validation strategies, clarity of reported results and incorporation of explainable AI techniques or equity-oriented evaluation criteria.

3. Theoretical and Conceptual Foundations

3.1. Urban Mobility Inequities: Population, Spatial, and Social Perspectives

Urban mobility, which is fundamental to sustainable city development, is a key determinant of social inclusion, economic opportunities, and environmental quality. However, access remains deeply uneven, particularly among marginalized populations. Persistent inequities, such as minority neighborhoods experiencing less transit access than majority white areas [12], reflect longstanding structural injustices in urban transportation systems.

These gaps extend beyond traditional public transit, with research revealing that up to 80% of residents in certain cities, particularly low-income groups, lack access to emerging micromobility options such as bike sharing and e-scooters [13], further restricting mobility and compounding social and economic exclusion. Intersectional barriers shaped by gender, age, disability, and income exacerbate disadvantages, necessitating equity assessments that account for complex, overlapping vulnerabilities. Environmental injustice intensifies these issues: disadvantaged neighborhoods often experience disproportionately higher exposure to pollutants from traffic. It was shown that ultrafine particle concentrations to be 34% higher in socioeconomically deprived Toronto districts [14,25]. Social and spatial segregation, especially in peripheral metropolitan areas, leaves many low-income and minority communities with limited transit access, reinforcing systemic cycles of exclusion from employment, healthcare, and education, and perpetuating spatial inequality [4].

Furthermore, limited access to transactions may unconstitutionally deprive certain populations of their civil rights. Freedom of movement entails that a citizen present within a state has not only the right to leave and return to that state, but also to travel to, reside in, and work in any part of the state without governmental interference [26].

For example, Article 13 of the Universal Declaration of Human Rights (“UDHR”) stipulates that “[27] everyone has the right to freedom of movement and residence within the borders of each state.” In general, limitations on civil rights must be imposed by law (or pursuant to a legislative act). By contrast, restricted access to transactions excludes certain groups from fully exercising this fundamental freedom. It thereby creates a *de facto* limitation on the right to movement, distinct from a formal, legally enacted restriction.

3.2. Accessibility and Spatial Equity Theories

Mobility barriers arise from interactions among the built environment, service provision, and social policy. Two influential frameworks guide spatial equity analysis.

1. **Right to the City:** This concept, advanced by Lefebvre and Harvey, asserts the collective right of urban residents to shape and access city spaces, placing emphasis on equitable transport as a foundation for inclusion [28,29].
2. **Capability Approach:** Sen’s framework interprets equity as the substantive freedoms individuals require to pursue valued outcomes, shifting the focus from mere physical mobility to flexibility and opportunity to achieve life goals [30].

Inclusion is evaluated across several key dimensions [31]:

- **Availability:** Presence and diversity of mobility options;

- **Accessibility:** Ease of reaching desired destinations;
- **Acceptability:** Cultural and social appropriateness;
- **Flexibility:** Adaptability to various user needs

These criteria provide a multidimensional basis to evaluate how transportation systems cultivate or constrain urban inclusion.

3.3. Built Environment and Inclusivity

The characteristics of the built environment, walkability, bikeability, and degree of transit integration critically affect mobility equity. Well-connected, safe, and accessible networks foster active travel and expand opportunities [32,33], whereas fragmented or underinvested infrastructure disproportionately hinders persons with disabilities, seniors, and low-income residents in marginalized neighborhoods [34]. Therefore, inclusive urban design and equitable planning are fundamental to reducing mobility gaps and improving the urban quality of life.

4. GeoAI Framework for Multimodal Urban Mobility

4.1. Evolution of GIScience in the Era of GeoAI

Traditional GIScience has historically focused on spatial data management, mapping, and foundational spatial analytics in urban studies. The recent paradigm shift toward GeoAI integrates machine learning (ML), deep learning (DL), and advanced spatial statistics with geospatial data, advancing from descriptive mapping to predictive modeling of complex, dynamic urban phenomena [17]. GeoAI leverages large-scale heterogeneous datasets, including satellite imagery, sensor feeds, and participatory maps, permitting automated interpretation of intricate mobility patterns, accessibility barriers, and equity outcomes [16].

4.2. Multimodal Geospatial Data Sources

Before describing specific geospatial datasets, it is important to clarify the distinction between multi-source and multimodal data, which are sometimes used interchangeably in the literature but represent different concepts. Multi-source data refers to datasets originating from different providers or collection systems, such as municipal transport databases, commercial GPS providers, and citizen-contributed OpenStreetMap edits. In contrast, multimodal data refers to fundamentally different data types or measurement modalities, such as satellite imagery, trajectory traces, sensor time series, semantic maps, or social sensing data. In this review, we focus specifically on multimodal geospatial data integration, where at least two distinct data modalities are combined to capture complementary aspects of urban mobility systems.

