

INTEGRATING GRAPH NEURAL NETWORKS AND MULTI-SOURCE URBAN DATA FOR FAIRNESS ASSESSMENT AND DYNAMIC OPTIMIZATION OF URBAN ACCESSIBILITY

Yanzai ZHU

*Faculty of Architecture, Building and Planning, The University of Melbourne, Melbourne,
Victoria, Australia, 3010
yzzhuedu@phc.ac.cn*

Abstract

Public transport accessibility fairness assessment helps identify underserved areas and support intervention prioritization. The existing accessibility indicators usually take travel impedance as a pre-defined input variable, and traffic-oriented graph models focus more on issues such as speed, traffic flow or demand forecasting, and their support for accessibility fairness analysis and governance optimization is still relatively limited. To address this limitation, this study proposes a dynamic graph-based framework integrating graph neural networks and multi-source urban data for grid-level accessibility fairness assessment. The factors such as scheduled travel time, service frequency, waiting time impedance, transfer resistance and fare zone impedance are converted into edge weights in the dynamic graph. Based on the graph representation learning method, the model further estimates the grid-level accessibility score, and thereby calculates the Gini coefficient, low accessibility ratio, population-weighted accessibility exposure, and supply-demand matching degree. In a case study conducted in Helsinki, Finland, this framework integrates multi-source data such as public transportation, road network, population distribution, service opportunities, and land use, builds a grid-level dataset, and conducts accessibility estimation, fairness assessment, and scheme comparison under peak, off-peak, and intervention scenarios. Experimental results show that the proposed model maintains a strong performance in accessibility score estimation, and compared with the comparison methods, its average Gini coefficient is the lowest and its average ΔJ value is the highest. Threshold sensitivity analysis further indicates that the main priority clustering results and the top-ranked governance scenarios have overall better stability.

Keywords: Urban transport network; Public transport accessibility; Multi-source data fusion; Graph neural networks; Accessibility fairness; Dynamic governance optimization.

1. INTRODUCTION

The assessment of public transportation accessibility is important in urban transportation planning, as it measures the convenience for residents to reach daily activity locations such as employment, education, healthcare, commercial services, and parks (Geurs & Van Wee, 2004; Hansen, 1959). Inequalities in accessibility distribution may further exacerbate the spatial disadvantages of residents who rely on public transportation, especially in areas with insufficient public transportation supply, inconvenient transfers, or fewer public service facilities (Wang et al., 2026). In high-density urban environments, transportation service levels are also influenced by factors such as service frequency, waiting time, transfer conditions, and fluctuations in travel time, resulting in significant differences in accessibility between different time

periods (Rivera-Gonzalez & Amaral, 2024). Therefore, conducting accessibility equity assessments at the grid scale helps identify areas with insufficient transportation services and provides a basis for optimizing transportation governance for different scenarios.

Existing studies have proposed various methods for analyzing the accessibility and fairness of public transportation. Traditional accessibility assessment mainly relies on indicators such as distance, travel time, cumulative opportunities, gravity models, and public transportation accessibility indices to measure the degree to which residents have access to services (Zhang et al., 2025). Furthermore, research on transportation equity further focuses on whether the distribution of accessibility resources is balanced among different regions and population groups (Rahmah et al., 2026). With the deepening of research, dynamic accessibility analysis has begun to incorporate factors such as time variations, such as service hours, actual travel time, service reliability, transfer conditions, and traffic disruptions, to more accurately reflect residents' travel experiences. Meanwhile, the development of graph neural networks provides new methods for depicting the complex relationships between roads, stations, transportation areas, and urban spatial units, which helps to improve the modeling of transportation networks and accessibility predictions (Mohamed et al., 2026). These studies significantly support accessibility measurement, fairness analysis, and representation of transportation networks.

However, the existing studies still lack a method that can integrate time-varying traffic impedance, graph representation learning, accessibility fairness assessment, and governance priority identification within a unified framework (Khorramisarvestani et al., 2025; Verduzco Torres & McArthur, 2024). This deficiency makes it difficult to further convert the changes in accessibility during peak and off-peak periods as well as different intervention scenarios into consistent grid-level fairness indicators, and also limits the ability to formulate precise governance plans for under-served areas.

To bridge this gap, this study proposes a framework based on dynamic graphs for evaluating the fairness of public transportation accessibility at the grid scale and supporting scenario-based governance optimization. This framework incorporates traffic characteristics such as scheduled travel time, service frequency, waiting time impedance, transfer resistance, and fare zone impedance into the dynamic graph modeling process, and describes the changes in travel impedance between different traffic units through edge weights. On this basis, graph representation learning is used to estimate the grid-level accessibility score, further calculate fairness indicators, and evaluate the potential impact of different intervention schemes. The empirical analysis is conducted in Helsinki, Finland, using as the research area, combined with multimodal HSL transportation networks and multi-source data such as resident population, service opportunities, road networks, and land use.

The dynamic optimization in this article refers to the process of re-evaluating accessibility based on scenario simulation and sorting governance solutions. The candidate intervention measures include adjusting service frequencies, optimizing branch connections, reducing transfer resistance, and increasing service opportunities, all of which are modeled by updating the graph structure or node attributes. For different intervention scenarios, the framework recalculates accessibility scores, inequality indicators, low accessibility areas, population-weighted accessibility exposure, and supply-demand matching degrees, and based on this, identifies governance solutions with greater potential for improving fairness.

This framework mainly consists of the following modules. Firstly, a dynamic impedance-weighted urban graph is constructed, where the urban grid or traffic units are regarded as nodes, and the edge weights represent the changing traffic impedance over time. Secondly, based on the graph representation learning method, the grid-level accessibility scores are estimated, and their relationships with accessibility inequality, the distribution of low accessibility areas, population-weighted accessibility exposure, public service opportunities, and supply-demand matching are further analyzed. Finally, considering the degree of accessibility deficiency, traffic supply gap, spatial clustering characteristics, and proxy variables related to demand, the governance priorities are determined, and the candidate scenarios are ranked based on the fairness improvement score.

The main contribution of this study lies in the proposal of a dynamic impedance-weighted urban graph construction method, which is used to depict the constantly changing traffic impedance during peak and off-peak periods as well as under different intervention scenarios. On this basis, a reachability scoring module based on graph representation learning is constructed, combining the dynamic graph modeling method with the grid-level reachability fairness index to achieve quantitative assessment of spatial reachability differences. Additionally, this study further proposes a contextual governance optimization mechanism, determining the spatial intervention priorities and candidate solution rankings based on the fairness assessment results, providing decision support for improving the fairness of public transportation services.

2. LITERATURE REVIEW

This section reviews related research on urban transportation accessibility, dynamic public transportation assessment, traffic equity analysis, graph model-based traffic modeling, and accessibility planning for governance. The existing research provides an important foundation for measuring spatial accessibility differences, evaluating traffic equity, and constructing transportation network models. However, in the assessment of public transportation accessibility during peak and off-peak hours as well as in different scenarios, there is still a lack of a unified and clear method framework on how to effectively connect

transportation impedance based on schedules, graph model-based accessibility estimation, equity evaluation indicators, and governance priority identification.

2.1. Accessibility Measures and Benchmark Score Construction

Urban transportation accessibility is usually measured through methods such as distance, travel time, cumulative opportunity model, gravitational model, and public transportation accessibility index (Dianin et al., 2024). These methods provide interpretable analytical tools for assessing the convenience of residents in accessing employment, education, healthcare, commercial facilities, parks, and other public services (Liu et al., 2024). Among them, methods based on distance and travel time have strong intuitiveness and can directly reflect spatial barriers and travel costs. The cumulative opportunity model and the gravitational model consider opportunity quantity and impedance decay

These methods provide important basis for constructing a basic accessibility evaluation system. Different indicators vary in impedance setting, opportunity weights, spatial scale, and data requirements, and their evaluation results also depend on specific assumptions and parameter choices (Tahmasbi et al., 2024). Therefore, traditional accessibility indicators are difficult to fully explain the dynamic transmission process of transportation services over time and accessibility in the urban network in a public transportation system that operates based on timetables (Wang & Loo, 2024).

2.2. Dynamic Public Transport Accessibility and Travel-Time Variability

Recent studies on public transportation accessibility have gradually incorporated factors such as timetable-based information, service frequency changes, uncertainty in waiting times, transfer conditions, service reliability, fare regional effects, and operational disruptions into the analysis (Chen et al., 2024). Relevant research indicates that the accessibility results obtained based on static assumptions or simplified impedance calculations may not fully reflect the actual accessibility levels during peak and off-peak periods as well as in different service scenarios. Factors such as travel time fluctuations, time period differences, service delays, and disruptions in the transportation network can all change the accessibility levels and their spatial distribution characteristics, and further affect the assessment results of accessibility inequality (Pot, 2025).

The above research indicates that dynamic traffic impedance has a significant impact on the analysis of accessibility equity. However, most existing methods still focus on recalculating accessibility under different travel time conditions, or comparing differences between planned schedules, peak/non-peak states, and hypothetical service scenarios (van Wee, 2025). In these studies, dynamic impedance is usually treated as an external parameter in accessibility calculations or scenario analyses, and is less directly integrated into graph models for learning the accessibility representation in the traffic network.

Therefore, the impact of impedance differences resulting from schedule changes on the accessibility scores based on graph models remains poorly explored.

2.3. *Transport Equity, Transit Gap, and Supply-Demand Fairness*

The research on transportation equity focuses on the distribution of transportation resources, travel convenience, and public service opportunities among different spatial regions and population groups (Lucas, 2012). From the perspective of accessibility equity, the evaluation process not only needs to consider the overall service level, but also should take into account whether residents relying on public transportation can obtain basic service opportunities within reasonable travel time and transfer conditions (Kyere-Gyeabour et al., 2024). Based on this approach, this study adopts a reachability-oriented transportation equity analysis framework, focusing on the differences in spatial reachability and the service acquisition situation of transportation-dependent groups. Existing research usually focuses on the differences between the center and the periphery regions, as well as the travel disadvantages of low-income residents, the elderly, carless families, and suburban residents who rely on public transportation (Pereira et al., 2017). Compared with identifying specific groups based solely on administrative regions or housing types, this study uses observable proxy variables such as population structure, demand scale, and transportation dependence degree to characterize potential transportation-dependent areas.

Based on the above perspective, this study assesses the fairness of public transportation accessibility from four dimensions, including regional accessibility inequality, population-weighted accessibility exposure, public service opportunities, and supply-demand matching degree (Gelb et al., 2026). Among them, regional accessibility inequality reflects the spatial differences between different grid units, population-weighted accessibility exposure indicates the actual situation of different demand groups in obtaining transportation services, public service opportunities measure the convenience for residents to access key facilities, and supply-demand matching degree reflects the coordination relationship between transportation supply and population demand. These four dimensions correspond to spatial fairness, group fairness, opportunity fairness, and supply-demand fairness, providing multiple perspectives for the comprehensive assessment of the fairness of public transportation accessibility.

However, the existing fairness indicators are usually used separately to measure the differences in accessibility in various aspects, and have not been fully integrated into a unified governance priority identification framework. Therefore, further mechanisms for analysis from fairness assessment to intervention plan ranking need to be established to support governance-oriented decision-making.

2.4. *Graph-Based Transportation Modeling*

Graph neural networks and other graph-based models have been widely applied in the field of transportation. Related research usually represents road sections, stations, traffic areas or urban spatial units as nodes, and uses road connection relationships, spatial adjacency relationships, OD flow, public transportation line relationships or functional connections to construct edges between nodes (Jain et al., 2026). Based on this, graph models have been used for tasks such as traffic speed prediction, traffic flow prediction, travel demand estimation, traffic assignment, and urban spatial representation.

