

Diagnosing public transport disadvantage in multi-activity accessibility: Opportunity-side and service-side signals

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ABSTRACT

Multi-activity daily travel requires access to several everyday opportunities within limited time budgets. Public transport (PT), however, often provides less effective door-to-door access to such opportunity combinations than private cars. Using scheduled PT and private-car travel times for access to eight categories of essential facilities across 229 South Korean city-level administrative units, this study develops a diagnostic framework that distinguishes facility-side reachability signals, weak co-location-based bundling signals, and PT-side penalty signals. First, under the national population-weighted mean reference lines used for the baseline classification, 114 of 229 units (49.8%) fall into the compound {F(s), F(d), T(c)} regime, in which all three signals co-occur. Second, an aging-related vulnerability pattern emerges: older-adult share is positively associated with all three diagnostic signals under the mean-based baseline, identifying units where aging-related vulnerability and potential-accessibility constraints warrant closer equity-focused assessment. Third, weak opportunity structure is the clearest common correlate across diagnostic signals, suggesting that PT disadvantage should be assessed alongside facility distribution and activity co-location, not only transit service conditions. By translating PT-car accessibility gaps into diagnostic signals, the framework indicates transport and land-use domains that warrant joint assessment before intervention design.

1. Introduction

Daily urban travel often involves multi-activity patterns, in which individuals combine several everyday tasks within a single tour rather than making separate trips (Daisy et al., 2020; Hensher and Reyes, 2000; Rafiq and McNally, 2021). In this study, multi-activity accessibility refers to access not only to individual facility types, but also to combinations of everyday opportunities within realistic travel-time budgets. This distinction is particularly important for public transport (PT), because walking access and egress, waiting, transfers, and timetable-dependent connections can accumulate when several activities must be reached using the same network. For trips involving dispersed opportunities, private cars may provide greater flexibility in connecting destinations, whereas PT may offer less competitive door-to-door access (Church et al., 2000; Currie and Delbosc, 2011; Foth et al., 2013; Lachapelle and Boisjoly, 2023).

From a planning perspective, the issue is not only where PT accessibility is weak, but also which conditions are associated with PT underperformance relative to cars (Lee et al., 2019). Accessibility

outcomes are shaped jointly by transport-system performance and the spatial distribution of opportunities (Geurs and Van Wee, 2004). Without a structured diagnosis, it remains difficult to determine whether subsequent assessment should focus on PT service and connectivity, facility siting and activity co-location, or coordination between these domains. This distinction matters because transport investment, land-use planning, and everyday service provision are often evaluated through separate institutional channels, although they jointly shape access (Bertolini et al., 2005; Ryan and Martens, 2023).

This study develops a diagnostic framework for potential multi-activity accessibility. Using door-to-door PT and private-car travel times across 229 South Korean city-level administrative units, including cities, counties, and districts, the framework distinguishes facility-side reachability signals, weak co-location-based bundling signals, PT-side penalty signals, and their overlap. The framework is intended as diagnostic planning support: it organizes PT-car accessibility gaps into interpretable diagnostic regimes and summarizes city-level correlates, rather than estimating realized trip chaining, causal effects, or the impacts of specific interventions.

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The study addresses two research questions: (1) How are city-level PT-car accessibility gaps for multi-activity access classified into facility-side reachability signals, weak co-location-based bundling signals, PT-side penalty signals, and their combinations? (2) Which city-level characteristics are associated with these diagnostic signals, particularly in relation to opportunity structure, settlement structure and urban form, aging-related sociodemographic vulnerability, transit supply, and public-expenditure context?

By answering these questions, this study links modal accessibility-gap measurement with a diagnostic account of how opportunity-side conditions, PT-side penalties, and city-level contextual factors combine across cities. [Section 2](#) reviews the literature on accessibility measurement, modal accessibility gaps, and multi-activity accessibility. [Section 3](#) describes the data and analytical framework. [Section 4](#) presents the diagnostic classifications and city-level correlates. [Section 5](#) discusses the methodological and planning implications of the framework. [Section 6](#) concludes with the main findings and limitations.

2. Literature review

2.1. Accessibility as a land-use–transport planning concept

Access to everyday services is shaped jointly by transport provision and the spatial organization of destinations. Accessibility provides an analytical bridge between these domains because it links the distribution of opportunities with the transport conditions required to reach them ([Geurs and Van Wee, 2004, 2026](#)). It is therefore not merely a measure of transport performance, but a land-use–transport planning concept for assessing how facility location and transport systems jointly shape potential participation in daily life.

This land-use–transport framing matters because planning responsibilities and implementation levers are often divided across institutional domains. Transport agencies can adjust routes, frequencies, stops, transfers, and service coverage, whereas land-use and facility-planning authorities influence facility siting, activity clustering, and the distribution of everyday services. Previous planning research has therefore emphasized accessibility as a basis for integrating transport investment, land-use planning, and service provision, rather than evaluating transport performance in isolation ([Bertolini et al., 2005](#); [Ryan and Martens, 2023](#)). From this perspective, an accessibility deficit should not be attributed automatically to a single sector. Similar low-access outcomes may call for closer examination of transit operations, facility distribution, or coordination between the two. Technical diagnostics do not determine planning decisions, but they can make cross-sector dependencies visible by indicating whether follow-up assessment should focus on transit service provision, opportunity distribution, or coordination between them. In this sense, the framework provides an evidence input for coordination among actors whose responsibilities for transport, land use, and everyday services are institutionally fragmented ([Hull, 2008](#); [Marsden and Reardon, 2017](#)).

The present study is positioned within the calculated-accessibility tradition. It uses calculated travel times and facility locations to examine whether public transport disadvantage is more closely associated with opportunity-side conditions, public-transport-side conditions, or their overlap. Accordingly, the study addresses potential accessibility constraints rather than perceived accessibility, realized travel behavior, individual capability, or the effects of specific interventions.

2.2. Public transport accessibility, service-side evaluation, and modal-gap diagnosis

PT accessibility has commonly been measured using cumulative-opportunity and travel-time-based indicators ([Boisjoly and El-Geneidy, 2016](#); [Hansen, 1959](#); [Wickstrom, 1971](#)). Schedule- and network-based routing has made it possible to estimate door-to-door PT travel times that include walking access and egress, waiting, transfers, and timetable

constraints ([Farber et al., 2014](#); [Tenkanen and Toivonen, 2020](#)). These measures have supported equity-oriented analyses, including transit-desert studies, assessments of spatial disparities across cities and trip purposes, and recent work linking local accessibility conditions with car ownership and mode share ([Janatabadi et al., 2023](#); [Jomehpour Chahar Aman and Smith-Colin, 2020](#); [Liao et al., 2020](#); [Schumann et al., 2026](#)). Such studies are essential for mapping the geography of weak PT access. However, because many are designed to compare accessibility levels across places, populations, or modes, they do not necessarily identify whether weak outcomes are more closely associated with PT service conditions, opportunity distribution, or their interaction.

Transit network evaluation and redesign research focuses more directly on service conditions. This literature examines schedule-based performance, service frequency, route structure, stop access, operational feasibility, and network efficiency, thereby identifying operational levers for improving PT provision ([Guihaire and Hao, 2008](#); [Institute for Transportation and Development Policy, 2017](#); [Sim and Cho, 2019](#)). However, service-side evaluation alone cannot determine whether an accessibility deficit reflects network configuration, the location of essential opportunities, or a mismatch between the two. As a result, route or service improvements may not fully resolve accessibility deficits where everyday opportunities remain poorly aligned with the PT network.

Modal accessibility gap studies address modal disadvantage more directly by comparing PT and car accessibility ([Liao et al., 2020](#)). [Kwok and Yeh \(2004\)](#) developed a normalized modal accessibility gap as a geographic information system (GIS)-based indicator for assessing and monitoring sustainable transport development. [Maharjan et al. \(2022\)](#) compared transit and automobile accessibility to employment, groceries, hospitals, and schools across multiple travel-time thresholds in Chicago to evaluate spatial equity across destination types and population groups. [Rodrigue et al. \(2023\)](#) combined PT–car accessibility comparisons with a decision framework for prioritizing fixed-route transit, demand-responsive transit, or land-use interventions for older adults in three Canadian metropolitan regions. These studies demonstrate that modal comparisons can support monitoring, equity assessment, and investment prioritization. However, modal-gap measures have more often served as final screening or prioritization indicators than as intermediate diagnostic inputs for separating opportunity-side and PT-side conditions. The present study uses PT–car gaps in this latter sense, reorganizing comparable modal indicators into facility-side reachability signals, weak co-location-based bundling signals, PT-side penalty signals, and their overlap. The car benchmark is therefore treated as a calculated reference for opportunities reachable under existing land-use and road-network conditions, not as a pure measure of facility distribution.

2.3. Multi-activity accessibility and facility co-location

Facility-location research addresses the opportunity component of accessibility, often through catchment-based methods and location-allocation models ([Chen and Jia, 2019](#); [Zhang et al., 2022](#)). These approaches are useful for evaluating spatial coverage and destination siting, but many applications simplify travel impedance or do not fully represent timetable-dependent PT constraints. They also tend to evaluate access to individual facility types, whereas everyday access often involves combining multiple activity purposes within a single outing. For this reason, the spatial concentration of different facility categories may matter even when each facility type appears reachable in isolation. Multi-activity accessibility therefore requires attention not only to whether individual facility types are reachable, but also to whether combinations of everyday opportunities can be reached within realistic travel-time budgets ([Suzuki and Hodgson, 2005](#)).

Recent studies have begun to examine the joint role of facility concentration and PT constraints in multi-activity access. [Eom et al. \(2019\)](#), for example, evaluated how facility concentration and PT inconvenience

jointly shape accessibility outcomes, while Eom and Hasegawa (2020) developed a facility-allocation model that considers the benefits of co-located services for daily multipurpose trips. These studies show that potential activity bundling depends on both the spatial organization of opportunities and the transport conditions under which they are reached. However, this evidence has more often taken the form of case-specific evaluations or facility-allocation models than a scalable diagnostic framework for separating opportunity-side and PT-side signals across cities and facility types.

Kang and Eom (2026) provide the measurement basis for this study by introducing opportunity reachability and co-location-based bundling potential for PT access to essential services. The present study uses these indicators for a different methodological purpose. Whereas Kang and Eom (2026) focus on PT-based multi-activity accessibility levels and regional disparities, this study computes comparable PT and car indicators and reorganizes them into a modal-gap diagnostic framework. This reorganization allows the same underlying indicators to be used to distinguish facility-side reachability signals, weak co-location-based bundling signals, PT-side penalty signals, and their combinations.

In this study, facility co-location is treated as a structural condition for potential activity bundling, not as direct evidence of observed trip chaining or behavioral multi-activity participation. The co-location-based measure does not capture sequential activity participation, facility quality, opening hours, individual preferences, or the compatibility of specific activity combinations. It is therefore used as a diagnostic signal for identifying cities where the spatial organization of everyday opportunities may limit potential bundling and where this limitation overlaps with additional PT-side penalties.

2.4. From accessibility measurement to diagnostic planning support

This study makes three contributions. First, it develops a diagnostic

use of PT-car accessibility gaps for multi-activity accessibility. Building on the opportunity-reachability and co-location-based bundling indicators introduced by Kang and Eom (2026), the framework computes comparable PT and car measures and reorganizes them into PT-car gap-based diagnostic signals. This shifts the analysis from reporting PT accessibility levels to examining whether PT disadvantage is associated with facility-side reachability signals, weak co-location-based bundling signals, PT-side penalty signals, or their overlap.

Second, the framework integrates transit-service evaluation and facility-location perspectives within a single diagnostic structure. Rather than treating PT connectivity, facility siting, and activity co-location as separate analytical domains, it examines how these conditions overlap in multi-activity accessibility deficits. The resulting categories are not intended to prescribe interventions directly. Instead, they clarify whether subsequent local assessment should focus on PT connectivity, facility distribution, activity co-location, or coordination across these domains.

Third, the study adds a descriptive city-level correlate analysis of the diagnostic signals. Because the diagnostic labels are produced by the rule-based accessibility classification, the subsequent model-explanation analysis is used only to summarize associations between city-level characteristics and diagnostic membership. These associations support interpretation of the diagnostic typology, but they are not treated as estimates of causal pathways or intervention effects.

3. Materials and methods

3.1. Study area and data

We analyze accessibility across 229 South Korean city-level administrative units, corresponding to si/gun/gu jurisdictions (Fig. 1; see Appendix A for the full list). Appendix Fig. A.1 shows the national

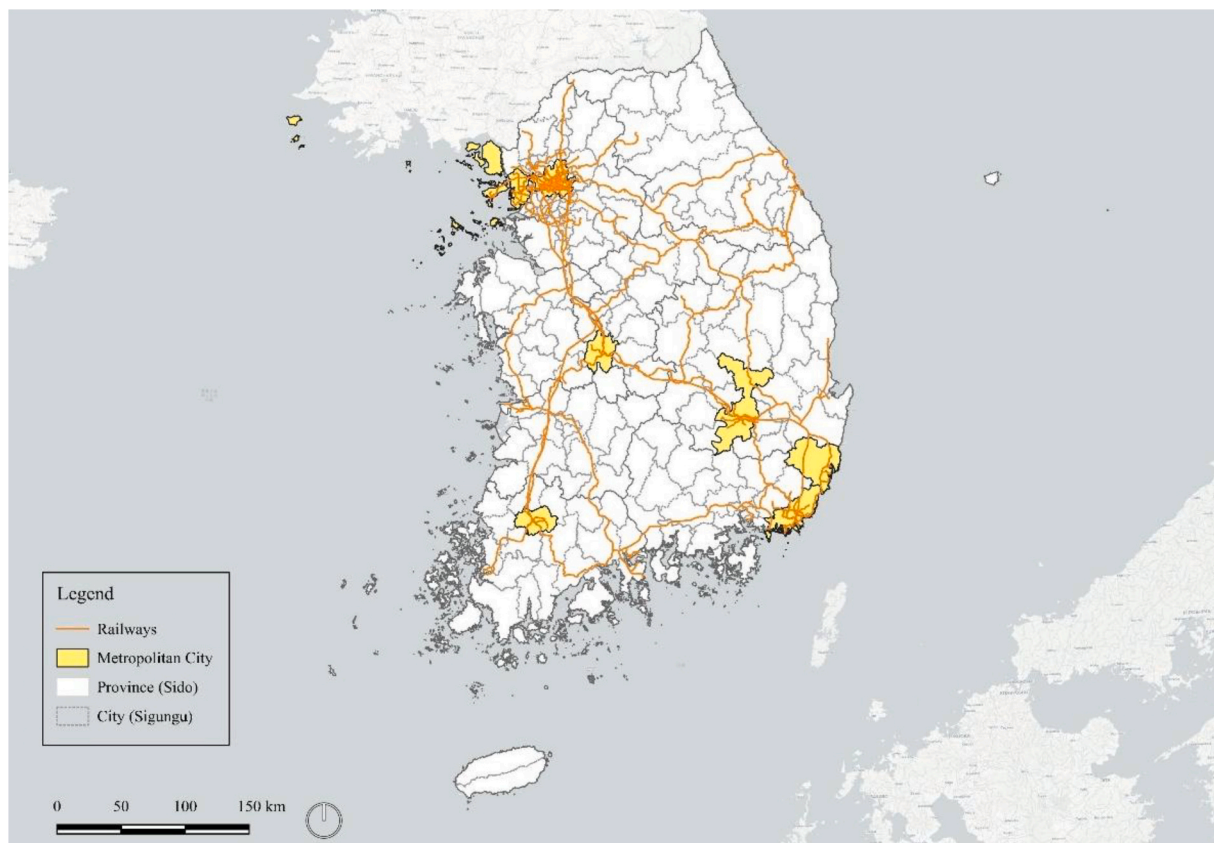


Fig. 1. Map of study area.

distribution of bus-stop density as contextual information on PT supply. Origins are represented by 500 m $\times$ 500 m population-grid cells. We considered the available 100 m and 250 m population grids. However, population counts below five in Statistical Geographic Information Service (SGIS) grid statistics are subject to disclosure-protection processing, making exact population values difficult to identify (Ministry of Data and Statistics, 2026). We therefore used the 500 m grid as a practical compromise to maintain a consistent nationwide population-weighting basis while retaining spatial resolution. Destinations are represented by 500 m $\times$ 500 m cells containing at least one facility from eight categories of everyday essential services aligned with the national minimum service standards defined by the Ministry of Land, Infrastructure and Transport (MOLIT, 2024). These categories are consistent with facility types examined in recent accessibility and equity studies (e. g., Bargahi et al., 2024; Blumenberg et al., 2024; Li et al., 2021, a, b; Pizzol et al., 2021; Sharma and Patil, 2021). Facility locations were compiled from national and local open datasets and screened to retain active records, yielding 227,325 facilities nationwide (Table 1).

For travel-time calculation, each origin cell and each facility-containing destination cell was represented by its geometric centroid and linked to the nearest routable point in the relevant transport network. Cells that could not be linked were excluded; the exclusion rates were 0.265% and 0.293% for origin cells on the walking and car

networks, respectively, and 0.138% and 0.148% for destination cells. Median linkage distances ranged from 37.9 to 78.3 m, while 79.7%–82.0% of origin cells and 92.6%–93.7% of destination cells were linked within 200 m. The resulting estimates should therefore be interpreted as city-level accessibility diagnostics rather than parcel- or address-level measures.

Accessibility thresholds follow MOLIT's national minimum service standards. A 10-min door-to-door travel-time threshold is applied to facilities expected to support frequent routine use, including senior centers, clinics, nurseries, grocery stores, and primary schools. A 15-min threshold is applied to facilities typically accessed less frequently, including parks, libraries, and public-service centers. These differentiated thresholds reflect nationally defined planning norms rather than arbitrary analytical cutoffs and are consistent with proximity-centered accessibility research showing that acceptable travel times vary by activity type (Silva et al., 2025). Because threshold-based classifications may be sensitive near the cutoff, Appendix B reports sensitivity tests using uniform ± 5 -min changes to the facility-specific thresholds.

Door-to-door travel times are computed for PT and private car. For PT, we use a nationwide General Transit Feed Specification (GTFS) feed and compute shortest scheduled door-to-door travel times for an 08:00 weekday departure using r5py (Conway et al., 2017, 2018; Conway and Stewart, 2019; Fink et al., 2022). The 08:00 departure is used as a fixed weekday reference scenario for scheduled PT accessibility and should not be interpreted as a full representation of daily PT variability. Because scheduled service conditions at 08:00 may be more favorable than those during some lower-service periods, the resulting PT disadvantages may be conservative in some contexts. However, 08:00 cannot be interpreted as a strict lower bound for all cities, routes, or time periods. To assess whether the diagnostic classifications depend on this departure-time assumption, Appendix B reports a sensitivity test using a 14:00 departure scenario. The 14:00 scenario tests whether units retain their diagnostic regimes when the departure time is changed; it does not test the temporal stability of continuous city rankings by diagnostic signal. In the departure-time-only scenario, 95.6% of units retained their baseline diagnostic regime.