The main categories of geospatial data sources, along with their associated challenges and equity implications, are summarized in Table 1.

Table 1. Summary of Geospatial Data Types for Urban Mobility Equity Assessment.

Data Type	Source	Challenge	Equity Impacts
Satellite Imagery	NASA, Copernicus	Cloud cover, resolution	Misses informal/ground detail [17]
GPS Traces	Phones, Taxis	Signal gaps, user bias	Skewed to affluent travelers [12]
OpenStreetMap	Crowdsourcing	Under-mapping	Underrepresents poor areas [35,36]
Social media	Twitter, Facebook	Sentiment, sample, privacy	Reflects perceptions, not all users [37]

Table 1. *Cont.*

Data Type	Source	Challenge	Equity Impacts
Participatory GIS	Citizen mapping	Engagement, data quality	Captures lived experience [38]
Census Data	National statistical offices	Coarse spatial/temporal resolution; undercounts	Masks intra-neighborhood disparities; may miss marginalized groups [39,40]
Municipal GIS Data	City planning/transport departments	Inconsistent coverage; update frequency	May omit informal areas; reflect institutional priorities [39,41]
Shade Maps	Remote sensing, urban climate models	Seasonal variability; model uncertainty	Misses micro-scale thermal stress along everyday paths: heat exposure is often highest for vulnerable groups [42,43]
Street-level Photos	Google Street View, Baidu, Mapillary	Coverage bias; occlusion; privacy	Overrepresents well-served areas; inequities in visual walkability and streetscape quality across neighborhoods [44,45]

This distinction is important because multimodal fusion allows GeoAI models to integrate heterogeneous representations of urban environments, improving the ability to analyze complex mobility patterns and equity-related accessibility outcomes. Multimodal geospatial data constitutes the foundational input layer of GeoAI systems, enabling the integration of heterogeneous urban information sources for mobility analytics. Traditional sources, such as static survey data, census records, and transit timetables, offer baselines for demographic and equity analysis but often lack the temporal and spatial precision needed to reveal mobility disparities [39]. In contrast, new geospatial data types, such as GPS trajectories, IoT sensor feeds, OpenStreetMap (OSM), high-resolution satellite imagery, and participatory mapping, provide rich, real-time information on movement, infrastructure, and experience [14,35]. Crowdsourced and participatory data, including citizen-generated maps and social media, further enrich analyses of lived experiences, perceptions, and unique mobility perspectives [37,38]. Additional sources such as census microdata, municipal GIS layers, shade maps, and street level imagery further enrich equity assessment by linking mobility with social structure, climate exposure, and perceived walkability.

This integrated approach demonstrates that a holistic, equity-oriented urban mobility analysis not only depends on technological advancements in data fusion, but also on critical evaluation of representational biases and accessibility within each data source.

4.3. GeoAI Model Architectures

GeoAI employs a diverse suite of models and computational paradigms, ranging from classical machine learning and spatial statistics, such as Random Forests (RF), Support Vector Machines (SVM), and Geographically Weighted Regression (GWR), which are foundational for analyzing land use, transit accessibility, and socioeconomic mobility outcomes [18,20], to convolutional and recurrent neural networks (CNNs/RNNs) that automate barrier detection from imagery and model service unreliability, often surfacing inequities in transit operations [19,46].

Graph Neural Networks (GNNs) represent urban street and transit networks as interconnected systems, enabling the prediction of connectivity gaps and accessibility vulnerabilities in urban street networks [47,48]. Transformer-based architectures fuse multimodal urban data and extract contextual dependencies for equity analyses. Complementing these, XAI techniques (e.g., SHAP, LIME) promote transparency and interpretability for fairness auditing and policy trust, and federated learning (FL) supports privacy-preserving,

collaborative analytics across jurisdictions, which is key for multi-city and multi-agency equity research [16,49,50].

4.4. Data Fusion Techniques

GeoAI-driven urban analytics benefit from multimodal data fusion strategies [51] that integrate heterogeneous sources such as sensors, satellite imagery, OpenStreetMap (OSM), and mobility traces to capture complex urban dynamics. According to the reviewed studies, three canonical fusion levels can be distinguished, each with different methodological implications:

Data-level fusion integrates raw heterogeneous datasets before feature extraction through spatial-temporal alignment, imputation, or generative augmentation. This approach preserves the maximum amount of original information and allows end-to-end learning across modalities; however, it requires careful preprocessing to address differences in spatial resolution, temporal frequency, and data quality, and it often incurs higher computational costs.

Feature-level fusion combines extracted features or learned embeddings from different data modalities to create a unified representation for model training. This strategy is widely used in deep learning architectures because it balances information integration and computational efficiency. Nevertheless, the interpretability of fused feature spaces can be limited, and careful design of feature extraction pipelines is required to ensure compatibility between modalities.

