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

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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 expose 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 AI with geographic information science, together with multimodal geospatial data fusion, provides powerful tools to diagnose and address these disparities by combining heterogeneous sources such as satellite imagery, GPS traces, transit records, volunteered geographic information, and social sensing into scalable, high-resolution urban mobility analytics. The main aim of this paper is presenting a systematical review of recent GeoAI studies that fuse multiple geospatial modalities for key tasks such as accessibility mapping, demand forecasting, and origin–destination flow prediction, with particular emphasis on inclusive and equity-oriented applications. The survey synthesizes methodological trends across data-, feature-, and decision-level fusion, highlights the growing use of deep learning architectures, and examines emerging techniques including knowledge graphs, federated learning, and explainable AI shape equity-relevant insights in diverse urban contexts. Building on this synthesis, the review identifies persistent gaps in population coverage, multimodal integration, equity optimization, explainability, validation, and governance that constrain the inclusiveness and robustness of current GeoAI practices, and proposes a structured research roadmap linking these gaps to actual methodological and governance directions—such as equity-aware loss functions, adaptive 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.

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

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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].

These inequities in transit and micro-mobility access can reinforce social segregation and limit opportunities for disadvantaged groups, including by gender and age, as mobility patterns and technological barriers further restrict access for certain populations [5–9]. These exclusions lead to layered disadvantages, including limited mobility options, increased social and economic gaps, and disproportionate exposure to environmental risks such as air pollution [10]. Social and spatial segregation further restricts vulnerable populations' access to jobs, healthcare, and education, perpetuating inequity over time.

Recent advances in Geospatial Artificial Intelligence (GeoAI) offer powerful and evidence-based pathways to diagnose and mitigate systemic mobility inequities that traditional approaches have long struggled to address. GeoAI, which emerged at the intersection of machine learning, geographic information science, and urban analytics in the early 2010s, integrates deep learning and AI methods with geospatial data to move beyond descriptive mapping toward predictive and prescriptive modeling of complex urban phenomena [1]. Unlike conventional transportation planning, which relies on periodic surveys and aggregated statistics, GeoAI leverages multimodal datasets—including satellite and street-level imagery, GPS mobility traces, sensor networks, and volunteered geographic information—to analyze urban environments with unprecedented spatial and temporal resolution [11–13]. This technological shift enables researchers and planners to detect fine-grained accessibility barriers, quantify service disparities at neighborhood scales, and identify under-served populations that are often invisible in coarser datasets, thereby grounding equity-focused interventions in evidence rather than assumption.

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 [14–18]. These methods address specific challenges that impede equitable urban mobility analytics:

- data heterogeneity—integrating diverse modalities with mismatched resolutions and formats[15];
- algorithmic bias—detecting and correcting systematic under-representation of marginalized communities in training data[16];
- scalability—processing large-volume geospatial big data across cities and regions[17]; and
- interpretability—using explainable AI techniques to ensure that model decisions can be audited and trusted by stakeholders[18].

Despite these technological advancements, significant challenges persist around data quality, representational bias, computational resource constraints, privacy and governance concerns, and the limited transferability of models across urban contexts [19–21]. Recent scholarship increasingly emphasizes the importance of transfer learning, large-scale multimodal fusion, federated learning, explainable AI (XAI), and human-in-the-loop approaches as essential for building GeoAI systems that are both technically robust and ethically sound [19–21]. Advances in user-friendly interfaces and natural language interpretability tools have further democratized access to sophisticated geospatial insights, making them accessible to urban planners and policymakers who may lack deep technical expertise [20].

This review contributes by systematically synthesizing state-of-the-art GeoAI approaches for inclusive urban mobility, analyzing current challenges and research gaps, and laying out strategic directions for equity-focused urban mobility analytics. The subsequent sections review the conceptual, methodological, and application-oriented progress in GeoAI and multimodal urban analytics before outlining future directions for research and practice grounded in both evidence and equity principles.