For walking legs, the main analysis assumes a walking speed of 1.00 m/s (3.6 km/h). This is an analytical reference setting rather than an estimate of average walking speed for the full population. The value is consistent with pedestrian-design guidance recommending 1.00 m/s where older pedestrians are prevalent (Rouphail et al., 1998). A common baseline provides a consistent national routing reference but is not intended to represent every demographic group. To examine sensitivity to slower mobility conditions, we additionally test 0.90 m/s and 0.75 m/s scenarios, reflecting walking speeds reported for older and mobility-limited pedestrians (Asher et al., 2012; Duim et al., 2017; Knoblauch et al., 1996). The baseline PT routing scenario uses the r5py default maximum of eight consecutive public-transport rides, corresponding to at most seven transfers. Appendix B reports sensitivity tests allowing at most 0, 1, 2, 3, or 7 transfers to assess whether the city-level diagnostic classifications depend on this routing assumption. For car travel, we compute driving times using OpenStreetMap and the Open Source Routing Machine (OSRM) as a standardized car reference (Giraud, 2022). Nationwide accessibility to everyday facilities requires a road network that covers not only major corridors but also the fine-grained local streets connecting residential cells to destinations. OSRM-based times do not incorporate time-varying congestion. A matched congestion-adjusted benchmark would require nationally consistent link-, direction-, and time-specific speed data of comparable quality across both major and local streets; such data were not available to this study in a form that could be integrated consistently with the national OSRM network. We did not apply a uniform national congestion multiplier because it would ignore variation by city, road class, direction, and time of day and would also slow uncongested local streets, potentially distorting cross-city comparisons.

Under a congestion-adjusted specification, both the diagnostic

Table 1
Data sources.

Data		Composition	Source	Year
Facility Location	Park	Urban parks	Public Data Portal	2025
	Senior Center	Senior welfare centers, community centers	Culture Bigdata Platform	2025
	Library	Public libraries	Public Data Portal, Seoul Data Square	2025
	Clinic	Medical clinics, excluding dental clinics	Public Health and Medical Bigdata System	2025
	Nursery	Kindergartens and children's daycare centers	Kindergarten Data Portal, Child School Information Portal	2025
	Grocery	Supermarkets, marts, and convenience stores	Local Government Open Data	2025
	School	Primary Schools	Public Data Portal	2025
	Public Service	Local government offices and community service centers	Address Information Open Service	2024
Transport Service	Transit	Nationwide GTFS (bus, subway, and rail)	Korean Transport Database	2023
	Supply Road Network	Road network and traffic restriction information	OpenStreetMap	2025
Population Data		500 m × 500 m population grid	Statistical Geographic Information Service	2023
Administrative Area		Administrative area (km ²) of each administrative unit	Korean Statistical Information Service (KOSIS)	2023
Built-up Area		Built-up land area derived from land-cover classification.	Public Data Portal	2023
Activity Diversity		For each 500 m grid j , D_j is the number of distinct essential-facility categories present; city-level activity diversity is the administrative-unit mean of D_j		2025
Activity Density		Density of essential facilities within each administrative unit (facilities per km ²)		2025
Proportion of Older Adults		Proportion of residents aged 65 years and older within each administrative unit (%).	KOSIS	2023
Transport- and Land-Sector Expenditures		Transport- and land-sector expenditures per capita (1000 KRW/person).	Local Finance Integrated Open System	2023

values and the corresponding population-weighted reference lines would be recomputed. The direction and magnitude of unit-level reclassification therefore cannot be determined without nationally consistent time-dependent car-speed data. Congestion-adjusted car travel times would likely narrow PT-car gaps in some congested urban areas, but the resulting changes in $T(c)$ assignments cannot be inferred a priori.

The 14:00 PT sensitivity test evaluates timetable dependence only and does not test sensitivity to car congestion. Accordingly, the PT-car comparison is used as a standardized diagnostic contrast, not as an estimate of absolute modal performance under a specific traffic state.

Because the datasets were released on different administrative schedules, the analysis combines nationally consistent facility, transport, population, and city-level contextual data from 2023 to 2025; this should be interpreted as a mid-2020s cross-sectional dataset rather than a single-date snapshot.

3.2. Accessibility indicators used for diagnosis

This section defines the two accessibility indicators used as inputs to the diagnostic procedure: opportunity reachability and co-location-based bundling potential. The definitions are adapted from Kang and Eom (2026). In the present study, these indicators are computed for both PT and private car and are then used to construct the modal-gap diagnostics described in Section 3.3.

Let i, j , and k index residential origin grid cells, destination grid cells, and everyday facility categories, respectively, and let $m \in \{PT, CAR\}$ denote the travel mode. Door-to-door travel time from origin cell i to destination cell j by mode m is denoted by t_{ij}^m . Let $J(k)$ denote the set of destination cells that contain at least one facility of category k . The minimum travel time to category k by mode m is defined as:

$$T_i^m(k) = \min_{j \in J(k)} t_{ij}^m$$

This formulation represents category-level nearest-opportunity reachability. It identifies the closest reachable cell containing the target facility category, but it does not imply that the selected facility fully satisfies the corresponding activity demand.

Opportunity reachability is measured as a binary coverage condition indicating whether at least one destination cell containing facility category k can be reached within the facility-specific travel-time threshold τ_k .

$$C_i^m(k) = \begin{cases} 1, & \text{if } T_i^m(k) \leq \tau_k, \\ 0, & \text{otherwise.} \end{cases}$$

Conditional on basic reachability being satisfied, the analysis then measures co-location-based bundling potential around reachable target-category anchors. For each origin cell i , mode m , and facility category k , the set of reachable destination cells containing the target category is defined as:

$$J_i^m(k) = \{j \in J(k) \mid t_{ij}^m \leq \tau_k\}$$

For each destination cell j , let D_j denote the number of distinct target facility categories present in that cell. This value captures category co-presence within a 500 m grid cell. For origins with $J_i^m(k) \neq \emptyset$, co-location-based bundling potential is defined as:

$$B_i^m(k) = \max_{j \in J_i^m(k)} D_j$$

The indicator $B_i^m(k)$ is therefore defined only for origin cells where $C_i^m(k) = 1$. Because it takes the maximum value across reachable target-category anchors, it should be interpreted as an upper-bound measure of co-location-based structural bundling potential under optimal anchor selection. It does not measure observed trip chaining, sequential activity participation, or actual multi-activity behavior.

The grid-level indicators are aggregated to the city-level administrative unit using population weights. Let r index city-level administrative units, $\mathcal{J}_r$ denote the set of origin grid cells in unit r , and P_i denote the population of grid cell i . City-level opportunity reachability for facility category k and mode m is computed as:

$$\bar{C}_r^m(k) = \frac{\sum_{i \in \mathcal{J}_r} P_i C_i^m(k)}{\sum_{i \in \mathcal{J}_r} P_i}$$

City-level co-location-based bundling potential is computed as the population-weighted average of $B_i^m(k)$ only among origin cells where basic reachability is satisfied:

$$\bar{B}_r^m(k) = \frac{\sum_{i \in \mathcal{J}_r, C_i^m(k)=1} P_i B_i^m(k)}{\sum_{i \in \mathcal{J}_r, C_i^m(k)=1} P_i}$$

This conditional aggregation ensures that bundling potential is evaluated only after the target facility category is reachable. Accordingly, $\bar{B}_r^m(k)$ should be interpreted together with $\bar{C}_r^m(k)$, not as a stand-alone population-wide accessibility measure. Both indicators are threshold-based measures of potential accessibility. They are used to evaluate whether category-level opportunities and co-located opportunity combinations are reachable within policy-relevant travel-time standards, rather than to model continuous destination choice, facility adequacy, or realized activity participation.

3.3. Modal-gap-based diagnostic procedure

This section describes the procedure used to classify city-level administrative units based on modal accessibility gaps. The procedure provides a relative diagnostic classification rather than a performance ranking. It uses the city-level indicators defined in Section 3.2 to organize PT-car differences into a parsimonious set of diagnostic signals for subsequent analysis.

As summarized in Figs. 2 and 3, the analysis proceeds in four steps: (1) computing modal accessibility gaps, (2) applying a two-stage classification procedure for opportunity reachability and co-location-based bundling potential, (3) combining the resulting facility-side and PT-side signals into diagnostic regimes, and (4) examining city-level characteristics associated with each diagnostic signal.

3.3.1. Modal accessibility gaps

For each facility category k , the opportunity-reachability gap ($\Delta C_r(k)$) and the co-location-based bundling-potential gap ($\Delta B_r(k)$) are computed using a normalized difference formulation (Kwok and Yeh, 2004):

$$\Delta C_r(k) = \frac{\bar{C}_r^{PT}(k) - \bar{C}_r^{CAR}(k)}{\bar{C}_r^{PT}(k) + \bar{C}_r^{CAR}(k)}$$

$$\Delta B_r(k) = \frac{\bar{B}_r^{PT}(k) - \bar{B}_r^{CAR}(k)}{\bar{B}_r^{PT}(k) + \bar{B}_r^{CAR}(k)}$$

The facility-specific gap measures are bounded between -1 and 1 when the denominator is positive. More negative values indicate larger PT disadvantage relative to the car benchmark. These gap measures summarize relative PT-car differences in opportunity reachability and co-location-based bundling potential, respectively.

3.3.2. Opportunity-reachability diagnosis

The first diagnostic stage focuses on opportunity reachability. Each city-level administrative unit r is positioned in a two-dimensional space defined by composite car-based coverage, $\bar{C}_r^{CAR}$, and the composite

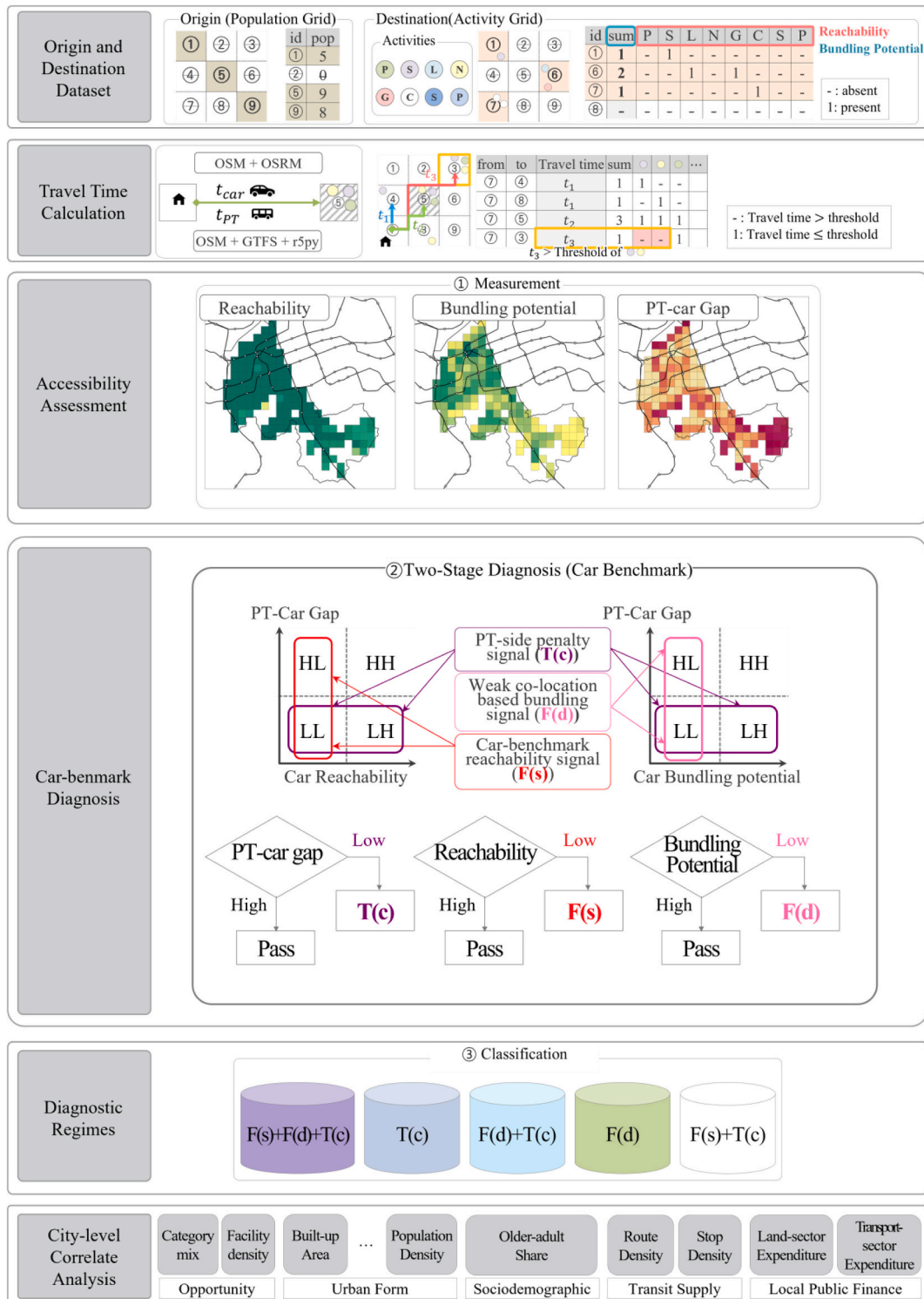


Fig. 2. Research framework.

PT-car coverage gap, $\Delta \bar{C}_r$. For each facility category k , car-based coverage $\bar{C}_r^{CAR}(k)$ is first min-max normalized to the [0,1] range across city-level administrative units. Composite car-based coverage is then constructed as the sum of these normalized values across the eight facility categories. The composite coverage gap is constructed as the sum of facility-specific gaps $\Delta \bar{C}_r(k)$ across the eight categories. Because this composite gap is a summed score, it is interpreted as a relative summary measure rather than as a bounded single-category index.

Low values of $\bar{C}_r^{CAR}$ are used as a facility-side reachability signal under the car benchmark, denoted as $F(s)$. This signal indicates that basic opportunities are not sufficiently reachable within the relevant threshold even under the car reference. It may reflect limited facility provision, a mismatch between facility locations and residential concentrations, dispersed settlement patterns, or road-network conditions under short time thresholds. Large negative values of $\Delta \bar{C}_r$ indicate an additional PT-side penalty relative to the car benchmark, denoted as T

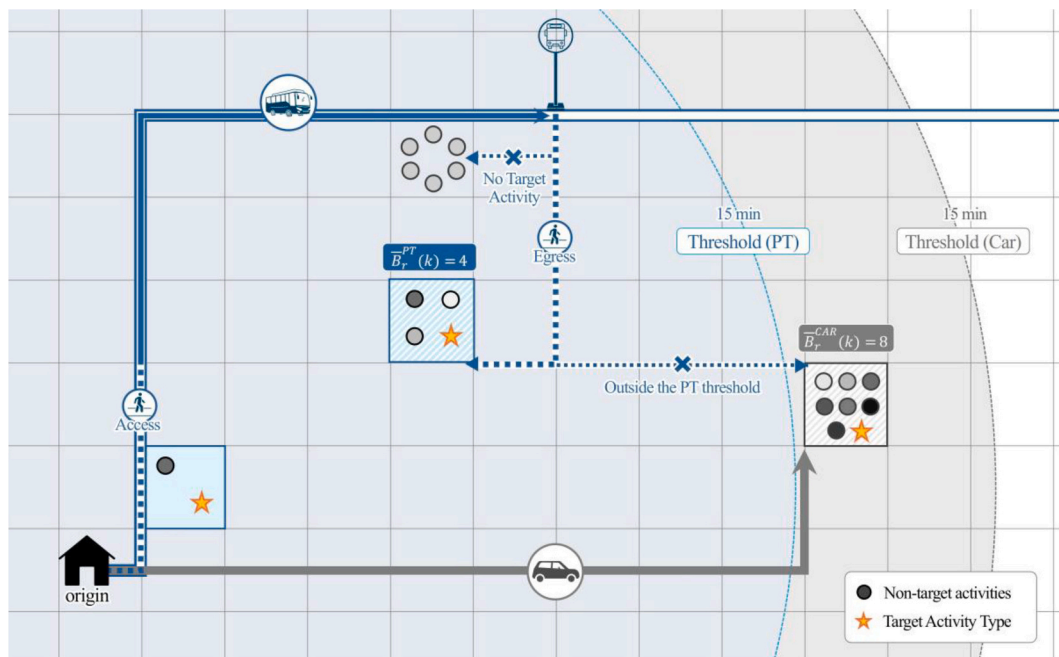


Fig. 3. Conceptual diagram.

(c).

For descriptive classification, quadrant reference lines are defined using national population-weighted mean values. These mean-based lines define the baseline classification reported in the main text. To assess sensitivity to the reference-line specification, the classification is recomputed using population-weighted median reference lines; the median-based results are reported in [Appendix C](#).

3.3.3. Co-location-based bundling-potential diagnosis

The second diagnostic stage focuses on co-location-based bundling potential. Each city-level administrative unit r is positioned in a two-dimensional space defined by composite car-based bundling potential, $\bar{B}_r^{CAR}$, and the composite PT-car bundling-potential gap, $\Delta\bar{B}_r$. As in the opportunity-reachability diagnosis, $\bar{B}_r^{CAR}$ is constructed by min-max normalizing facility-category values to the $[0, 1]$ range and summing them across the eight target categories. The composite bundling-potential gap, $\Delta\bar{B}_r$, is constructed as the sum of facility-specific PT-car bundling-potential gaps.

Low values of $\overline{B}_r^{CAR}$ are used as a weak co-location-based bundling signal, denoted as F(d). Because this indicator is based on the car benchmark, it is interpreted as a signal of limited co-location-based bundling potential under existing land-use and road-network conditions, rather than as a pure measure of facility dispersion. Large negative values of $\Delta \overline{B}_r$ indicate an additional PT-side penalty in reaching activity-rich anchors, denoted as T(c). Quadrant reference lines are again defined using national population-weighted mean values for the baseline classification. The corresponding median-based sensitivity specification is reported in [Appendix C](#).