Decision-level fusion aggregates predictions from multiple models trained on different data modalities, typically through ensemble or late-fusion techniques. This approach is computationally flexible and modular, allowing individual models to be updated independently; however, it captures cross-modal interactions only at the prediction stage and may therefore miss deeper relationships between modalities that earlier fusion strategies can exploit.

4.5. Participatory Approaches and Human-in-the-Loop Design

Open-source geospatial platforms such as QGIS or GeoPandas, and Google Earth Engine have lowered technical and financial barriers to conducting spatial analyses, particularly for researchers, local governments, and civil society groups with limited proprietary software access. Citizen-generated maps and social sensing, including OpenStreetMap edits, participatory GIS, and geotagged social media, embed lived experiences in mobility models and make it easier for non-specialist contributors to shape how urban environments are represented.

Human-in-the-loop GeoAI workflows and co-designed workshops promote procedural justice by embedding stakeholder engagement directly into analysis and decision-making processes [35,36].

4.6. GeoAI Data Fusion Pipeline

The overall GeoAI multimodal data fusion workflow is summarized in Figure 2. The pipeline integrates diverse geospatial inputs, including satellite imagery, GPS trajectories, participatory GIS data, census records, municipal GIS layers, street-level imagery, and social media data through data-level, feature-level, and decision-level fusion. These inputs are processed using spatial machine learning models, deep learning architectures, graph-based GeoAI methods, and explainable AI tools to produce accessibility maps, equity indicators, and demand forecasts that support inclusive urban mobility planning.

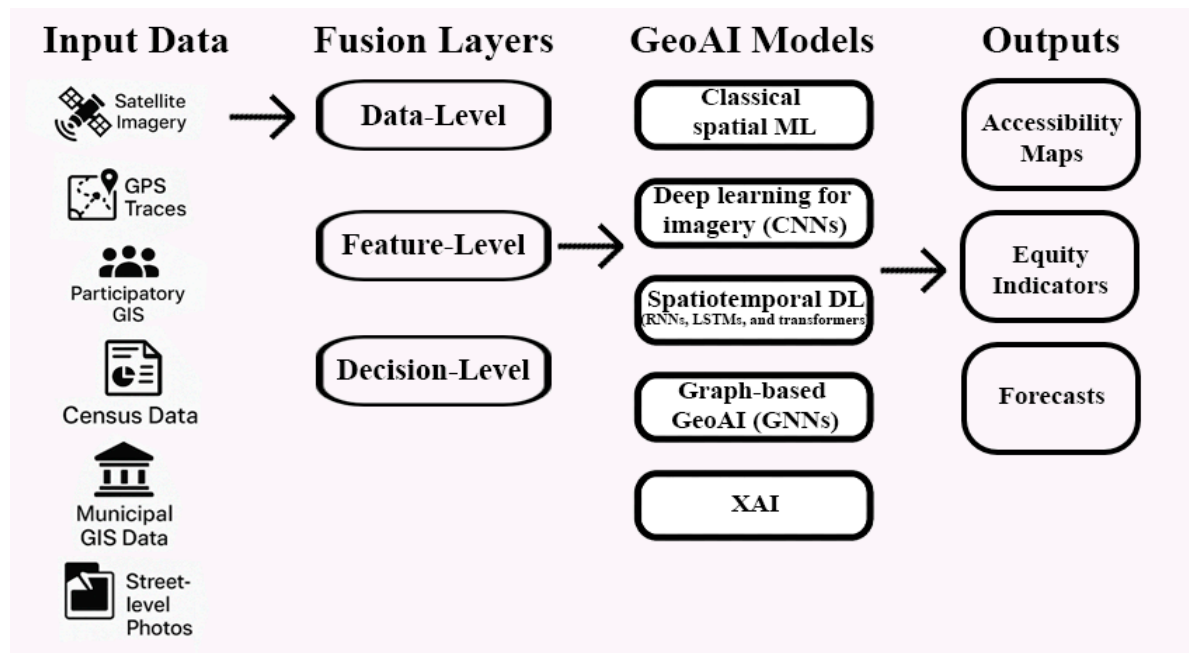


Figure 2. GeoAI multimodal data fusion pipeline for urban mobility equity analysis.

The pipeline highlights how multimodal GeoAI models support equity-oriented urban mobility analysis by integrating heterogeneous geospatial data with fairness-aware evaluation to identify accessibility disparities and mobility gaps across different population groups.

5. Systematic Survey Results

The comparative analysis summarized in Table 2 reveals several methodological patterns in recent multimodal GeoAI studies for urban mobility. Among the 18 studies included in the systematic survey, the majority focus on mobility demand forecasting, traffic prediction, or origin–destination (OD) flow modeling, reflecting the strong emphasis on predictive mobility analytics in contemporary GeoAI research. Approximately two-thirds of the reviewed studies address forecasting tasks, while a smaller subset examines travel mode choice, walkability assessment, or accessibility analysis. This imbalance suggests that behavioral and equity-oriented mobility questions remain comparatively underexplored relative to predictive mobility modeling.