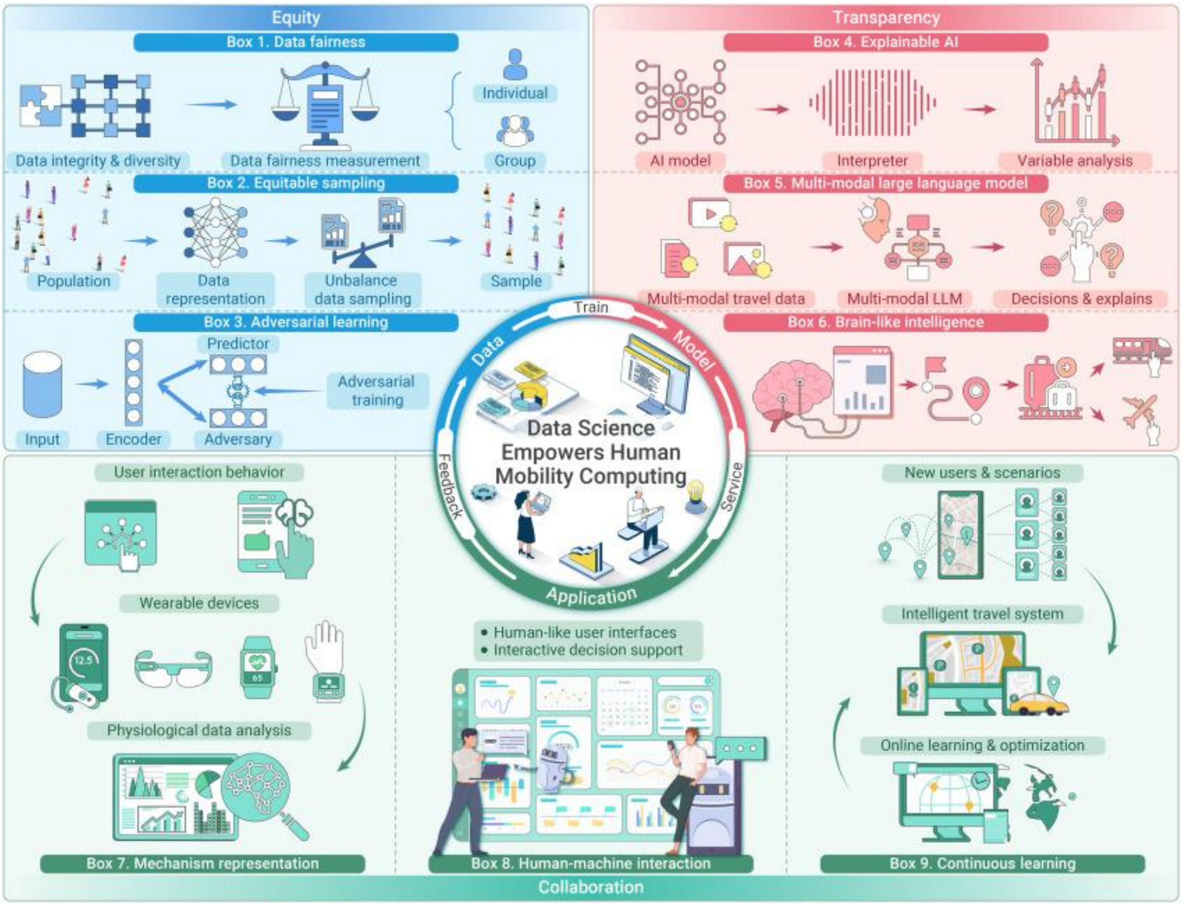

Figure 1. GeoAI and multimodal data fusion framework for inclusive urban mobility, emphasizing equity, transparency, and application layers [22].

2. Theoretical and Conceptual Foundations

2.1. 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 [10], 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 [11], 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 [12,23]. 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].

2.2. 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.

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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 [24,25].
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 [26].

Inclusion is evaluated across several key dimensions [27]:

- **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.

2.3. 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 [28,29], whereas fragmented or underinvested infrastructure disproportionately hinders persons with disabilities, seniors, and low-income residents in marginalized neighborhoods [30]. Therefore, inclusive urban design and equitable planning are fundamental to reducing mobility gaps and improving the urban quality of life.