3.3.4. Combining diagnostic signals into regimes

The diagnostic outcome for each city-level administrative unit is obtained by combining the signals identified in the two diagnostic stages. The classification uses the set $\{F(s), F(d), T(c)\}$, where:

- F(s) denotes a facility-side reachability signal under the car benchmark;
- F(d) denotes a weak co-location-based bundling signal under the car benchmark; and

- $T(c)$ denotes a PT-side penalty signal relative to the car benchmark.

A city-level administrative unit is assigned to T(c) when either diagnostic stage indicates a below-reference PT-car gap signal. The resulting combinations define mutually exclusive diagnostic regimes, meaning that each city-level administrative unit is assigned to one non-overlapping combination category. This exclusivity applies only to the final regime assignment; F(s), F(d), and T(c) are identified using distinct criteria but are not assumed to be statistically or causally independent or mutually exclusive. The component signals may co-occur, and their overlap is itself a substantive diagnostic outcome. These regimes summarize which signals are flagged for each unit and whether PT disadvantage is associated with facility-side reachability, weak co-location-based bundling signals, PT-side penalties, or their overlap.

When car-based coverage is below the reference line but the PT-car coverage-gap score is above the reference line, the facility-side reachability signal is marked as F(s)*. This notation indicates a secondary facility-side reachability signal that warrants local verification but is not treated as a primary diagnostic signal.

3.3.5. City-level correlates of diagnostic signals

After the rule-based diagnostic classification, we conducted a descriptive correlate analysis to examine which city-level characteristics are associated with each diagnostic signal. The diagnostic labels F(s), F(d), and T(c) are defined by the accessibility classification described above and do not depend on the machine-learning model. XGBoost is used only in a subsequent step as a flexible descriptive model for summarizing potentially nonlinear associations between city-level characteristics and diagnostic membership (Chen and Guestrin, 2016). The integrated national model is used to examine, under a common analytical reference, the city-level contexts in which each diagnostic signal tends to occur across the full set of 229 units. It is not intended to estimate city-type-specific causal pathways or intervention effects. Separate models by city size or region would shift the analysis away from this national comparative purpose and would also create small and uneven subsamples for several signals. Appendix Table A.1 therefore provides descriptive regional-status context to guide follow-up local assessment.

For exposition, predictors are grouped into five domains: (i) opportunity structure, including category mix (measured as activity diversity)

and facility density (measured as activity density); (ii) settlement structure and urban form, including population density, administrative area, built-up area, and the population-distribution Gini coefficient; (iii) aging-related sociodemographic vulnerability, represented by the proportion of older adults; (iv) transit supply, including route density and stop density; and (v) public-expenditure context, including per capita transport-sector and land-sector expenditures. Route density and stop density were computed jointly from the combined GTFS feed across bus, subway, and rail services. Stops were assigned to city-level administrative units according to their locations. Route density was calculated as the number of distinct GTFS route IDs serving at least one stop within each unit divided by its total administrative area, while stop density was calculated as the number of distinct GTFS stop IDs located within each unit divided by its total administrative area. A route serving multiple units was counted once in each unit it served.

Model adequacy was evaluated using repeated stratified five-fold cross-validation with 20 repeats rather than a single training-testing split. In each iteration, approximately 80% of city-level administrative units were used for model fitting and 20% were held out for evaluation, while preserving the class distribution of each diagnostic signal. This procedure produced 100 out-of-fold evaluations for each diagnostic signal, reference-line specification, and model type. XGBoost was benchmarked against logistic regression and random forest using the same cross-validation design. Accuracy, precision, recall, F1-score, and receiver operating characteristic area under the curve (ROC-AUC) are reported as model-adequacy checks for post hoc interpretation, not as substantive predictive findings.

XGBoost used a binary logistic objective with log-loss as the evaluation metric. The parameter settings comprised a learning rate of 0.03, a maximum tree depth of 3, a minimum child weight of 2, subsample and column-subsample ratios of 0.80, L1 regularization of 0, and L2 regularization of 1. Class imbalance was addressed by setting the positive-class weight to the ratio of negative to positive observations. The repeated cross-validation benchmark used 300 boosting trees. For the final models used for Shapley Additive Explanations (SHAP) and Accumulated Local Effects (ALE), the maximum number of boosting rounds was set to 5000. A stratified 20% internal validation set was used for early stopping, and training was stopped when validation log-loss did not improve for 100 consecutive rounds. The selected number of boosting rounds was then used to refit each model to all available observations. The base random seed was set to 42, with deterministic fold-specific seeds used in the repeated cross-validation procedure.

Several additional steps were taken to reduce overfitting risk and assess possible target leakage. First, variables directly used to construct the diagnostic classification, including the composite modal-gap and car-benchmark accessibility measures, were excluded from the predictor set. Second, the predictor set was restricted to the same 11 variables across all three diagnostic models. Third, for logistic regression and random forest, median imputation was fitted separately within each cross-validation training fold, ensuring that information from held-out observations was not used during preprocessing; XGBoost handled missing predictor values internally. Finally, a permuted-label check was conducted by randomly shuffling the diagnostic labels before model fitting. The permuted-label receiver operating characteristic area under the curve values remained close to 0.50 across diagnostic signals and reference-line specifications, providing no indication of direct target leakage.

Shapley Additive Explanations (SHAP) are used to summarize global feature importance and signed model associations, and one-dimensional Accumulated Local Effects (ALE) functions are used to examine the direction and shape of selected predictor associations (Apley and Zhu, 2020; Lundberg and Lee, 2017). SHAP values were computed using TreeExplainer, and the one-dimensional ALE profiles were estimated using up to eight quantile-based intervals for each predictor. These post hoc explanation results are interpreted as descriptive model associations, not as causal effects or estimates of intervention impacts.

Under the mean-based baseline classification, all three models showed adequate discrimination for post hoc interpretation (Table 2). The median-based sensitivity specification produced comparable model-adequacy results (Appendix Table C.1). XGBoost was retained not because it uniformly outperformed the alternatives, but because it allowed nonlinear association profiles to be summarized consistently through SHAP and ALE.

4. Results

4.1. Descriptive accessibility patterns

Figs. 4 and 5 summarize the descriptive accessibility patterns before the modal-gap diagnostic classification. Fig. 4 reports facility-category averages of coverage, $\bar{C}_r^m(k)$, and co-location-based bundling potential, $\bar{B}_r^m(k)$, for PT and car travel. Across the eight facility categories, car-based outcomes are concentrated near high coverage and high bundling-potential values. PT outcomes are lower and more dispersed across facility categories, indicating that PT access is more uneven across everyday facility types and reachable activity environments.

Fig. 5 shows the corresponding city-level distributions by facility category and travel mode. Each point represents one city-level administrative unit. The horizontal position indicates coverage, $\bar{C}_r^m(k)$, and the vertical position indicates co-location-based bundling potential, $\bar{B}_r^m(k)$. Across most facility categories, PT observations are shifted leftward and downward relative to car observations. This pattern shows that, within the same facility-specific travel-time thresholds, PT provides lower reachability and lower access to activity-rich reachable anchors than car travel.

The vertical segments in Fig. 5 provide an auxiliary comparison within the set of reachable target-category anchors. They indicate the difference between the activity count at the minimum-travel-time reachable anchor and the maximum co-location-based bundling potential available among reachable anchors. Longer segments therefore indicate a larger within-threshold gain in activity diversity: although the nearest reachable anchor is reached first, another anchor that remains within the same travel-time threshold contains more co-located activity categories. These segments are used only to illustrate within-threshold variation in reachable activity environments; they are not used to define the diagnostic classification.

Together, Figs. 4 and 5 show that PT disadvantage appears in both dimensions used in the subsequent diagnosis: basic opportunity reachability and co-location-based bundling potential. These descriptive patterns motivate the two-stage diagnostic classification in Section 4.2, which separately examines facility-side reachability signals, weak co-location-based bundling signals, and PT-side penalty signals.

4.2. Spatial distribution of diagnostic regimes

This section reports the spatial distribution and composition of the diagnostic classifications derived from the modal-gap procedure. Fig. 6 summarizes the opportunity-reachability diagnosis ($\Delta\bar{C}_r - \bar{C}_r^{CAR}$) and the co-location-based bundling-potential diagnosis ($\Delta\bar{B}_r - \bar{B}_r^{CAR}$). In the diagnostic labels, G denotes the PT-car gap dimension, C denotes car-based coverage, and B denotes car-based bundling potential. H and L indicate above- and below-reference positions relative to the national population-weighted mean reference lines. Because the gap scores are signed, below-reference values on the gap dimension indicate a larger PT disadvantage relative to the car benchmark.

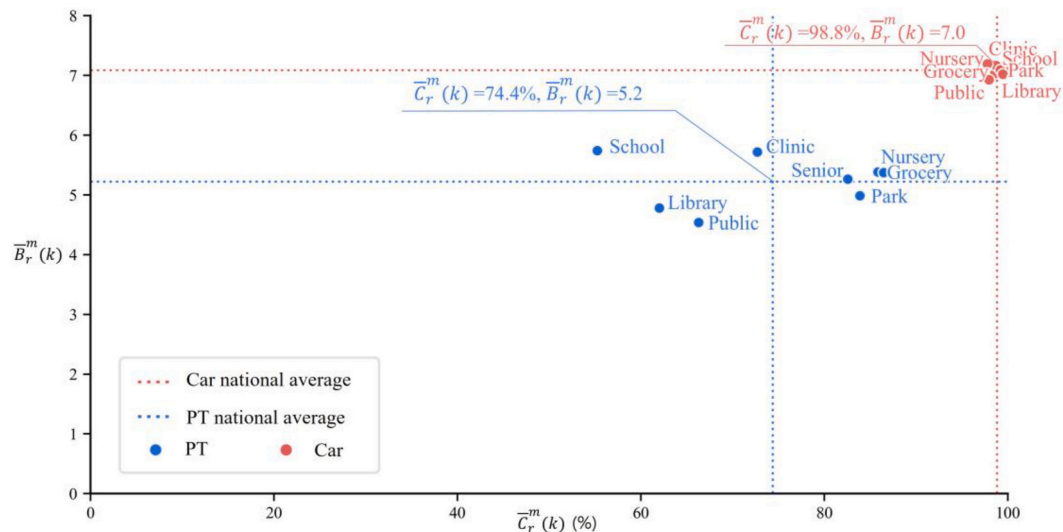
In the opportunity-reachability diagnosis, Fig. 6(a) shows that 51.1% of city-level administrative units fall into the $L_G L_C$ category. These units are below the national reference on both the PT-car coverage-gap score and car-based coverage. Under the diagnostic rules, they are classified as showing both a facility-side reachability signal, $F(s)$, and a PT-side

Table 2

Model adequacy checks for the mean-based baseline diagnostic classification using repeated stratified cross-validation.

Diagnostic Signal	Signal prevalence	Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
F(s)	0.511	XGBoost	0.947 (0.031)	0.964 (0.042)	0.933 (0.049)	0.947 (0.031)	0.971 (0.025)
		Logistic regression	0.939 (0.034)	0.952 (0.041)	0.929 (0.055)	0.939 (0.035)	0.983 (0.016)
		Random forest	0.950 (0.030)	0.972 (0.033)	0.930 (0.053)	0.949 (0.031)	0.976 (0.021)
F(d)	0.686	XGBoost	0.811 (0.052)	0.905 (0.046)	0.811 (0.064)	0.854 (0.043)	0.896 (0.041)
		Logistic regression	0.824 (0.052)	0.948 (0.036)	0.787 (0.068)	0.858 (0.046)	0.928 (0.034)
		Random forest	0.831 (0.048)	0.893 (0.045)	0.859 (0.064)	0.874 (0.038)	0.897 (0.044)
T(c)	0.786	XGBoost	0.895 (0.041)	0.977 (0.028)	0.889 (0.049)	0.930 (0.029)	0.960 (0.024)
		Logistic regression	0.889 (0.044)	0.981 (0.024)	0.876 (0.052)	0.925 (0.032)	0.967 (0.024)
		Random forest	0.899 (0.047)	0.955 (0.038)	0.916 (0.046)	0.934 (0.031)	0.962 (0.024)

Note: Values are means with standard deviations in parentheses from repeated stratified five-fold cross-validation with 20 repeats. Accuracy is defined as $\frac{TP + TN}{TP + TN + FP + FN}$, precision as $\frac{TP}{TP + FP}$, recall as $\frac{TP}{TP + FN}$ and F1-score as $\frac{2(Precision \cdot Recall)}{Precision + Recall}$. Receiver operating characteristic area under the curve (ROC-AUC) summarizes discrimination based on the ranking of predicted probabilities. These metrics are used as model-adequacy checks for post hoc interpretation and are not interpreted as substantive predictive findings. Signal prevalence indicates the proportion of cities assigned to each diagnostic signal. F(s) = facility-side reachability signal; F(d) = co-location-based bundling signal; T(c) = public-transport-side penalty signal.

**Fig. 4.** Averages of coverage and co-location-based bundling potential by facility type.

penalty signal, T(c). Spatially, this category is concentrated mainly among non-metropolitan jurisdictions outside the largest metropolitan cores. By contrast, H_GH_C units, which are above the reference lines on both dimensions, account for 33.2% and are concentrated mainly in the Seoul Metropolitan Area and other large urban cores. The L_GH_C category accounts for 14.8% and indicates units where car-based coverage is above the reference line but the PT-car gap score is below the reference line, consistent with a stronger PT-side penalty signal. The H_GH_C cell is rare rather than empty in the mean-based baseline classification, accounting for 0.9% of units.

The co-location-based bundling-potential diagnosis shows a different spatial pattern. Fig. 6(b) indicates that the H_GH_B group, which is above the reference lines on both the PT-car bundling-potential gap and car-based bundling potential, is largely confined to the largest urban cores and accounts for 14.8% of city-level administrative units. Outside these

cores, the dominant category is H_GH_B , which accounts for 36.2%. Together with L_GH_B , below-reference car-based bundling-potential categories account for 68.6% of units. This pattern points to a widespread opportunity-side bundling signal: in many units, limited co-location-based bundling potential is already observed under the car benchmark, rather than appearing only as an additional PT-side penalty. By contrast, the L_GH_B group accounts for 16.6% and identifies units where car travel reaches activity-rich anchors above the reference line, but PT shows a below-reference gap score, indicating a stronger PT-side penalty signal in reaching those anchors.

Fig. 6(c) cross-tabulates the two diagnostic stages, and Fig. 7 reorganizes the joint cells into diagnostic regimes based on F(s), F(d), and T(c). Because national car-based coverage is near-saturated, the L_C category indicates below-reference car-based coverage rather than absolute absence of car access. When car-based coverage is below the

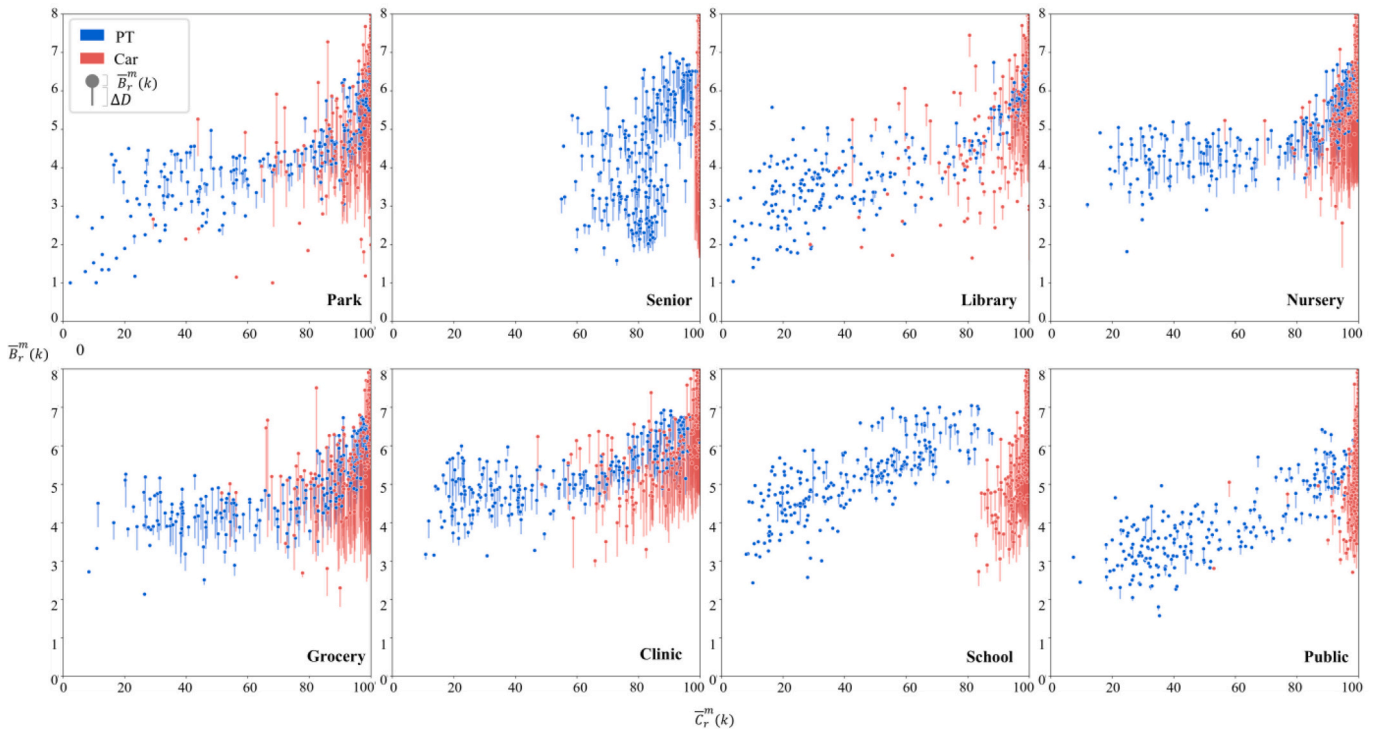


Fig. 5. City-level distributions of coverage $\bar{C}_r^m(k)$ and co-location-based bundling potential $\bar{B}_r^m(k)$ by facility type and travel mode. Each point represents one city-level administrative unit; blue and red indicate PT and car, respectively. Vertical segments show ΔD , the within-threshold gain in activity diversity between the nearest reachable anchor and the most activity-rich reachable anchor. Longer segments indicate greater additional activity diversity available within the same travel-time threshold. The main comparison is the relative position of PT and car distributions in the $\bar{C} - \bar{B}$ space.

reference line but the PT–car coverage-gap score is above the reference line, the facility-side reachability signal is marked as F(s)*. This notation indicates a secondary facility-side reachability signal that warrants follow-up assessment but is not treated as a primary diagnostic signal.