Table 2. Key characteristics of the 18 multimodal GeoAI studies included in the systematic survey, including methodology, prediction task, data modalities, and geographic scope.

Framework Name	Core Methodology	Prediction Target	Geographic Scope	Data Modalities Combined	Study
Hierarchical Evaluation Framework	DS-HRNet (Detail-Strengthened High-Resolution Network, deep learning)	Urban walkability	Wuhan, China	Street imagery, road network, built environment indicators	[52]
Spatially Explicit Explainable GeoAI	GCN (Graph Convolutional Network) + GNNExplainer (Graph Neural Network Explainer.)	Traffic volume prediction	Wuhan, China	Traffic sensor data, road network, spatial features	[53]

Table 2. Cont.

Framework Name	Core Methodology	Prediction Target	Geographic Scope	Data Modalities Combined	Study
GT-LSTM (Geospatial-Temporal Long Short-Term Memory)	Attention mechanisms and Recurrent Neural Networks	Urban mobility patterns	Not reported in the original study	Multi-modal urban transportation dataset	[54]
FusionTransNet	Graph neural networks	Origin–destination (OD) flow prediction	Shenzhen and New York	Taxi GPS, shared bike, bus data	[55]
Matrix Trifactorization	Matrix factorization	Travel mode choice	Santiago, Chile	Mobile phone data, travel surveys, smart card data, OSM infrastructure	[56]
Software platform	Not specified	Travel mode choice	Urban areas (unspecified)	Survey data, GPS traces, weather, transport models, built environment	[57]
Late Fusion Network	CNNs (Convolutional Neural Network) and LSTMs (Long Short-Term Memory) with attention	Origin–destination flow prediction	Urban areas (unspecified)	Bus transit records, temporal features	[58]
ST-MDF	Spatio-temporal multimodal demand forecasting framework	Mobility demand forecasting	Medium to large cities	Taxi, bicycle rental, weather data	[59]
STKG	Knowledge graph completion	Next POI prediction	New York, Beijing, Shanghai	Foursquare check-ins, WeChat location data, POI categories	[60]
MDTP	Multi-source bridging using Sum and Concat	Demand forecasting	New York City, Chicago	Taxi and bike sharing data	[61]
GSABT	Graph Sparse Attention + Bidirectional Temporal Convolutional Network	Joint multimodal traffic prediction	Not reported in the original study (3 real datasets)	Multiple traffic modes (e.g., bus, taxi, bike)	[62]
STGATN	GCN + Bi-LSTM + weather attention + Transformer	Bike-sharing e-fence demand	Shenzhen, China (Nanshan District)	Bike usage, POI-based zones, weather	[63]
GAN-based taxi forecaster	GAN (Generative Adversarial Network) with RNN (Recurrent Neural Network) + CNN (Convolutional Neural Network)	Taxi demand	Wuhan, China	Taxi GPS, road network, weather, POIs	[64]
Low-dimensional bike demand model	Three-level clustering + regression	Bike-sharing demand	New York City	Bike trips, temperature, precipitation	[65]
Data-fusion mode choice (DAE+RF)	Stacking, denoising autoencoder + Random Forest	Individual travel mode choice	Germany & Switzerland	Travel diary surveys, socio-demographics, built environment	[66]
Smartphone-survey mode ID	SVM (Support Vector Machine) + GBDT (Gradient Boosted Decision Trees)	Trip mode (classification)	Hangzhou, China	Smartphone GPS, survey labels, A-Map API	[67]
Integrated survey + Amap API	XGBoost, Random Forest + SHAP	Travel mode choice	Chinese city (Not reported in the original study)	Revealed preference survey, Amap path/time/cost	[68]
Stacking Machine Learning for mode choice	Stacking ensemble	Travel mode choice	Jinan, China	Large-scale travel survey, socio-demographics	[69]

In terms of modeling approaches, deep learning architectures dominate the literature, particularly graph neural networks (GNNs), recurrent neural networks (RNNs), convolutional neural networks (CNNs), and hybrid spatiotemporal models. These architectures are frequently used to integrate heterogeneous data streams, including GPS trajectories,

sensor data, weather information, and points of interest (POIs), allowing models to capture complex spatial–temporal dependencies in urban mobility systems. As shown in Table 2, multimodal fusion typically combines mobility traces with contextual urban data layers such as weather conditions, infrastructure attributes, and socioeconomic indicators. This integration enables improved prediction accuracy compared with single-source approaches and supports more detailed representations of urban mobility dynamics.