Previous studies have shown that graph structures can effectively capture the spatial correlations and interdependencies within transportation networks. However, the main outputs of existing traffic graph neural network models typically focus on variables such as speed, flow, demand, line status, or traffic distribution, and research that treats accessibility fairness as the core prediction target is still relatively limited. Moreover, although dynamic graph information has been widely used to enhance the spatio-temporal modeling capabilities of traffic predictions, its application in accessibility ranking, identification of low accessibility areas, population-weighted accessibility exposure analysis, and determination of governance priorities is still relatively scarce (Gamal & Ibrahim, 2025; Wu & Mu, 2025).

2.5. *Research Gaps and Position of This Study*

Current research has made significant progress in areas such as accessibility measurement, dynamic public transportation assessment, traffic equity analysis, and graph-based traffic modeling. However, the existing methods still have some shortcomings.

Firstly, time variation factors and traffic impedance based on timetables are usually taken as input parameters for the assessment of accessibility fairness, which have not fully participated in the modeling of the graph structure. Meanwhile, the existing graph-based traffic models are mainly used for tasks such as traffic state prediction, demand estimation, and path allocation. The grid-level accessibility score and fairness indicators are rarely analyzed as model outputs. Moreover, the existing fairness diagnosis methods mostly focus on the identification of accessibility differences, and the comprehensive consideration of low accessibility levels, public transportation supply gaps, spatial clustering characteristics, and demand differences is still limited. The spatial priority rules for governance decisions still need to be further improved.

This study positions its contribution at dynamic impedance modeling, graph-based accessibility estimation, and governance-oriented fairness assessment. The proposed framework incorporates the traffic impedance that changes over time and scenarios into the graph structure representation, estimates the

grid-level reachability level, and identifies the spatial intervention priorities based on the fairness assessment results, contributing to the optimization of public transportation resource allocation.

3. METHODOLOGY

3.1. Problem Definition

This study focuses on the assessment of grid-level public transportation accessibility equity during peak and off-peak periods as well as under different scenarios. The study area is represented as a set of spatial units $V = \{v_1, v_2, \dots, v_N\}$, where each unit can be a regular grid, a planning area, or other comparable spatial units. Each spatial unit v_i contains multiple urban attributes, including population demand, public transportation supply, public service opportunities, demographic and transportation-dependent proxy variables, and local built environment characteristics.

The research objective is to estimate the accessibility score of each spatial unit under the given time or scenario condition t . Let x_i represent the node feature vector of spatial unit v_i , and e_{ij} represent the spatial or transportation connection relationship between spatial units v_i and v_j . Different from static accessibility assessment methods, this study considers the characteristic that transportation service conditions change with time and scenarios. It assumes that the connection strength between spatial units will be affected by factors such as scheduled travel time, waiting time impedance, service frequency, transfer resistance, and fare area impedance. Therefore, the urban transportation system is represented as a dynamic weighted graph $G^{(t)} = (V, E, W^{(t)}, X)$, where $W^{(t)}$ represents the edge weight matrix that changes with time or scenarios, and X represents the node feature matrix.

Based on this, the study constructs an accessibility scoring function based on graph representation learning, mapping node features X and dynamic edge weight matrix $W^{(t)}$ to grid-level accessibility scores $\hat{A}_i^{(t)}$. These scores are then further used to assess the degree of accessibility inequality, identify low accessibility areas, measure the population-weighted accessibility exposure, and analyze the matching relationship between transportation supply and service demand. Based on the above evaluation results, the study further determines the governance priority levels under different scenarios. Therefore, this issue not only involves the estimation of accessibility levels, but also focuses on how to utilize the accessibility results to conduct fairness analysis and support spatial intervention decisions for planning purposes.

3.2. Overall Framework

To integrate time-varying traffic impedance, graph-based accessibility scores, fairness assessment, and governance priority identification, this study proposes a dynamic graph model framework for evaluating the fairness of public transportation accessibility. As shown in Figure 1, the framework contains five

connected steps: multi-source data representation, dynamic impedance-weighted graph construction, graph-based accessibility scoring, fairness indicator calculation, and threshold-based governance priority assessment.

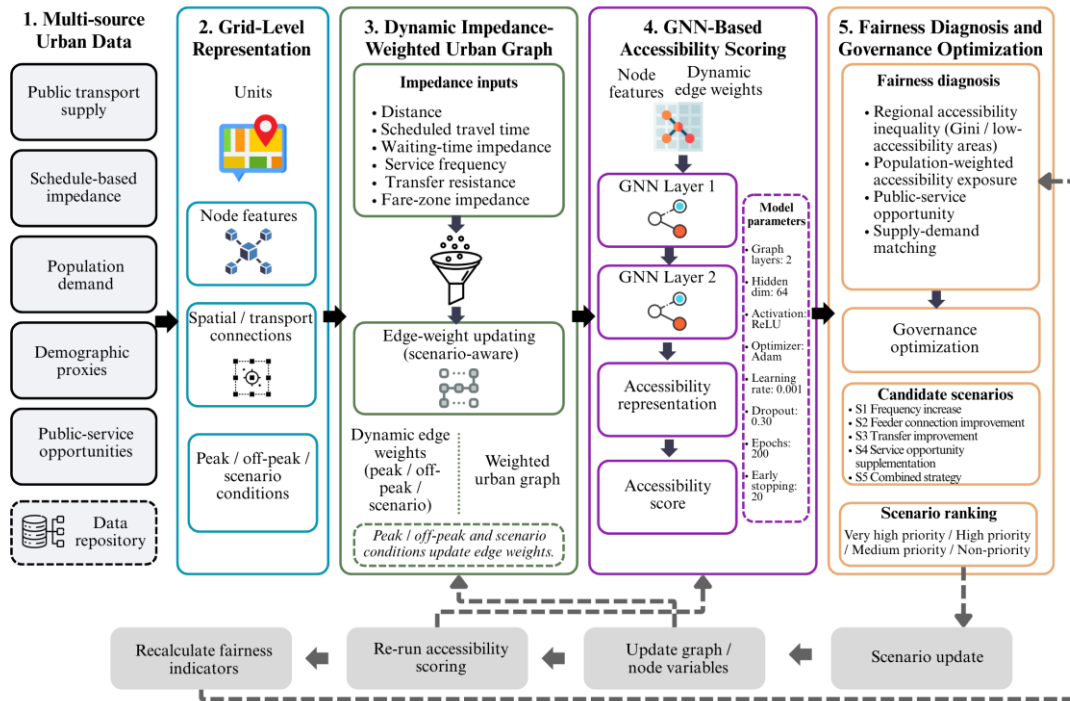


FIGURE 1 - OVERALL FRAMEWORK OF DYNAMIC GRAPH-BASED ACCESSIBILITY FAIRNESS ASSESSMENT AND SCENARIO-BASED GOVERNANCE OPTIMIZATION.

First, public transport supply, road-network connectivity, scheduled travel-time indicators, service-frequency indicators, population demand, available demographic or transport-dependence proxy variables, and public service opportunities are spatially matched to grid-level units. These data are converted into node features, graph edges, and time- or scenario-dependent impedance variables. Then, a dynamic impedance-weighted urban graph is constructed. Dynamic edge weights comprehensively take into account factors such as distance, scheduled travel time, waiting time impedance, service frequency, transfer resistance, and fare zone impedance, etc., to describe the connection costs between different spatial units and reflect the changes in the transportation network during peak and off-peak hours as well as under different scenarios. Based on this graph structure, the accessibility scoring module, in combination with node characteristics and dynamic edge weights, estimates the accessibility level of each spatial unit. The obtained accessibility scores are further utilized to assess the fairness of public transportation, including measuring the degree of accessibility inequality between regions, identifying low accessibility areas, analyzing the population-weighted accessibility exposure, and evaluating the match between public service opportunities and traffic supply and demand. Based on this, the governance

priority module, in combination with the distribution of low accessibility areas, the degree of accessibility deficiency, the traffic supply gap, spatial clustering characteristics, and proxy variables related to demand, conducts a comprehensive assessment of different spatial units and classifies them into four governance levels: non-priority, medium priority, high priority, and very high priority.

3.3. *Dynamic Impedance-Weighted Urban Graph Construction*

The dynamic impedance-weighted graph construction module represents time- or scenario-dependent transport conditions within the graph structure. This model assumes that the effective connection relationship between two spatial units is not only determined by physical distance or spatial proximity, but also influenced by traffic factors such as scheduled travel time, waiting time impedance, frequency of public transportation services, transfer resistance, and fare zone impedance. Therefore, the dynamic traffic impedance is directly encoded as the edge weights in the graph structure, used to describe the connection costs between spatial units that change over time and scenarios.

For different time periods or situational conditions, the urban transportation system is represented as a dynamic weighted graph:

$$G^{(t)} = (V, E, W^{(t)}, X), \quad (1)$$

where V denotes grid-level spatial units, E denotes spatial or transport connections, X is the node feature matrix, and $W^{(t)}$ is the dynamic edge-weight matrix. When two spatial units have a spatial proximity relationship, exist a public transportation connection, or can be connected through the road network within the preset distance and travel time thresholds, an edge is established between them.

For each connected pair (v_i, v_j) , the schedule-based impedance variation indicator is:

$$CI_{ij}^{(t)} = \text{clip} \left(\frac{T_{ij}^{(t)} - T_{ij}^{\text{off}}}{T_{ij}^{\text{off}} + \epsilon}, 0, 1 \right), \quad (2)$$

Among them, $T_{ij}^{(t)}$ represents the scheduled travel time under condition t or the travel time under the scenario setting, and T_{ij}^{off} represents the scheduled travel time under non-peak hours or the reference condition. ϵ is used to ensure the stability of the calculation process and avoid division by zero situations. $CI_{ij}^{(t)}$ is used to measure the degree of change in travel impedance compared to the reference state under the given conditions. The higher the value, the more significant the increase in connection costs between spatial units.

The integrated dynamic impedance is calculated as:

$$r_{ij}^{(t)} = \lambda_d \tilde{d}_{ij} + \lambda_t \tilde{T}_{ij}^{(t)} + \lambda_c CI_{ij}^{(t)} + \lambda_f (1 - \tilde{F}_{ij}^{(t)}) + \lambda_\tau \tilde{\tau}_{ij}^{(t)} + \lambda_z \tilde{Z}_{ij}^{(t)}, \quad (3)$$

where $\tilde{d}_{ij}$, $\tilde{T}_{ij}^{(t)}$, $\tilde{F}_{ij}^{(t)}$, and $\tilde{\tau}_{ij}^{(t)}$ denote normalized distance, scheduled travel time, waiting-time impedance, transit service frequency, transfer resistance, and fare-zone impedance, respectively. Because higher service frequency reduces impedance, frequency enters the formulation as $1 - \tilde{F}_{ij}^{(t)}$. The coefficients λ_d , λ_t , λ_c , λ_q , λ_f , λ_τ , and λ_z are non-negative parameters determined through validation-set tuning.

The dynamic edge weight is obtained through impedance decay:

$$w_{ij}^{(t)} = A_{ij} \cdot \exp(-r_{ij}^{(t)}), \quad (4)$$

Therefore, the differences in travel time caused by travel conditions or changes in scenarios are exerted on the graph structure through the relationship $CI_{ij}^t \rightarrow r_{ij}^t \rightarrow w_{ij}^t$. Meanwhile, factors such as waiting time impedance, service frequency, transfer resistance, and fare zone impedance directly influence the calculation of r_{ij}^t . These factors collectively represent the connection costs between spatial units under different transportation conditions, enabling the traffic changes during peak and off-peak hours as well as specific intervention scenarios to affect the accessibility estimation through the graph structure.