3. Overview of GeoAI and Multimodal Data Fusion Methods

3.1. Evolution of GIScience in the Era of GeoAI

Traditional GIScience has centered 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 [15]. 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 [14].

3.2. Machine Learning, Deep Learning, and Explainable AI (XAI)

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 [16,18], to convolutional and recurrent neural networks (CNNs/RNNs) that automate barrier detection from imagery and model service unreliability, often surfacing inequities in transit operations [17,31]. GNNs represent urban street and transit networks as interconnected systems, enabling the prediction of connectivity gaps and accessibility vulnerabilities in urban street networks [32,33]. 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 [14,34,35].

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3.3. Data Fusion Techniques

GeoAI-driven urban analytics benefit from multimodal data fusion strategies [36] that integrate heterogeneous sources—sensors, satellite imagery, OSM, and mobility traces—to capture complex urban dynamics. These span three canonical levels identified across reviewed studies:

-Data-level fusion- Integrates raw heterogeneous data before feature engineering via spatial/temporal alignment, imputation, or generative augmentation;

-Feature-level fusion- combines extracted features/embeddings to unify information from disparate sources;

-Decision-level fusion- aggregates outputs from individual models, supporting ensemble predictions and robust scenario analyses.

3.4. 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 [37,38].

3.5. GeoAI Data Fusion Pipeline

The overall GeoAI multimodal data fusion workflow is summarized in Figure 2. GeoAI multimodal data fusion pipeline for urban mobility equity. Diverse geospatial inputs (satellite imagery, GPS traces, participatory GIS, census and municipal GIS data, street-level photos, and social media) are integrated through data- level, feature- level, and decision-level fusion, processed with classical spatial machine learning, deep learning for imagery, spatiotemporal models, graph-based GeoAI, and explainable AI, to produce accessibility maps, equity indicators, and demand forecasts for inclusive urban mobility planning.

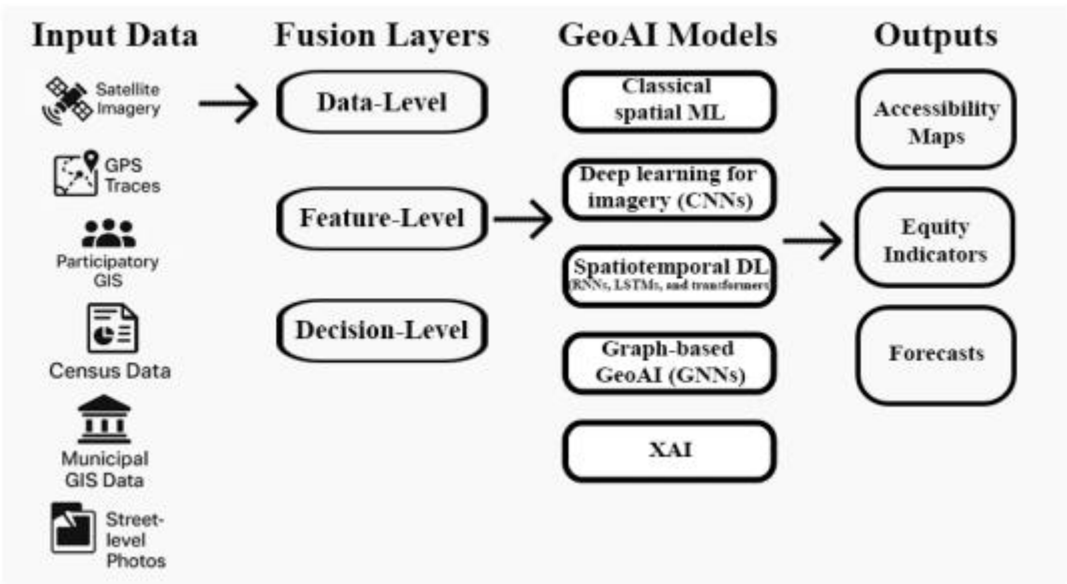

Figure 2. GeoAI multimodal Data Fusion Pipeline.