Across the reviewed studies, feature-level fusion emerges as the most common integration strategy, enabling models to combine learned representations from multiple geospatial modalities within deep learning pipelines. Data-level fusion and decision-level fusion appear less frequently and are typically associated with simpler multimodal datasets or ensemble forecasting frameworks. Geographically, the literature remains highly concentrated in data-rich urban environments, particularly in cities in China and the United States, while comparatively few studies examine cities in Latin America, Africa, or other data-constrained contexts. This geographic imbalance limits the transferability of current GeoAI models to regions where mobility inequities are often most pronounced.

The reviewed studies are evaluated primarily using predictive performance metrics, including RMSE, MAE, MAPE, accuracy, and F1-score. While these metrics demonstrate improvements in forecasting accuracy, relatively few studies explicitly incorporate equity evaluation, explainable AI techniques, or participatory validation approaches. As a result, most multimodal GeoAI models continue to prioritize predictive performance over fairness, transparency, and policy relevance. These findings highlight both the rapid methodological progress in multimodal GeoAI and the need for future research to integrate equity-aware modeling, interpretable analytics, and geographically diverse case studies to better support inclusive urban mobility planning.

6. Application Domains

6.1. Walking, Micromobility, and Accessibility

a. Accessibility Mapping and Equity Assessment

GeoAI-driven data fusion has significantly advanced accessibility analytics by integrating street-level imagery, transit network topology, IoT sensor streams, participatory mapping, and census microdata to assess how transport infrastructure is spatially distributed and uncover fine-grained access disparities [12,35,70–72]. For example, some studies use CNNs to extract pedestrian barrier features from street-level imagery, then fused this with transit schedules and population demographic data to map accessibility neighborhoods where seniors and people with disabilities face compounded barriers. The model identified that 34% of bus stops in low-income census tracts lacked accessible sidewalk connections, compared to just 8% in affluent areas, quantifying an equity gap that traditional audits often miss [50,70].

However, critical limitations persist. Street-level imagery itself exhibits significant geographic bias: Google Street View provides comprehensive coverage in wealthy North American and European cities but sparse or outdated coverage in the Global South, informal settlements, and rural areas [44,45]. Studies employing this data source therefore risk invisibilizing the very populations most affected by accessibility barriers [38]. Furthermore, models trained in high-income cities often fail when transferred to low-income urban contexts, where informal transportation modes (paratransit, informal settlements without formal address systems) and non-standard infrastructure dominate [17]. Only a handful of reviewed studies [50,70] explicitly address this transferability challenge through domain adaptation or fairness constraints; most assume that a model trained in New York or London can be deployed in Santiago or Lagos without context-specific validation—an assumption that equity-oriented research should systematically reject.

Additionally, accessibility mapping alone does not guarantee equity outcomes. A study mapping gaps may identify where to invest, but without participatory co-design with affected communities, technical recommendations may overlook local knowledge about safety, cultural appropriateness, and actual usage patterns [37,38].

b. Demand Forecasting and Scenario Analysis

Integrating heterogeneous data modalities, including mobile phone records, transit smart card uses, and social media sentiment, GeoAI enables accurate forecasting of mobility demand and user flows [73]. Deep learning models such as RNNs and transformers predict ridership patterns and evaluate the impact of events or urban changes on travel demand [4,72]. Furthermore, scenario analysis tools, enhanced by multimodal data fusion, support mobility system resilience testing and policy-driven simulations for future urban growth or disruption scenarios [74]. This limitation suggests that scenario analysis tools should be coupled with real-time participatory feedback mechanisms and continuous model retraining, practices still uncommon in deployed systems.

c. Infrastructure Planning and Policy Decision Support

GeoAI applications have improved transport infrastructure planning by fusing satellite imagery, crowdsourced maps, and IoT sensor data to assess current conditions, forecast maintenance needs, and optimize network expansion [17,39]. Federated learning frameworks enable multi-agency collaboration without compromising privacy and supporting regional and cross-jurisdictional transport analyses [74]. Equitable investment prioritization and policy evaluation tools now leverage spatial and temporal fusion models to ensure that benefits reach communities that are most in need [4]. Critically, deploying optimized plans without meaningful community engagement risks reproducing existing power imbalances. Optimization algorithms make assumptions about what constitutes “demand” or “benefit” based on historical data, which reflect past investment patterns and may encode historical exclusions. Recent work emphasizing participatory and human-in-the-loop approaches [35,36] demonstrates that integrating community priorities and lived experience can substantially revise infrastructure priorities, yet this integrative approach remains rare in practice.

d. Specialized Domains: Maritime Mobility, Micromobility

Beyond traditional urban transit, GeoAI techniques have been applied to specialized domains, such as maritime mobility and emerging micromobility services. In maritime studies, multimodal data fusion of Automatic Identification System vessel trajectories, satellite imagery, and geospatial databases uncover routing patterns, detect illegal activity (“dark vessel” detection), and improve port accessibility analysis [75,76]. For micromobility (e-scooters and bike-share), fusion models combine GPS traces, crowdsourced infrastructure data, and real-time user feedback to study safety, accessibility, and usage equity [5,20]. This application highlights an important potential: GeoAI can surface invisible economic actors and exclusions, though the focus typically remains on surveillance and enforcement rather than empowerment.

