International Journal of Computer Applications Technology and Research
Volume 14–Issue 12, 01 – 15, 2025, ISSN:-2319–8656
DOI:10.7753/IJCATR1412.1001

Modeling Active Transportation Demand using GIS-Integrated Spatial Econometrics to Evaluate Infrastructure Accessibility, Sustainability, and Equity in Urban Mobility

Adewumi Augustine Adepitan
Sid and Reva Dewberry
Department of Civil,
Environmental, and
Infrastructure Engineering,
George Mason University,
USA

Abstract: Active transportation primarily walking and cycling has become a central pillar of sustainable urban mobility, yet its adoption remains uneven across cities due to disparities in infrastructure quality, accessibility, and socio-spatial conditions. As municipalities pursue climate goals, congestion reduction, and public-health improvements, the ability to accurately model active transportation demand has become essential for targeted planning and equitable policy design. Geographic Information Systems (GIS) now serve as powerful platforms for integrating multimodal infrastructure data, land-use patterns, demographic distributions, and environmental variables, enabling a comprehensive spatial understanding of mobility behavior. However, traditional statistical models often fail to capture the inherently spatial nature of travel decisions, including neighborhood clustering, geographic spillover effects, and the influence of adjacent infrastructure networks. Spatial econometric methods such as spatial lag, spatial error, and geographically weighted regression offer a robust analytical framework to address these complexities by explicitly modeling spatial dependence and heterogeneity. When combined with GIS-based accessibility metrics, these techniques allow researchers to quantify how sidewalk continuity, cycling-network density, intersection safety, and transit interconnectivity shape active travel outcomes across heterogeneous urban landscapes. This integration also supports the evaluation of equity implications, revealing whether marginalized communities face disproportionate barriers to safe, connected, and sustainable mobility infrastructure. By linking spatially explicit infrastructure supply with observed or forecasted demand, GIS-integrated spatial econometrics enables planners to identify high-impact investment zones, prioritize low-access neighborhoods, and assess long-term sustainability benefits. Ultimately, this modeling approach moves beyond traditional mobility analyses by providing a multidimensional view of accessibility, environmental performance, and social fairness. It equips decision-makers with a data-driven foundation to design resilient, inclusive, and future-oriented active transportation systems that align with broader urban sustainability goals.

Keywords: Active transportation; GIS; spatial econometrics; accessibility modeling; sustainable mobility; urban equity

1. INTRODUCTION

1.1 Urban Mobility Transitions and the Rise of Active Transportation

Cities worldwide are undergoing major mobility transitions driven by environmental pressures, congestion, public-health priorities, and evolving expectations for urban livability [1]. Active transportation walking, cycling, micromobility, and emerging hybrid modes has accelerated as governments seek low-carbon mobility systems that reduce emissions, reclaim street space, and promote healthier communities. As populations grow denser and vehicle ownership patterns shift, many urban residents increasingly demand transport systems that are flexible, multimodal, and accessible. These transitions are also propelled by rising concerns over air quality, particularly in high-density neighborhoods disproportionately burdened by vehicular pollution [2]. In parallel, rapid expansion of cycling infrastructure, pedestrian corridors, and integrated public-transport networks reflects a strategic reorientation toward sustainable mobility planning.

Economic incentives play a significant role as well: cities invest in active transportation because these modes lower long-term infrastructure costs, reduce roadway maintenance burdens, and generate positive externalities across public-health and environmental domains [3]. Technological adoption such as shared bike fleets, e-scooter systems, and mobile navigation platforms has further normalized non-automotive travel, making mode switching more seamless and socially accepted [4]. However, as active transportation diversifies and increases in scale, understanding the spatial dynamics behind adoption, access, and behavior becomes more challenging. Travel flows no longer follow traditional peak-hour patterns, and multimodal interactions create layered mobility networks shaped by micro-geographies, land-use characteristics, and socioeconomic conditions [5]. Such complexity highlights the need for analytical tools capable of representing heterogeneous movement at high spatial resolution. Ultimately, urban mobility transitions are reshaping how cities conceptualize both transportation infrastructure and resident behavior, prompting a re-examination of planning frameworks built around automobiles rather than people-centered mobility principles [6].

1.2 Limitations of Traditional Mobility Modeling and the Spatial Challenge

Traditional mobility models—trip-generation tools, gravity models, and aggregate travel-demand forecasting frameworks—struggle to capture the emerging complexity of active transportation networks [7]. These models were designed for automotive flow prediction, relying on assumptions of linear travel behavior, uniform accessibility, and homogenous spatial interactions. Active transportation, however, behaves non-linearly: route choice depends on micro-scale attributes such as street quality, safety perception, shading, gradient, and proximity to amenities, which conventional models often treat as exogenous or irrelevant [2]. As a result, predictions become inaccurate when applied to multimodal environments where local context heavily influences mobility decisions.

Another limitation lies in spatial aggregation. Traditional models frequently operate at coarse geographic units—traffic analysis zones or census tracts—masking neighborhood-level heterogeneity and obscuring local constraints such as sidewalk discontinuities, cycling-infrastructure gaps, and intersection-level safety risks [8]. This aggregation problem is especially problematic for active transportation flows that vary block-by-block based on micro-infrastructure and land-use attractors. Additionally, legacy models rarely incorporate real-time or high-frequency datasets such as GPS traces, sensor-derived pedestrian counts, or micromobility telemetry, which now provide unprecedented spatial precision [9].

Traditional methodologies also assume independence among spatial units, whereas mobility data inherently exhibits spatial autocorrelation—nearby locations influence each other. For example, installing a bike lane in one corridor may shift flows in adjacent neighborhoods or change demand distribution across a broader network. Without spatially explicit modeling, these interdependencies remain invisible. Moreover, classical models often inadequately represent socio-spatial inequities, failing to capture disparities in access, safety, infrastructure quality, and affordability that shape who can participate in active mobility systems [10]. These shortcomings reveal methodological gaps that hinder accurate mobility planning and limit the ability of cities to design equitable transportation systems that reflect real-world spatial dynamics.

1.3 The Need for GIS-Integrated Spatial Econometric Approaches

As urban mobility becomes increasingly multimodal and spatially heterogeneous, GIS-integrated spatial econometric methods provide a more rigorous foundation for analyzing movement patterns and infrastructure interactions [3]. Unlike traditional models, spatial econometrics explicitly incorporates spatial dependence, spatial heterogeneity, and diffusion effects central elements of active transportation behavior that cannot be ignored. By leveraging GIS layers on land use, infrastructure quality, topology, and demographic distribution, analysts can construct models that reflect how environmental context shapes mobility outcomes [4]. This integration allows for detailed investigation into how proximity to cycling lanes, transit stops, retail clusters, or green corridors influences route choice and trip frequency.

Spatial lag and spatial error models help quantify spillover effects, demonstrating how infrastructure in one location affects mobility outcomes elsewhere [7]. This is critical for active transportation networks, where interventions such as protected bike lanes or pedestrian plazas can create ripple effects across surrounding streets and districts. Spatial Durbin models extend this by capturing both direct and indirect effects, enabling policymakers to evaluate full network impacts rather than isolated site improvements [1]. GIS-enabled econometric analysis also supports identification of spatial clusters areas of over- or under-utilization helping planners prioritize investments and address inequitable access.

The growing availability of fine-grained mobility datasets strengthens the capacity of these tools. GPS traces, smartphone mobility logs, crowdsourced cycling data, pedestrian counters, and micromobility fleet telemetry offer unprecedented spatial accuracy, making spatial econometrics even more powerful [8]. When combined with GIS-based micro-infrastructure mapping, these data streams allow planners to detect localized constraints such as conflict zones, surface defects, or infrastructural discontinuities that significantly influence active transportation uptake. Overall, GIS-integrated spatial econometric approaches bridge the gap between empirical evidence and spatial reality, offering a methodological foundation suited for contemporary mobility transitions [6].

2. CONCEPTUAL AND THEORETICAL FOUNDATIONS

2.1 Socio-Behavioral and Built-Environment Determinants of Active Travel

Active travel patterns walking, cycling, and micromobility emerge from an interplay between human behavior, environmental conditions, and socio-spatial context. Unlike motorized travel, which is strongly influenced by network speed and vehicular capacity, active mobility decisions depend on perceived safety, streetscape comfort, and accessibility of destinations within manageable physical distance [7]. Built-environment configurations shape how easily residents can integrate walking or cycling into daily routines, while behavioral determinants influence whether individuals feel motivated, confident, or socially supported to choose non-motorized modes. Land-use diversity, housing density, sidewalk connectivity, and traffic-calming measures create environmental affordances that reduce travel friction and encourage active mode substitution [8]. At the same time, demographic and socioeconomic conditions income, gender, age, and cultural attitudes affect exposure to mobility barriers and incentives.