4. Multimodal Geospatial Data in Urban Mobility

Integrating data from diverse established and emerging sources is essential for robust, inclusive urban mobility research. 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].

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 [15]
GPS Traces	Phones, Taxis	Signal gaps, user bias	Skewed to affluent travelers [10]
OpenStreetMap	Crowdsourcing	Under-mapping	Underrepresents poor areas [37,38]
Social media	Twitter, Facebook	Sentiment, sample, privacy	Reflects perceptions, not all users [47]
Participatory GIS	Citizen mapping	Engagement, data quality	Captures lived experience [46]
Census Data	National statistical offices	Coarse spatial/temporal resolution; undercounts	Masks intra-neighborhood disparities; may miss marginalized groups [39,48]
Municipal GIS Data	City planning/transport departments	Inconsistent coverage; update frequency	May omit informal areas; reflect institutional priorities [39,49]
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 [50,51]
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 [52,53]

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 [12,37]. Crowdsourced and participatory data, including citizen-generated maps and social media, further enrich analyses of lived experiences, perceptions, and unique mobility perspectives [46,47]. 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.

5. Methods: Systematic Survey

5.1. Review Design and Scope

This study adopts a structured, state-of-the-art survey with systematic elements to synthesize recent advances in GeoAI and multimodal geospatial data fusion for urban mobility. Rather than conducting a full PRISMA-style systematic review, the approach combines transparent search procedures, explicit inclusion criteria, and comparative synthesis, which is well suited to a rapidly evolving, interdisciplinary field where terminology, data modalities, and evaluation practices vary across geography, transportation science, and artificial intelligence.

The scope focuses on empirical urban mobility studies that integrate two or more geospatial data modalities using machine learning or deep learning methods, with particular attention to accessibility, demand forecasting, origin–destination (OD) flows, and equity-relevant mobility outcomes.

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5.1.1. Literature Search Strategy

A semantic literature search was conducted using the Elicit platform, which aggregates and indexes publications from Semantic Scholar and OpenAlex, covering more than 138 million academic records. Semantic search was selected to capture conceptually relevant 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 methods 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.

The initial search returned to 57 candidate studies deemed highly relevant based on semantic similarity and citation context.

5.1.2. Study Screening and Selection

Study selection was performed using a two-stage screening process. First, titles and abstracts were reviewed to exclude papers that: (i) addressed non-urban or non-mobility domains; (ii) relied on a single data modality; or (iii) focused on purely conceptual or methodological topics without empirical application.

Second, full-text screening was conducted to retain only the studies that:

- Two or more geospatial data modalities (e.g., GPS traces, mobile phone data, satellite imagery, transit records, crowdsourced maps) were employed;
- Data-, feature-, or decision-level fusion techniques were applied;
- 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.

5.1.3. 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.

5.1.4. Synthesis and Evaluation Approach

Given the heterogeneity of data sources, prediction targets, 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.

In practice, the comparative synthesis proceeded along two main dimensions: fusion strategy and application task. For each study, multimodal fusion models were contrasted with their

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corresponding single--source or non--fusion baselines, focusing on relative gains in accuracy, stability across time and space, and changes in interpretability. Where available, subgroup results (for example, performance across different neighborhoods or time periods) were also examined. This approach enabled a qualitative comparison of how data, feature, and decision--level fusion perform for different mobility problems, rather than relying solely on raw error metrics.

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

5.2. Summary of Included Studies

The convergence of geospatial artificial intelligence (GeoAI), multimodal data fusion, and urban mobility research represents a rapidly evolving frontier in intelligent transportation systems and smart city development. This review synthesizes recent advances across these interconnected domains to provide context for the state--of--the--art survey on GeoAI and multimodal geospatial data fusion for inclusive urban mobility. Table 2 summarizes eighteen multimodal GeoAI studies by core methodology, prediction task, geographic scope, data modalities, and study identifier, spanning applications such as walkability assessment, traffic and OD--flow forecasting, mode choice classification, demand prediction, and next--place recommendation.