6.2. Implications for Urban Planning and Policy

Emerging GeoAI research points to several implications for how planners and policy-makers might use these tools in practice, while also highlighting important cautions. Recent work suggests that multimodal GeoAI can support the identification of “service deserts” by revealing neighborhoods with systematic gaps in transit, walking, or micromobility access, which in turn can guide more targeted investments in routes, stations, or pedestrian infrastructure [77]. Studies also show that GeoAI can be used to evaluate alternative policy and planning scenarios, enabling public authorities to rely on quantitative simulations to

optimize implementation and reduce social and financial costs in smart and healthy city initiatives [51].

Scenario-based applications further allow planners to assess how interventions such as transit expansion, land-use changes, or new micromobility regulations affect accessibility across different population groups. This provides a more nuanced understanding of distributional impacts compared to traditional aggregate indicators. The integration of real-time and high-frequency data from GPS, sensor networks, and crowdsourced sources also enables continuous monitoring of system performance and rapid detection of service disruptions that disproportionately affect vulnerable populations.

However, these data-driven approaches also present significant challenges. They may unintentionally prioritize corridors and user groups that generate dense digital traces, potentially reinforcing existing inequalities. As a result, proactive safeguards are necessary to ensure that monitoring frameworks do not further marginalize areas with limited data coverage [51,78]. At the same time, incorporating participatory GIS, human-in-the-loop workflows, and community-based review of model outputs can help ground technical insights in local knowledge, improve the legitimacy of decisions, and identify mismatches between modeled accessibility and lived experience. Nevertheless, such approaches require sustained institutional commitment, facilitation capacity, and long-term stakeholder engagement.

From a decision-support perspective, fairness-constrained models and equity-oriented evaluation criteria can be used to prioritize infrastructure upgrades and service expansions toward communities with the greatest mobility gaps, rather than focusing solely on aggregate efficiency. However, these tools do not replace political judgment, as definitions of equity and fairness are inherently normative and must be continuously debated and refined as conditions evolve.

Finally, while insights derived from large, data-rich urban environments provide valuable methodological guidance, their transferability to medium-sized or resource-constrained cities remain limited. Differences in institutional capacity, data availability, and mobility cultures necessitate careful context-sensitive adaptation rather than direct one-to-one policy transfer across urban settings.

7. Technical, Ethical, and Practical Challenges

GeoAI for urban mobility operates at the intersection of complex technical systems, sensitive social contexts, and institutional constraints, creating a range of technical, ethical, and governance challenges that shape how multimodal models are designed, deployed, and interpreted.

7.1. Data Heterogeneity and Resolution Mismatch

Integrating multimodal geospatial data remains technically challenging owing to differences in spatial resolution, data formats, and coverage. Satellite imagery, GPS traces, crowdsourced OSM layers, and sensor streams often provide information at incompatible scales, resulting in analytical and fusion gaps [17,74]. For example, high-resolution satellite imagery may clearly capture narrow informal footpaths or curb ramps, while coarser census or traffic analysis zones aggregate these features into single units, making it difficult to align fine-grained pedestrian barriers with zone-level accessibility indicators. Resolution mismatches particularly affect the mapping of informal settlements and nuanced pedestrian barriers, which are frequently overlooked in coarse datasets.

7.2. Bias, Representation, and Validation Issues

Equity-oriented urban mobility analytics are persistently affected by biases in data sources and models. OSM and social media datasets commonly underrepresent low-income areas, older adults, and non-digitally connected users [35]. Model training can inherit and amplify these biases if not carefully evaluated [50]. The validation of equity outcomes thus demands careful attention to representative sampling, transparency, and fairness assessments [70,73].

7.3. Ethical, Fairness, and Governance Principles in GeoAI

GeoAI applications increasingly intersect ethical and governance concerns, spanning user privacy, consent for data use, and algorithmic accountability. Federated learning approaches offer privacy-preserving alternatives for distributed model training; however, governance frameworks for data sharing, anonymization, and inclusion are still evolving, especially when fusing personally identifiable mobility traces that require robust protection and ethical review. In parallel, knowledge-guided GeoAI integrates domain expertise, causal reasoning, and contextual constraints into model design, which can improve both predictive performance and the ethical validity of inferences. Fairness-aware GeoAI moves beyond post hoc bias correction toward embedding equity objectives directly into model training and optimization, for example by enforcing minimum service thresholds for marginalized communities. Finally, reproducibility and openness—through transparent documentation, appropriate open data sharing, and participatory co-design with affected populations—strengthen trust, replicability, and the long-term impact of urban mobility analytics [16,36,39,50].