Under the mean-based baseline classification, 114 of 229 units (49.8%) fall into the compound {F(s), F(d), T(c)} regime. This overlap is a central diagnostic result rather than an exceptional case: facility-side reachability signals, weak co-location-based bundling signals, and PT-side penalty signals frequently co-occur. The remaining regimes are {T(c)} (15.3%), no flagged signal (14.8%), {F(d), T(c)} (12.2%), {F(d)} (6.6%), and {F(s), T(c)} (1.3%). Appendix Table A.1 reports the within-group distribution of diagnostic regimes across three regional-status categories, while Appendix Table A.2 summarizes the descriptive characteristics of the study units.

Robustness checks indicate that the broad diagnostic classification is stable across alternative mobility assumptions, accessibility thresholds, and reference lines, although individual boundary cases remain sensitive. Across the 29 non-baseline mobility scenarios varying walking speed, transfer limits, and departure time, 94.8%–96.9% of units retained the baseline diagnostic regime (mean, 95.6%). The corresponding shares were 93.0% under the –5-min threshold scenario and 94.8% under the +5-min scenario. When population-weighted median rather than mean reference lines were used, 84.3% of units retained the same regime (Appendix C). Thus, the overall regime structure is reasonably stable across the tested assumptions, but classifications near the reference lines should be interpreted cautiously.

4.3. City-level correlates of diagnostic signals

This section reports descriptive city-level correlates under the mean-based baseline classification. The purpose is not to identify causal effects or pathways, but to examine the city-level contexts in which the rule-based diagnostic signals tend to occur and whether multiple signals

share broader contexts, including low-density settlement, weak opportunity structure, and aging-related vulnerability. SHAP summarizes feature importance and signed model associations, whereas one-dimensional ALE profiles show how selected associations vary across observed predictor ranges. Appendix Figs. C.3–C.7 compare the mean- and median-based SHAP results and report the corresponding median-based ALE profiles as a reference-line sensitivity analysis.

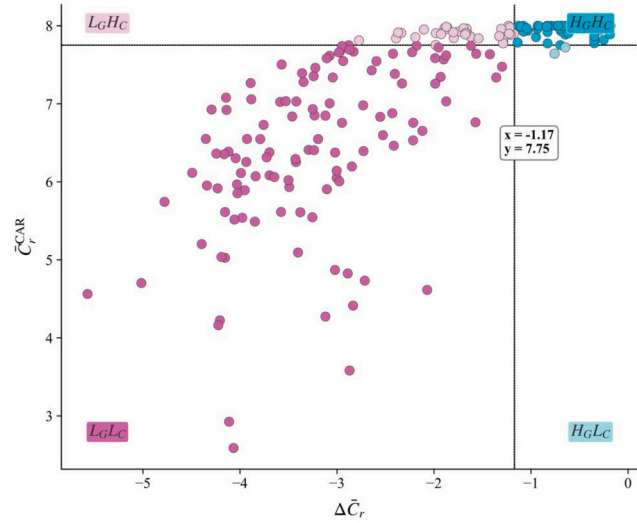
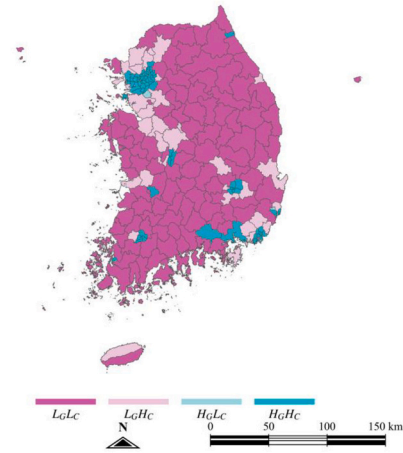
Under the baseline classification, opportunity-structure variables provide the clearest common signal. Activity diversity ranks among the most important correlates for F(s), F(d), and T(c), while activity density is especially prominent for F(s) and F(d). The ALE profiles generally show lower model-estimated membership probabilities at higher levels of activity diversity and density, although these nonlinear patterns should not be interpreted causally (Figs. 8–12).

For F(s), population density is the most important correlate, followed by activity diversity and activity density (Fig. 8). This pattern indicates that F(s) is associated with low-density settlement conditions and weak opportunity structure. F(s) should therefore not be interpreted as a pure measure of facility scarcity; it also reflects the relationship among opportunity locations, population distribution, and car-benchmark reachability under short travel-time thresholds (Fig. 11).

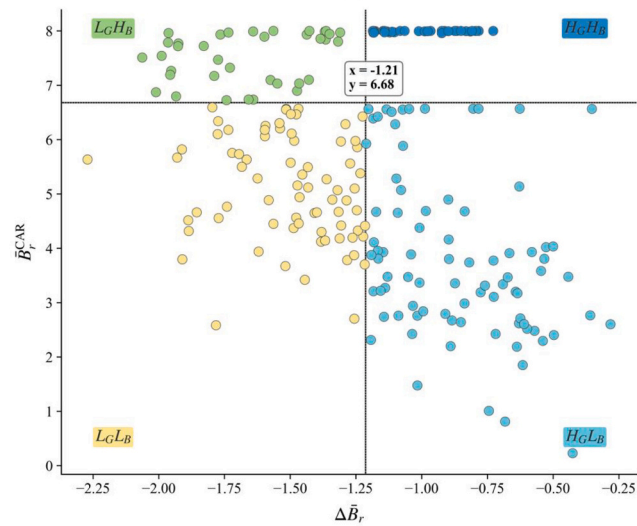
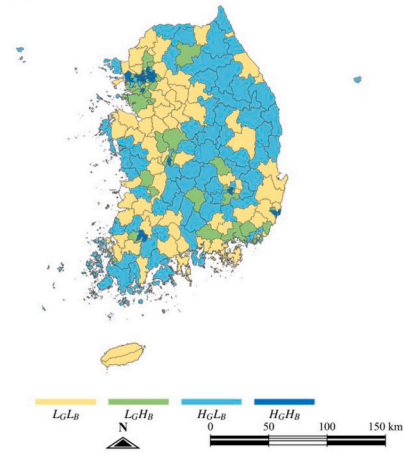
For F(d), activity diversity and activity density are the two most important correlates in the baseline model (Fig. 9). Public-expenditure variables, population density, and older-adult share provide additional contextual information, but they should not be interpreted as direct mechanisms. The association with older-adult share is examined further in Section 5.4 (Figs. 11 and 12). Activity diversity and F(d) both draw on grid-level facility-category co-presence. Accordingly, their association is interpreted as descriptive consistency with the signal construction rather than as an independent explanatory relationship.

For T(c), activity diversity is the most important correlate, followed by transport-sector expenditure and older-adult share in the baseline model (Fig. 10). Built-up area and administrative area also provide

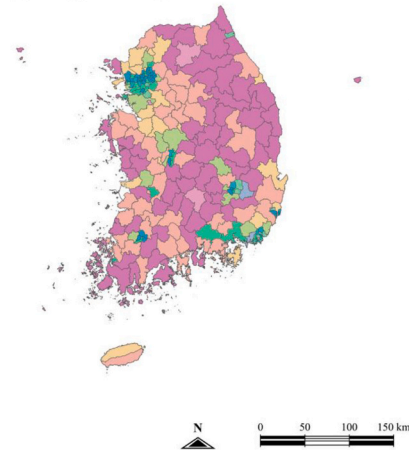
(a) Reachability classification



(b) Bundling-potential classification



(c) Integrated diagnostic classification



Bundling-potential class ($\Delta\bar{B}_r - \bar{B}_r^{CAR}$)	Reachability class ($\Delta\bar{C}_r - \bar{C}_r^{CAR}$)			
	LGLc	LcHc	HGLc	HcHc
HcHB	0.0% n=0	0.0% n=0	0.0% n=0	14.8% n=34
HGLB	28.8% n=66	0.9% n=2	0.0% n=0	6.6% n=15
LcHB	1.3% n=3	5.7% n=13	0.9% n=2	8.7% n=20
LGLB	21.0% n=48	8.3% n=19	0.0% n=0	3.1% n=7

Fig. 6. City-level diagnostic outcomes of opportunity reachability and co-location-based bundling potential. (a) Opportunity-reachability diagnosis based on the PT-car coverage gap, $\Delta\bar{C}_r$, and car-based coverage, $\bar{C}_r^{CAR}$. (b) Bundling-potential diagnosis based on the PT-car bundling-potential gap, $\Delta\bar{B}_r$, and car-based bundling potential, $\bar{B}_r^{CAR}$. (c) Joint classification of the two diagnostic stages.

contextual information, whereas stop and route density have lower importance in the baseline model. T(c) should therefore be interpreted as a PT-side penalty signal associated with both opportunity structure and broader urban context, not as a direct measure of any single transit-

supply factor (Figs. 11 and 12).

The recurrence of activity diversity across all three diagnostic signals should be read as an empirical property of the national diagnosis rather than as evidence that the signals are interchangeable. The diagnostic

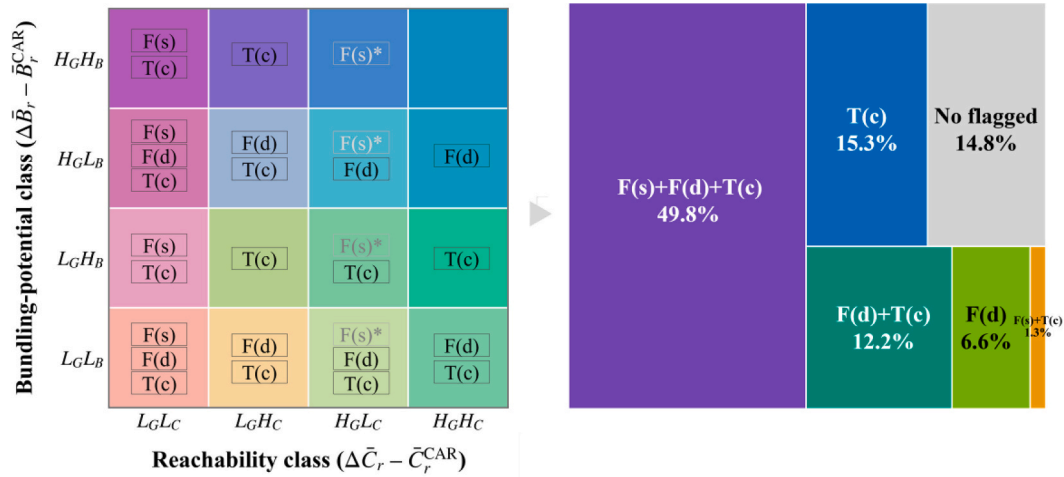


Fig. 7. Diagnostic regimes derived from the joint classification. F(s) denotes a facility-side reachability signal under the car benchmark; F(d) denotes a weak co-location-based bundling signal under the car benchmark; and T(c) denotes a PT-side penalty signal relative to the car benchmark. F(s)* indicates below-reference car-based reachability under L_C , but without a below-reference PT-car gap signal under H_G ; it is therefore treated as a secondary facility-side reachability signal.

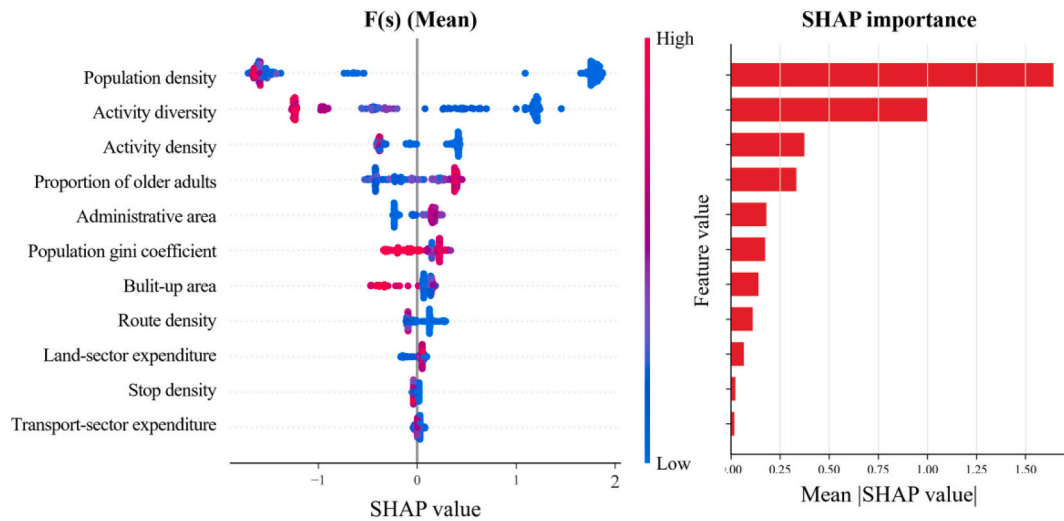


Fig. 8. SHAP summary for the F(s) diagnostic signal. F(s) denotes a facility-side reachability signal under the car benchmark. Points show signed SHAP values for individual cities, and bars show mean absolute SHAP values.

labels are assigned deterministically by the rule-based classification described in Section 3.3, so shared correlates cannot alter which signals a unit receives. The signals also separate empirically. Signal prevalence differs across them (0.511 for F(s), 0.686 for F(d), and 0.786 for T(c)). More directly, 81 of 229 units (35.4%) are assigned to single- or two-signal regimes rather than to the compound regime: 35 units are assigned to {T(c)}, 15 to {F(d)}, 28 to {F(d), T(c)}, and 3 to {F(s), T(c)}. The presence of these partial combinations demonstrates that the three signals do not coincide mechanically. Their secondary correlate structures also differ: population density leads for F(s), opportunity-structure variables dominate for F(d), and transport-sector expenditure, older-adult share, and settlement-extent variables follow activity diversity for T(c), while stop and route density rank comparatively low.

The shared association with activity diversity is consistent with a common contextual dependence on opportunity structure. Where activity-rich anchors are scarce or spatially remote from residential concentrations, both car-benchmark accessibility and PT accessibility may be constrained, while PT may face additional access, waiting, and transfer burdens. However, the correlate analysis does not establish that sparse activity-rich anchors cause T(c) or produce the compound regime, nor does the comparatively low model importance of stop and

route density imply that transit supply is unimportant. The results therefore support an opportunity-structure interpretation in which the three signals remain distinguishable in assignment while sharing a common contextual correlate. Detailed rankings of secondary correlates should be interpreted cautiously.

5. Discussion

5.1. Interpreting PT-car gaps as diagnostic signals

The main methodological implication of the results is that PT-car accessibility gaps should not be interpreted as a single type of PT-service problem. Similar aggregate gaps may correspond to different combinations of opportunity-side and PT-side conditions. In some cities, basic opportunities are already weakly reachable under the car benchmark. In others, car travel can reach activity-rich anchors within the relevant time thresholds, whereas PT access is more restricted by door-to-door burdens related to access, waiting, transfers, and in-vehicle travel time (Guo and Wilson, 2011; Iseki and Taylor, 2009; Wardman, 2004). The diagnostic value of the framework lies in separating these situations before moving to local planning assessment.

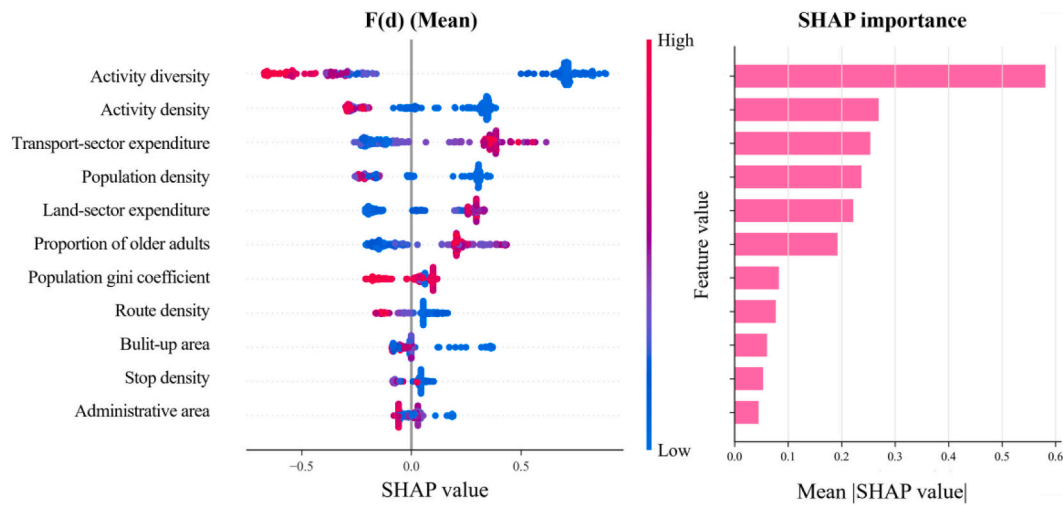


Fig. 9. SHAP summary for the F(d) diagnostic signal. F(d) denotes a weak co-location-based bundling signal under the car benchmark. Points show signed SHAP values for individual cities, and bars show mean absolute SHAP values.

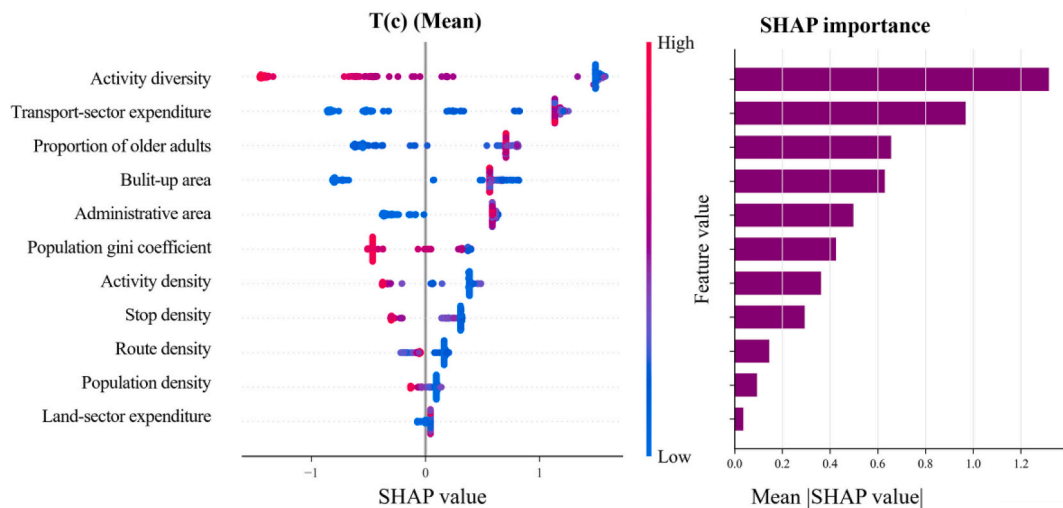


Fig. 10. SHAP summary for the T(c) diagnostic signal. T(c) denotes a PT-side penalty signal relative to the car benchmark. Points show signed SHAP values for individual cities, and bars show mean absolute SHAP values.