Temporal patterns also matter: individuals respond to daily rhythms, climate variations, and seasonal shifts, creating fluctuating mobility intensities across time and space [9].

International Journal of Computer Applications Technology and Research
Volume 14–Issue 12, 01 – 15, 2025, ISSN:-2319–8656
DOI:10.7753/IJCATR1412.1001

High granular variability makes active travel especially sensitive to micro-scale influences, such as block-level safety perception, shading, noise exposure, and infrastructure continuity. A single barrier an unsafe intersection, sidewalk discontinuity, or missing bike-lane segment can disrupt likely routes, suppress demand, and shift travel away from active modes [10]. Additionally, social norms and lifestyle preferences shape long-term patterns, influencing whether cycling or walking becomes habitual. Thus, active travel cannot be modeled solely through physical distance or infrastructure presence; it requires frameworks that blend environmental constraints with behavioral complexity.

2.1.1 Built Environment, Land-Use Mix, and Urban Form Drivers

The built environment serves as a structural determinant of active travel by influencing the practicality and attractiveness of walking or cycling options. Dense, mixed-use neighborhoods create shorter trip distances and support multi-purpose travel chains that favor non-motorized modes [11]. Fine-grained street networks enhance route choice flexibility, while continuous sidewalks, protected bike lanes, and pedestrian-priority corridors reduce exposure to vehicular risk. Urban form configurations block size, intersection density, and transit adjacency shape movement patterns by defining permeability and accessibility across spatial units [12]. High land-use mix and clustered amenities strengthen local connectivity, making active travel competitive with motorized alternatives for daily tasks such as shopping, dining, or commuting. Conversely, sprawled environments impose long trip distances, segregated land use, and car-oriented street hierarchies, all of which constrain active mode adoption. These structural drivers create spatially uneven mobility opportunities that must be evaluated holistically when analyzing active transportation outcomes.

2.1.2 Behavioral, Demographic, and Temporal Factors

Behavioral and demographic variables significantly influence active travel decisions, interacting with environmental affordances to shape mobility patterns. Personal preferences, health motivations, and risk tolerance affect likelihood of choosing active modes, while perceptions of safety especially concerning traffic exposure, lighting, and crime strongly impact participation rates [13]. Demographic factors such as age, gender, income, and household structure shape mobility constraints and access to supportive infrastructure. Youth and elderly populations may face vulnerability risks, whereas higher-income groups may access personal micromobility devices or reside in more walkable neighborhoods. Temporal factors further complicate modeling: weather conditions, seasonal daylight changes, and time-of-day variations lead to pronounced fluctuations in pedestrian and cycling activity [14]. Behavioral inertia also affects adoption; repeated positive experiences can normalize active travel, whereas negative encounters can discourage long-term use. Understanding these interacting components is essential for modeling demand with fidelity.

2.2 Spatial Dependence, Spillovers, and Urban Mobility Networks

Active transportation networks inherently exhibit spatial dependence: conditions in one location influence behavior in adjacent areas, creating patterns that spread across neighborhoods and districts [15]. When a new bike lane or pedestrian plaza is installed, usage effects ripple through nearby corridors, shifting route choices and altering local accessibility dynamics. These spillover effects challenge traditional modeling assumptions of independent spatial units. Instead, mobility decisions are shaped by interconnected street networks, land-use clusters, and geographic proximity. Spatial autocorrelation emerges when high- or low-activity zones cluster together, reflecting shared environmental attributes such as mixed-use density or traffic calming within contiguous areas [9]. Network connectivity further amplifies spatial effects by structuring how movement flows distribute across corridors, intersections, and micro-geographies.

Spatial heterogeneity is equally important: neighborhoods differ in socioeconomic composition, infrastructure quality, and cultural norms, producing location-specific mobility signatures. Ignoring spatial dependence oversimplifies active travel behavior, particularly in multimodal environments where infrastructure investments reshape mobility opportunities non-linearly. Spatial spillovers also influence equity outcomes because improvements in one area may benefit or disadvantage populations in adjacent neighborhoods depending on connectivity and accessibility interactions [16]. Traditional regression approaches without spatial terms fail to capture these cross-boundary influences, underestimating or mischaracterizing the impact of built-environment interventions.

Network characteristics centrality, betweenness, and edge density shape route choice and determine how resilient mobility pathways are to disruptions. Active transportation relies heavily on micro-scale connectivity; missing links or hazardous intersections can disproportionately suppress demand across multiple blocks. As networks become increasingly integrated with micromobility systems and emerging transport modes, spatial dependence intensifies, demanding analytical frameworks that explicitly incorporate both direct and indirect spatial effects [10].

2.3 Gaps in Traditional Regression Approaches for Transportation Planning

Classical regression methods ordinary least squares and standard multivariate models are limited in their ability to capture spatial complexity because they assume independence among observations and treat spatial effects as noise rather than structure [7]. This poses significant challenges in urban mobility analysis, where spatial autocorrelation is intrinsic to movement patterns. When spatial relationships are ignored, estimates of built-environment impacts become biased and inefficient, leading planners to misinterpret causal mechanisms. Traditional frameworks also struggle with multicollinearity triggered by spatial clustering for example, dense areas often co-locate with mixed-use districts and high pedestrian activity, making it difficult to disentangle individual effects without spatial controls [12].

Another gap involves scale sensitivity. Standard models often rely on large administrative units census tracts or zones that mask micro-scale variation crucial for active travel. Aggregation error becomes substantial in contexts where a single unsafe intersection or infrastructure discontinuity disrupts pedestrian or cycling flow [17]. Moreover, classical approaches inadequately represent network structure; they do not account for how spatial connectivity, route alternatives, or proximity to key nodes influence demand.

Traditional models also lack mechanisms to capture spillover dynamics. For instance, an improvement in one corridor may increase cycling activity in adjacent blocks due to safer or more direct routing options, but standard regressions cannot quantify such indirect effects. As cities incorporate real-time mobility data GPS traces, sensor counts, micromobility telemetry the shortcomings of traditional statistical methods become more evident, underscoring the need for spatially explicit modeling frameworks that capture geographic context, network relationships, and spatial dependency structures.

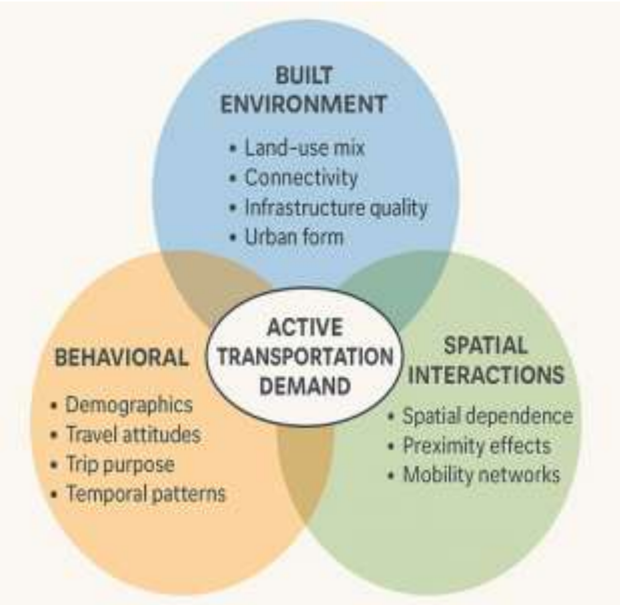

Figure 1: Conceptual Framework Connecting Behavioral, Environmental, and Spatial Drivers of Active Transportation Demand**.**

3. GIS FOUNDATIONS FOR ACTIVE TRANSPORTATION MODELING

3.1 Key GIS Data Sources and Spatial Layers

GIS provides the foundational spatial architecture required to interpret, model, and visualize active transportation systems, enabling analysts to integrate infrastructure, demographic, environmental, and behavioral datasets into unified analytical frameworks [14]. Because active mobility patterns emerge from complex relationships between built environments, user characteristics, and local geography, GIS layers serve as the structural backbone that transforms raw spatial inputs into meaningful analytical units. These layers support the interpretation of micro-scale access barriers, multimodal interactions, and route-level decision processes that would be invisible using non-spatial datasets [15]. Moreover, GIS datasets reveal geographic disparities in access, allowing planners to identify underserved neighborhoods where safety hazards, infrastructure gaps, or environmental burdens constrain active travel activity [16]. Network layers, land-use grids, census surfaces, and environmental indices collectively provide a multiscalar perspective that aligns with how travel behavior unfolds in real urban contexts [17].