3.4. Graph-Based Accessibility Scoring

The graph-based accessibility scoring module estimates the accessibility level of each spatial unit by integrating the urban attributes of the spatial unit itself and the transportation connection information between adjacent units. This module assumes that the accessibility of public transportation at the grid scale is not only influenced by local population demand, public service opportunities, and transportation supply, but is also closely related to the conditions of surrounding areas and interconnected units in the transportation network.

Let $H^{(0)} = X$ represent the initial node feature matrix. During the graph propagation process, $W^{(t)}$ is first normalized to obtain $\bar{W}^{(t)}$. For the graph propagation on the l -th layer, the node representations are updated as follows:

$$H^{(l+1)} = \sigma(\bar{W}^{(t)} H^{(l)} \Theta^{(l)}), \quad (5)$$

where $\bar{W}^{(t)}$ is the normalized dynamic edge-weight matrix, $H^{(l)}$ is the node representation at layer l , $\Theta^{(l)}$ is a trainable parameter matrix, and $\sigma(\cdot)$ is a nonlinear activation function. Therefore, dynamic transport conditions participate in graph convolution through $\bar{W}^{(t)}$.

After Lgraph propagation layers, the accessibility score of unit v_i is estimated as:

$$\hat{A}_i^{(t)} = \sigma(W_o h_i^{(L)} + b_o), \quad (6)$$

Among them, $h_i^{(L)}$ represents the final node representation after multiple layers of propagation, W_o and b_o represent the parameters of the output layer. The model's output $\hat{A}_i^{(t)}$ represents the accessibility score of grid-level public transportation.

The model training uses the benchmark accessibility score $A_i^{\text{ref},t}$ as the supervisory signal. This score comprehensively considers the available public service opportunities and the travel impedance calculated based on travel conditions. The training objective is defined as follows:

$$\mathcal{L}_{\text{acc}} = \frac{1}{N} \sum_{i=1}^N (\hat{A}_i^{(t)} - A_i^{\text{ref},t})^2 + \lambda \|\Theta\|_2^2, \quad (7)$$

Among them, the first item is used to measure the error between the model's prediction results and the benchmark score, while the second item is used to control the model's complexity and enhance its generalization ability. The final obtained accessibility score is further used for the calculation of fairness indicators and the assessment of governance priorities.

3.5. Accessibility Fairness and Scenario-Based Governance Optimization

The accessibility equity module is based on the grid-level accessibility score, further constructing equity indicators and providing an evaluation basis for subsequent governance optimization. This module measures spatial differences, population exposure, and the relationship between transportation supply and demand.

Regional accessibility inequality is measured by the Gini coefficient:

$$G = \frac{\sum_{i=1}^N \sum_{j=1}^N |\hat{A}_i - \hat{A}_j|}{2N^2 \bar{A}}, \quad (8)$$

Among them, $\hat{A}_i$ and $\hat{A}_j$ respectively represent the estimated accessibility scores of spatial units v_i and v_j , while $\bar{A}$ represents the average accessibility level. The Gini coefficient in the experimental results is based on the accessibility scores predicted using Eq. (8).

Low-accessibility areas are identified as:

$$L_i = \begin{cases} 1, & \hat{A}_i < Q_{20}(\hat{A}), \\ 0, & \text{otherwise.} \end{cases} \quad (9)$$

Among them, $Q_{20}(\hat{A})$ represents the 20th percentile of the accessibility score distribution. For the reference score $A_i^{\text{ref},t}$, the same threshold is used to determine the low accessibility area of the reference, and the low accessibility identification accuracy is calculated by comparing the prediction results with the reference labels.

The population-weighted accessibility exposure and the degree of supply-demand matching are defined as follows:

$$\text{PAE} = \frac{\sum_{i=1}^N P_i^v \hat{A}_i}{\sum_{i=1}^N P_i^v}, \quad (10)$$

$$\text{SDM}_i = \frac{S_i}{D_i + \epsilon}, \quad (11)$$

P_i^v represents the population demand weight or the proxy variable weight for transportation dependence in spatial unit v_i . S_i represents the level of public transportation supply or service opportunities, D_i represents the demand scale, and ϵ is used to avoid division by zero issues during the calculation process.

The governance priority index is calculated as:

$$\Pi_i = L_i(\beta_1 \text{Sev}_i + \beta_2 \text{TG}_i + \beta_3 C_i + \beta_4 D_i), \quad (12)$$

where L_i is the low-accessibility indicator defined in Eq. (9), Sev_i denotes normalized accessibility severity, TG_i denotes the normalized transit-supply gap derived from route coverage, stop accessibility, and related supply variables, C_i represents the spatial concentration of neighboring low-accessibility grids, and D_i denotes population demand or an available demand-related proxy variable. The four priority components are normalized to a common scale before weighted aggregation.

By construction, $\Pi_i = 0$ for grids not identified as low-accessibility areas. Among low-accessibility grids, those with relatively limited accessibility severity or demand pressure are classified as medium priority; grids with larger accessibility and transit-supply gaps are classified as high priority; and grids with the highest combined priority scores are classified as very high priority. All other grids are classified as non-priority.

Candidate governance scenarios are defined as:

$$\mathcal{U} = \{u_1, u_2, \dots, u_K\}, \quad (13)$$

Among them, each u_k will update variables such as traffic supply S_i , impedance $r_{ij}^{(t)}$, transfer resistance τ_i , fare zone impedance Z_{ij} , and service opportunities. For instance, when low accessibility and high demand occur simultaneously, interventions can be made by increasing service frequency or optimizing

branch connections. A lower match between supply and demand indicates the need to adjust the line layout or supply structure.

The expected fairness-improvement score is:

$$\Delta J(u_k) = \eta_1(G^{(t)} - G^{(t,u_k)}) + \eta_2(LR^{(t)} - LR^{(t,u_k)}) + \eta_3(PAE^{(t,u_k)} - PAE^{(t)}) + \eta_4(SDM^{(t,u_k)} - SDM^{(t)}), \quad (14)$$

LR represents the low accessibility ratio, SDM represents the average supply-demand matching degree, PAE represents the population-weighted accessibility exposure, and η_1 – η_4 are non-negative weights. The candidate scenarios are ranked as follows:

$$u^* = \arg \max_{u_k \in \mathcal{U}} \Delta J(u_k). \quad (15)$$

Thus, dynamic optimization refers to scenario-based reassessment and ranking, rather than direct real-time policy deployment.

3.6. Training and Inference Procedure

The training process is used to learn the mapping relationship between multi-source urban attributes and dynamic graph structures, and to generate benchmark accessibility scores. The model input includes the node feature matrix X , the dynamic edge weight matrix W^t , and the benchmark score $A_i^{\text{ref},t}$. The model parameters are optimized through the loss function described in Section 3.4. The validation set is used to determine the number of graph layers, the hidden dimension, the learning rate, the Dropout ratio, and the weight decay parameters. The test set evaluates the fixed weight coefficients and normalizes them within each group so that their sum is 1. Higher weights are mainly allocated to the planned travel time, the degree of accessibility deficiency, the gap in public transportation supply, as well as the reduction of inequality and the reduction of indicators related to low accessibility areas. The specific settings are shown in Table 1.

TABLE 1. MODEL HYPERPARAMETERS AND WEIGHT SETTINGS

Parameter	Setting
Graph layers	2
Hidden dimension	64
Activation function	ReLU
Optimizer	Adam
Learning rate	0.001
Dropout rate	0.30
Weight decay	1×10^{-4}
Training epochs	200
Early stopping	Patience = 20
Data split	70% / 15% / 15%
Impedance weights	$\lambda_d = 0.15, \lambda_t = 0.25, \lambda_c = 0.10, \lambda_q = 0.15,$ $\lambda_f = 0.15, \lambda_r = 0.12, \lambda_z = 0.08$
Governance-priority weights	$\beta_1 = 0.35, \beta_2 = 0.30, \beta_3 = 0.15, \beta_4 = 0.20$
Fairness-improvement weights	$\eta_1 = 0.30, \eta_2 = 0.30, \eta_3 = 0.20, \eta_4 = 0.20$

During inference, the trained model takes the node features X and the dynamic edge weights W^t as input, and outputs the grid-level accessibility score A_i^t . Based on these scores, the Gini coefficient, low accessibility areas, population-weighted accessibility exposure, and supply-demand matching indicators are further calculated, and the Π_i is computed by the governance module to determine the intervention priority.

During the scenario optimization process, each candidate intervention measure u_k is updated through the modification of the graph structure or the representation of node variables. Frequency adjustment updates S_i and service impedance, transfer node optimization reduces $\tilde{\tau}_{ij}^t$, and facility supplementation updates the service opportunity variables. The updated scenario is then re-input into the model to calculate the new accessibility score and fairness index. The candidate solutions are ranked based on $\Delta J(u_k)$, with a larger value indicating a more significant expected improvement in fairness.

All node features and edge weights are normalized before training. The test set is only used for the final model evaluation. The research results should be understood as support for accessibility diagnosis and scenario ranking based on open data, rather than a direct proof of the implementation effect of transportation policies.

3.7. Algorithm Summary

Algorithm 1 summarizes the dynamic governance optimization process based on training and scenario analysis, which includes dynamic graph construction, reachability scoring, fairness assessment, and intervention scheme ranking.

Algorithm 1. Dynamic Graph-Based Accessibility Fairness Assessment and Governance Optimization

Input: Multi-source urban data, spatial units V , connections E , scenario t , benchmark scores A^{ref} , thresholds, candidate scenarios.

Output: Accessibility scores, fairness indicators, priority levels, ranked scenarios.

- 1: Divide the study area into grid-level spatial units.
- 2: Construct node feature matrix X .
- 3: Construct spatial and transport connections E .
- 4: Calculate dynamic impedance $r_{ij}(t)$ from scheduled travel time, service frequency, waiting-time impedance, transfer resistance, and fare-zone impedance.
- 5: Convert $r_{ij}(t)$ into edge weights $W_{ij}(t)$.
- 6: Normalize X and $W(t)$.
- 7: Train the accessibility scoring model with A^{ref} .
- 8: Estimate accessibility scores $\hat{A}_i(t)$.
- 9: Compute Gini, low-accessibility areas, PAE, and SDM.
- 10: Calculate governance priority index Π_i .
- 11: Assign priority levels by percentile thresholds.
- 12: Generate candidate governance scenarios U .
- 13: For each u_k , update graph or node variables such as service supply, transfer resistance, fare-zone impedance, or service-opportunity variables.
- 14: Recalculate $\hat{A}_i(t, u_k)$, fairness indicators, and Π_i .
- 15: Compute $\Delta J(u_k)$.
- 16: Rank scenarios and return maps, priority areas, and selected scenarios.

This process indicates that impedance changes based on the schedule will affect the weights of graph edges, and the fairness indicators recalculated through the assessment of graph propagation are used to evaluate the reachability results obtained from the graph and the candidate governance schemes.

4. EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

4.1. Study Area

As shown in Figure 2, the study area is Helsinki, Finland, including the administrative boundaries of Helsinki and the public transportation network of Helsinki Region Transport (HSL). The embedded map further shows the location of Helsinki in the new region (Uusimaa) and within Finland. Helsinki is suitable as a case for evaluating the fairness of grid-level accessibility, with its central area featuring dense transportation hubs and transfer nodes, as well as residential areas and coastal and peripheral areas with varying levels of public transportation accessibility.