This interpretation extends modal accessibility-gap studies that use PT-car comparisons to monitor sustainable transport performance, assess spatial equity across destination types, and prioritize transit or land-use interventions (Kwok and Yeh, 2004; Maharjan et al., 2022; Rodrigue et al., 2023). The present study builds on this line of work but uses PT-car gaps to distinguish diagnostic conditions rather than as final monitoring or prioritization scores. In this framework, modal gaps help assess whether PT disadvantage is more closely associated with facility-side reachability signals, limited co-location-based bundling potential, PT-side penalty signals, or their overlap.

The car benchmark should be interpreted in two ways. First, car travel times are derived from static OSRM routing and do not account for time-of-day congestion. The resulting PT-car gaps should therefore be read as diagnostic differences relative to a static car-accessible opportunity benchmark, not as observed peak-hour modal travel-time differences. Second, car-based accessibility is not an unconstrained measure of facility distribution. It represents opportunities reachable by car under existing land-use, settlement, road-network, and routing conditions within the specified travel-time thresholds. This use of a benchmark is consistent with Yang et al. (2021), who assessed railway network performance by comparing observed accessibility with an

idealized network condition while retaining the spatial distributions of population and facilities. In the same spirit, the car benchmark in this study is not intended to remove urban context; rather, it provides a calculated reference for assessing additional PT-side disadvantage under existing urban and road-network conditions. This interpretation is consistent with accessibility theory, which treats accessibility as jointly shaped by land-use, transport, temporal, and individual conditions (Geurs and Van Wee, 2004, 2026).

The spatial distribution of the diagnostic regimes provides some descriptive reassurance regarding the national conclusion. Of the 114 compound-regime units, 100 (87.7%) are non-metropolitan jurisdictions, whereas all 34 units with no flagged signal are located in the capital metropolitan region or metropolitan cities (Appendix Table A.1). This pattern indicates that the national prominence of the compound regime is not driven solely by metropolitan units that are likely to be most affected by peak-period congestion. It does not, however, provide a formal bound on congestion sensitivity. Under a congestion-adjusted specification, the diagnostic values and population-weighted reference lines would both be recomputed, so withdrawals and new assignments of T(c) cannot be ruled out. The 14:00 scenario provides evidence only on sensitivity to the PT departure time and does not directly validate the

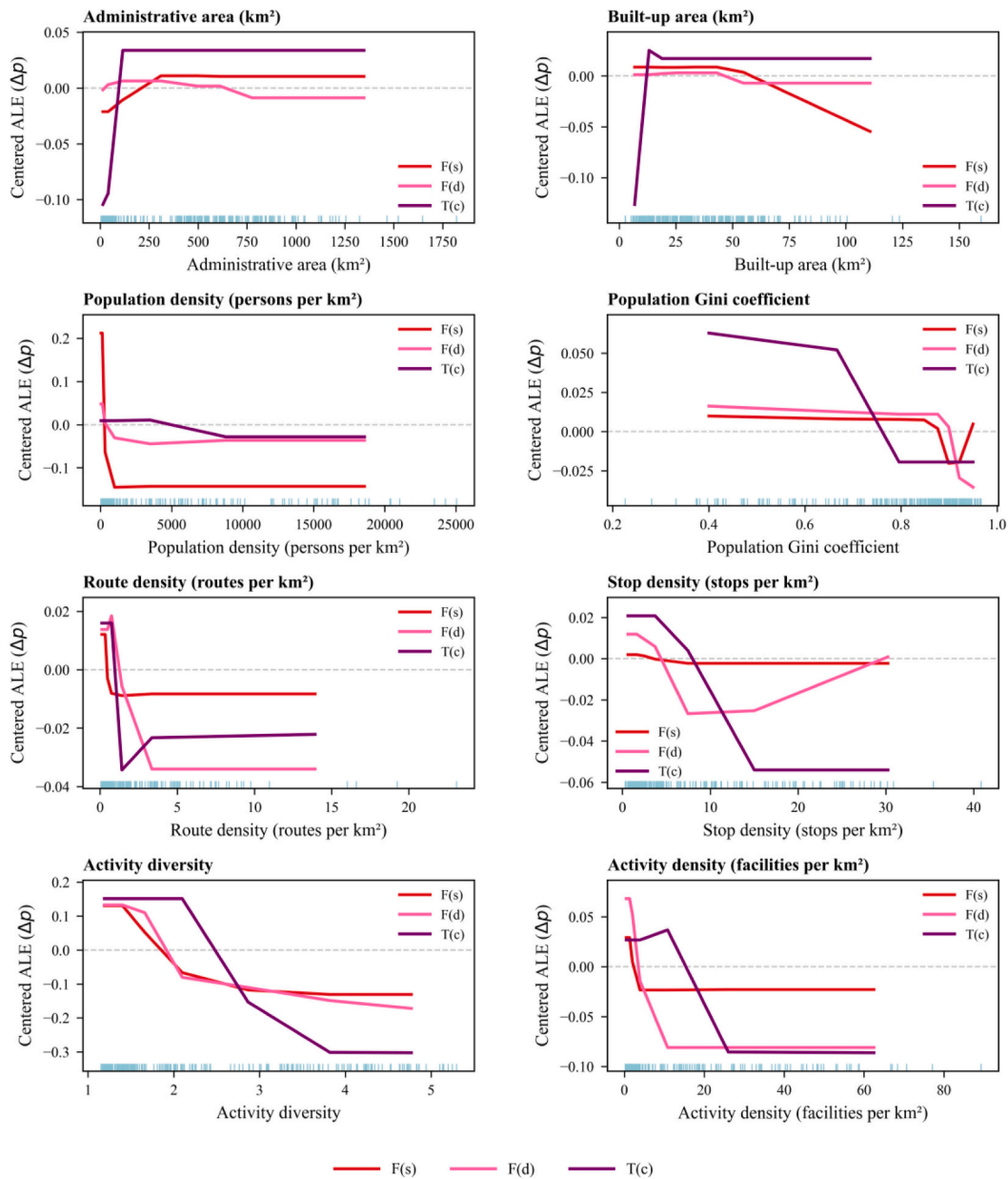


Fig. 11. ALE profiles for urban-form, transit-supply, and opportunity-structure variables across diagnostic signals F(s), F(d), and T(c). (a) Urban form; (b) Transit supply; (c) Opportunity structure under the mean-based reference-line specification.

static car benchmark. T(c) assignments for individual metropolitan units should therefore be interpreted with additional caution, and a matched time-dependent PT-car analysis remains necessary as a future extension.

Accordingly, the framework should be interpreted as a diagnosis of calculated potential accessibility. It identifies whether PT disadvantage appears mainly as an additional PT-side gap relative to the car benchmark, or whether it is compounded by opportunity-side conditions captured through car-based reachability and co-location-based bundling potential. It does not demonstrate observed multi-stop behavior, perceived accessibility, facility adequacy, causal effects, or the impacts of specific interventions.

5.2. Compound deficits as a land-use–transport coordination problem

The presence of the compound {F(s), F(d), T(c)} regime in 114 of 229 units (49.8%) shows that signal overlap is the dominant national pattern rather than an exception. PT disadvantage should therefore not

be interpreted as a purely service-side issue. In this regime, the car benchmark identifies below-reference opportunity-side conditions, including facility-side reachability signals and weak co-location-based bundling signals, while the PT-car gaps indicate additional PT-side disadvantages relative to that benchmark. This pattern is consistent with accessibility theory, which treats access as jointly shaped by the spatial distribution of opportunities and the transport system that connects people to them (Geurs and Van Wee, 2004; Martens, 2016). It also supports planning arguments that accessibility should be evaluated through the coordination of transport investment, land-use planning, and service provision, rather than through transport performance alone (Bertolini et al., 2005; Ryan and Martens, 2023).

The regime-specific classifications are best interpreted as prompts for follow-up assessment, not as direct intervention prescriptions. Cases involving T(c) suggest that local assessment should examine PT-side conditions, including access to stops, route and service coverage, waiting, transfers, service frequency, and connections between stops and

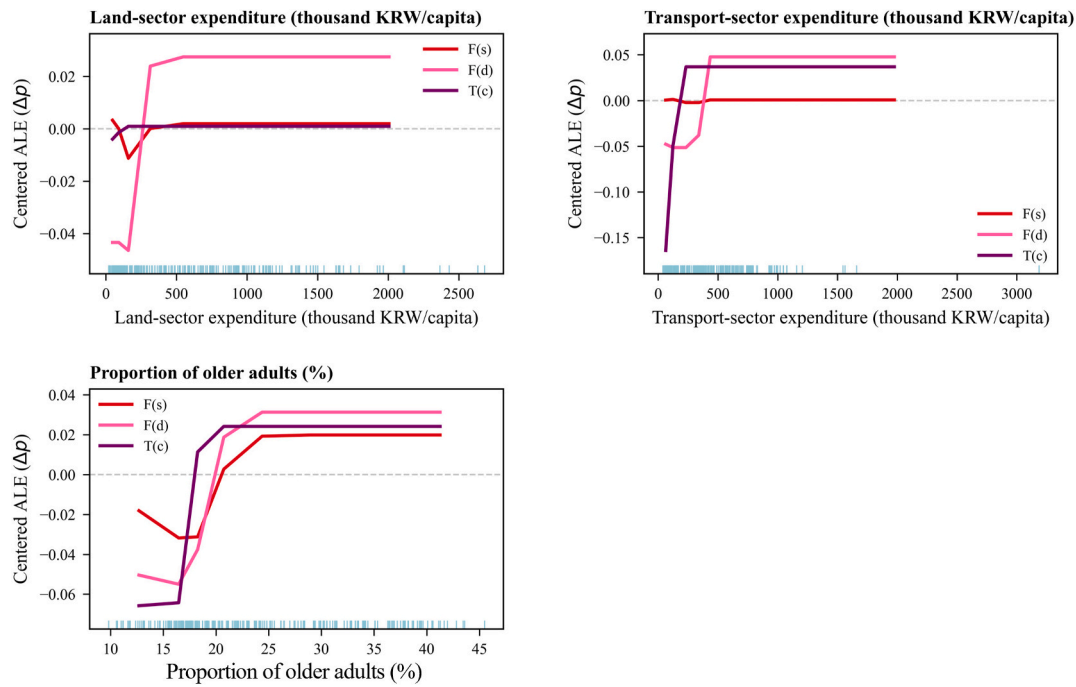


Fig. 12. ALE profiles for public-expenditure and aging-related sociodemographic variables across diagnostic signals F(s), F(d), and T(c) under the mean-based reference-line specification.

activity-rich destinations. Cases involving F(d) suggest that the issue may not be basic reachability alone, but the spatial organization of activity opportunities around reachable anchors. In these cases, improving PT connectivity without examining activity co-location may leave part of the diagnostic pattern unresolved. Cases involving F(s) suggest that further assessment should examine whether basic opportunities are insufficient in number, poorly aligned with residential concentrations, or difficult to reach under existing settlement and road-network conditions. Where F(s)* appears, it should be treated as a secondary facility-side reachability signal requiring local verification.

The city-level correlate analysis reinforces this cross-sector reading. Activity diversity is associated with all three diagnostic signals, which is consistent with opportunity structure being relevant to both car-benchmark conditions and additional PT-side penalties. This pattern does not show that the three signals arise from a single mechanism or that opportunity structure causally produces the compound regime. Rather, it indicates that compound-regime units warrant follow-up assessment across both transport and land-use domains. Transit-side measures may need to be assessed alongside the spatial distribution of activity-rich anchors, while facility-siting measures may need to be assessed alongside door-to-door PT burdens. The relevant planning questions therefore span transit agencies, land-use and facility-planning authorities, and city-level or regional governments responsible for service standards and spatial development. Because the correlate analysis is cross-sectional and descriptive, these results identify overlapping contextual conditions rather than common causal mechanisms or demonstrated intervention effects.

5.3. Public-expenditure variables as contextual correlates

Land- and transport-sector expenditures show non-negligible associations in the baseline model explanations, but their relative importance varies across diagnostic signals. These variables are therefore treated as contextual indicators of municipal conditions, not as evidence that expenditure causes accessibility deficits or that changing expenditure would alter diagnostic membership.

Because expenditure is measured per capita, high values may reflect

fixed service costs spread across smaller populations rather than greater effective investment capacity (Bel and Warner, 2015; Carruthers and Ulfarsson, 2003). The public-expenditure results therefore indicate that accessibility deficits should be interpreted alongside city-level context, including service-maintenance burden, settlement structure, and land-use–transport coordination (Hull, 2008; Marsden and Reardon, 2017).

5.4. Older adults and diagnostic equity concerns

The older-adult result is best interpreted as an aging-related city-level vulnerability marker. Under the mean-based baseline, older-adult share is positively associated with all three diagnostic signals, indicating that aging-related municipal contexts tend to coincide with multiple forms of potential-accessibility disadvantage. Cities with higher older-adult shares may also share broader structural conditions, including non-metropolitan location, lower density, population decline, greater service-maintenance burdens, and less favorable PT service conditions (Hospers, 2014; Rodrigue et al., 2023; Wiechmann and Pallagst, 2012). The association should therefore be read as a city-level contextual signal, not as evidence that age composition alone explains the diagnostic signals or that older individuals are directly excluded from services.

This more cautious interpretation still has equity relevance. Transport disadvantage can reinforce social exclusion when access to key services is limited, especially for groups with greater mobility constraints (Lucas, 2012; Pereira et al., 2017). Older adults may be particularly affected by door-to-door PT burdens, including walking access, waiting, transfers, and other trip components that make public transport difficult to use in everyday travel (Hess, 2009; Vecchio et al., 2024). A weak co-location-based bundling signal is also relevant because it indicates that fewer facility categories are co-located at reachable anchors, although the present measure does not show whether older residents actually make separate trips. Because the framework measures calculated potential accessibility rather than realized travel behavior or perceived accessibility, the equity implication is diagnostic: it identifies cities where aging-related vulnerability coincides with diagnostic

signals of potential accessibility disadvantage. The slower-walking-speed sensitivity analysis in [Appendix B](#) indicates that the broad diagnostic classification is not driven solely by the baseline walking-speed assumption, but it does not establish realized exclusion among older adults.

6. Conclusion

This study developed a diagnostic framework that compares PT and car accessibility across 229 South Korean city-level administrative units to distinguish opportunity-side diagnostic signals from additional PT-side penalty signals. Three conclusions emerge. First, 114 of 229 units (49.8%) fall into the compound {F(s), F(d), T(c)} regime, showing that weak reachability, limited co-location-based bundling potential, and PT-side penalties frequently overlap. Second, the diagnostic signals are associated with different city-level contexts, suggesting that similar aggregate PT–car gaps may reflect different combinations of opportunity structure, settlement form, transit supply, public expenditure, and demographic composition. Third, the association between older-adult share and the diagnostic signals should be interpreted as a contextual vulnerability marker rather than as direct evidence of realized exclusion.

The framework is most useful as a diagnostic planning-support tool. It does not prescribe interventions or estimate their effects. Instead, it helps narrow the transport and land-use domains that warrant joint follow-up assessment, including PT connectivity, facility siting, activity co-location, and land-use coordination.

Some limitations should be acknowledged. First, the co-location-based bundling measure is based on category co-presence within 500 m destination cells. It provides a parsimonious proxy for structural bundling potential, but it should not be interpreted as observed multi-activity participation or as evidence that multiple activity needs are behaviorally satisfied. The measure does not capture within-category differences in facility quality, size, capacity, attractiveness, service range, opening hours, or compatibility with individual activity demands, nor does it capture activity sequencing or realized trip chaining. Second, the use of 500 m grid cells introduces spatial uncertainty because the representative point of each cell may not coincide with the exact residential or facility location. Third, the travel-time comparison is based on scheduled PT data and static car routing. PT travel times may not reflect delays, irregular headways, or other real-time operating conditions, while the car benchmark is a calculated reference under existing land-use, road-network, and routing assumptions rather than an unconstrained measure of facility distribution. Because free-flow car routing is least realistic during peak periods in dense areas, T(c) assignments for individual metropolitan units may be overstated. The concentration of compound-regime units outside metropolitan areas

provides some descriptive reassurance, but it does not bound the effect of congestion on the national diagnosis. Fourth, the diagnostic classification is relative to the selected reference lines and travel-time thresholds. Sensitivity analyses indicate that the broad diagnostic structure is stable, but boundary cases can change under alternative assumptions. Fifth, the pooled city-level correlate analysis is cross-sectional and may mask heterogeneity across metropolitan and non-metropolitan contexts. SHAP and ALE summarize model associations but do not identify causal pathways or intervention effects. Finally, the datasets combine nationally consistent facility, transport, population, and city-level contextual data from 2023 to 2025; the results should therefore be interpreted as a mid-2020s cross-sectional diagnosis rather than a single-date snapshot.

Future research could test alternative spatial resolutions and distance-based activity-mix measures, examine heterogeneity across city types, and evaluate the effects of coordinated PT service changes and facility-siting strategies. A matched time-dependent PT–car analysis would additionally require nationally consistent link- or origin–destination-specific car speed data together with scheduled or observed PT travel times, allowing both modes to be evaluated under comparable temporal conditions.

Declaration of generative AI use

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) solely to assist with language editing and to improve clarity and readability. The generative AI tool was not used to generate scientific content, interpret results, or draw conclusions. All AI-assisted text was carefully reviewed and edited by the authors, who take full responsibility for the content of the published article.

CRediT authorship contribution statement

Minji Kang: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Sunyong Eom:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

We have no conflict of interest to declare.

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Appendix A. Study area characteristics and diagnostic regime distribution

Table A.1

Distribution of city-level administrative units by diagnostic regime and regional status.

Regional status	F(s) + F(d) + T(c)	F(d)	F(d) + T(c)	F(s) + T(c)	T(c)	No flagged
Capital metropolitan region (n = 66)	10 (15.2%)	6 (9.1%)	9 (13.6%)	1 (1.5%)	15 (22.7%)	25 (37.9%)
Metropolitan city/Sejong (n = 41)	4 (9.8%)	9 (22.0%)	7 (17.1%)	0 (0.0%)	12 (29.3%)	9 (22.0%)
Non-metropolitan province (n = 122)	100 (82.0%)	0 (0.0%)	12 (9.8%)	2 (1.6%)	8 (6.6%)	0 (0.0%)
All units (n = 229)	114 (49.8%)	15 (6.6%)	28 (12.2%)	3 (1.3%)	35 (15.3%)	34 (14.8%)

Note. Values are reported as n (row % within regional status); the final row reports n (overall % of all 229 units). The unit of analysis is the city-level administrative unit (si/gun/gu). Regional status was coded according to the upper-level jurisdiction: capital metropolitan region refers to Seoul, Incheon, and Gyeonggi; metropolitan city/Sejong refers to Busan, Daegu, Gwangju, Daejeon, Ulsan, and Sejong, with Sejong treated as a single-tier special self-governing city; and non-metropolitan

province refers to all remaining provinces. Percentages sum to 100% within each regional-status group, subject to rounding.