GIS data sources also serve as preprocessing tools for advanced econometric modeling, providing derived features distance buffers, connectivity indices, slope gradients, network impedance measures that shape how statistical relationships are interpreted. Because active travel is highly sensitive to spatial context, incorporating diverse GIS layers enriches explanatory detail and improves the robustness of downstream modeling frameworks [18]. Additionally, GIS enables scenario testing by simulating changes in infrastructure conditions, land-use configuration, and network geometry to anticipate mobility impacts under alternative planning interventions [19]. Each dataset contributes unique analytical value and supports evaluations that integrate physical, social, and ecological determinants essential for accurate modeling of non-motorized mobility [20]. Ultimately, leveraging multi-layer GIS data ensures that analytical efforts reflect the full spatial complexity underlying active transportation systems [21].

3.1.1 Multimodal Infrastructure Networks

Multimodal infrastructure layers represent the core structural conditions governing how pedestrians, cyclists, and micromobility users navigate urban environments [22]. These GIS datasets typically include sidewalk inventories, bike-lane classifications, shared-use paths, street centerlines, transit stop nodes, and intersection geometries. Together, they define the operational envelope within which active travelers form route preferences. Network topology intersection density, link lengths, surface conditions, and connectivity directly influences perceived safety, travel time, and comfort [14]. GIS also captures micro-infrastructure features such as curb ramps, pedestrian islands, shade structures, and conflict zones, which are critical for high-fidelity modeling. Importantly, multimodal layers support computation of network-based distances rather than Euclidean approximations, enabling realistic accessibility and impedance calculations [16]. Including these layers ensures that spatial models properly reflect how infrastructure constraints shape route choice and trip feasibility.

3.1.2 Demographic, Land-Use, and Environmental Layers

Demographic, land-use, and environmental datasets enrich modeling by embedding social and ecological context within spatial frameworks [17]. Census-derived layers capture socioeconomic profiles income, age, gender composition, car-ownership rates that influence active travel likelihood. Land-use layers provide information on residential density, commercial clusters, institutional anchors, and mixed-use intensity, enabling precise mapping of trip origins and destinations [18]. Environmental datasets add further nuance, incorporating variables such as greenness indices, air-quality burdens, heat-exposure gradients, terrain slope, and noise levels, all of which meaningfully influence walking and cycling behavior [20]. These layers also help identify spatial inequities, highlighting areas where hazardous environmental conditions or limited infrastructure limit safe active mobility opportunities [23]. Integrating these contextual layers ensures that econometric modeling captures multi-dimensional influences on travel behavior.

3.2 Accessibility and Network-Distance Modeling Techniques

Accessibility modeling lies at the center of GIS-based mobility analysis, linking infrastructure availability with the opportunities individuals can reach within reasonable time or effort thresholds [15]. Unlike motorized accessibility frameworks that emphasize speed and regional connectivity, active transportation models rely heavily on local-scale network conditions block lengths, intersection quality, grade changes, and path continuity all of which determine perceived and actual accessibility [19]. Network-distance metrics computed using GIS capture realistic travel paths that reflect existing sidewalk, trail, and cycle-lane structures instead of relying on straight-line distances, which significantly underestimate travel effort for active modes [22].

Techniques such as service-area polygons, buffer rings, isochrone modeling, and shortest-path analysis allow analysts to quantify reachability to workplaces, schools, transit hubs, parks, and commercial amenities [21]. These methods illuminate spatial mismatches between where active travel demand exists and where infrastructure remains insufficient. Accessibility indices can also be weighted by demographic vulnerability factors, environmental burdens, or slope-based effort indices to assess equity-sensitive accessibility patterns.

Network-based impedance modeling captures friction elements steep grades, unsafe intersections, missing links, and high-traffic conditions that suppress active mode choice [17]. In addition, multi-criteria accessibility metrics integrate land-use mix, pathway quality, and perceived safety proxies to evaluate spatial suitability for non-motorized mobility. Advanced methods incorporate probabilistic route-choice models and activity-space estimation, enabling more behaviorally grounded representations of travel patterns.

GIS-based accessibility models also support scenario evaluation, testing how new bike lanes, pedestrian corridors, or traffic-calming redesigns alter mobility reach. Because accessibility is both a spatial and behavioral construct, GIS plays a crucial role in translating abstract planning decisions into spatially explicit outcomes grounded in real-world geographic constraints [24]. Ultimately, accessibility and network-distance modeling provide the analytical link between infrastructure conditions and the behavioral likelihood of active transportation uptake.

3.3 Geoprocessing, Spatial Joins, and Feature Engineering for Econometric Modeling

Geoprocessing operations serve as the analytical engine that transforms raw GIS layers into structured inputs for spatial econometric models. Processes such as buffering, clipping, dissolving, and intersecting allow analysts to shape spatial datasets into operational units aligned with modeling requirements [16]. Spatial joins connect point- or line-based features such as crash locations, bike counters, or micromobility trip origins with polygon layers such as neighborhoods or census blocks, enabling aggregation of spatial events into statistical units [18]. These operations reduce noise, reveal spatial patterns, and ensure consistent attribution across heterogeneous data sources.

Feature engineering extends these processes by generating derived variables that represent complex spatial phenomena. Examples include intersection density metrics, land-use entropy scores, sidewalk continuity indices, slope-adjusted travel-cost surfaces, and exposure measures to traffic volume or pollution hotspots [20]. Such engineered features strengthen explanatory power by capturing spatial mechanisms that directly influence active travel. Spatial lag features and contiguity matrices further position datasets for spatial econometric analysis, embedding neighborhood effects and adjacency relationships essential for modeling spatial dependence [23].

Geoprocessing workflows also enable multi-scale analysis by reprojecting or aggregating layers to different spatial granularities, ensuring that model specifications reflect the appropriate level of geographic detail. Data cleaning and topological correction removing gaps, overlaps, and invalid geometries ensure statistical validity and improve computational stability [14]. Ultimately, geoprocessing and spatial feature engineering bridge the gap between raw GIS datasets and rigorous analytical modeling, enabling the development of spatially informed econometric frameworks that reflect real-world mobility dynamics [19].

Table 1: Primary GIS Datasets Used in Active Transportation Modeling and Their Analytical Contribution

GIS Dataset Category	Example Data Layers	Analytical Contribution to Active Transportation Modeling
Multimodal Infrastructure Networks	Street centerlines, sidewalk inventories, bike-lane classifications,	Defines the physical mobility network; enables network-distance modelling,

International Journal of Computer Applications Technology and Research
Volume 14–Issue 12, 01 – 15, 2025, ISSN:-2319–8656
DOI:10.7753/IJCATR1412.1001

GIS Dataset Category	Example Data Layers	Analytical Contribution to Active Transportation Modeling
	trail networks, intersection geometry, transit-stop locations	isochrone generation, impedance calculations, route-choice modeling, identification of missing links, and evaluation of connectivity patterns.
Land-Use and Urban Form Data	Zoning layers, parcel data, land-use mix indices, building footprints, employment density, residential density	Supports accessibility modeling, trip-generation estimation, origin–destination mapping, and the identification of areas with high latent demand for active travel; essential for capturing structural determinants of walking and cycling.
Demographic and Socioeconomic Data	Census blocks, population density, income, age distribution, car-ownership rates, educational attainment	Allows equity analysis, demographic-weighted accessibility scoring, vulnerability assessment, and modeling behavioral differences across socio-spatial groups.
Environmental and Terrain Data	Elevation and slope models, vegetation/green space layers, air-quality surfaces, noise exposure, urban heat island indices	Used to estimate physical effort for walking and cycling, environmental stressors, exposure risks, and the relationship between environmental conditions and active mobility uptake.
Safety and Traffic Data	Pedestrian/cyclist crash hotspots, traffic volumes, speed profiles, conflict zones, signal timing	Enables modeling of safety-driven deterrence, intersection-level risk analysis, and safety-weighted accessibility; essential for understanding behavioral suppression and infrastructure
		vulnerability.
Mobility Behavior and Trip Data	GPS traces, micromobility trip logs, pedestrian counters, cycling sensor data, smartphone mobility data	Supports route-choice modeling, temporal activity profiling, calibration of econometric models, and validation of accessibility outputs with real-world behavior.
Urban Amenities and Service Points	Schools, healthcare, retail, transit hubs, parks, community facilities	Allows catchment modeling, destination accessibility evaluation, and scenario testing of network modifications on access to essential services.