Existing work can be grouped into two broad strands: multimodal and spatiotemporal demand forecasting, and data--fusion--based travel mode analysis. On the demand side, several frameworks combine heterogeneous mobility and contextual data to predict short--term demand or flows, typically showing that multimodal integration reduces error relative to single--source baselines. GT--LSTM integrates LSTM with attention over multimodal transport and geographic features, reducing MAPE and RMSE compared with ConvLSTM and GCN baselines on a multimodal urban dataset. FusionTransNet and the Spatio--Temporal Mobility Demand Forecaster (ST--MDF) fuse taxi, bike, bus, and weather or temporal features using graph neural networks or spatiotemporal machine learning, demonstrating that learning from multiple modes jointly improves OD--flow and demand forecasts in large and medium–large cities. MDTP applies simple multi--source fusion operators (sum and concatenation) over taxi and bike--sharing data in New York and Chicago, showing that relatively lightweight fusion schemes can still enhance cross--mode demand prediction. At a finer operational level, GSABT employs graph sparse attention with a bidirectional temporal convolutional network to jointly predict multimodal traffic, while STGATN targets bike--sharing e--fence demand using a hybrid of GCN, Bi--LSTM, weather attention, and Transformer modules; both report state--of--the--art accuracy on real multimodal datasets. Complementary low--dimensional and rule--based bike--sharing models indicate that hierarchical clustering with regression or interpretable rule sets can yield competitive-level forecasts when combining trip and weather data, which is attractive for practitioners prioritizing transparency and low computational cost over maximal accuracy.

On the behavioral side, mode choice and mode detection studies emphasize fusing survey, passive sensing, and environmental data. Matrix Trifactorization in Santiago integrates mobile phone traces, travel surveys, census information, smart--card records, and OSM data to estimate municipal--level mode split, illustrating how combining rich but noisy passively collected traces with traditional surveys can reduce bias and improve spatial coverage. At the individual level, stacking models with denoising autoencoders and Random Forests, as well as other stacking ensembles, exploit travel diaries, socio--demographics, and built--environment indicators to classify travel mode with high accuracy while surfacing influential factors such as car ownership, urban density, and transit accessibility.

Smartphone--based mode identification in Hangzhou uses SVM and gradient boosting on GPS trajectories labeled via surveys and enriched with A--Map API information, showing that combining phone sensors with detailed network attributes substantially improves mode classification

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performance. More recent interpretable machine--learning frameworks that integrate traditional travel surveys with Amap API path, time, and cost attributes demonstrate that multimodal, multi--source fusion can be both accurate and capable of explaining mode choice behavior in ways that are usable for policy analysis.

Taken together, the studies in the updated table highlight a consistent pattern: heterogeneous data fusion across modes, sensors, and contextual layers, coupled with spatiotemporal deep architectures such as LSTMs with attention, GNNs, CNN–RNN hybrids, and Transformer--style components, systematically outperforms single--source or single--modal baselines for both demand prediction and mode choice [63,64,67,68,70,72–74,76–79]. In parallel, a line of work on lower--dimensional or interpretable models explores how to balance accuracy, transparency, and deployment complexity by combining simpler regression or rule--based structures with carefully designed multimodal features. Collectively, these studies show that multimodal urban mobility models are evaluated predominantly with RMSE, MAE, MAPE, accuracy, and F1 and that dense mobile traces and POI information tend to provide the strongest individual predictive signals [61–70,72–79].

Table 2. Key characteristics of multimodal GeoAI studies reviewed, including methodology, prediction task, data sources, and geographic scope.