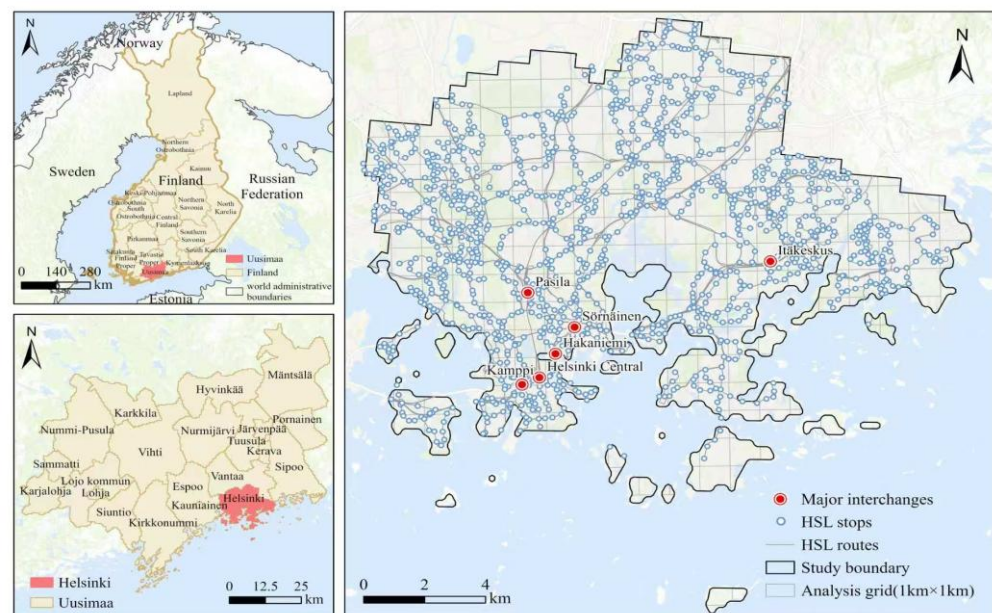


FIGURE 2 - STUDY AREA, ANALYSIS GRID, AND HSL PUBLIC TRANSPORT NETWORK WITH MAJOR INTERCHANGES IN HELSINKI, FINLAND.

Helsinki Central, Kamppi, Pasila, Hakaniemi, Sörnäinen, and Itäkeskus serve as the main transfer reference points in the spatial analysis. This public transportation system includes various modes such as trams, buses, metro, commuter rail, and ferries. The HSL lines are presented on a unified network layer, while ordinary stations and major transfer stations are separately identified. Due to factors such as operating frequency, waiting time, transfer conditions, fare zone differences, travel time variations, and distribution of public services, the accessibility levels may still differ at different times and in different scenarios.

The Helsinki study area was divided into 1 km × 1 km grid units. Population demand, public transportation supply, public service opportunities, population or transportation dependency proxy variables, and dynamic impedance variables were associated with the corresponding grids to support the identification of low accessibility areas, the calculation of population-weighted accessibility exposure, the analysis of supply-demand mismatch, and the determination of governance priority areas.

4.2. Data Description and Reference Score Construction

This section introduces the multiple data sources, preprocessing procedures, and the construction method of the reference accessibility score. This study utilized public space data and public transportation data from the Helsinki region, covering administrative boundaries, population grids, road and pedestrian networks, HSL public transportation networks, service timetables, transfer rules, fare zone information, as well as spatial variables such as public service facilities, medical institutions, and land use.

4.2.1. Data Sources

This article collects and integrates multi-source data about the research area within a unified reference period. The research scope, road and pedestrian network, public service facilities, medical institutions, and land use variables are all derived from the Geofabrik Finnish OpenStreetMap data snapshot released on June 1, 2026. The regional data on public transportation routes, stations, schedules, transfer information, and fares come from the HSL GTFS and open data snapshot generated on the same day, covering the regular services from June 1 to August 31, 2026. The population demand and demographic proxy variables are derived from the 2024 HSY population grid data. All data are uniformly limited to the administrative boundaries of Helsinki and are spatially aggregated according to the analysis grids. Table 2 summarizes each dataset and corresponding reference period.

TABLE 2. DATA SOURCES AND VARIABLES

Data type	Variables	Source	Year/period	Use
Study-area boundary	Helsinki administrative boundary, coastline, and water boundary	OpenStreetMap / Geofabrik Finland extract	1 June 2026 snapshot	Study-area delineation and spatial aggregation
Road and walking network	Road links, pedestrian paths, intersections, and network distance	OpenStreetMap / Geofabrik Finland extract	1 June 2026 snapshot	Graph-edge construction and access-distance calculation
Public transport network	Routes, stops, stations, route geometry, and transport mode	HSL GTFS / HSL open data	Snapshot generated 1 June 2026; service period 1 June–31 August 2026	Route connectivity and transit-supply measurement

Data type	Variables	Source	Year/period	Use
Public transport schedule	Trips, stop times, service calendars, and peak/off-peak service frequency	HSL GTFS / HSL open data	Snapshot generated 1 June 2026; service period 1 June–31 August 2026	Service-frequency and waiting-time estimation
Transfer and fare-zone data	Transfer links, minimum transfer time, fare zones, and fare combinations	HSL GTFS / HSL open data	1 June 2026 snapshot	Transfer-resistance and fare-zone impedance calculation
Population demand	Grid-level population, age structure, and demographic proxy variables	HSY population grid / Helsinki Region Infoshare	2024 reference year; released in 2025	Population-demand and exposure measurement
Public-service opportunities	Education, commercial, recreational, community, and daily-service facilities	OpenStreetMap spatial data / Geofabrik Finland extract	1 June 2026 snapshot	Public-service opportunity measurement
Healthcare-related opportunities	Hospitals, clinics, pharmacies, and other health-service points	OpenStreetMap spatial data / Geofabrik Finland extract	1 June 2026 snapshot	Healthcare-related accessibility measurement
Land-use-related variables	Residential, commercial, green-space, public-facility, and transport-related proxies	OpenStreetMap spatial data / Geofabrik Finland extract	1 June 2026 snapshot	Built-environment feature construction

4.2.2. Data Preprocessing

All spatial data were first converted to a unified projection coordinate system and then clipped to the administrative boundaries of Helsinki. The study area was further divided into 1 km × 1 km grid units, and population demand, demographic proxy variables, road and pedestrian connections, public transportation stations and routes, public service opportunities, and land use variables were all mapped to the corresponding grids.

Public transport supply is characterized by indicators such as station density, route coverage, service frequency, accessibility distance, transfer resistance, and fare impedance. The availability of public services is measured by the weighted density of educational, medical, commercial, recreational, community and daily service facilities within each grid or within the reachable time range. Population-weighted accessibility exposure is calculated by combining the population demand of the grid and the available population statistical proxy variables.

The corresponding graph structures are constructed for peak and off-peak periods respectively. For each time condition t , the dynamic edge weight matrix W_t comprehensively considers factors such as road connectivity, pedestrian accessibility, public transportation connection, service frequency, planned travel time impedance, waiting time impedance, transfer resistance, and fare zone impedance. Among them, the public transportation impedance is calculated by combining station accessibility, line connection, planned travel time, waiting time based on service frequency, transfer resistance, and fare zone impedance. All node features and edge weights are normalized before model training. Missing values are filled using the mean or median of the neighboring grid, and data exceeding the 1st and 99th percentiles are winsorized.

4.2.3. Reference Accessibility Score Construction

The reference accessibility score is calculated based on the public service opportunities and timetable-driven traffic impedance using the gravity model. The accessibility score for grid cell i under time or scenario t is defined as follows:

$$A_i^{\text{ref},t} = \sum_{m=1}^M O_m \exp[-\beta T_{im}(t)] \quad (16)$$

Among them, O_m represents the number or weight of corresponding public service opportunities, and $T_{im}(t)$ represents the time cost of public transportation required for grid cell i to obtain such opportunities under condition t , and β is the impedance attenuation coefficient. Public service opportunities include education, healthcare, commerce, recreation, community and daily service facilities. $T_{im}(t)$ takes into account factors such as station accessibility, line connection, planned travel time, waiting time based on service frequency, transfer resistance, and fare area impedance.

$A_i^{\text{ref},t}$ will be used as a reference value for model training and evaluation. The low accessibility label is defined as follows:

$$L_i^{\text{ref},t} = \begin{cases} 1, & A_i^{\text{ref},t} < Q_{20}(A^{\text{ref},t}) \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

$Q_{20}(A^{\text{ref},t})$ is calculated based on the reference accessibility scores of all grid cells and is used as the threshold for dividing low accessibility areas. Grid cells with scores lower than this threshold are marked as low accessibility areas.

4.3. Experimental Settings

The experiment compared the proposed model with seven benchmark methods, covering traditional reachability models, non-graph structure machine learning methods, basic graph models, and recent

spatio-temporal deep learning models. Among them, the cumulative opportunity model and the gravity method model represent classic reachability evaluation methods. Random Forest serves as the non-graph structure benchmark for comparing the performance of traditional machine learning methods. Static GCN is used to test the spatial information propagation ability under a fixed edge-weight graph structure. STPGNN, SSL-STMFormer, and PatchSTG, as recent spatio-temporal benchmark models, were adapted and used for estimating grid-level reachability scores during peak and off-peak periods.

TABLE 3 - BASELINE MODELS AND EVALUATION METRICS

Category	Item	Description
Baseline model	Cumulative opportunity model(Wachs & Kumagai, 1973)	Counts reachable public-service opportunities within a travel-time threshold.
Baseline model	Gravity-based accessibility model(Hansen, 1959)	Weights public-service opportunities by travel impedance decay.
Baseline model	Random Forest(Breiman, 2001)	Uses grid-level urban attributes without graph propagation.
Baseline model	Static GCN(Kipf & Welling, 2016)	Uses fixed spatial or transport connections without dynamic edge weights.
Baseline model	STPGNN(Kong et al., 2024)	Spatio-temporal GNN baseline adapted for accessibility score estimation.
Baseline model	SSL-STMFormer(Li et al., 2025)	Self-supervised spatio-temporal Transformer baseline adapted for accessibility score estimation.
Baseline model	PatchSTG(Fang et al., 2025)	Large-scale spatio-temporal Transformer baseline adapted for accessibility score estimation.
Proposed model	Dynamic impedance-weighted graph model	Converts dynamic impedance into graph edge weights and links accessibility scores to fairness indicators.
Evaluation metric	MAE ↓	Measures the average error between estimated and reference accessibility scores.
Evaluation metric	Spearman ↑	Measures spatial ranking consistency of accessibility scores.
Evaluation metric	Gini ↓	Measures regional accessibility inequality.
Evaluation metric	ΔJ ↑	Measures fairness improvement under candidate governance scenarios.

The experimental parameters are set as shown in Table 1, including two layers, 64 hidden dimensions, ReLU activation function, Adam optimizer, learning rate of 0.001, dropout ratio of 0.30, weight decay of 1×10^{-4} , 200 epochs, and an early stopping strategy with 20 cycles. The training set, validation set, and test set are divided in a ratio of 70% / 15% / 15%.

MAE is used to measure the estimation error of the model for the reference accessibility score in Section 4.2. Spearman is used to evaluate the consistency of spatial sorting. Gini is used to analyze the degree of accessibility inequality under peak and off-peak conditions, and ΔJ is used to compare the changes in fairness indicators under different governance scenarios. This indicator takes into account the impact of service frequency, travel time, waiting time impedance, transfer resistance, fare area impedance, and service opportunity adjustment.