4. SPATIAL ECONOMETRIC MODELING FRAMEWORK

4.1 Spatial Autocorrelation in Active Mobility Behavior

Spatial autocorrelation is a foundational concept in active mobility analysis because walking and cycling behaviors rarely occur independently across space. Instead, they cluster in patterned ways, influenced by built-environment similarities, shared socioeconomic attributes, and interconnected infrastructures that create correlated behavior among nearby geographic units [22]. In practice, this means that a neighborhood with high active-travel uptake often influences adjacent neighborhoods, not only through direct physical connectivity but also through indirect behavioral cues perception of safety, social norms, and visible infrastructure quality. As a result, observed mobility outcomes typically depart from the assumption of independent observations, a core limitation of traditional regression models.

Positive spatial autocorrelation occurs when high-usage areas are spatially clustered, often due to dense, mixed-use corridors, well-connected cycling infrastructure, and transit-adjacent networks [23]. Conversely, negative autocorrelation may emerge in fragmented environments where barrier major roadways, unsafe intersections, or environmental hazards disrupt spatial continuity, leading to isolated pockets of active travel. Global Moran's I and Local Indicators of Spatial Association (LISA) are widely used to quantify these patterns, revealing statistically significant mobility clusters at various scales [24].

In active transportation planning, ignoring spatial autocorrelation can introduce bias, underestimate spillover effects, and distort interpretations of built-environment variables. For example, adding a protected bike lane may not only increase cycling volume on the immediate street but also influence parallel routes, feeding into a wider spatial propagation process. Furthermore, socio-demographic variables income, vehicle access, educational attainment often cluster spatially, reinforcing underlying spatial dependence in mobility behavior [25]. Recognizing autocorrelation is therefore essential for selecting appropriate econometric tools and ensuring that model residuals reflect true randomness rather than unaccounted spatial structure. Spatial autocorrelation ultimately signals that mobility behavior must be interpreted through the lens of spatial relationships rather than isolated geographic units [26].

4.2 Global Spatial Models (SAR, SEM, SDM) for Mobility Demand

Global spatial econometric models address the challenges posed by spatial dependence by explicitly incorporating geographic relationships into model structures. These models Spatial Autoregressive (SAR), Spatial Error (SEM), and Spatial Durbin Models (SDM) offer distinct ways of representing how mobility outcomes propagate across space [27]. Each model responds to different theoretical assumptions about mobility behavior, network spillovers, and the role of unobserved spatial processes.

SAR models incorporate a spatially lagged dependent variable, capturing direct behavioral spillovers across locations. SEM models instead absorb spatial dependence into the error term, isolating unmeasured but spatially structured influences such as cultural norms or infrastructure maintenance variability. SDM, a generalization of SAR, includes spatially lagged independent variables to account for indirect spillovers caused by built-environment conditions in neighboring areas [22]. These distinctions are crucial because active transportation often involves both behavioral propagation and infrastructural interdependencies.

Spatial weights matrices based on contiguity, distance bands, or network topology define the channels through which influence travels. In active mobility, network-based weights are increasingly favored over Euclidean alternatives because travel occurs along sidewalks, intersections, and bike corridors rather than straight-line distances [28]. Model performance and interpretation are highly sensitive to these weight choices.

Global spatial models improve estimation accuracy by addressing multicollinearity resulting from spatial clustering and correcting biases caused by omitted spatial relationships. They are particularly useful in evaluating policy interventions, such as the introduction of micromobility lanes or pedestrianization of central districts, because they estimate how these interventions reshape both local and regional travel demand. Moreover, SDM models capture both direct effects (e.g., a new bike lane increasing usage locally) and indirect effects (e.g., increased usage on adjacent streets), offering a more comprehensive understanding of mobility systems [29].

Global models also support scenario testing, enabling planners to evaluate hypothetical interventions at the citywide scale. For example, the predicted impact of new cycling corridors can be simulated by adjusting built-environment variables and assessing how changes propagate spatially. In the context of climate goals, equity planning, and sustainable mobility transitions, global spatial models provide indispensable tools for understanding how transportation behaviors evolve across spatial networks [30].

4.2.1 Modeling Behavioral Spillovers Using SAR

SAR models are specifically designed to represent behavioral spillovers situations where active-travel decisions in one area influence behaviors in adjoining neighborhoods. In mobility systems, these spillovers emerge from visual cues, infrastructure continuity, perceived safety gradients, and network connectivity [25]. By incorporating a spatial lag of the dependent variable, SAR models quantify how changes in cycling or walking volume in one location propagate across the broader network.

For example, constructing a protected bike corridor on a major street may encourage cycling in nearby residential blocks by increasing perceived safety and reducing route impedance. SAR models capture these dynamics through the spatial autoregressive coefficient, which measures the strength of interdependence. A high coefficient suggests strong cross-boundary feedback, indicating that interventions must be evaluated at a regional rather than corridor-level scale [27].

SAR is particularly useful for understanding mode-shift dynamics how increases in active travel in one area encourage neighboring shifts away from car dependency. It is also effective in representing “network diffusion,” where new infrastructure induces adoption waves across adjacent links. Importantly, SAR models highlight that mobility outcomes often cannot be attributed to local characteristics alone; instead, spatial context fundamentally conditions behavior [28].

4.2.2 Handling Unobserved Spatial Effects Using SEM

SEM models focus on capturing spatial dependence that arises not from behavioral spillovers but from unobserved contextual factors that cluster geographically. These latent influences may include enforcement practices, neighborhood culture, political priorities, or small-scale infrastructure deficiencies that are not directly measured but influence active travel behavior [24]. The model incorporates a spatially autocorrelated error term, allowing these hidden processes to be absorbed into the estimation rather than contaminating coefficient interpretations.

SEM is particularly valuable when datasets lack complete built-environment detail or when behavioral variables are difficult to measure. For example, perceived neighborhood safety or informal pedestrian paths may influence behavior but remain unrecorded in GIS layers. SEM corrects for the resulting bias by modeling spatial dependence in the residual structure [22].

In the context of performance evaluation, SEM helps determine whether observed improvements in mobility result from interventions or broader unobserved trends. Because many urban environments display systematic clustering affluent districts with superior infrastructure, marginalized neighborhoods facing structural barriers the SEM framework ensures that these patterns do not distort key relationships. SEM thereby enhances the credibility of policy evaluations and provides a more realistic interpretation of model coefficients, especially in data-limited settings [26].

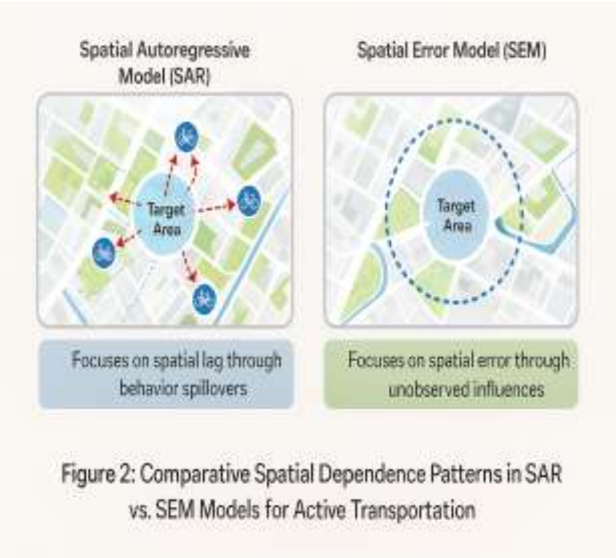

Figure 2: Comparative Spatial Dependence Patterns in SAR vs. SEM Models for Active Transportation.

4.3 Local Spatial Models: GWR and MGWR for Neighborhood-Sensitive Analysis

While global models assume relationships remain constant across space, local spatial models challenge this assumption by allowing coefficients to vary geographically. Geographically Weighted Regression (GWR) captures how built-environment characteristics influence mobility differently across neighborhoods by estimating a separate regression equation for each location [23]. This is particularly important in active transportation research because local street quality, demographic composition, and urban form characteristics vary substantially across short distances.

GWR reveals spatial heterogeneity in relationships such as how density influences walking more strongly in compact urban centers than in suburban corridors. By mapping coefficient surfaces, planners can identify high-sensitivity zones where policy interventions bike lanes, pedestrian safety improvements, transit-oriented development would have the greatest impact [29]. However, traditional GWR assumes a single bandwidth across all variables, potentially oversimplifying conditions where some predictors exert localized effects (e.g., intersection quality) while others operate at broader scales (e.g., land-use mix).