Framework name	Core methodology	Prediction target	Geographic scope	Data modalities combined	Study
Hierarchical Evaluation Framework	DS-HRNet, a Detail-Strengthened High-Resolution Network (deep learning model)	Urban walkability	Wuhan, China	Multimodal data	61
Spatially Explicit Explainable GeoAI	GCN + GNNExplainer	Traffic volume prediction	Wuhan, China	Multimodal data	62
GT-LSTM	Attention mechanisms and RNNs	Urban mobility patterns	Not specified	Multi-modal urban transportation dataset	63
FusionTransNet	Graph neural networks	OD flows	Shenzhen and New York	Taxi GPS, shared bike, bus data	64
Matrix Trifactorization	Matrix factorization	Travel mode choice	Santiago, Chile	Mobile phone data, travel surveys, smart card data, OSM infrastructure	65
Software platform	Not specified	Travel mode choice	Urban areas (unspecified)	Survey data, GPS traces, weather, transport models, built environment	66
Late Fusion Network	CNNs and LSTMs with attention	OD flows	Urban areas (unspecified)	Bus transit records, temporal features	67
ST-MDF	Not specified	Demand forecasting	Medium to large cities	Taxi, bicycle rental, weather data	68
STKG	Knowledge graph completion	Next POI prediction	New York, Beijing, Shanghai	Foursquare check-ins, WeChat location data, POI categories	69
MDTP	Multi-source bridging using Sum and Concat	Demand forecasting	New York City, Chicago	Taxi and bike sharing data	70
GSABT	Graph sparse attention + bi-TCN	Joint multimodal traffic prediction	Not specified (3 real datasets)	Multiple traffic modes (e.g., bus, taxi, bike)	72
STGATN	GCN + Bi-LSTM + weather attention + Transformer	Bike-sharing e-fence demand	Shenzhen, China (Nanshan District)	Bike usage, POI-based zones, weather	73

GAN-based taxi forecaster	GAN with RNN + CNN	Taxi demand	Wuhan, China	Taxi GPS, road network, weather, POIs	74
Low-dimensional bike demand model	Three-level clustering + regression	Bike-sharing demand	New York City	Bike trips, temperature, precipitation	75
Data-fusion mode choice (DAE+RF)	Stacking, denoising autoencoder + Random Forest	Individual travel mode choice	Germany & Switzerland	Travel diary surveys, socio-demographics, built environment	76
Smartphone-survey mode ID	SVM, GBDT	Trip mode (classification)	Hangzhou, China	Smartphone GPS, survey labels, A-Map API	77
Integrated survey + Amap API	XGBoost, Random Forest + SHAP	Travel mode choice	Chinese city (not specified)	Revealed preference survey, Amap path/time/cost	78
Stacking ML for mode choice	Stacking ensemble	Travel mode choice	Jinan, China	Large-scale travel survey, socio-demographics	79

At the same time, they reveal systematic gaps: a strong bias toward large, instrumented cities, limited transferability to medium--sized or under--resourced contexts, equity and fairness objectives rarely embedded in model design, validation focused on aggregate accuracy within single metropolitan areas, and minimal integration of participatory or human--in--the--loop workflows [61–70,72–79]. As a result, GeoAI and multimodal fusion form a powerful but not yet equity--configured toolkit; realizing their potential for inclusive urban mobility will require equity--aware loss functions and evaluation criteria, participatory validation with affected communities, and governance and interoperability frameworks that regulate how multimodal mobility data are collected, shared, and used in decision--making across diverse urban environments.

6. Application Domains

6.1. Walking, Micromobility, and Accessibility

6.1.1. 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 [10,37,54–56]. Which used CNNs to extract pedestrian barrier features (curb ramps, crosswalks, tactile paving) 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 [35,54].

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 [52,53]. Studies employing this data source therefore risk invisibilizing the very populations most affected by accessibility barriers [46]. 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 [15]. Only a handful of reviewed studies ([35,54]) 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.

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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 [46,47].

6.1.2. Demand Forecasting and Scenario Analysis

Integrating heterogeneous data modalities, including mobile phone records, transit smart card uses, and social media sentiment, GeoAI enables the accurate forecasting of mobility demand and user flows [57]. Deep learning models such as RNNs and transformers predict ridership patterns and evaluate the impact of events or urban changes on travel demand [4,56]. 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 [58]. 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.

6.1.3. 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 [15,39]. Federated learning frameworks enable multi-agency collaboration without compromising privacy and supporting regional and cross-jurisdictional transport analyses [58]. 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 ([37,38], demonstrates that integrating community priorities and lived experience can substantially revise infrastructure priorities, yet this integrative approach remains rare in practice.