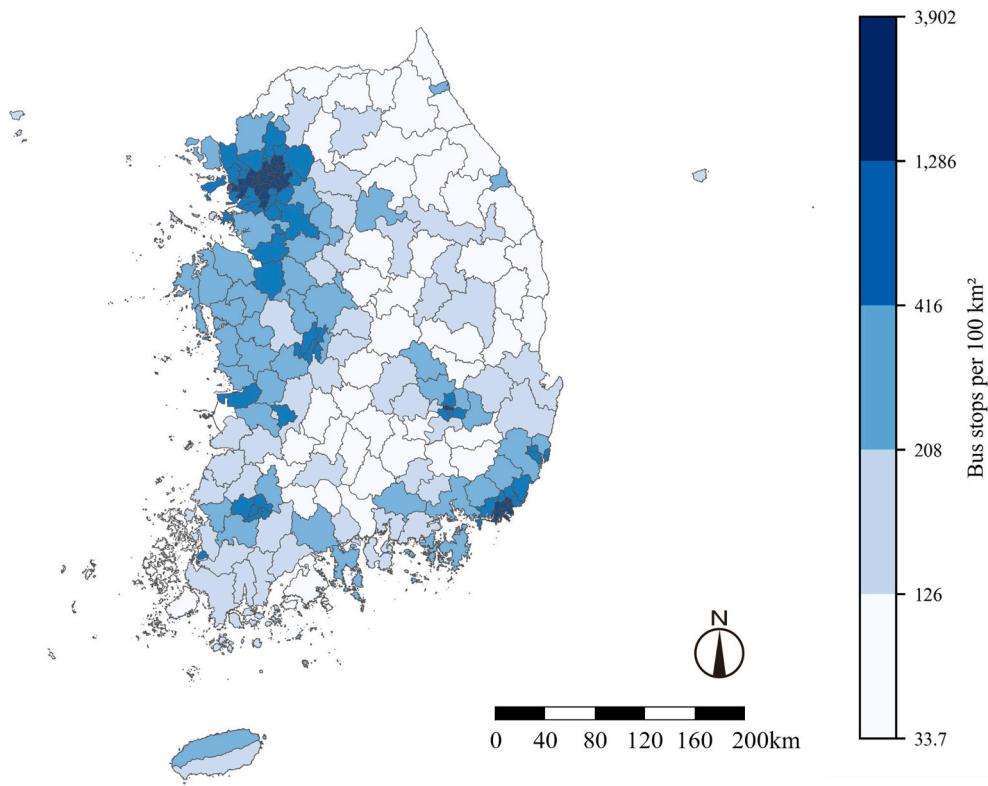


Fig. A.1. National distribution of bus-stop density (stops per 100 km²).

Table A.2
Descriptive characteristics and mean-based diagnostic signals for the 229 city-level administrative units.

Administrative unit	F(s)	F(d)	T(c)	Regional status	Population	Area (km²)	Population density (persons/km²)	Urban-designated area share (%)
Seoul								
Jongno-gu			○	CMR	146,179	23.91	6112.9	100.00
Jung-gu				CMR	127,576	9.96	12,808.9	100.00
Yongsan-gu				CMR	214,791	21.87	9822.3	100.00
Seongdong-gu				CMR	277,683	16.82	16,509.0	100.00
Gwangjin-gu				CMR	348,160	17.06	20,404.6	100.00
Dongdaemun-gu				CMR	355,999	14.22	25,042.3	100.00
Jungnang-gu				CMR	376,621	18.50	20,361.0	100.00
Seongbuk-gu				CMR	432,874	24.58	17,612.3	100.00
Gangbuk-gu				CMR	284,155	23.60	12,040.3	100.00
Dobong-gu				CMR	299,931	20.65	14,523.8	100.00
Nowon-gu		○		CMR	492,979	35.44	13,910.6	100.00
Eunpyeong-gu				CMR	452,988	29.71	15,246.9	100.00
Seodaemun-gu				CMR	320,168	17.63	18,164.2	100.00
Mapo-gu				CMR	361,380	23.85	15,149.7	100.00
Yangcheon-gu				CMR	422,248	17.41	24,258.7	100.00
Gangseo-gu				CMR	549,557	41.45	13,257.7	100.00
Guro-gu				CMR	423,397	20.12	21,040.5	100.00
Geumcheon-gu		○		CMR	245,860	13.02	18,882.5	100.00
Yeongdeungpo-gu				CMR	400,544	24.55	16,314.6	100.00
Dongjak-gu				CMR	384,089	16.36	23,481.8	100.00
Gwanak-gu				CMR	493,677	29.57	16,696.1	100.00
Seocho-gu			○	CMR	385,267	46.97	8203.1	100.00
Gangnam-gu				CMR	511,084	39.50	12,939.6	100.00
Songpa-gu				CMR	630,744	33.88	18,618.9	100.00
Gangdong-gu				CMR	446,561	24.59	18,160.0	100.00
Busan								
Jung-gu				MC	40,487	3.01	13,437.5	75.29
Seo-gu		○		MC	103,883	13.97	7435.1	49.01
Dong-gu	○	○	○	MC	87,477	10.12	8642.7	84.79
Yeongdo-gu		○		MC	109,389	14.20	7703.2	26.75
Busanjin-gu		○	○	MC	355,644	29.67	11,988.2	100.00

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Table A.2 (continued)

Administrative unit	F(s)	F(d)	T(c)	Regional status	Population	Area (km ²)	Population density (persons/km ²)	Urban-designated area share (%)
Dongnae-gu		○	○	MC	265,047	16.63	15,937.1	100.00
Nam-gu			○	MC	258,412	26.82	9633.6	66.96
Buk-gu		○		MC	270,951	39.37	6881.5	100.00
Haeundae-gu		○	○	MC	370,849	51.52	7197.8	98.34
Saha-gu			○	MC	298,826	41.78	7151.5	49.17
Geumjeong-gu		○		MC	221,890	65.28	3399.1	100.00
Gangseo-gu		○	○	MC	144,102	182.16	791.1	67.22
Yeonje-gu		○		MC	198,491	12.11	16,396.1	100.00
Suyeong-gu		○		MC	170,220	10.22	16,659.7	78.50
Sasang-gu			○	MC	208,245	36.10	5767.8	100.00
Gijang-gun			○	MC	175,691	218.34	804.7	98.54
Daegu								
Jung-gu		○		MC	85,775	7.06	12,157.0	100.00
Dong-gu		○	○	MC	335,589	182.11	1842.8	80.62
Seo-gu				MC	161,396	17.32	9316.5	100.00
Nam-gu			○	MC	141,259	17.43	8104.4	100.00
Buk-gu		○		MC	430,146	93.95	4578.6	100.00
Suseong-gu		○	○	MC	396,295	76.54	5177.9	100.00
Dalseo-gu				MC	539,884	62.37	8656.0	100.00
Dalseong-gun			○	MC	267,045	428.36	623.4	88.59
Gunwi-gun	○	○	○	MC	21,799	614.33	35.5	1.18
Incheon								
Jung-gu		○	○	CMR	157,326	140.38	1120.7	99.95
Dong-gu		○		CMR	59,364	7.25	8191.1	100.00
Yeonsu-gu			○	CMR	408,476	56.19	7269.5	100.00
Namdong-gu		○		CMR	500,087	57.45	8704.2	100.00
Bupyeong-gu				CMR	498,558	32.01	15,577.3	100.00
Gyeyang-gu			○	CMR	279,818	45.57	6141.0	100.00
Seo-gu				CMR	621,848	119.06	5223.1	85.07
Michuhol-gu			○	CMR	414,941	24.84	16,705.4	100.00
Ganghwa-gun	○	○	○	CMR	66,246	411.41	161.0	4.26
Ongjin-gun	○	○	○	CMR	19,286	172.95	111.5	2.33
Gwangju								
Dong-gu				MC	112,016	49.32	2271.3	100.00
Seo-gu				MC	284,014	47.74	5948.8	100.00
Nam-gu			○	MC	211,536	60.96	3470.0	99.75
Buk-gu				MC	432,033	120.26	3592.5	100.00
Gwangsan-gu			○	MC	417,491	222.69	1874.8	90.58
Daejeon								
Dong-gu			○	MC	230,134	136.69	1683.6	87.48
Jung-gu				MC	220,292	62.19	3542.1	90.97
Seo-gu			○	MC	469,031	95.54	4909.2	78.06
Yuseong-gu	○	○	○	MC	379,100	176.61	2146.5	100.00
Daedeok-gu		○		MC	171,779	68.74	2499.0	100.00
Ulsan								
Jung-gu			○	MC	203,534	37.00	5500.3	100.00
Nam-gu				MC	308,537	74.02	4168.3	100.00
Dong-gu				MC	157,071	36.07	4354.0	100.00
Buk-gu		○	○	MC	214,918	157.35	1365.8	76.39
Ulsu-gun	○	○	○	MC	223,372	758.38	294.5	53.45
Sejong City								
Sejong City			○	MC	386,261	464.96	830.7	30.57
Gyeonggi-do								
Suwon-si			○	CMR	1,226,362	121.10	10,126.9	100.00
Seongnam-si			○	CMR	903,116	141.63	6376.6	100.00
Uijeongbu-si			○	CMR	458,966	81.55	5628.1	100.00
Anyang-si			○	CMR	537,159	58.50	9182.1	100.00
Bucheon-si		○		CMR	803,512	53.46	15,030.7	100.00
Gwangmyeong-si		○		CMR	275,397	38.52	7149.2	100.00
Pyeongtaek-si		○	○	CMR	605,678	458.45	1321.1	32.80
Dongducheon-si		○	○	CMR	91,301	95.67	954.3	35.08
Ansan-si		○	○	CMR	709,147	156.47	4532.2	64.15
Goyang-si		○	○	CMR	1,047,592	268.13	3907.1	73.19
Gwacheon-si		○	○	CMR	76,824	35.87	2141.7	100.00
Guri-si				CMR	183,048	33.34	5490.6	100.00
Namyangju-si	○	○	○	CMR	716,123	458.13	1563.1	52.87
Osan-si	○		○	CMR	243,832	42.69	5711.5	100.00
Siheung-si			○	CMR	568,455	139.94	4062.2	100.00
Gunpo-si				CMR	263,939	36.42	7247.4	100.00
Uiwang-si			○	CMR	154,788	54.03	2864.8	100.00
Hanam-si			○	CMR	320,562	92.99	3447.4	100.00
Yongin-si		○	○	CMR	1,066,979	591.25	1804.6	66.16
Paju-si		○	○	CMR	495,339	673.96	735.0	12.07
Icheon-si	○	○	○	CMR	228,695	461.46	495.6	18.00

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Table A.2 (continued)

Administrative unit	F(s)	F(d)	T(c)	Regional status	Population	Area (km ²)	Population density (persons/km ²)	Urban-designated area share (%)
Anseong-si	○	○	○	CMR	210,390	553.51	380.1	28.16
Gimpo-si		○	○	CMR	496,323	276.60	1794.4	37.85
Hwaseong-si			○	CMR	974,156	700.64	1390.4	40.90
Gwangju-si	○	○	○	CMR	394,667	430.99	915.7	35.24
Yangju-si			○	CMR	269,641	310.49	868.4	48.82
Pocheon-si		○	○	CMR	157,111	827.17	189.9	4.74
Yeoju-si	○	○	○	CMR	116,045	608.21	190.8	4.36
Yeoncheon-gun	○	○	○	CMR	41,007	677.94	60.5	4.41
Gapyeong-gun	○	○	○	CMR	59,893	842.82	71.1	9.71
Yangpyeong-gun	○	○	○	CMR	119,320	877.82	135.9	5.84
Gangwon State								
Chuncheon-si	○		○	NMP	292,504	1116.42	262.0	30.03
Wonju-si	○	○	○	NMP	364,912	868.29	420.3	10.22
Gangneung-si	○	○	○	NMP	213,786	1040.83	205.4	7.49
Donghae-si		○	○	NMP	86,222	180.31	478.2	58.88
Taebaek-si	○	○	○	NMP	38,425	303.44	126.6	21.93
Sokcho-si		○	○	NMP	80,497	105.75	761.2	33.42
Samcheok-si	○	○	○	NMP	63,542	1187.84	53.5	6.23
Hongcheon-gun	○	○	○	NMP	65,109	1820.57	35.8	1.69
Hoengseong-gun	○	○	○	NMP	45,789	998.00	45.9	0.99
Yeongwol-gun	○	○	○	NMP	35,581	1127.41	31.6	2.34
Pyeongchang-gun	○	○	○	NMP	38,959	1464.26	26.6	1.14
Jeongseon-gun	○	○	○	NMP	32,793	1219.78	26.9	3.49
Cheorwon-gun	○	○	○	NMP	40,702	890.13	45.7	2.97
Hwacheon-gun	○	○	○	NMP	22,372	909.09	24.6	1.46
Yanggu-gun	○	○	○	NMP	20,943	661.99	31.6	0.56
Inje-gun	○	○	○	NMP	31,490	1646.20	19.1	0.90
Goseong-gun	○	○	○	NMP	27,811	660.77	42.1	1.81
Yangyang-gun	○	○	○	NMP	26,577	629.78	42.2	1.91
Chungcheongbuk-do								
Chungju-si	○	○	○	NMP	215,990	983.26	219.7	11.26
Jecheon-si	○	○	○	NMP	131,583	882.77	149.1	6.53
Cheongju-si			○	NMP	870,358	941.05	924.9	36.51
Boeun-gun	○	○	○	NMP	30,226	584.26	51.7	3.03
Okcheon-gun	○	○	○	NMP	47,771	537.28	88.9	10.25
Yeongdong-gun	○	○	○	NMP	44,331	846.91	52.3	3.68
Jincheon-gun	○	○	○	NMP	94,405	407.38	231.7	7.36
Goesan-gun	○	○	○	NMP	37,607	842.01	44.7	1.48
Eumseong-gun	○	○	○	NMP	104,615	520.12	201.1	7.21
Danyang-gun	○	○	○	NMP	26,473	780.15	33.9	4.56
Jeungpyeong-gun		○	○	NMP	38,122	81.80	466.0	16.55
Chungcheongnam-do								
Cheonan-si		○	○	NMP	689,851	636.15	1084.4	22.79
Gongju-si	○	○	○	NMP	105,498	864.16	122.1	6.96
Boryeong-si	○	○	○	NMP	96,890	586.86	165.1	5.68
Asan-si		○	○	NMP	376,632	542.80	693.9	17.33
Seosan-si	○	○	○	NMP	178,618	742.28	240.6	18.43
Nonsan-si	○	○	○	NMP	115,925	556.25	208.4	8.86
Gyeryong-si		○	○	NMP	44,822	60.69	738.5	81.09
Dangjin-si	○	○	○	NMP	174,955	705.62	247.9	10.76
Geumsan-gun	○	○	○	NMP	53,124	577.21	92.0	5.11
Buyeo-gun	○	○	○	NMP	60,991	624.65	97.6	6.95
Seocheon-gun	○	○	○	NMP	49,294	366.12	134.6	6.28
Cheongyang-gun	○	○	○	NMP	29,972	479.25	62.5	1.40
Hongseong-gun	○	○	○	NMP	100,015	446.69	223.9	8.03
Yesan-gun	○	○	○	NMP	79,229	542.72	146.0	6.90
Taeon-gun	○	○	○	NMP	60,516	516.05	117.3	3.60
Jeonbuk-State								
Jeonju-si			○	NMP	658,032	206.01	3194.2	95.51
Gunsan-si		○	○	NMP	265,764	398.02	667.7	29.36
Iksan-si			○	NMP	274,350	506.59	541.6	15.01
Jeongeup-si	○	○	○	NMP	102,507	693.30	147.9	6.90
Namwon-si	○	○	○	NMP	74,554	752.09	99.1	4.07
Gimje-si	○	○	○	NMP	79,663	545.98	145.9	8.10
Wanju-gun	○	○	○	NMP	101,002	821.38	123.0	18.27
Jinan-gun	○	○	○	NMP	22,843	789.14	28.9	0.81
Muju-gun	○	○	○	NMP	22,401	632.06	35.4	1.96
Jangsu-gun	○	○	○	NMP	19,914	533.18	37.3	1.03
Imsil-gun	○	○	○	NMP	24,509	597.17	41.0	3.01
Sunchang-gun	○	○	○	NMP	25,368	495.93	51.2	2.04
Gochang-gun	○	○	○	NMP	50,731	607.48	83.5	5.34
Buan-gun	○	○	○	NMP	46,853	495.00	94.7	9.57
Jeollanam-do								
Mokpo-si			○	NMP	217,950	51.73	4213.2	44.93

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Table A.2 (continued)