Multiscale GWR (MGWR) resolves this limitation by assigning different spatial scales to different variables, allowing more nuanced interpretation of mobility determinants [30]. MGWR is therefore better suited for understanding complex, layered mobility systems where behavioral responses operate across multiple spatial ranges. Both GWR and MGWR offer powerful tools for identifying equity gaps, highlighting neighborhoods where infrastructure shortcomings disproportionately constrain mobility choices [22]. Compared to global models, local frameworks deepen insights into how active travel responds to spatial heterogeneity, enabling geographically targeted interventions.

4.4 Diagnostics, Model Specification, and Validation Tools

Robust spatial econometric analysis requires diagnostics that validate model assumptions and ensure correct specification. Tests such as Moran's I on residuals verify whether spatial autocorrelation remains after model fitting, signaling whether SAR, SEM, or SDM structures were appropriate [27]. Lagrange Multiplier tests help select between SAR and SEM specifications by detecting the dominant spatial process spillovers or unobserved clustering. Variance inflation checks address multicollinearity often amplified by spatial clustering [24]. Out-of-sample validation and cross-validation strengthen model reliability, particularly for GWR and MGWR models sensitive to bandwidth selection. Diagnostics ultimately ensure credible inference in mobility research [28].

5. EVALUATION OF ACCESSIBILITY, SUSTAINABILITY, AND EQUITY

5.1 Accessibility Metrics Derived from GIS–Econometric Integration

Accessibility metrics derived from GIS–econometric integration provide a quantitative foundation for evaluating how easily residents can reach essential destinations workplaces, schools, transit stops, grocery stores, healthcare facilities, and recreational amenities using active transportation modes [28]. Unlike purely GIS-based accessibility mapping, GIS–econometric integration incorporates behavioral and spatial-dependence effects, producing accessibility measures that better reflect real-world route choice behavior, infrastructure quality, and socio-spatial constraints. Traditional accessibility frameworks often rely on simplified distance measures or coarse buffer rings; however, active travel requires fine-grained network-level assessments that incorporate slope, safety hazards, shading, intersection complexity, and land-use heterogeneity [29].

By integrating econometric models SAR, SEM, SDM, or MGWR accessibility scores can incorporate both local and neighboring influences. For instance, if adjacent neighborhoods benefit from high-quality bike lanes or pedestrian corridors, spatial spillover terms can elevate accessibility potential even in zones lacking their own infrastructure [30]. This blended approach helps identify "latent accessibility," which emerges from regional network strength rather than only local amenities. Additionally, GIS features such as isochrones, network-impedance layers, micro-infrastructure attributes, and demographic weighting functions allow for multidimensional accessibility indicators that reflect physical, social, and safety conditions.

Integrated accessibility metrics also support system-wide scenario modeling. Analysts can test how interventions like new protected bike lanes, wider sidewalks, or traffic-calming measures change not just local access but regional mobility ecosystems [31]. These tools help identify where marginal improvements yield the greatest accessibility gains, especially in corridors that exhibit strong spatial autocorrelation and demand clustering [32]. In sum, GIS–econometric accessibility indicators combine spatial realism with behavioral insight, offering a more accurate representation of how residents experience urban mobility systems.

5.1.1 Network-Distance, Time-Cost, and Intersection Safety Accessibility

Network-distance accessibility metrics measure the true travel effort along pedestrian and cycling networks rather than simplistic straight-line paths. GIS-derived network distances incorporate turn penalties, intersection delay, road hierarchy, surface quality, and slope gradients that significantly influence travel friction [33]. Time-cost accessibility builds on this by estimating expected travel time incorporating traffic signals, crosswalk delays, or cycling-speed adjustments based on gradient. Time-based metrics capture user-centered convenience more effectively than spatial distances alone.

Intersection-safety accessibility evaluates exposure to hazardous crossings, vehicle conflict points, or substandard pedestrian infrastructure. By encoding crash hotspots, lighting quality, and traffic-calming elements into accessibility scores, planners can understand how safety risks suppress active mobility participation [28]. These metrics, when integrated into econometric models, help identify safety-driven spatial inequities.

5.1.2 Catchment Modeling and Distance-Decay Effects

Catchment models estimate how far individuals are likely to walk or cycle to reach specific amenities or transit nodes, capturing the realistic behavioral limits of active mobility [29]. Walking catchments often range between 400–800 meters, while cycling catchments may extend several kilometers depending on infrastructure quality and trip purpose. GIS tools generate catchments using isochrone surfaces derived from network-speed assumptions, barriers, and route impedances.

Distance-decay functions describe how the likelihood of choosing active travel decreases with travel distance or time. Integrating decay curves into econometric models ensures behavioral realism by weighting accessibility more strongly near destinations and attenuating influence as distance grows [34]. This is especially important for modeling school travel, transit access, shopping trips, and social amenities.

5.2 Sustainability Indicators in Active Mobility Systems

Active mobility has become a central component of urban sustainability strategies due to its capacity to reduce emissions, improve public health, and lower energy demand across transport systems. GIS–econometric sustainability indicators evaluate how mobility behavior interacts with environmental and health outcomes at both local and regional scales [30]. When integrated into spatial econometric frameworks, these indicators reveal how infrastructure supply, land-use patterns, and neighborhood characteristics shape sustainability performance across heterogeneous environments [31]. Indicators such as emissions avoided, particulate matter exposure reduced, energy efficiency gains, and physical-activity uplift allow for a multi-dimensional sustainability assessment that aligns with broader climate-action and public-health goals.

Sustainability indicators derived from GIS data make it possible to map spatial disparities in environmental burdens or health vulnerabilities. Neighborhoods lacking safe pedestrian infrastructure or suffering from poor air quality often experience compounded disadvantages that suppress active travel adoption. Incorporating spatial dependence terms helps quantify how nearby environmental conditions influence sustainability outcomes, capturing ripple effects as mobility behaviors shift between adjacent areas [28]. By connecting mobility changes to environmental and health outcomes, GIS–econometric tools help cities evaluate not just mobility shifts but their broader sustainability consequences.

5.2.1 Environmental Impacts: Emissions, Air Quality, and Energy Efficiency

GIS–econometric models allow emissions reductions to be estimated by modeling active-travel substitution effects, evaluating how walking or cycling replaces short-distance car trips and reduces VMT (vehicle miles traveled) [33]. Reductions in CO_2, NO_2, and $PM_{2.5}$ can be computed spatially, highlighting where environmental benefits are maximized. Air-quality indicators integrate pollutant exposure surfaces, enabling assessment of how improved mobility infrastructure reduces population-weighted exposure to harmful emissions.

Energy-efficiency indicators quantify modal shift impacts, measuring reductions in fuel consumption and improvements in per-capita transport energy use. Spatial models incorporate local spillovers, recognizing that improvements in one corridor can influence emissions patterns in adjacent neighborhoods due to traffic re-routing or increased cycling uptake [34].

5.2.2 Public-Health, Safety, and Activity-Level Indicators

Public-health indicators evaluate how active travel patterns influence physical-activity levels, obesity prevalence, cardiovascular risk, and respiratory burden. GIS-based exposure models combine sidewalk availability, greenness, and air-quality surfaces to quantify how environmental conditions support or hinder health-positive mobility [29]. Safety indicators track crash risk, near-miss encounters, and conflict-zone exposure, using spatial regressions to examine how changes in infrastructure reduce injuries and fatalities [31].

Activity-level indicators measure how infrastructure improvements alter walking and cycling duration across demographic groups, highlighting where gains are equitable or uneven. GIS–econometric models improve these assessments by controlling for spatial dependence, capturing whether health benefits cluster or disperse across neighborhoods [35].

5.3 Equity Assessment Across Socio-Spatial Groups

Equity assessment examines how mobility benefits and burdens are distributed among different socio-spatial groups. GIS–econometric tools support equity analysis by identifying underserved communities, quantifying disparities, and isolating structural barriers that constrain active travel participation [30]. Because inequities often cluster spatially, spatial econometric techniques capture how disadvantage diffuses across adjacent neighborhoods or becomes reinforced by land-use and infrastructure patterns [28]. Equity assessments must therefore consider both local and regional influences.

GIS-based equity analysis uses demographic layers income, race, disability prevalence, age distribution and infrastructure quality metrics to evaluate whether active travel opportunities align with mobility needs. For example, low-income neighborhoods may exhibit high latent demand but lack safe cycling corridors or high-quality sidewalks. Spatial lag models help quantify how inequities in adjacent areas influence mobility conditions in target neighborhoods, such as spillover effects of infrastructure investment or deferred maintenance in nearby districts [32].