7.4. Computational Resource Constraints

Machine learning models, particularly deep networks and ensemble fusion frameworks, are computationally intensive and often require significant resources for training, storage, and real-time predictions [16,20]. This creates barriers to equitable deployment in resource-limited municipalities and organizations.

8. Validation Approaches and Assessment Gaps

Validation remains one of the weakest links in GeoAI for urban mobility applications. Many studies report predictive accuracy or cross-validation metrics, but few systematically evaluate equity, robustness, or generalizability, and transferability between cities or demographic contexts is rarely tested beyond a single held-out area or time slice [20,70,72]. In several cases, models that perform well on average error metrics nonetheless misrepresent demand in low-income or transit-dependent neighborhoods, indicating that conventional validation can mask distributional harm.

To better operationalize equity-oriented validation, a simple taxonomy of evaluation approaches can be distinguished. First, subgroup performance metrics compare prediction errors or model outputs across demographic or spatial groups (e.g., income levels, minority populations, or disadvantaged neighborhoods). Second, accessibility and service equity indicators measure disparities in predicted accessibility or mobility service provision between advantaged and vulnerable areas. Third, fairness-oriented metrics evaluate whether model outcomes satisfy minimum service thresholds or avoid systematic disparities across population groups.

Explainable AI (XAI) techniques such as SHAP and LIME are increasingly used to audit decision processes and uncover model bias, yet their usefulness in real-world planning is constrained by context-dependent interpretation, sensitivity to model specification, and the difficulty practitioners face in translating local feature attributions into actionable

interventions [4,50]. Incorporating expert and stakeholder input through workshops, participatory mapping, or community review of model output offers a practical route for validating equity implications and identifying unforeseen barriers, for example when residents flag unsafe walking routes or unserved areas that are invisible in routinely collected data. However, such participatory workflows are not yet standard practice and often face scalability, resource, and sustained engagement challenges [79].

Overall, current validation practices rely heavily on technical performance metrics rather than holistic equity or social-impact assessments. Achieving meaningful accountability and distributive justice in urban mobility analytics will require integrating participatory approaches, transparent reporting of model limitations, and explicit equity benchmarks—such as subgroup performance targets or minimum service thresholds—into both evaluation protocols and decision-making processes [35,39].

9. Research Gaps and Future Directions

9.1. Research Gaps

Despite notable advances, several persistent gaps have limited the full realization of GeoAI's promise for urban mobility equity. First, a population coverage gap exists, as current research disproportionately focuses on large global cities, leaving medium-sized and marginalized populations underrepresented and limiting the generalizability of models. Second, a methodological gap persists, current models overwhelmingly optimize predictive accuracy or employ post hoc fairness audits but rarely embed equity and interpretability as integral design objectives.

Multimodal integration remains both technically and ethically challenging. Researchers struggle to align heterogeneous modalities (imagery, GPS, census, social media) and to address spatial bias, data quality, and interoperability, especially in underserved contexts. Most GeoAI solutions measure equity post hoc, with few actively optimizing for fairness during model training. Explainability and auditability gaps are also evident—popular tools like SHAP and LIME can be unstable and are rarely validated for real-world policy impact.

Reproducibility and participatory design lag: workflow and data sharing are limited, and stakeholder or lived experience integration is rare [39]. Governance and institutional gaps arise from fragmented data custodianship and insufficient cross-sector collaboration, while an implementation gap reflects a lack of robust evaluation of GeoAI solutions for equity or policy goals in truly diverse, real-world urban settings. Finally, there is a stakeholder engagement gap—participatory co-design and evaluation are rarely standard practices in GeoAI system development.

9.2. Recommendations and Roadmap for Advancing the Field

To bridge the identified gaps, future work should develop unified, interdisciplinary frameworks that integrate technical, policy, and social perspectives, enabling GeoAI systems to be designed and evaluated in ways that are both scalable and context sensitive. Within such frameworks, equity-aware modeling and validation need to move beyond post hoc fairness checks toward embedding fairness constraints, systematic auditing, and robust equity evaluation directly into model training and deployment workflows. At the data level, scalable and quality-focused fusion pipelines are required to confront spatial bias, interoperability challenges, and persistent validation limitations when integrating heterogeneous geospatial modalities.

Advancing GeoAI for urban mobility also depends on opening analytic pipelines to broader stakeholder participation and scrutiny. Open and participatory workflows—grounded in co-design workshops, transparent evaluation protocols, and mechanisms

for stakeholder feedback can support meaningful empowerment and help ensure that model outputs align with local priorities and lived experiences. In parallel, governance innovations such as urban data trusts and cross-sector regulatory frameworks are needed to provide ethical and sustainable structures for data sharing, privacy protection, and accountability in large-scale deployments.