6.1.4. 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 [59,60]. For micromobility (e-scoters and bike-share), fusion models combine GPS traces, crowdsourced infrastructure data, and real-time user feedback to study safety, accessibility, and usage equity [5,18]. 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 policymakers 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 [80]. 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 [81].

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Scenario--based GeoAI applications allow planners to simulate how transit expansion, land--use change, or new micromobility regulations could alter accessibility for different demographic groups, offering a more explicit lens on distributional impacts than traditional aggregate indicators. Real--time or high--frequency fusion of GPS, sensor, and crowdsourced data creates opportunities for continuous monitoring of system performance and faster detection of service disruptions that disproportionately affect vulnerable populations. At the same time, several studies caution that such approaches risk privileging corridors and user groups that generate dense digital traces, so proactive safeguards are needed to ensure that data--driven monitoring frameworks do not further marginalize areas with weak data coverage [81,82].

Incorporating participatory GIS, human--in--the--loop workflows, and community review of model outputs can help ground technical insights in local knowledge, improve the legitimacy of decisions, and surface mismatches between modeled accessibility and lived experience, although such practices demand time, facilitation capacity, and sustained institutional commitment. 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 largest mobility gaps, rather than simply maximizing aggregate efficiency. However, these tools do not replace political judgment: equity constraints are themselves normative choices that must be debated and revisited as conditions change.

Finally, experiences from large, data--rich cities offer valuable methodological lessons for medium--sized or resource--constrained urban areas, but transferability remains limited when institutional capacities, data infrastructures, and mobility cultures differ substantially, underscoring the need for careful local adaptation rather than one--to--one policy transfer.

7. Technical, Ethical, and Practical Challenges

GeoAI for urban mobility operates at the intersection of complex technical systems, sensitive social contexts, and constrained institutional capacities, which creates a set of recurring challenges that shape how multimodal models are designed, deployed, and interpreted. These challenges are not merely implementation details; they influence whose mobility is visible in the data, which forms of exclusion are prioritized, and how reliably equity claims can be supported.

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 [15,58]. 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 [37]. Model training can inherit and amplify these biases if not carefully evaluated [35]. The validation of equity outcomes thus demands careful attention to representative sampling, transparency, and fairness assessments [54,57].

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

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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 [14,35,38,39].

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 [14,18]. 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 [18,54,56]. 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 harms.

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 [4,35]. 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 [71].

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 [37,39].

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 gap exists in 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.

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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.

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

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.

10. Conclusions

This survey demonstrates that GeoAI, through multimodal geospatial data integration and advanced machine learning, has transformed the analysis of urban mobility equity by enabling nuanced, actionable insights at the intersection of accessibility, infrastructure patterns, and social disparities. While advances in data fusion, explainable models, and participatory analytics have provided new tools for diagnosing and addressing mobility gaps, persistent challenges, such as population bias, methodological limitations, data heterogeneity, and fragmentation in governance, continue to hinder the achievement of just and inclusive mobility systems. Critical issues remain, as models are still frequently optimized for accuracy rather than equity, datasets replicate spatial and demographic biases, and validation seldom extends beyond technical accuracy to encompass fairness, robustness, or social impacts. To advance the field, research and policy must prioritize designing and evaluating models within underrepresented and marginalized urban contexts; embed equity and explainability as core objectives rather than afterthoughts; develop stronger methods for integrating and harmonizing multimodal and heterogeneous data; and create participatory pipelines involving stakeholders and community engagement throughout the research lifecycle. Additionally, robust open-source governance, transparent data-sharing frameworks, and coordinated cross-sectoral collaboration are essential for sustainable equitable GeoAI deployment. Looking forward, the future of GeoAI for urban mobility will hinge not only on technical sophistication but also on its capacity to facilitate procedural and distributive justice. As data sources expand and machine learning matures, frameworks that are collaborative, equity-aware, and transparent will be decisive in realizing urban environments that are not only smarter but also fundamentally fairer, more inclusive, and sustainable. By synthesizing these theoretical, methodological, and ethical imperatives, this review provides both a critical assessment of the current limitations and a practical roadmap for harnessing multimodal GeoAI as a transformative force for urban mobility equity.

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