All models were run five times each and the results were evaluated. A two-sided Welch t-test was used to compare the differences between the proposed model and the Static GCN, SSL-STMFormer, and

PatchSTG. In the test, the assumption of equal variances was not made. The significance level was set at $\alpha = 0.05$. The average difference was calculated as the result of the proposed model minus the baseline model. The 95% confidence interval and p-value are shown in Table 5.

4.4. Model Performance Comparison

Table 4 compares the performance of the proposed model with those of seven benchmark models. The results are presented as the mean $\pm$ standard deviation of five independent runs. MAE and Spearman are used to evaluate the estimation error of accessibility scores and the consistency of spatial sorting, while Gini and ΔJ are used to measure the fairness performance and the optimization effect of scenarios. Table 5 further reports the statistical test results between the proposed model and the best benchmark model as well as Static GCN.

TABLE 4. MODEL PERFORMANCE COMPARISON

Model	MAE ↓	Spearman ↑	Gini ↓	ΔJ ↑
Cumulative opportunity model	0.146 $\pm$ 0.011	0.684 $\pm$ 0.026	0.318 $\pm$ 0.020	0.041 $\pm$ 0.009
Gravity-based accessibility model	0.121 $\pm$ 0.009	0.742 $\pm$ 0.021	0.291 $\pm$ 0.018	0.055 $\pm$ 0.010
Random Forest	0.107 $\pm$ 0.008	0.763 $\pm$ 0.019	0.276 $\pm$ 0.016	0.061 $\pm$ 0.011
Static GCN	0.098 $\pm$ 0.007	0.795 $\pm$ 0.017	0.261 $\pm$ 0.015	0.068 $\pm$ 0.012
STPGNN	0.092 $\pm$ 0.006	0.816 $\pm$ 0.015	0.252 $\pm$ 0.014	0.074 $\pm$ 0.013
SSL-STMFormer	0.088 $\pm$ 0.006	0.823 $\pm$ 0.016	0.258 $\pm$ 0.017	0.071 $\pm$ 0.014
PatchSTG	0.094 $\pm$ 0.007	0.835 $\pm$ 0.014	0.249 $\pm$ 0.013	0.076 $\pm$ 0.012
Proposed	0.090 $\pm$ 0.005	0.829 $\pm$ 0.013	0.236 $\pm$ 0.012	0.086 $\pm$ 0.012

TABLE 5. STATISTICAL COMPARISONS BETWEEN THE PROPOSED MODEL AND SELECTED BASELINES

Comparison	Metric	Mean difference	95% CI	p-value	Result
Proposed vs. SSL-STMFormer	MAE	0.002	[−0.0061, 0.0101]	0.583	ns
Proposed vs. PatchSTG	Spearman	−0.006	[−0.0257, 0.0137]	0.503	ns
Proposed vs. Static GCN	Gini	−0.025	[−0.0450, −0.0050]	0.021	*
Proposed vs. Static GCN	ΔJ	0.018	[0.0005, 0.0355]	0.045	*
Proposed vs. SSL-STMFormer	Gini	−0.022	[−0.0439, −0.0001]	0.049	*
Proposed vs. SSL-STMFormer	ΔJ	0.015	[−0.0041, 0.0341]	0.107	ns
Proposed vs. PatchSTG	Gini	−0.013	[−0.0313, 0.0053]	0.139	ns
Proposed vs. PatchSTG	ΔJ	0.010	[−0.0075, 0.0275]	0.224	ns

Note: The mean difference is calculated by subtracting the result of the baseline model from the result of the proposed model.

Negative values indicate a decrease in MAE or Gini, while positive values indicate an increase in Spearman or ΔJ . Each model was run five times and compared using a two-sided Welch t-test. * indicates $p < 0.05$, and ns indicates $p \geq 0.05$.

Figure 3 presents the performance of different models in four indicators and compares the results for both reachability prediction and fairness assessment.

INTEGRATING GRAPH NEURAL NETWORKS AND MULTI-SOURCE URBAN DATA FOR FAIRNESS ASSESSMENT AND DYNAMIC OPTIMIZATION OF URBAN ACCESSIBILITY

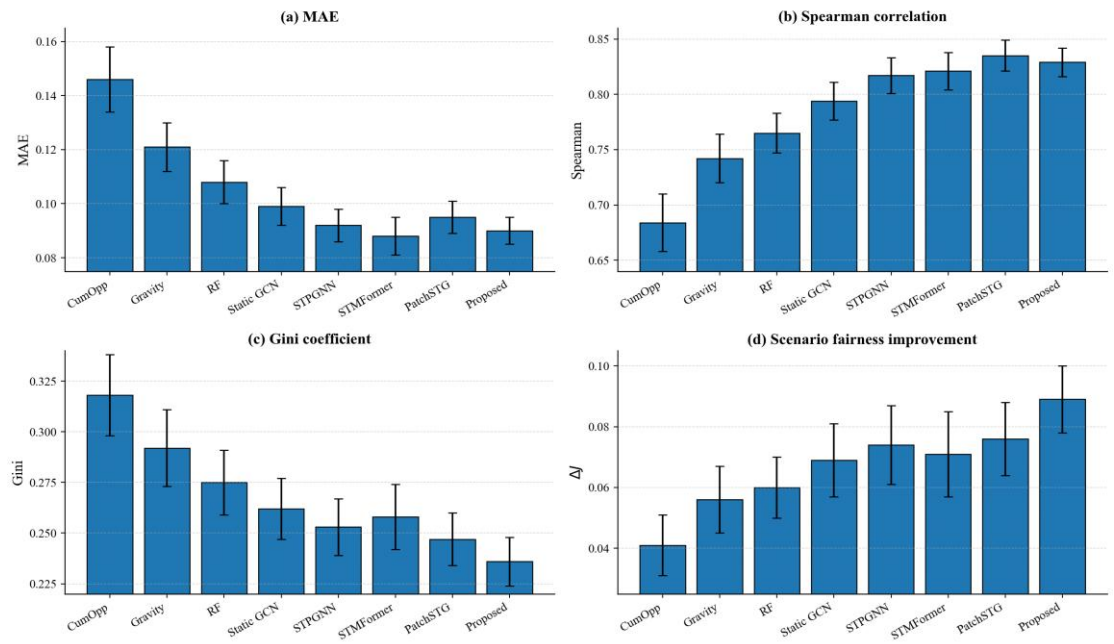


FIGURE 3 - COMPARISON OF MODEL PERFORMANCE WITH BENCHMARK METHODS: (A) MAE OF ACCESSIBILITY SCORE ESTIMATION; (B) SPEARMAN CORRELATION COEFFICIENT OF SPATIAL RANKING CONSISTENCY; (C) DEGREE OF ACCESSIBILITY INEQUALITY (GINI COEFFICIENT); (D) IMPROVEMENT EFFECT OF FAIRNESS BASED ON SCENARIO ANALYSIS (ΔJ).

The cumulative opportunity model has the highest MAE and lowest Spearman value, indicating that fixed travel-time thresholds provide a coarse accessibility representation. The gravity-based model improves performance through impedance decay. Random Forest further reduces MAE but remains weaker than graph-based methods in ranking consistency.

Static GCN outperforms Random Forest in MAE and Spearman, confirming the value of graph propagation. Among recent baselines, SSL-STMFormer achieves the lowest mean MAE and PatchSTG the highest mean Spearman, but neither obtains the best mean Gini or ΔJ .

The proposed model has a slightly higher MAE than SSL-STMFormer and a slightly lower Spearman value than PatchSTG, with neither difference significant ($p = 0.583$ and $p = 0.503$). It nevertheless achieves the lowest mean Gini and highest mean ΔJ .

Compared with Static GCN, the proposed model reduces MAE from 0.098 ± 0.007 to 0.090 ± 0.005 , lowers Gini from 0.261 ± 0.015 to 0.236 ± 0.012 , and increases ΔJ from 0.068 ± 0.012 to 0.086 ± 0.012 . The Gini reduction ($p = 0.021$) and ΔJ improvement ($p = 0.045$) are significant, supporting dynamic impedance weighting over fixed-edge propagation.

Compared with SSL-STMFormer, the Gini reduction is significant ($p = 0.049$), whereas the ΔJ difference is not ($p = 0.107$). Against PatchSTG, the differences in Gini and ΔJ did not reach a significant level ($p = 0.139$ and $p = 0.224$), indicating that their performance in fairness indicators is similar to that of the recent benchmark models. Therefore, the model advantages vary under different evaluation indicators.

Overall, Tables 4, 5 and Figure 3 show that the dynamic impedance weighting method outperforms the static GCN in fairness assessment and scenario ranking. The proposed model achieves the best results in the average Gini and ΔJ indicators, while the recent benchmark models still maintain strong competitiveness in the prediction-related indicators.

4.5. Spatial Distribution of Accessibility Fairness

Figure 4 shows the distribution of estimated accessibility scores for Helsinki grid cells during peak and off-peak hours. For most grid cells, the median accessibility score during peak hours is lower than that during off-peak hours, but the decline degree varies across different regions. The central area and inner urban areas typically have higher median scores, and the score distribution is relatively concentrated. The scores in the peripheral areas and waterfront edge areas fluctuate more and have a wider distribution range. In some peripheral areas and grids heavily relying on transfers, there are many low-value outliers, indicating that the accessibility disadvantage is spatially unevenly distributed.

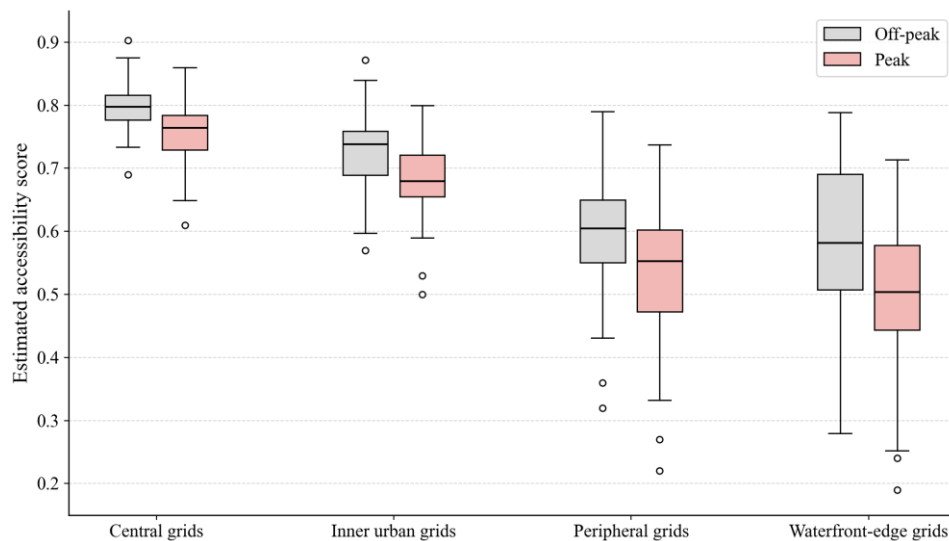


FIGURE 4 - ACCESSIBILITY SCORE DISTRIBUTION UNDER OFF-PEAK AND PEAK CONDITIONS ACROSS HELSINKI GRID GROUPS.

The accessibility decline in peak periods demonstrates significant spatial differences. The central urban areas close to major HSL hubs still maintain a relatively high level, but some peripheral regions, waterfront edges, and areas relying on branch connections have experienced more pronounced declines. This result

is consistent with the transportation spatial structure of Helsinki: the central urban area has more dense service facilities and public transportation lines; the surrounding areas rely more on branch services, pedestrian connections, and transfer connections for travel. The box plot further illustrates the accessibility distribution characteristics of different areas before the spatial priority analysis.