Finally, targeted technological innovation should focus on methods that improve adaptability, robustness, and policy relevance. Promising directions include the use of digital twins, foundation models, and self-supervised learning to better capture complex urban dynamics and transfer knowledge across data-rich and data-scarce settings. Closer integration between modeling efforts and concrete policy and socioeconomic objectives is essential so that GeoAI systems are iteratively evaluated and refined against real-world planning goals and diverse urban applications. A gap-mapping table (Table 3) aligns these research gaps with specific objectives and recommendations to guide future GeoAI-driven urban mobility research and practice.

Table 3. Mapping of Identified Gaps, Objectives, and Anticipated Impacts in Multimodal GeoAI for Inclusive Urban Mobility.

Gap Type	What's Missing	Thesis Objective/Proposed Solution	Expected Contribution
Population Gap	Global city bias; lack of inclusivity	Apply to medium/marginal cities with participatory data	Demonstrated GeoAI transferability to critical contexts
Methodological Gap	Accuracy focus, weak fairness/XAI integration	Embed equity-aware objectives, integrate XAI	Explainable, fairness-constrained GeoAI for actionable plans
Multimodal Integration	Heterogeneous, misaligned data	Develop adaptive multimodal fusion pipeline	Holistic equity assessment using multimodal data
Equity Optimization Gap	Equity only measured post hoc	Formulate equity-aware loss functions	Moves equity from evaluation to optimization
Explainability/Auditability	Unstable XAI, lack of rigorous validation	Integrate policy-adaptive XAI, fairness auditing	Reliable, policy-ready equity validation
Reproducibility/Participation	Limited open workflows, little community voice	Open-source workflows, participatory validation	Procedural justice/transparency in GeoAI
Governance/Institutional	Siloed data custodianship, poor collaboration	Propose urban data trusts/multi-sector frameworks	Sustainable governance for equitable GeoAI/data use
Socioeconomic/Implementation	Limited real-world policy/scalability validation	Test GeoAI in diverse urban/policy contexts	Practical, scalable GeoAI impact on equity
Stakeholder Engagement	Weak participatory design/evaluation	Co-design and review with citizens, officials	Inclusive, socially embedded GeoAI implementations

9.3. Limitations of This Survey

This review has several limitations. First, the literature search relied primarily on databases aggregated by the Elicit platform, which may exclude relevant studies indexed elsewhere. Second, the diversity of modeling approaches and evaluation protocols across studies prevented a formal meta-analysis or standardized quality scoring. Third, many studies focus on large data-rich cities in North America, Europe, and East Asia, which may limit the generalizability of findings to smaller or resource-constrained urban contexts.

10. Conclusions

This survey demonstrates that GeoAI combined with multimodal geospatial data integration and advanced machine learning techniques has significantly advanced the analysis of urban mobility equity, enabling more nuanced and data-driven insights into accessibility patterns, infrastructure distribution, and spatial disparities. Recent progress in multimodal data fusion, explainable artificial intelligence (XAI), and participatory geospatial analytics provides powerful tools for identifying mobility gaps and supporting evidence-based urban planning and policy decisions.

Despite these advances, several important challenges remain. Persistent issues such as population bias, methodological limitations, heterogeneous data quality, and fragmented governance frameworks continue to constrain the development of equitable and inclusive mobility systems. Many existing GeoAI models remain optimized primarily for predictive accuracy rather than equity outcomes, while commonly used datasets often reproduce spatial and demographic biases. Furthermore, validation practices frequently focus on technical performance metrics and rarely evaluate broader dimensions such as fairness, robustness, or social impact.

Addressing these limitations requires future research to prioritize equity-aware modeling frameworks, particularly through the development and evaluation of models in underrepresented or data-constrained urban contexts. Greater emphasis is also needed on improving the integration and harmonization of heterogeneous multimodal datasets, alongside explainable modeling approaches that enhance transparency, accountability, and trust in GeoAI systems.

Beyond technical innovation, the advancement of equitable GeoAI systems depends on participatory research processes and collaborative governance structures. Integrating stakeholder engagement, community knowledge, and human-in-the-loop validation can help ensure that model outputs reflect lived mobility experiences and support more legitimate planning and policy decisions. Transparent data-sharing frameworks, open scientific workflows, and cross-sector collaboration between researchers, public agencies, and civil society are therefore essential for the responsible deployment of GeoAI technologies.

Looking forward, the long-term impact of GeoAI on urban mobility will depend not only on improvements in predictive performance but also on the integration of equity-aware objectives, participatory validation practices, and governance mechanisms that support ethical data use. As geospatial data ecosystems expand and machine learning methods continue to evolve, collaborative and transparent analytical frameworks will play a critical role in shaping urban environments that are not only technologically advanced but also more just, inclusive, and sustainable.

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