Administrative unit	F(s)	F(d)	T(c)	Regional status	Population	Area (km ²)	Population density (persons/km ²)	Urban-designated area share (%)
Yeosu-si	○	○	○	NMP	267,392	512.33	521.9	28.60
Suncheon-si	○	○	○	NMP	272,041	911.04	298.6	21.14
Naju-si	○	○	○	NMP	117,012	608.49	192.3	17.29
Gwangyang-si	○	○	○	NMP	147,378	464.86	317.0	35.85
Damyang-gun	○	○	○	NMP	43,763	455.07	96.2	29.33
Gokseong-gun	○	○	○	NMP	26,273	547.29	48.0	2.82
Gurye-gun	○	○	○	NMP	22,894	442.96	51.7	2.46
Goheung-gun	○	○	○	NMP	58,735	807.17	72.8	2.70
Boseong-gun	○	○	○	NMP	35,955	664.59	54.1	3.22
Hwasun-gun	○	○	○	NMP	59,354	787.17	75.4	9.41
Jangheung-gun	○	○	○	NMP	33,396	622.38	53.7	5.70
Gangjin-gun	○	○	○	NMP	31,266	500.90	62.4	4.57
Haenam-gun	○	○	○	NMP	62,459	1045.13	59.8	4.75
Yeongam-gun	○	○	○	NMP	59,689	612.43	97.5	12.75
Muan-gun	○	○	○	NMP	90,426	450.94	200.5	6.42
Hampyeong-gun	○	○	○	NMP	29,259	392.10	74.6	6.57
Yeonggwang-gun	○	○	○	NMP	49,493	474.55	104.3	7.77
Jangseong-gun	○	○	○	NMP	40,187	518.35	77.5	20.95
Wando-gun	○	○	○	NMP	47,655	396.87	120.1	2.14
Jindo-gun	○	○	○	NMP	29,233	440.11	66.4	2.28
Sinan-gun	○	○	○	NMP	34,858	655.86	53.1	0.33
Gyeongsangbuk-do								
Pohang-si		○	○	NMP	493,394	1130.72	436.4	32.10
Gyeongju-si	○	○	○	NMP	259,505	1324.95	195.9	35.04
Gimcheon-si	○	○	○	NMP	137,413	1010.05	136.0	6.40
Andong-si	○	○	○	NMP	154,581	1522.27	101.5	5.21
Gumi-si			○	NMP	407,458	615.48	662.0	30.19
Yeongju-si	○	○	○	NMP	100,479	670.17	149.9	7.53
Yeongcheon-si	○	○	○	NMP	100,492	919.23	109.3	6.38
Sangju-si	○	○	○	NMP	92,990	1254.71	74.1	4.00
Mungyeong-si	○	○	○	NMP	66,535	912.05	73.0	4.15
Gyeongsan-si		○	○	NMP	296,453	411.88	719.8	30.05
Uiseong-gun	○	○	○	NMP	47,920	1174.59	40.8	2.77
Cheongsong-gun	○	○	○	NMP	23,099	846.13	27.3	0.73
Yeongyang-gun	○	○	○	NMP	15,197	815.87	18.6	1.41
Yeongdeok-gun	○	○	○	NMP	33,492	741.28	45.2	2.02
Cheongdo-gun	○	○	○	NMP	40,008	695.36	57.5	3.04
Goryeong-gun	○	○	○	NMP	30,518	384.24	79.4	8.46
Seongju-gun	○	○	○	NMP	41,073	616.15	66.7	1.72
Chilgok-gun	○	○	○	NMP	112,465	451.05	249.3	33.01
Yecheon-gun	○	○	○	NMP	54,263	661.58	82.0	2.51
Bonghwa-gun	○	○	○	NMP	28,430	1202.70	23.6	0.79
Uljin-gun	○	○	○	NMP	45,697	990.63	46.1	4.84
Ulleung-gun	○	○	○	NMP	8418	73.03	115.3	14.36
Gyeongsangnam-do								
Jinju-si			○	NMP	348,272	712.94	488.5	38.70
Tongyeong-si	○	○	○	NMP	121,626	239.91	507.0	6.94
Sacheon-si	○	○	○	NMP	109,008	398.82	273.3	20.01
Gimhae-si			○	NMP	548,672	463.55	1183.6	57.60
Miryang-si	○	○	○	NMP	102,738	798.69	128.6	7.69
Geoje-si		○	○	NMP	238,671	403.88	591.0	20.93
Yangsan-si		○	○	NMP	355,411	485.70	731.7	64.34
Changwon-si			○	NMP	1,007,142	749.23	1344.2	48.78
Uiryeong-gun	○	○	○	NMP	24,827	482.91	51.4	3.35
Haman-gun	○	○	○	NMP	62,173	416.61	149.2	9.64
Changnyeong-gun	○	○	○	NMP	58,475	532.67	109.8	9.25
Goseong-gun	○	○	○	NMP	48,650	518.02	93.9	3.06
Namhae-gun	○	○	○	NMP	39,706	357.78	111.0	2.04
Hadong-gun	○	○	○	NMP	39,125	675.30	57.9	2.57
Sancheong-gun	○	○	○	NMP	32,892	794.71	41.4	1.32
Hamyang-gun	○	○	○	NMP	35,505	724.73	49.0	2.67
Geochang-gun	○	○	○	NMP	58,588	803.96	72.9	4.01
Hapcheon-gun	○	○	○	NMP	39,667	983.12	40.3	2.39
Jeju								
Jeju-si		○	○	NMP	495,553	978.77	506.3	20.10
Seogwipo-si	○	○	○	NMP	181,214	871.51	207.9	24.41

Note. ○ indicates that the corresponding diagnostic signal was flagged under the mean-based baseline classification. CMR = Capital Metropolitan Region; MC = metropolitan cities and Sejong City; NMP = non-metropolitan provinces. Population density was calculated as population divided by total administrative area. Urban-designated area share indicates the percentage of land area designated as urban area in the 2023 Urban Planning Status Statistics (Korea Land and Geospatial Informatix Corporation, 2024).

Appendix B. Robustness checks of the diagnostic classification

This appendix reports two robustness checks for the proposed diagnostic classification: (i) mobility-assumption sensitivity and (ii) accessibility-threshold sensitivity. The baseline classification used in the main text is retained as the reference case. The national batch calculation used r5py travel-time matrices, which return origin–destination travel times but not the full itinerary-level transfer counts needed to report a transfer distribution. We therefore evaluated the influence of transfer assumptions by rerunning the analysis with maximum transfer limits of 0, 1, 2, 3, and 7. In r5py, these scenarios were implemented by setting the maximum number of consecutive public-transport rides to 1, 2, 3, 4, and 8, respectively. For each sensitivity scenario, the population-weighted mean reference lines were recalculated using the same procedure as in the baseline classification.

The first robustness check evaluates whether the diagnosis is sensitive to PT routing assumptions. We generated all combinations of walking-speed, transfer-limit, and departure-time scenarios. Walking speed was varied across 1.00, 0.90, and 0.75 m/s; the maximum number of transfers was varied across 0, 1, 2, 3, and 7, implemented in r5py as maximum public-transport ride counts of 1, 2, 3, 4, and 8, respectively; and departure time was varied between 08:00 and 14:00. This produced 30 scenario combinations, including the baseline scenario of a 1.00 m/s walking speed, a maximum of seven transfers, and an 08:00 departure. The 29 non-baseline scenarios were compared with the baseline classification.

Table B.1

Mobility-assumption sensitivity results.

Varied mobility assumption	No. of scenarios	Units retaining the baseline diagnostic regime	
		Mean (%)	Range (%)
Walking speed only	2	96.1%	95.2–96.9%
Transfer limit only	4	95.3%	95.2–95.6%
Departure time only	1	95.6%	95.6%
Walking speed and transfer limit	8	96.0%	94.8–96.9%
Walking speed and departure time	2	95.4%	95.2–95.6%
Transfer limit and departure time	4	95.6%	95.6%
Walking speed, transfer limit, and departure time	8	95.4%	94.8–95.6%

The second robustness check examines whether the diagnosis is sensitive to the facility-specific accessibility thresholds used to define reachable opportunities. The baseline thresholds are 15 min for parks, libraries, and public-service facilities, and 10 min for senior facilities, childcare facilities, grocery stores, clinics, and schools. We then applied uniform ± 5 -min changes to all facility-specific thresholds.

Table B.2

Accessibility-threshold sensitivity results.

Threshold Change	Units retaining the baseline diagnostic regime (%)	Units retaining the baseline regime (n of 229)
–5 min	93.0	213
Baseline	100.0	229
+5 min	94.8	217

Appendix C. Reference-line sensitivity analysis

Table C.1

Model adequacy checks for the median-based sensitivity classification using repeated stratified cross-validation.

Diagnostic Signal	Signal prevalence	Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
F(s)	0.620	XGBoost	0.943 (0.029)	0.963 (0.034)	0.947 (0.035)	0.954 (0.023)	0.980 (0.018)
		Logistic regression	0.938 (0.028)	0.960 (0.032)	0.941 (0.037)	0.950 (0.023)	0.984 (0.013)
		Random forest	0.952 (0.026)	0.973 (0.029)	0.950 (0.036)	0.961 (0.021)	0.986 (0.013)
		XGBoost	0.840 (0.048)	0.928 (0.037)	0.840 (0.066)	0.880 (0.039)	0.940 (0.027)
		Logistic regression	0.845 (0.047)	0.962 (0.035)	0.814 (0.059)	0.880 (0.039)	0.940 (0.027)
		Random forest	0.862 (0.041)	0.913 (0.038)	0.891 (0.052)	0.901 (0.031)	0.919 (0.035)
F(d)	0.707	XGBoost	0.914 (0.030)	0.972 (0.029)	0.913 (0.038)	0.941 (0.022)	0.968 (0.019)
		Logistic regression	0.906 (0.035)	0.981 (0.026)	0.892 (0.043)	0.934 (0.026)	0.975 (0.016)
		Random forest	0.916 (0.036)	0.965 (0.034)	0.922 (0.041)	0.942 (0.025)	0.965 (0.020)
		XGBoost	0.914 (0.030)	0.972 (0.029)	0.913 (0.038)	0.941 (0.022)	0.968 (0.019)
		Logistic regression	0.906 (0.035)	0.981 (0.026)	0.892 (0.043)	0.934 (0.026)	0.975 (0.016)
		Random forest	0.916 (0.036)	0.965 (0.034)	0.922 (0.041)	0.942 (0.025)	0.965 (0.020)
T(c)	0.747	XGBoost	0.914 (0.030)	0.972 (0.029)	0.913 (0.038)	0.941 (0.022)	0.968 (0.019)
		Logistic regression	0.906 (0.035)	0.981 (0.026)	0.892 (0.043)	0.934 (0.026)	0.975 (0.016)
		Random forest	0.916 (0.036)	0.965 (0.034)	0.922 (0.041)	0.942 (0.025)	0.965 (0.020)
		XGBoost	0.914 (0.030)	0.972 (0.029)	0.913 (0.038)	0.941 (0.022)	0.968 (0.019)
		Logistic regression	0.906 (0.035)	0.981 (0.026)	0.892 (0.043)	0.934 (0.026)	0.975 (0.016)
		Random forest	0.916 (0.036)	0.965 (0.034)	0.922 (0.041)	0.942 (0.025)	0.965 (0.020)

Table C.2
Reference-line values used for the diagnostic classifications.

Criterion	$\bar{C}_r^{CAR}$	$\Delta \bar{C}_r$	$\bar{B}_r^{CAR}$	$\Delta \bar{B}_r$
Mean	7.750	-1.171	6.681	-1.213
Median	7.952	-1.078	6.898	-1.369

Note. The mean-based reference lines are national aggregate population-weighted mean reference values, whereas the median-based reference lines are population-weighted median values across the 229 city-level administrative units. $\bar{C}_r^{CAR}$ and $\bar{B}_r^{CAR}$ are facility-wise min-max-normalized composite car-benchmark indicators reported on the 0–8 scale. $\Delta \bar{C}_r$ and $\Delta \bar{B}_r$ are summed normalized PT-car gap scores across the eight facility categories.

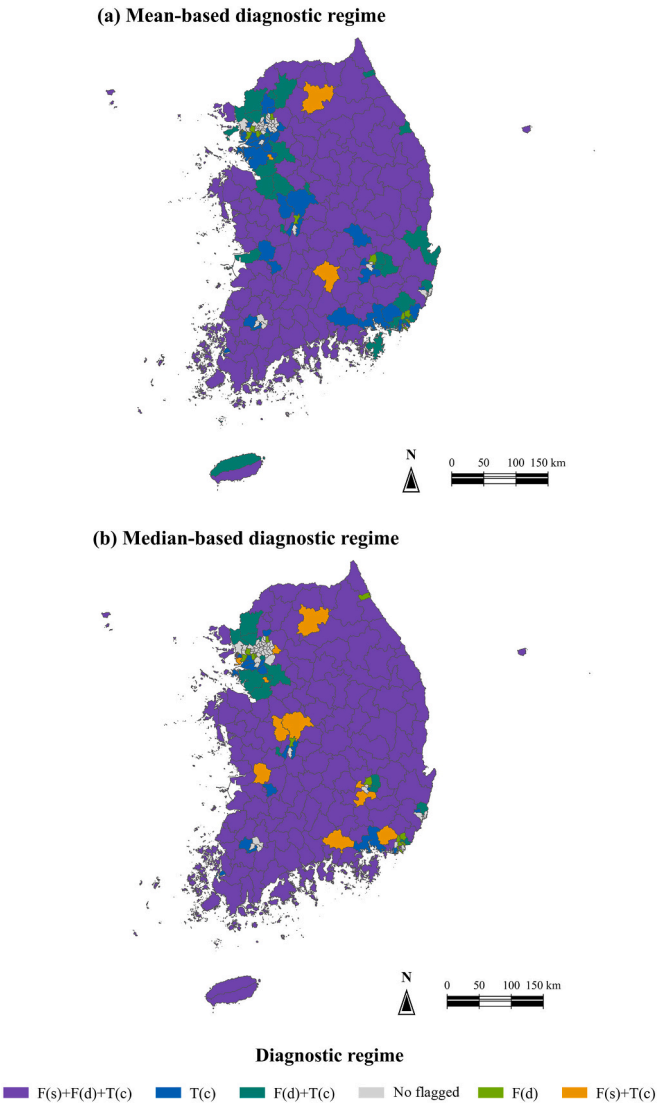


Fig. C.1. Spatial distribution of diagnostic regimes by reference-line specification: (a) population-weighted mean reference lines and (b) population-weighted median reference lines.

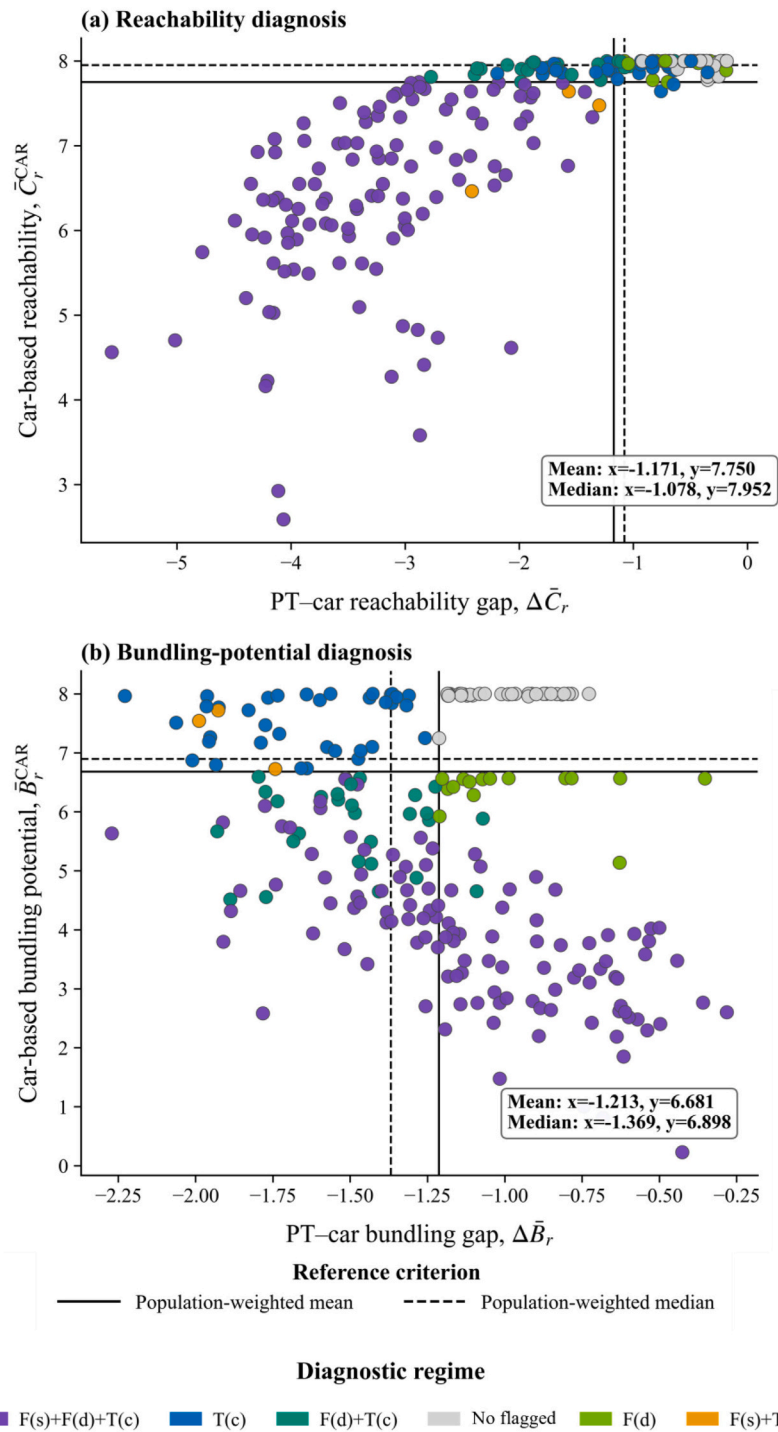


Fig. C.2. Distribution of diagnostic classifications by reference-line specification: (a) opportunity-reachability diagnosis and (b) bundling-potential diagnosis.