Figure 5 presents the low accessibility areas in Helsinki and their governance priorities. Based on the determined Q20 value based on the reference accessibility distribution. The threshold classifies the estimated accessibility scores of the model to identify low-accessibility grids. Subsequently, the governance priorities are determined based on the degree of accessibility deficiency, the gap in public transportation supply, spatial clustering characteristics, and demand-related proxy variables. Low-accessibility areas do not necessarily correspond to the highest governance priority. Some grids are classified as medium priority due to comprehensive factors, while areas with more significant accessibility decline, greater supply deficiency, or higher demand pressure are classified as high priority or extremely high priority.

Figure 5(a) shows the spatial distribution of low accessibility grids, and Figure 5(b) presents the corresponding governance priority results. The results indicate that the areas with low accessibility and high priority mainly concentrate in the urban periphery, areas with insufficient line coverage, and some waterfront edge zones, while the central areas and the surrounding regions of major HSL transfer hubs are mainly non-priority areas.

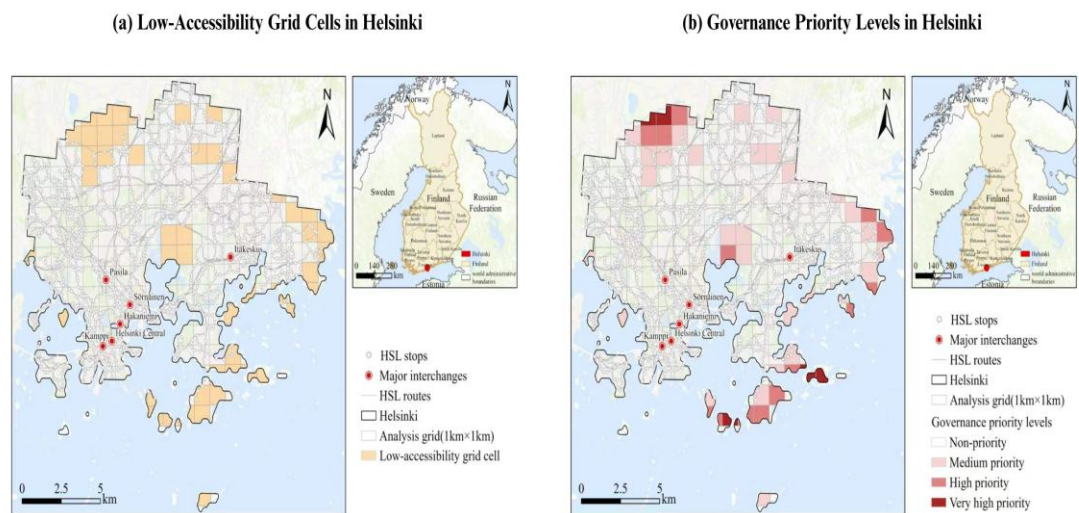


FIGURE 5 - SPATIAL DISTRIBUTION OF LOW-ACCESSIBILITY AREAS AND GOVERNANCE PRIORITY LEVELS IN HELSINKI. (A) LOW-ACCESSIBILITY GRID CELLS IN HELSINKI. (B) GOVERNANCE PRIORITY LEVELS IN HELSINKI

4.6. Fairness Indicator Analysis

Table 6 shows the accessibility equity indicators of off-peak and peak periods, which is consistent with the equity evaluation module proposed in Section 3.5. Figure 6 further illustrates the changes of the four equity indicators between the two periods.

TABLE 6 - ACCESSIBILITY FAIRNESS INDICATORS UNDER PEAK AND OFF-PEAK CONDITIONS

Scenario	Gini ↓	Low-accessibility ratio ↓	PAE ↑	SDM ↑
Off-peak	0.236 ± 0.012	0.201 ± 0.013	0.684 ± 0.028	0.713 ± 0.026
Peak	0.267 ± 0.016	0.232 ± 0.021	0.646 ± 0.034	0.699 ± 0.031
Difference	$+0.031 \pm 0.011$	$+0.031 \pm 0.018$	-0.038 ± 0.022	-0.014 ± 0.019

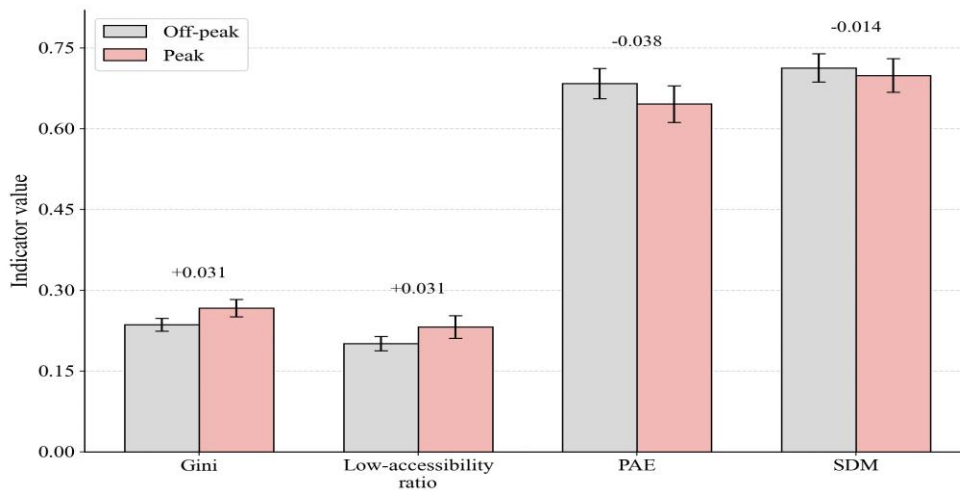


FIGURE 6 - PEAK-OFF-PEAK CHANGES IN ACCESSIBILITY FAIRNESS INDICATORS.

As shown in Table 6, the Gini coefficient increased from 0.236 ± 0.012 during off-peak hours to 0.267 ± 0.016 during peak hours, and the low accessibility ratio also rose from 0.201 ± 0.013 to 0.232 ± 0.021 . This result is consistent with the distribution characteristics shown in Figure 4. In some grid cells during peak hours, the degree of separation of accessibility became more discrete. At the same time, the standard deviation of the low accessibility ratio during peak hours increased, indicating that the differences between different regions further expanded.

PAE decreased from 0.684 ± 0.028 to 0.646 ± 0.034 , while SDM decreased slightly from 0.713 ± 0.026 to 0.699 ± 0.031 . Compared with SDM, the decline and fluctuation range of PAE were greater, indicating that population-weighted accessibility exposure is more sensitive to the changes in traffic impedance during peak hours, while the impact on supply-demand matching is relatively smaller. The spatial distribution in Figure 5 further confirms this result, with high-priority and extremely high-priority areas mainly concentrated in regions with lower accessibility, insufficient public transportation supply, and high demand pressure.

By considering all four indicators, it can be seen that PAE and the low accessibility ratio have a more obvious response to the changes during peak hours, while SDM is relatively stable. This indicates that relying solely on average accessibility or the Gini coefficient is insufficient to comprehensively reflect the differences in fairness. Table 6 and Figure 6 depict the overall changes in accessibility inequality, low accessibility areas, population-weighted accessibility exposure, and supply-demand matching between peak and off-peak hours, providing quantitative support for the spatial distribution shown in Figures 4 and 5.

4.7. Scenario-Based Dynamic Governance Optimization

To evaluate the optimized effects of different intervention measures, this paper has designed five candidate governance scenarios, as detailed in Table 7. For each scenario, the input is reconstructed by updating the graph structure or node variables, and the accessibility and fairness indicators are recalculated to compare the improvement effects of different governance schemes.

TABLE 7 - CANDIDATE GOVERNANCE SCENARIOS

Scenario	Quantified variable update	Planning meaning
S1 Frequency increase	For high- and very-high-priority grids with service frequency below the study-area median, set $S_i' = 1.10S_i$ and reduce waiting-time impedance by 8%.	Increase service frequency in underserved HSL corridors.
S2 Feeder connection improvement	For grids with $A_i < Q_{20}(\bar{A})$ and $\Pi_i \geq Q_{80}(\Pi)$, reduce access impedance by 10% and add feeder links to the nearest major HSL stop or interchange.	Improve first/last-mile connection in high-priority areas.
S3 Transfer improvement	For transfer-related edges connected to grids with transfer resistance above Q_{75} , set $\bar{\tau}_{ij}^t = 0.85\bar{\tau}_{ij}^t$.	Reduce transfer burden at high-resistance nodes.
S4 Service opportunity supplementation	For grids with SDM below Q_{25} , set $O_i' = 1.08O_i$.	Add or redistribute public-service opportunities in supply-deficient areas.
S5 Combined strategy	For very-high-priority grids, set $S_i' = 1.08S_i$ and $O_i' = 1.05O_i$, and set $\bar{\tau}_{ij}^t = 0.90\bar{\tau}_{ij}^t$ for the associated transfer-related edges.	Combine moderate transit, transfer, and service-opportunity adjustments.

The assessment results of each scenario are summarized in Table 8, where the current situation corresponds to the peak-hour conditions in Table 6. All results are presented as the average value $\pm$ standard deviation of five repeated experiments.

TABLE 8 - SCENARIO-BASED GOVERNANCE OPTIMIZATION RESULTS

Scenario	Gini ↓	Low-accessibility ratio ↓	PAE ↑	SDM ↑	ΔJ ↑
Current condition	0.267 ± 0.016	0.232 ± 0.021	0.646 ± 0.034	0.699 ± 0.031	—
S1 Frequency increase	0.253 ± 0.018	0.214 ± 0.024	0.676 ± 0.031	0.711 ± 0.029	0.067 ± 0.014
S2 Feeder improvement	0.248 ± 0.017	0.205 ± 0.022	0.668 ± 0.036	0.724 ± 0.027	0.074 ± 0.013
S3 Transfer improvement	0.241 ± 0.015	0.218 ± 0.025	0.662 ± 0.033	0.707 ± 0.032	0.065 ± 0.015
S4 Service supplementation	0.259 ± 0.019	0.221 ± 0.023	0.657 ± 0.038	0.737 ± 0.030	0.061 ± 0.016
S5 Combined strategy	0.245 ± 0.017	0.198 ± 0.020	0.686 ± 0.032	0.731 ± 0.028	0.086 ± 0.012

Figure 7 compares the ΔJ values under different governance scenarios. From the results, it can be seen that different intervention measures have different focuses on improving fairness: increasing service frequency and optimizing branch connections mainly reduce low accessibility exposure; improving transfer conditions have a more significant effect on reducing accessibility inequality; and supplementing public service facilities mainly enhance the SDM level.