5.3.1 GIS-Based Identification of Underserved Zones

Identifying underserved zones involves mapping infrastructure gaps, environmental burdens, and demographic vulnerabilities. GIS tools flag areas with low sidewalk connectivity, missing bike lanes, high crash exposure, or long network distances to essential amenities [33]. Incorporating socio-demographic layers allows planners to identify compounded disadvantage areas where infrastructure constraints overlap with economic hardship or health vulnerabilities. Hotspot analysis and cluster detection tools reveal spatial concentrations of inequity.

Machine-learning-enhanced GIS layers can further classify underserved zones by combining built-environment, demographic, and environmental metrics. When integrated into econometric models, these classifications support targeted policy interventions to improve mobility access [29].

5.3.2 Spatial Econometric Equity Gap Modeling

Spatial econometric equity models quantify disparities by estimating how accessibility, safety, and environmental quality differ across neighborhoods after controlling for structural covariates [34]. Models such as SDM and SEM capture how inequities propagate across space revealing whether disadvantage is localized or diffuses into adjacent areas. GWR and MGWR further uncover spatial heterogeneity in equity drivers, highlighting neighborhoods where small infrastructure upgrades could yield substantial improvements.

These models help diagnose structural inequities such as persistent mobility deficits in marginalized communities or overlooked safety needs at corridor edges. By explicitly modeling spatial dependence, they ensure equity assessments capture both direct and indirect spatial processes influencing mobility opportunities [35].

Table 2: Accessibility, Sustainability, and Equity Indicators and Their Measurement Methods in GIS–Spatial Econometric Models

Indicator Category	Specific Indicators	GIS Measurement Methods	Spatial Econometric Contributions
Accessibility Indicators	• Network-distance accessibility • Time-cost accessibility • Intersection safety accessibility • Catchment-based access scores • Distance-decay weighted accessibility	• Network-distance computation using multimodal street/sidewalk/cycle networks • Isochrone modeling and service-area polygons • Safety overlays: crash hotspots, conflict zones, lighting quality • Buffering and catchment generation (400–800 m walking; 1–5 km cycling) • Travel-time surfaces incorporating slope and impedance	• Spatial lag effects show spillover-driven access improvements • SDM models capture indirect access impacts from adjacent neighborhoods • MGWR reveals scale-varying access relationships across local contexts • SEM controls for unobserved spatial factors influencing accessibility
Sustainability Indicators	**Environmental:** • Emissions avoided via mode shift	• Emissions modeling using mode-shift VMT reduction layers • Pollution and	• Spatial spillover modeling of environmental gains across

Indicator Category	Specific Indicators	GIS Measurement Methods	Spatial Econometric Contributions
	• Air-quality exposure reduction • Energy-efficiency improvements **Health & Safety:** • Physical activity uplift • Injury risk reductions • Exposure to hazards (heat, noise, pollution)	air-quality raster overlays • Heat island, noise, and environmental burden mapping • Pedestrian/cyclist crash mapping and safety layers • Greenness indices and walkability scores	districts • Spatial error models isolate unobserved environmental influences • MGWR reveals neighborhood-specific sustainability drivers • Spatial clustering identifies high- and low-benefit areas
Equity Indicators	• Distribution of accessibility scores across income groups • Infrastructure provision gaps across socio-spatial categories • Safety burden disparities • Exposure to environmental injustice zones • Spatial equity gap indices	• Demographic overlays (income, race, age, disability, car ownership) • Infrastructure gap mapping: sidewalk continuity, bike-lane density • Hotspot analysis for inequitable safety or environmental hazards • Vulnerability mapping with composite demographic-environment indices	• Spatial econometric equity-gap modeling using SDM/SEM • Local spatial models (GWR/MGWR) reveal spatial heterogeneity in inequities • Lag terms identify diffusion of disadvantage across boundaries • Equity scores corrected for spatial autocorrelation for unbiased assessment

6. POLICY APPLICATIONS, PLANNING TOOLS, AND FUTURE DIRECTIONS

6.1 Translating Model Outputs into Urban Planning Decisions

Spatial econometric and GIS-integrated models provide city planners with empirical clarity on how infrastructure, behavior, and environmental conditions interact across neighborhoods, enabling more data-driven planning decisions [32]. Rather than relying solely on descriptive mapping or intuition, planners can evaluate the magnitude, direction, and spatial diffusion of mobility relationships such as how intersection safety improvements influence walking uptake or how bike-lane installations reshape regional cycling volumes. These outputs reveal which spatial drivers matter most and where interventions will yield the strongest results. Importantly, they differentiate between localized effects and broader spillover patterns, allowing planners to assess whether improvements must occur in clusters or along corridor networks to achieve the desired mobility shift [33].

Model outputs also help determine infrastructure prioritization. When accessibility scores, spatial lag effects, and distance-decay patterns are layered together, cities can identify corridors where strategic investment will unlock significant network-wide benefits. Planners can compare alternative scenarios protected bike lanes, pedestrian plazas, speed-reduction zones to estimate which interventions maximize mobility gains given limited resources [34]. This ensures planning decisions are not only spatially explicit but also cost-efficient and performance-oriented.

Moreover, econometric diagnostics uncover structural inequities embedded in network design. If spatial models show that socio-demographic variables strongly predict limited active travel uptake even after accounting for infrastructure differences, planners can recognize the need for parallel non-infrastructure interventions such as safety programs or community engagement. By translating statistical relationships into spatial insights, model outputs help shift cities toward more evidence-based, equity-aware transportation planning [35]. Ultimately, these tools transform complex mobility behaviors into actionable guidance for zoning, budgeting, street design, and multimodal network expansion [36].

6.2 Designing Targeted Interventions for Low-Access Communities

GIS–econometric outputs identify low-access zones by analyzing patterns of accessibility deficits, safety risks, infrastructure gaps, and demographic vulnerability [37]. These results enable planners to design finely targeted interventions, aligning infrastructure improvements with the specific spatial, social, and behavioral barriers that limit mobility. For example, a community with strong latent cycling demand but high crash exposure may benefit more from protected bike lanes and traffic calming than from additional route density. Conversely, areas with poor sidewalk continuity may require micro-scale repairs, crosswalk upgrades, and ADA improvements before larger investments can be effective.

Spatial spillover modeling helps planners understand whether small-scale improvements within a low-access neighborhood will produce meaningful change or whether interventions must extend into adjacent areas for larger impact. Additionally, models capturing distance-decay effects reveal the geographic scale at which improvements must be delivered; for instance, pedestrian upgrades must often occur within a 400–800 meter radius to meaningfully influence walking rates [32].

Targeted interventions grounded in modeling outputs help cities allocate budgets more efficiently, ensuring resources are directed to communities where improvements can produce substantial access and equity benefits. Combining spatial and econometric evidence ensures that mobility interventions are both geographically precise and socially responsive [38].

6.3 Integrating Models into Governance and Long-Term Mobility Plans

Integrating spatial econometric modeling into governance frameworks ensures that mobility decisions remain consistent, transparent, and strategically aligned with long-term planning objectives [39]. Governance structures benefit from standardized modeling protocols embedded across city departments transportation, planning, sustainability, and public health. When models inform annual budgeting, capital investment cycles, and performance evaluations, cities maintain continuity even as leadership or political priorities shift.

Spatial models also strengthen stakeholder accountability. By documenting how planning decisions are derived from empirical evidence, governance bodies can justify infrastructure investments to policymakers, community groups, and funding agencies. Long-term mobility plans increasingly rely on dynamic modeling systems rather than static master plans, enabling cities to continuously update strategies based on new mobility data, demographic changes, and emerging spatial patterns [36]. This adaptability is essential in rapidly evolving urban contexts where micromobility growth, land-use changes, and technological adoption alter travel behavior.

Furthermore, integrating models within governance helps institutionalize equity evaluation. If equity indicators or SDM-derived accessibility gaps remain persistent, governance structures can mandate corrective action within planning cycles. Through this integration, cities transition from reactive to anticipatory mobility management, ensuring resilience and long-term sustainability [40].

6.4 Innovations: AI, Digital Twins, and Next-Generation Mobility Modeling

AI and digital-twin technologies are transforming how cities simulate, evaluate, and forecast active mobility systems. Digital twins virtual replicas of urban environments synchronize with real-time mobility, infrastructure, and environmental data to create dynamic simulations of walking and cycling behavior [34]. These platforms allow planners to test interventions before implementation, evaluating how changes in infrastructure, land use, or weather conditions influence mobility flows. By integrating spatial econometric coefficients, digital twins replicate not only physical environments but also behavioral and spatial dependence patterns [35].