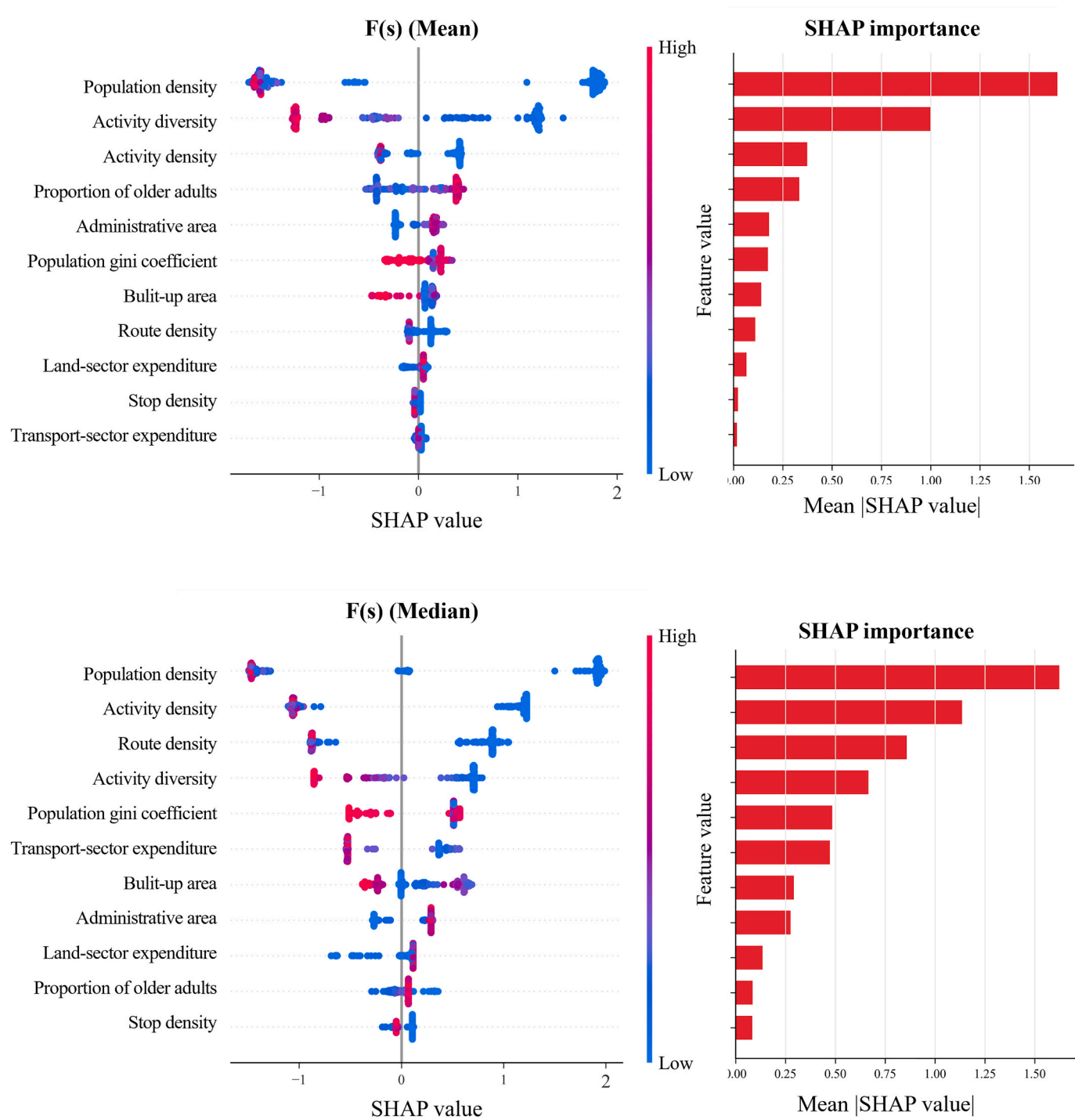


Fig. C.3. Comparison of SHAP summaries for the $F(s)$ diagnostic signal under the mean- and median-based reference-line specifications. Points show signed SHAP values for individual cities, and bars show mean absolute SHAP values.

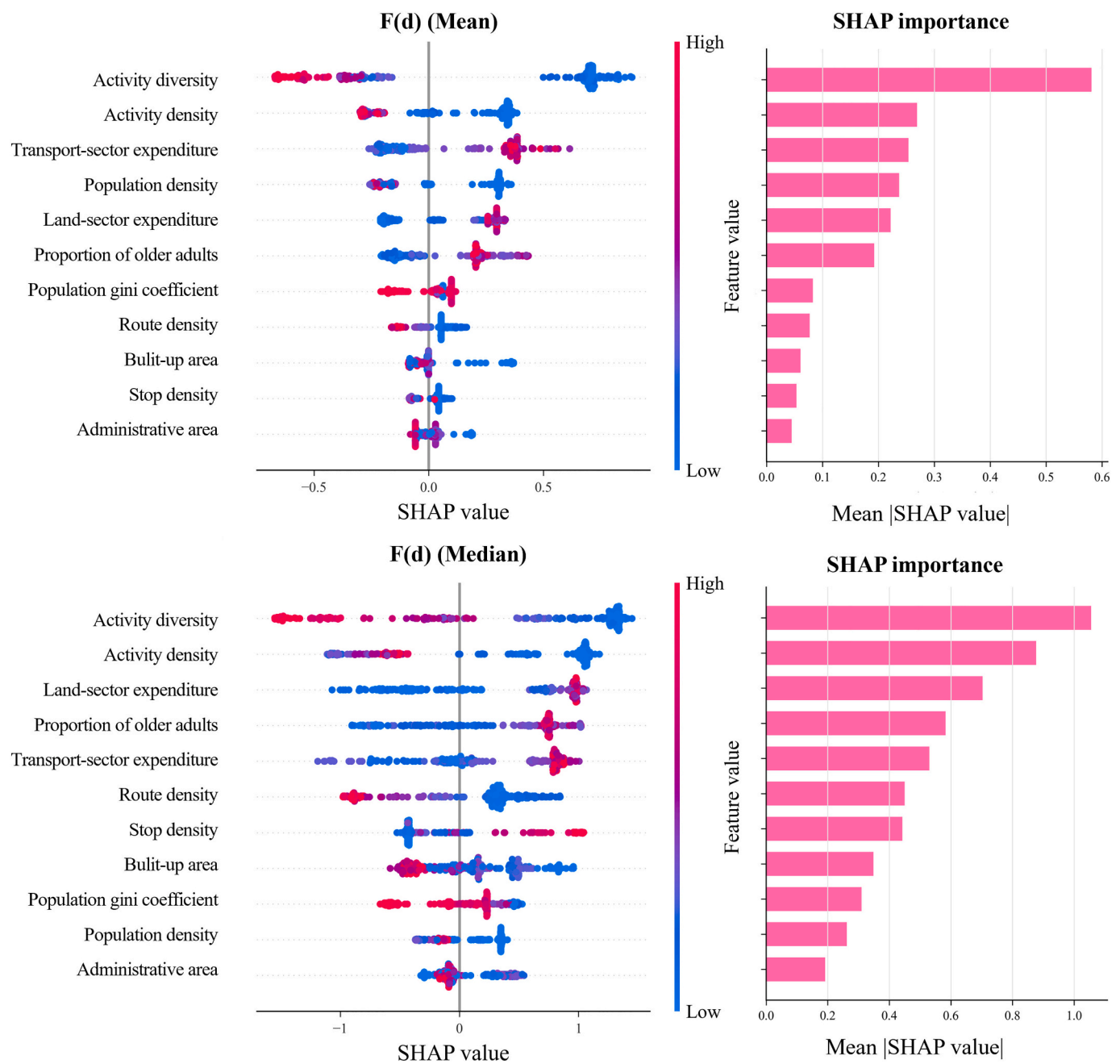


Fig. C.4. Comparison of SHAP summaries for the F(d) diagnostic signal under the mean- and median-based reference-line specifications. Points show signed SHAP values for individual cities, and bars show mean absolute SHAP values.

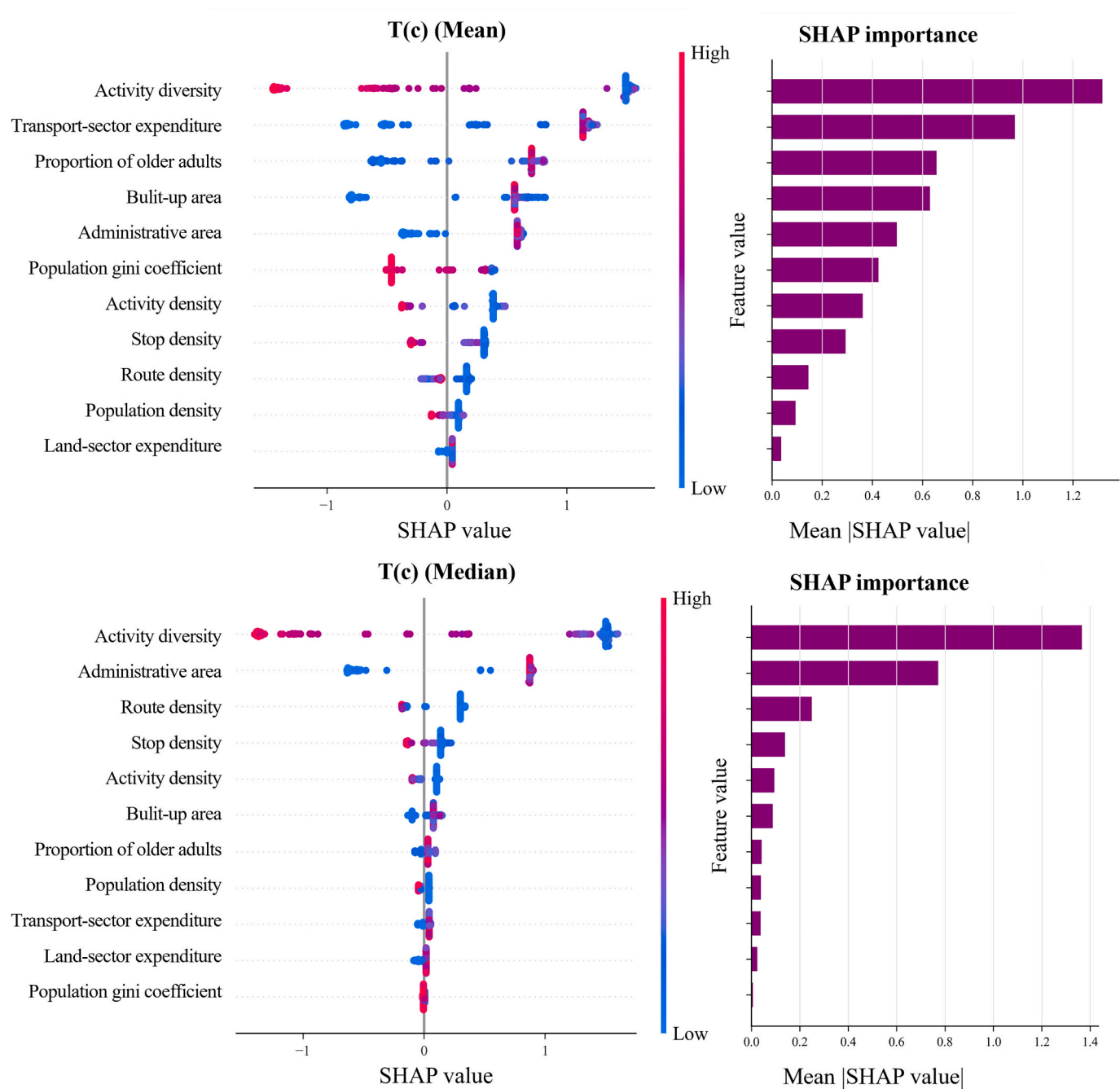


Fig. C.5. Comparison of SHAP summaries for the T(c) diagnostic signal under the mean- and median-based reference-line specifications. Points show signed SHAP values for individual cities, and bars show mean absolute SHAP values.

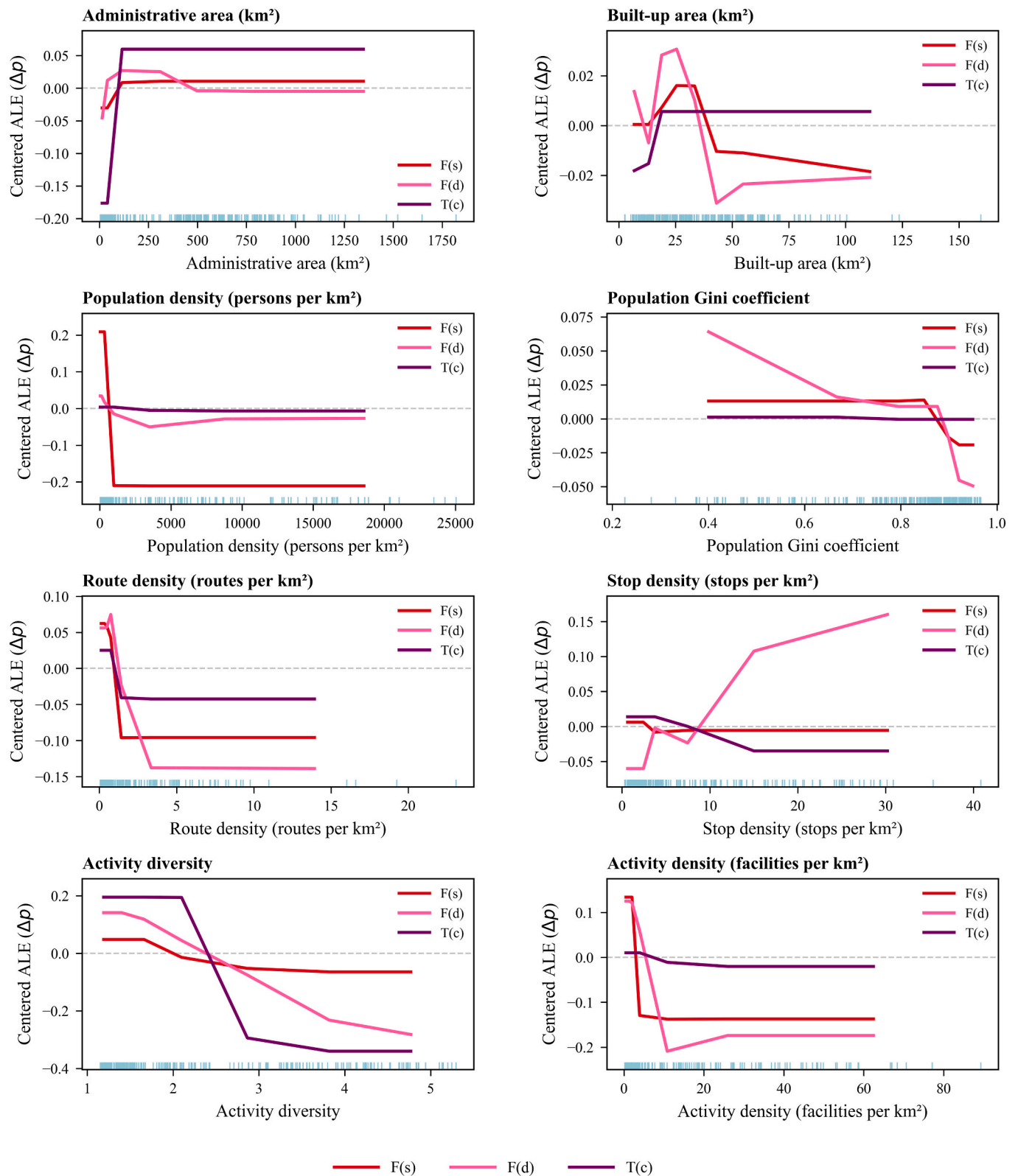


Fig. C.6. ALE profiles of urban form, transit supply, and opportunity structure for the F(s), F(d), and T(c) diagnostic signals under the median-based reference-line specification.

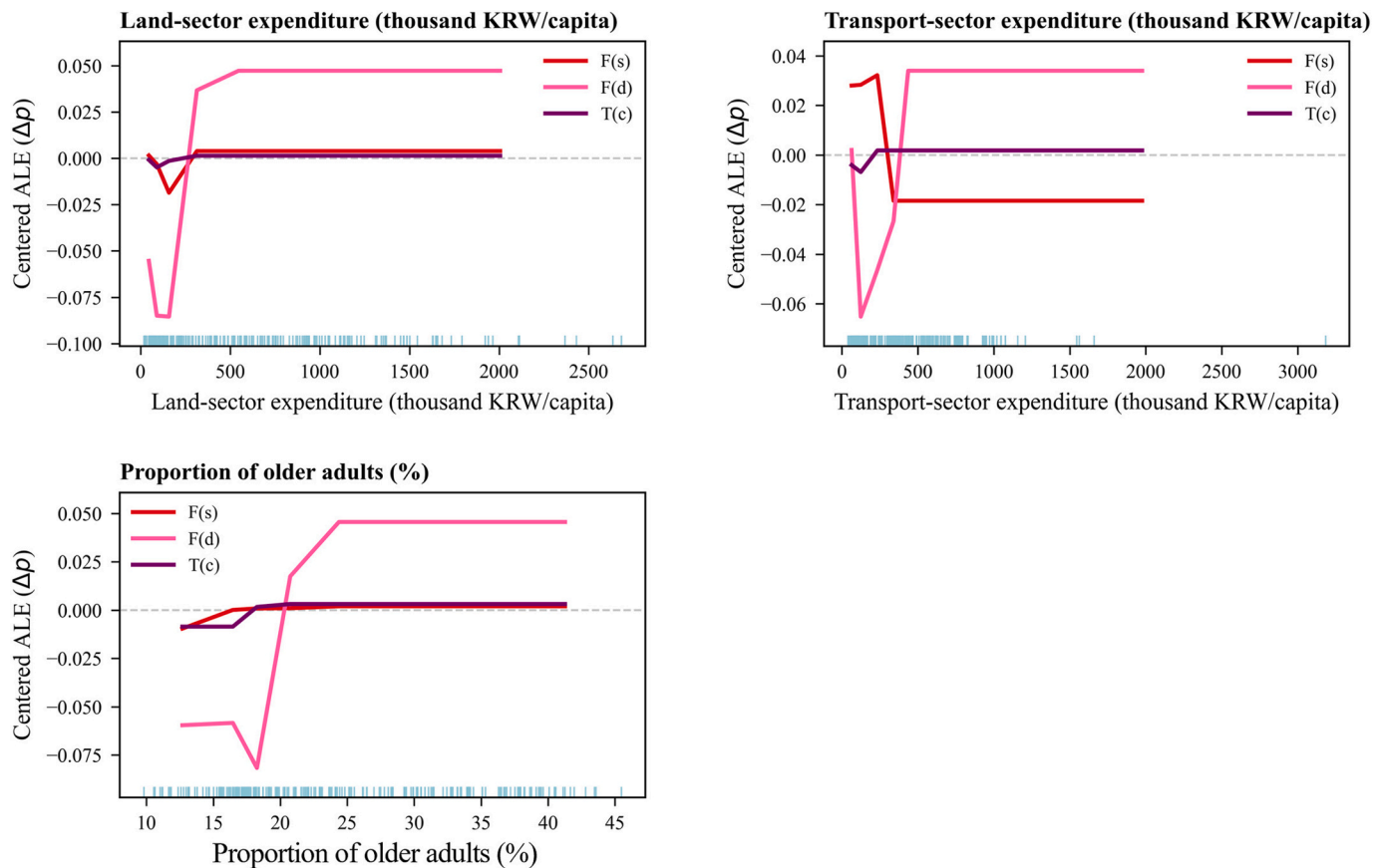


Fig. C.7. ALE profiles of public-expenditure and aging-related sociodemographic variables for the F(s), F(d), and T(c) diagnostic signals under the median-based reference-line specification.

Data availability

All data used in this study are publicly available from the open data sources listed in Table 1, including the Korean Transport Database (KTDB), the Public Data Portal, the Korean Statistical Information Service (KOSIS), the Local Finance Integrated Open System, and other national or local open-data platforms. They can be accessed at <https://www.ktdb.go.kr/www/index.do>, <https://www.data.go.kr/index.do>, <https://kosis.kr/index/index.do> and <https://www.lofin365.go.kr/> respectively. Data-processing and analysis scripts are available from the corresponding author upon reasonable request.

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