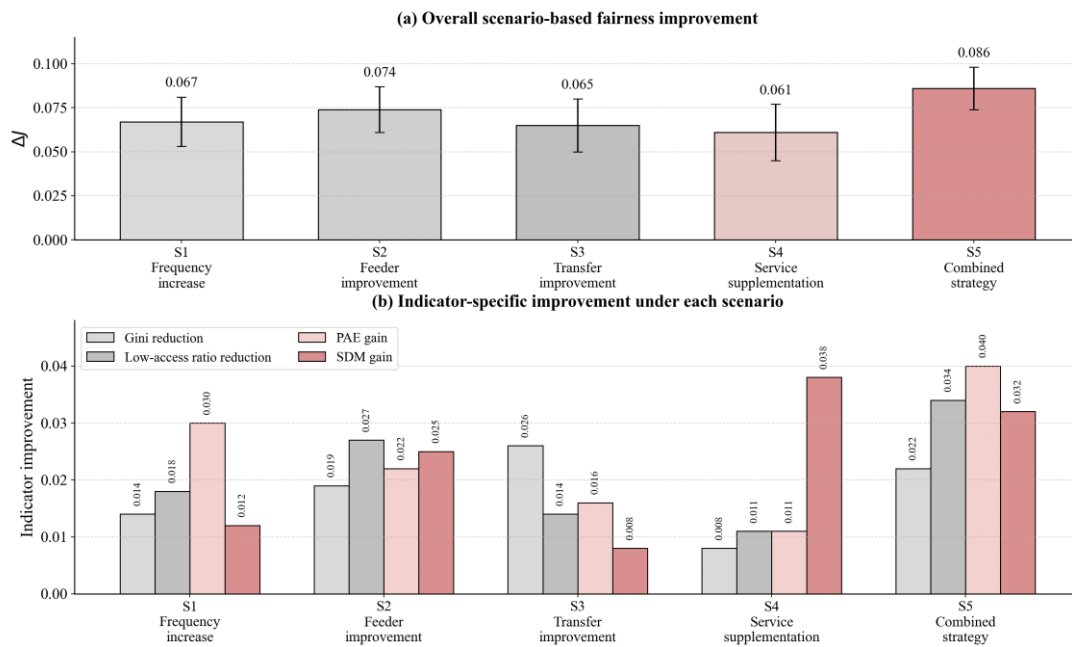


FIGURE 7 - SCENARIO-BASED FAIRNESS IMPROVEMENT UNDER CANDIDATE GOVERNANCE STRATEGIES: (A) OVERALL ΔJ VALUES WITH STANDARD DEVIATIONS; (B) INDICATOR-SPECIFIC IMPROVEMENTS RELATIVE TO THE CURRENT PEAK-PERIOD CONDITION.

The performance of different governance scenarios in various fairness indicators varies to some extent (Table 8, Figure 7). Among them, the ΔJ value of S5 is the highest, but the Gini coefficient is not the lowest; the Gini coefficient of S3 is the lowest, but the low accessibility ratio and ΔJ performance are relatively average; S4 achieved the highest SDM, but its Gini coefficient and low accessibility ratio were still higher than those of S2 and S5.

The various indicators of S2 are relatively balanced, and its comprehensive ranking is second. It has achieved a good balance among indicators such as the Gini coefficient, low accessibility rate, SDM, and ΔJ . By referring to Figure 5(b), it can be observed that this scenario mainly corresponds to marginal areas, waterfront regions, and high-priority grids that rely on transfers. In contrast, S1 is more suitable for areas with better coverage of existing HSL lines, while S4 is more applicable to regions with relatively insufficient public service opportunities.

During the scenario optimization process in Tables 7 and 8, each candidate solution updates the graph structure or node variables based on the corresponding intervention measures, recalculates the accessibility score and fairness index, and then conducts a comprehensive ranking based on ΔJ . To further test the stability of the results, in this paper, the low accessibility threshold is adjusted from Q20 to Q10 and Q30 respectively, and the related results are shown in Table 9.

TABLE 9 - THRESHOLD SENSITIVITY AND SCENARIO RANKING STABILITY

Low-accessibility threshold	Low-accessibility ratio	Main priority-grid pattern	Top-ranked scenario	Second-ranked scenario
Q_{10}	0.109 ± 0.015	Concentrated in severe peripheral and waterfront-edge grids	S5	S3
Q_{20}	0.232 ± 0.021	Distributed across peripheral, transfer-dependent, and service-gap grids	S5	S2
Q_{30}	0.321 ± 0.027	Expanded to additional inner-edge and feeder-dependent grids	S5	S2

Figure 8 presents the sensitivity analysis results under different thresholds. As the low accessibility threshold increases from Q10 to Q30, the proportion of low accessibility grids identified also increases, indicating that the results are influenced by the threshold setting. However, the overall ranking of each scenario remains relatively stable. S5 always ranks first, while the second place is adjusted from S3 under the Q10 condition to S2 under the Q20 and Q30 conditions.

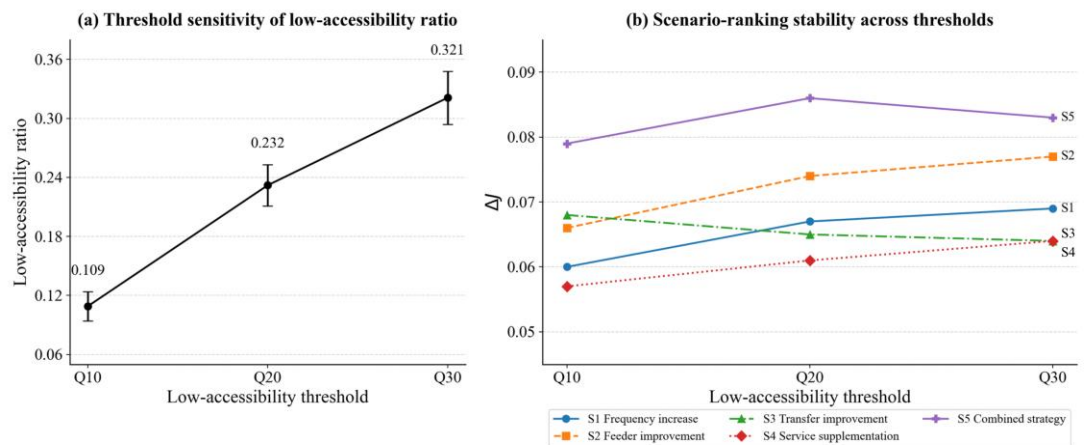


FIGURE 8 - THRESHOLD SENSITIVITY OF LOW-ACCESSIBILITY IDENTIFICATION AND SCENARIO RANKING STABILITY: (A) LOW-ACCESSIBILITY RATIO UNDER Q10, Q20, AND Q30 THRESHOLDS; (B) SCENARIO-BASED FAIRNESS IMPROVEMENT SCORES ACROSS THRESHOLDS.

When the low accessibility threshold changes, the number of identified grids will also be adjusted accordingly. The scenario with the highest ranking is always S5, but under a stricter Q₁₀ threshold, the second-ranked scenario changes, indicating that the ranking of scenarios is still influenced by the threshold setting. Overall, the spatial distribution of the main priority areas remains relatively stable, but the attribution of some grids and the ranking of secondary scenarios will still change with the threshold.

4.8. Ablation Analysis of Dynamic Graph Components

To verify whether the test results are dependent on the construction method of the dynamic impedance weighted graph, this paper further conducted ablation experiments. By removing the key impedance components in the model, the impact was analyzed. Specifically, each experimental variant removed the impedance components of planned travel time, service frequency, waiting time, transfer resistance, and fare zone. Additionally, a static edge weight variant was set up, keeping the graph edge weights unchanged during peak/non-peak hours and under different scenarios. All experimental results were presented as the average value $\pm$ standard deviation of five repeated runs.

TABLE 10 - ABLATION RESULTS OF DYNAMIC IMPEDANCE COMPONENTS

Variant	MAE $\downarrow$	Spearman $\uparrow$	Gini $\downarrow$	ΔJ $\uparrow$
Proposed	0.090 $\pm$ 0.005	0.829 $\pm$ 0.013	0.236 $\pm$ 0.012	0.086 $\pm$ 0.012
w/o scheduled travel time	0.097 $\pm$ 0.007	0.812 $\pm$ 0.016	0.248 $\pm$ 0.014	0.077 $\pm$ 0.012
w/o service frequency	0.096 $\pm$ 0.006	0.816 $\pm$ 0.015	0.247 $\pm$ 0.013	0.079 $\pm$ 0.013
w/o waiting-time impedance	0.094 $\pm$ 0.006	0.821 $\pm$ 0.014	0.245 $\pm$ 0.014	0.081 $\pm$ 0.012
w/o transfer resistance	0.098 $\pm$ 0.007	0.809 $\pm$ 0.017	0.254 $\pm$ 0.015	0.075 $\pm$ 0.014
w/o fare-zone impedance	0.091 $\pm$ 0.006	0.830 $\pm$ 0.014	0.242 $\pm$ 0.013	0.084 $\pm$ 0.012
Static edge weights	0.101 $\pm$ 0.008	0.799 $\pm$ 0.018	0.258 $\pm$ 0.016	0.072 $\pm$ 0.013

Figure 9 summarizes the degradation of normalized performance under different ablation variants, which is used for an intuitive comparison of the relative impact after removing each component; Table 10 further presents the specific changes in indicators. The degree of influence of different components varies. Removing the static edge weight constraints and traffic impedance information will lead to more significant performance degradation, while removing the impact of fare zone impedance has a relatively smaller effect and the results fluctuate more.

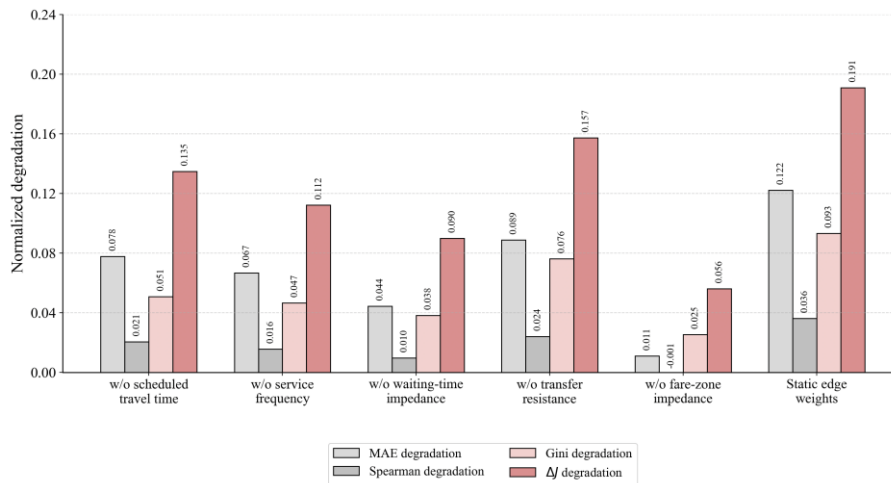


FIGURE 9 - PERFORMANCE DEGRADATION UNDER ABLATED DYNAMIC GRAPH COMPONENTS.

As shown in Table 10, after eliminating different variables, the overall performance of the model has declined, but the impact on each evaluation indicator varies. Among them, the performance of the static-edge variant has decreased the most significantly: MAE increased from 0.090 ± 0.005 to 0.101 ± 0.008 , Gini rose from 0.236 ± 0.012 to 0.258 ± 0.016 , while ΔJ decreased from 0.086 ± 0.012 to 0.072 ± 0.013 . This result indicates that in tasks for fairness assessment, compared to fixed connection relationships, considering time and scenario changes in dynamic edge weights can more effectively depict the state of the transportation network.

The impact of different impedance components on the model performance varies. After removing the transfer resistance, the changes in Gini and ΔJ were the most significant, indicating that the transfer conditions have a considerable influence on the accessibility fairness assessment; while removing the planned travel time mainly led to a decrease in MAE and consistency of spatial ranking. Waiting time impedance and service frequency also affect the model results, but the change range is relatively limited, so their influence should not be overinterpreted. In contrast, removing the impedance of ticket area had a smaller impact on MAE and Spearman, but still caused an increase in Gini and a decrease in ΔJ .