AI enhances model precision by identifying complex, nonlinear relationships that traditional models may overlook. Machine-learning algorithms gradient boosting, random forests, neural networks support feature engineering, anomaly detection, and predictive modeling, complementing spatial econometric frameworks without replacing their interpretability [38]. Moreover, AI enhances rapid scenario testing by generating high-resolution predictions that can inform tactical urbanism projects and modular infrastructure deployments.

Next-generation models incorporate multimodal datasets from smartphones, micromobility fleets, crowdsourced platforms, and sensor networks, enabling unprecedented granularity in mobility understanding. As cities pursue climate goals and equity commitments, these technologies help forecast how future infrastructure, zoning policies, and behavioral trends will reshape mobility landscapes [37]. Together, AI and digital twins represent the future of adaptive, data-driven urban mobility management.

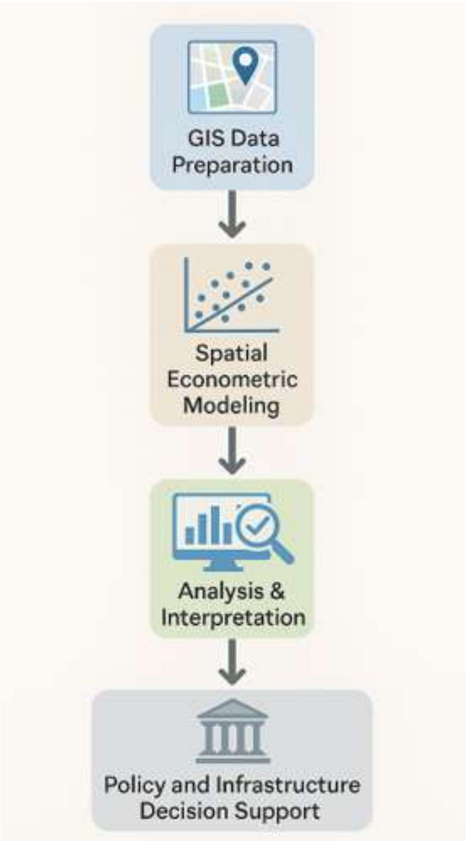

Figure 3: Integrated GIS–Spatial Econometric Workflow Feeding Into Policy and Infrastructure Decision Systems.

7. CONCLUSION

7.1 Synthesis of Key Findings

This study demonstrates that active transportation behavior is shaped by the interplay of built-environment structure, socio-behavioral influences, and spatial interdependencies that unfold across urban networks. GIS provided the spatial backbone for capturing micro-scale variation in infrastructure quality, land-use diversity, and demographic conditions, while spatial econometric models offered the analytical precision needed to identify spatial spillovers, neighborhood effects, and multi-scale heterogeneity. Together, these tools revealed how accessibility, sustainability, and equity outcomes emerge from the complex interactions between local conditions and broader network dynamics. The findings highlight that interventions cannot be evaluated solely at individual sites; rather, they require an understanding of how changes propagate through connected corridors and surrounding communities. The integration of global and local spatial models further demonstrated that relationships influencing active travel are neither uniform nor independent, emphasizing the importance of geographically adaptive planning strategies that account for localized constraints and opportunities.

7.2 Pathways for Future Interdisciplinary Research

Future research should expand interdisciplinary integration by combining spatial econometrics with advanced machine-learning techniques, digital-twin simulations, and real-time mobility data to capture dynamic patterns in active transportation systems. As micromobility, e-bikes, and emerging shared-mode technologies continue to reshape urban behavior, new models must account for temporal volatility and multimodal interactions. Scholars should also deepen investigation into equity-centered mobility, developing tools that actively identify structural disparities and evaluate how targeted interventions influence long-term socio-spatial outcomes. Incorporating climate resilience metrics heat exposure, flood risk, air-quality variability will be crucial for understanding how environmental stressors shape mobility decisions under future conditions. Finally, expanding participatory and human-centered approaches that integrate resident perceptions, community knowledge, and behavioral data can strengthen the relevance of spatial models for policy and planning. These interdisciplinary pathways will help produce more responsive, just, and sustainable mobility systems for cities worldwide.

8. REFERENCE

1. Zaroujtaghi A, Mansourihanis O, Tayarani M, Mansouri F, Hemmati M, Soltani A. A Systematic Review of GIS Evolution in Transportation Planning: Towards AI Integration. Future Transportation. 2025 Aug 1;5(3):97.
2. Adalıoğlu İ, Ergün M. Enhancing Logit Modeling With GIS Integration for Advanced Spatial Analysis: A Case Study of Multimodal Transport Preferences Between Istanbul and Ankara. Transactions in GIS. 2025 Feb;29(1):e70017.
3. Daniel ONI. TOURISM INNOVATION IN THE U.S. THRIVES THROUGH GOVERNMENTBACKED HOSPITALITY PROGRAMS EMPHASIZING CULTURAL PRESERVATION, ECONOMIC GROWTH, AND INCLUSIVITY. International Journal Of Engineering Technology Research & Management (IJETRM). 2022Dec21;06(12):132–45.
4. Solarin A, Chukwunweike J. Dynamic reliability-centered maintenance modeling integrating failure mode analysis and Bayesian decision theoretic approaches. *International Journal of Science and Research Archive*. 2023 Mar;8(1):136. doi:10.30574/ijsra.2023.8.1.0136.
5. Chibueze, T. *Access to credit and financial inclusion of MSMEs in sub-Saharan Africa: Challenges and opportunities.* International Journal of Financial Management and Economics,(2025). 8(2), 12. https://doi.org/10.33545/26179210.2025.v8.i2.609
6. Prince Enyiorji. AGENTIC AI ECOSYSTEMS INTEGRATING GOVERNANCE CONTROLS, PROGRAM MANAGEMENT STRUCTURES, AND ADAPTIVE PERSONALIZATION TO BALANCE CONSUMER AUTONOMY, TRANSPARENCY, AND FINANCIAL SYSTEM ACCOUNTABILITY. International Journal Of Engineering Technology Research & Management (IJETRM). 2024Dec21;08(12):579–95.
7. Eze Dan-Ekeh. DEVELOPING ENTERPRISE-SCALE MARKET EXPANSION STRATEGIES COMBINING TECHNICAL PROBLEM-SOLVING AND EXECUTIVE-LEVEL NEGOTIATIONS TO SECURE TRANSFORMATIVE INTERNATIONAL ENERGY PARTNERSHIPS. International Journal Of Engineering Technology Research & Management (IJETRM). 2018Dec21;02(12):165–77.
8. John BI. *Strategic Oversight of AI-Enabled Manufacturing Transformation: Advancing Process Automation, Quality Assurance, System Reliability, and Enterprise-Wide Operational Performance Excellence.* International Journal of Research Publication and Reviews. 2024 Dec;5(12):6182-6194. ISSN: 2582-7421.
9. Alabede LA, Maimako SM. Optimizing autonomous drone deployment strategies to improve geological structural mapping accuracy in complex mines. *International Journal of Computer Applications Technology and Research*. 2019;8(12):634-646.
10. Alabede LA. Enhancing underground drone endurance by optimizing battery efficiency, communication robustness, and navigation autonomy. *International Journal of Computer Applications Technology and Research*. 2016;5(12):831-843
11. Oriakhi VN, Takpah NEA, Kayode B. Securing the intelligent supply chain: the convergence of AI, IoT and Blockchain technologies. *Open Access Research Journal of Engineering and Technology*. 2025;8(1):32-43. doi:10.53022/oarjet.2025.8.1.0023
12. B. F. Kayode *et al*., "Temporal-Spatial Attention Network (TSAN) for DoS Attack Detection in Network Traffic," *2025 10th International Conference on Machine Learning Technologies (ICMLT)*, Helsinki, Finland, 2025, pp. 413-426, doi: 10.1109/ICMLT65785.2025.11193363