Overall, the ablation experiments verified the effectiveness of the dynamic impedance weighted graph construction method for the assessment of accessibility fairness. At the same time, the experimental results also indicated that the contribution degrees of different components were not the same. The decline in model performance was mainly reflected in the changes after removing the dynamic edge weight mechanism, transfer resistance, and planned travel time, which further demonstrated that time-related impedance and traffic connection conditions are important factors affecting the fairness assessment.

5. DISCUSSIONS

This study proposes a framework based on dynamic graphs for evaluating the fairness of public transportation accessibility and comparing the potential effects of different governance scenarios. This framework takes into account the characteristics of changes in public transportation operation conditions over time and scenarios, incorporating factors such as planned travel time, service frequency, waiting time, transfer conditions, and fare zones into the traffic network modeling. This enables the accessibility assessment to reflect the differences between peak and off-peak hours. The model ultimately outputs accessibility scores at the grid scale, and combines fairness indicators and governance priority rules to identify underserved areas and compare intervention plans.

This framework combines dynamic traffic conditions with fairness assessment. Through a dynamic graph structure, the model can describe the changes in traffic connection relationships over different time

periods, and comprehensively consider the characteristics of each spatial unit and its surrounding traffic connections to estimate the accessibility level at the grid scale. On this basis, the fairness analysis further assesses the differences in accessibility between regions, low accessibility exposure, population-weighted accessibility exposure, and supply-demand matching situations. The governance module then determines spatial priorities based on these results and compares the improvement degrees under different scenarios.

The experimental results show that the proposed method exhibits excellent comprehensive performance among traditional reachability models, non-graph machine learning methods, static graph models, and spatio-temporal baseline models. Although some spatio-temporal models still have advantages in tasks such as reachability score estimation and spatial sorting, this method achieves the best results in terms of the average Gini coefficient and ΔJ index. It should be noted that the superiority of this method over recent baseline models may vary depending on the evaluation indicators. The reachability assessment method that combines dynamic traffic conditions and fairness indicators can effectively support the identification of underserved areas and provide a basis for the comparison of different governance schemes.

From a planning perspective, low accessibility areas are not necessarily priority intervention areas. In addition to the accessibility level, judgments need to be made by considering population needs, residents' accessibility exposure, distribution of public services, and the matching of supply and demand. In the Helsinki case, the central area, peripheral areas, waterfront edge areas, and grid units that rely on transfers exhibit different characteristics in terms of accessibility, demand pressure, and service opportunities.

This research still has some aspects that need to be further improved. Firstly, the reference accessibility score adopted in this paper is calculated based on public data and the gravity model, and no actual travel behavior data has been used for calibration. Then, the impedance variables in the model mainly come from timetable information, transfer rules, fare zone settings, spatial distance, and public service proxy variables, and may not fully capture the time variations and individual route choices in actual travel. Finally, the scenario analysis is used to compare the potential effects of different governance schemes and does not represent the actual impact of HSL service adjustments. Future research can further combine smart card records, passenger flow data, actual transfer behaviors, mobile signaling data, and data over a longer time range for verification.

6. CONCLUSIONS

This study addresses the issue of insufficient connection among dynamic public transportation impedance, accessibility equity assessment, and governance priority. It proposes an analysis framework based on dynamic graphs. This framework represents traffic factors such as planned travel time, service frequency, waiting time, transfer conditions, and fare zones as edge weights that change over time and scenarios. Furthermore, it combines the accessibility score at the grid scale with equity indicators and governance priority assessment.

Taking Helsinki, Finland as an example, the study integrated HSL public transportation data, OpenStreetMap road and pedestrian network data, population grid data, public service facility information, and land use-related variables. The results showed that compared with the fixed-edge-weight GCN method, dynamic edge weights could improve the estimation effect of accessibility scores; there were significant differences in the accessibility equity levels under different time conditions; the scenario analysis module could further support the comparison and ranking of different governance schemes.

The research findings indicate that the improvement of low accessibility areas requires comprehensive consideration of specific spatial characteristics and service gaps. Different measures, such as increasing service frequency, optimizing connection routes, improving transfer conditions, or providing additional service opportunities, may correspond to different improvement directions. It should be noted that the scenario results reflect the planning simulation based on open data, rather than the actual effects after policy implementation.

Future studies could use observed travel behavior data and longer-term observations to further evaluate the applicability of the proposed framework. At the same time, conducting tests in more cities and at different spatial scales will help assess the applicability and promotion value of this framework.

REFERENCES

- Breiman, L. (2001). Random forests. *Machine learning*, 45(1), 5-32. <https://doi.org/10.1023/A:1010933404324>
- Chen, P., Wang, W., Qian, C., Cao, M., & Yang, T. (2024). Gravity-based models for evaluating urban park accessibility: Why does localized selection of attractiveness factors and travel modes matter?. *Environment and Planning B: Urban Analytics and City Science*, 51(4), 904-922. <https://doi.org/10.1177/23998083231206168>
- Dianin, A., Gidam, M., Hauger, G., & Ravazzoli, E. (2024). Measuring public transport accessibility to fixed activities and discretionary opportunities: a space-time approach. *European Transport Research Review*, 16(1), 9. <https://doi.org/10.1186/s12544-024-00636-2>
- Fang, Y., Liang, Y., Hui, B., Shao, Z., Deng, L., Liu, X., ... & Zheng, K. (2025, July). Efficient large-scale traffic forecasting with transformers: A spatial data management perspective. In *Proceedings of the*

- 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining V. 1 (pp. 307-317). <https://doi.org/10.1145/3690624.3709177>
- Gamal, M., & Ibrahim, O. A. (2025). Graph neural networks for real-time optimization of autonomous urban transit systems. *Discover Cities*, 2(1), 102. <https://doi.org/10.1007/s44327-025-00145-4>
- Gelb, J., Alizadeh, H., & Desjardins, L. (2026). Towards fair transit: a toolbox for equity diagnostics in spatial accessibility. *Public Transport*, 1-32. <https://doi.org/10.1007/s12469-025-00412-y>
- Geurs, K. T., & Van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport Geography*, 12(2), 127-140. <https://doi.org/10.1016/j.jtrangeo.2003.10.005>
- Hansen, W. G. (1959). How accessibility shapes land use. *Journal of the American Institute of Planners*, 25(2), 73-76. <https://doi.org/10.1080/01944365908978307>
- Jain, P., Kapatsila, B., & Grisé, E. (2026). Whose access is enhanced? An equity prioritization framework for evaluating proposed transit route alignments in Edmonton, Canada. *Journal of Transport Geography*, 133, 104648. <https://doi.org/10.1016/j.jtrangeo.2026.104648>
- Khorramisarvestani, S., Gauthier, P., & Eicker, U. (2025). Exploring sustainable accessibility through multimodal networks: Assessing healthy food access in Montreal. *Journal of Urban Mobility*, 8, 100170. <https://doi.org/10.1016/j.urbmob.2025.100170>
- Kipf, T. N., & Welling, M. (2016). Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907. <https://doi.org/10.48550/arXiv.1609.02907>
- Kong, W., Guo, Z., & Liu, Y. (2024, March). Spatio-temporal pivotal graph neural networks for traffic flow forecasting. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 38, No. 8, pp. 8627-8635). <https://doi.org/10.1609/aaai.v38i8.28707>
- Kyere-Gyeabour, E., Sivakumar, A., & Agyei-Mensah, S. (2024). Transit and fairness: Exploring spatial equity in Accra's public transport system. *African Transport Studies*, 2, 100012. <https://doi.org/10.1016/j.aftran.2024.100012>
- Li, Z., Hu, Z., Han, P., Gu, Y., & Cai, S. (2025, April). Ssl-stmformer self-supervised learning spatio-temporal entanglement transformer for traffic flow prediction. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 39, No. 11, pp. 12130-12138). <https://doi.org/10.1609/aaai.v39i11.33321>
- Liu, L., Porr, A., & Miller, H. J. (2024). Measuring the impacts of disruptions on public transit accessibility and reliability. *Journal of Transport Geography*, 114, 103769. <https://doi.org/10.1016/j.jtrangeo.2023.103769>
- Lucas, K. (2012). Transport and social exclusion: Where are we now?. *Transport policy*, 20, 105-113. <https://doi.org/10.1016/j.tranpol.2012.01.013>
- Mohamed, G. A., Ayad, H. M., & Saadallah, D. M. (2026). Assessing public transport equity: The case of Alexandria, Egypt. *Alexandria Engineering Journal*, 141, 96-108. <https://doi.org/10.1016/j.aej.2026.03.006>
- Pereira, R. H., Schwanen, T., & Banister, D. (2017). Distributive justice and equity in transportation. *Transport reviews*, 37(2), 170-191. <https://doi.org/10.1080/01441647.2016.1257660>
- Pot, F. J. (2025). Perceived accessibility and transport equity: Does satisfaction imply perceived sufficiency of opportunities?. *Transportation Research Part A: Policy and Practice*, 198, 104497. <https://doi.org/10.1016/j.tra.2025.104497>

- Rahmah, U. A., Delbosc, A., & Kamruzzaman, L. (2026). Spatial Accessibility for Women: A Systematic Literature Review. *Transportation Research Record*, 2680(3), 637-655. <https://doi.org/10.1177/03611981251388618>
- Rivera-Gonzalez, C., & Amaral, J. C. (2024). Assessment of freight accessibility in New York City: a spatial-temporal approach. *Journal of Transport Geography*, 114, 103777. <https://doi.org/10.1016/j.jtrangeo.2023.103777>
- Tahmasbi, B., Hajian, P., Tahmasbi, F., & He, Q. (2024). Measuring integrated accessibility for sustainable mobility: A fuzzy set approach case study. *Computational Urban Science*, 4(1), 35. <https://doi.org/10.1007/s43762-024-00146-w>
- van Wee, B. (2025). Equity and Accessibility in Urban Mobility. In *Urban Human Mobility* (pp. 21-28). CRC Press. <https://doi.org/10.1201/9781003503262-5>
- Verduzco Torres, J. R., & McArthur, D. P. (2024). Public transport accessibility indicators to urban and regional services in Great Britain. *Scientific Data*, 11(1), 53. <https://doi.org/10.1038/s41597-023-02890-w>
- Wachs, M., & Kumagai, T. G. (1973). Physical accessibility as a social indicator. *Socio-Economic Planning Sciences*, 7(5), 437-456. [https://doi.org/10.1016/0038-0121\(73\)90041-4](https://doi.org/10.1016/0038-0121(73)90041-4)
- Wang, H., & Loo, B. P. (2024). The public transport disadvantaged in a highly transit-oriented city: An analytical framework, key challenges and opportunities. *Journal of Transport Geography*, 120, 103983. <https://doi.org/10.1016/j.jtrangeo.2024.103983>
- Wang, J., Kwan, M. P., Liu, D., Liu, Y., & Wang, L. (2026). From proximity to equity: Rethinking X-minute-city policies for accessibility equity through a spatial optimization perspective. *Journal of Transport Geography*, 132, 104581. <https://doi.org/10.1016/j.jtrangeo.2026.104581>
- Wu, S., & Mu, R. (2025). Toward Sustainable and Inclusive Cities: Graph Neural Network-Enhanced Optimization for Disability-Inclusive Emergency Evacuation in High-Rise Buildings. *Sustainability*, 17(22), 10387. <https://doi.org/10.3390/su172210387>
- Zhang, Y., Liang, K., & Loo, B. P. (2025). Measuring dynamic accessibility by metro system under travel time uncertainty based on smart card data. *Journal of Transport Geography*, 127, 104294. <https://doi.org/10.1016/j.jtrangeo.2025.104294>