13. Enyiorji P. Designing a self-optimizing cloud-native autonomous finance system for SMEs using multi-agent reinforcement learning. *International Journal of Financial Management and Economics.* 2025;8(1):596–605. doi:10.33545/26179210.2025.v8.i1.660.
14. Alabede LA, Maimako SM, Abdullahi FI, Opoku JM. Integrating AI-Driven Drone Navigation to Enhance Blasting Assessment, Haul-Road Monitoring, and Operational Safety. Int J Sci Eng Appl. 2024;13(12):68-80. doi:10.7753/IJSEA1312.1012
15. Obinna Nweke. STRATEGIC DATA UTILIZATION FOR MINORITY-OWNED BUSINESSES: ENHANCING MARKET PENETRATION, CUSTOMER INSIGHTS, AND REVENUE GROWTH. International Journal of Engineering Technology Research & Management (IJETRM). 2025Mar29;09(03).
16. During D. Machine-driven quantitative modeling approaches for measuring liquidity risk propagation across interconnected financial systems. International Journal of Computer Applications Technology and Research. 2022;11(12):753–764. doi:10.7753/IJCATR1112.1033.
17. Kibirige KS, Wandabwa J. Enhancing access to service delivery through information transparency: a RAG-based AI-powered conversational chatbot for algorithmic transparency and regulatory compliance in digital governance. *International Journal of Science and Engineering Applications*. 2025;14(9):59-75. doi:10.7753/IJSEA1409.1008.
18. Nweke O, Adelusi O. Utilizing AI-driven forecasting, optimization, and data insights to strengthen corporate strategic planning. *International Journal of Research Publication and Reviews*. 2025;6(3):4260-4271. doi: https://doi.org/10.55248/gengpi.6.0325.1209
19. Ibitoye J. Zero-Trust cloud security architectures with AI-orchestrated policy enforcement for U.S. critical sectors. International Journal of Science and Engineering Applications. 2023 Dec;12(12):88-100. doi:10.7753/IJSEA1212.1019.
20. Enyiorji P. Does widespread use of AI recommendation engines reduce consumer financial choice diversity? *International Journal of Science and Engineering Applications*. 2023;12(4):163–173. doi:10.7753/IJSEA1204.1052.
21. Emi-Johnson O, Fasanya O, Adeniyi A. Predictive crop protection using machine learning: A scalable framework for U.S. agriculture. International Journal of Science and Research Archive. 2024;12(02):3065-3083. doi:10.30574/ijsra.2024.12.2.1536.
22. Otoko J. Microelectronics cleanroom design: precision fabrication for semiconductor innovation, AI, and national security in the U.S. tech sector. Int Res J Mod Eng Technol Sci. 2025;7(2)
23. Tetteh C. Reading against the Colonial Archive: Using AI to Recover the Hidden Economic Contributions of Market Women in Ghana (1890–1957) and African American Washerwomen in the U.S. South (1865–1920). *International Journal of Research Publication and Reviews.* 2024;5(12):6153-6168. Available from: https://ijrpr.com/uploads/V5ISSUE12/IJRPR36944.pdf
24. During D. Advanced financial engineering strategies integrating statistical inference to improve robustness of market risk assessment. World J Adv Res Rev. 2024;24(3):3595-3609. doi:10.30574/wjarr.2024.24.3.3852
25. Olanlokun Y, Taiwo M. Quantifying economic impact of COVID-19-induced disruptions in Nigeria's medicine supply chains: prices, availability and out-of-pocket burdens. World J Adv Res Rev. 2020;7(3):357-371. doi:10.30574/wjarr.2020.7.3.0346
26. Rumbidzai Derera. HOW FORENSIC ACCOUNTING TECHNIQUES CAN DETECT EARNINGS MANIPULATION TO PREVENT MISPRICED CREDIT DEFAULT SWAPS AND BOND UNDERWRITING FAILURES. International Journal of Engineering Technology Research & Management (IJETRM). 2017Dec21;01(12):112–27.
27. Nweke Obinna, Adelusi Oluwatosin. Utilizing AI Driven Forecasting, Optimization, and Data Insights to Strengthen Corporate Strategic Planning. *International Journal of Research Publication and Reviews*. 2025 Mar;6(3):4260-4271. doi: 10.55248/gengpi.6.0325.1209.
28. Omogiate PM. Designing automated audit mechanisms to evaluate compliance of generative AI platforms with federal authorship and ownership disclosure requirements. *International Journal of Science and Research Archive*. 2023;10(2):1536–1549. doi:10.30574/ijsra.2023.10.2.1099.
29. During D. Applied statistical methods for stress-testing credit portfolios and forecasting default probabilities in volatile markets. Int J Sci Res Arch. 2022;7(2):924-937. doi:10.30574/ijsra.2022.7.2.036
30. Afolabi OS, Kolawole TO, Issa MO. Effect of Lap Length on Shear Failure in Steel–Concrete Composite Connections Using Epoxy Adhesives. World J Adv Res Rev. 2024;24(3):3583-3594. doi:10.30574/wjarr.2024.24.3.3780
31. Enyiorji P. Blockchain-enforced data lineage architectures with formal verification workflows enabling auditable AI decision chains across regulated fintech compliance regimes and supervisory reporting. *International Journal of Science and Research Archive*. 2023;9(2):1201–1217. doi:10.30574/ijsra.2023.9.2.0559.
32. Atanda ED. EXAMINING HOW ILLIQUIDITY PREMIUM IN PRIVATE CREDIT COMPENSATES ABSENCE OF MARK-TO-MARKET OPPORTUNITIES UNDER NEUTRAL INTEREST RATE ENVIRONMENTS. International Journal Of Engineering Technology Research & Management (IJETRM). 2018Dec21.;2(12):151-64.
33. Nwenekama Charles-Udeh. Leveraging financial innovation and stakeholder alignment to execute high-impact growth strategies across diverse market environments. Int J Res Finance Manage 2019;2(2):138-146. DOI: 10.33545/26175754.2019.v2.i2a.617

34. Lukman A. Alabede, Samuel Mohammed Maimak, Joel Mintah Opoku. LEVERAGING MULTISPECTRAL DRONE IMAGING TECHNOLOGIES FOR MONITORING OPEN-PIT MINES AND IMPROVING PRODUCTION EFFICIENCY. International Journal Of Engineering Technology Research & Management (IJETRM). 2020Dec21;04(12):199–212.
35. Obinna Nweke. STRATEGIC DATA UTILIZATION FOR MINORITY-OWNED BUSINESSES: ENHANCING MARKET PENETRATION, CUSTOMER INSIGHTS, AND REVENUE GROWTH. International Journal of Engineering Technology Research & Management (IJETRM). 2025Mar29;09(03).
36. Eze Dan-Ekeh. Engineering high-value commercialization frameworks integrating technical innovation with strategic sales leadership to drive multimillion-dollar growth in global energy markets. World J Adv Res Rev. 2019;4(2):256-268. doi:10.30574/wjarr.2019.4.2.0152
37. Issa MO, Afolabi OS. Ultra-High-Performance Concrete (UHPC) in Bridge Rehabilitation: A Critical Review of Global Practices, Performance, and Life-Cycle Economics. World J Adv Res Rev. 2023;20(3):2401-2411. doi:10.30574/wjarr.2023.20.3.2596
38. John BI. *Data-driven resource optimization approaches enhancing capacity planning, labor utilization, material efficiency and continuous improvement across manufacturing project lifecycles.* GSC Advanced Research and Reviews. 2023;17(3):220–236. doi: https://doi.org/10.30574/gscarr.2023.17.3.0467
39. Kayode B, Adebola NT, Akerele S. The State of AI-Driven Cybersecurity: Trends, Challenges, and Opportunities. *J Artif Intell Mach Learn & Data Sci*. 2025;3(2):2731-2739. doi:10.51219/JAIMLD/Bisola-Kayode/577
40. Nosakhare VO, Kayode B, Akerele S, et al. Machine Learning in Cybersecurity: A Multi-Industry Case Study Analysis for Enhanced Threat Detection and Response. *J Artif Intell Mach Learn & Data Sci*. 2025;3(2):2684-2691. DOI: doi.org/10.51219/JAIMLD/Victor-Oriakhi-Nosakhare/568
41. Ogunola AA, Dugbartey AN. AI-powered financial tools for student debt management in the U.S.: Enhancing financial literacy and economic stability. World Journal of Advanced Research and Reviews. 2024;24(02):868–891. doi:10.30574/wjarr.2024.24.2.3441.
42. Olanlokun Y, Taiwo M. Policy and regulatory reforms needed to accelerate local pharmaceutical manufacturing in Nigeria: A comparative analysis with India and Bangladesh. Magna Scientia Advanced Biology and Pharmacy. 2025;14(01):53–68. doi:10.30574/msabp.2025.14.1.0010.
43. Abresch J, Hanson A, Heron SJ, Reehling PJ, editors. Integrating Geographic Information Systems into Library Services: A Guide for Academic Libraries: A Guide for Academic Libraries. IGI Global; 2008 Apr 30.
44. Wieczerak TJ. Understanding Combined Sewer Overflow (CSO) and Green Infrastructure Interaction in New Jersey: An Economic Analysis. Montclair State University; 2021.
45. Alexander ER, Khakee A, Woltjer J. Evaluation for participation and sustainability in planning. Hull A, editor. London: Routledge; 2011 Jun 21.