

From Static Reachability to Dynamic Transport Equity: A Multi-Source Spatiotemporal Framework for Identifying Supply–Demand Mismatches

1st Senthilal Kumaran
Taylor's University
Subang Jaya, Malaysia
SenthilaKumaran@outlook.com

Abstract—Transport equity is frequently assessed through static measures of network proximity, stop coverage, or all-day accessibility. These measures remain useful, but they cannot reveal whether scheduled service is aligned with the timing and social distribution of observed demand. This paper develops a reproducible dynamic transport-equity framework that integrates schedule-based supply, hourly observed station entries, and a demand-side equity signal to identify time-specific supply – demand mismatches. The framework is demonstrated with a synchronised New York City Subway case study, combining the official General Transit Feed Specification (GTFS) schedule valid on 15 September 2026, the Metropolitan Transportation Authority (MTA) hourly ridership dataset, station-complex coordinates, and the share of entries paid with the MTA Fair Fare category. Supply was represented by scheduled platform stop-events within a 250-m station-complex catchment; demand was represented by station-complex entries in each clock hour; and equity pressure was defined as the difference between standardised log demand and standardised log scheduled supply plus a transparent Fair Fare weighting term. The resulting panel contained 7,249 station-hour observations across 427 spatially matched station complexes from 06:00 to 22:00. Static daily and dynamic equity-pressure indicators were positively associated (Spearman's $\rho = 0.708$, $p < 0.001$), yet the static indicator failed to identify 49 of 107 dynamic top-quartile priority stations. Dynamic priorities were disproportionately located in Brooklyn, Queens, and the Bronx, while several high-pressure locations occurred in early-morning, morning-peak, or mid-afternoon windows that daily aggregation obscured. Rank ordering remained substantively stable when the equity weight varied from 0 to 0.50 ($\rho = 0.939 - 0.963$ relative to the baseline). The study contributes a transparent bridge between static accessibility and operationally meaningful equity diagnostics. It also demonstrates that a station-hour framework can direct attention from generic coverage expansion toward targeted frequency, timing, transfer, and affordability interventions. The indicator is not a measure of vehicle crowding or a complete definition of justice; rather, it is a reproducible screening instrument whose normative assumptions and data limitations are explicit.

Keywords—dynamic transit accessibility, transport equity, supply-demand mismatch, GTFS, hourly ridership, spatiotemporal analysis

I. INTRODUCTION

Transport networks distribute more than movement. They distribute the practical ability to reach work, education, care,

social life, and public services. Consequently, unequal service quality can compound unequal opportunity, especially where households have restricted access to private vehicles or face unstable work and care schedules. Accessibility-based research has supplied a powerful vocabulary for examining this problem, and recent scholarship has shown that equity conclusions depend strongly on how population groups, benefits, and distributive criteria are defined [1]. Nonetheless, a substantial share of applied practice still treats accessibility as a static condition: a stop lies within a distance band, a route passes a neighbourhood, or a daily mean frequency exceeds a threshold. Such indicators communicate coverage, but they can conceal whether people encounter service when they actually travel.

The problem is not that static accessibility is incorrect; it is that it is incomplete for a system whose services, disruptions, transfers, and demands unfold over time. A nominally accessible station can have weak service in the hour when local entries peak. Conversely, an area with modest all-day frequency can experience an adequate temporal match during the periods that matter most to its users. Studies of time-dependent public transport accessibility have shown that accessibility and its distribution can vary substantially across time periods, whether the focus is employment access [2], health-care accessibility [3], temporal aggregation effects [4], or access to essential services [5]. The choice of time window is therefore not a technical afterthought. It is a substantive decision about which lived conditions are made visible.

Research on transport supply–demand mismatch has advanced beyond simple stop-counting by combining transport provision with observed or estimated travel demand [6]. This line of work is particularly valuable because it frames inequity as a relationship between provision and need, rather than as a simple absence of infrastructure. Yet demand is often inferred from static socioeconomic proxies alone, while supply is aggregated over a whole day or assumed to conform to a published timetable. Those choices are understandable when data are scarce. They become harder to justify where hourly ridership, static schedules, operational data, fare-category information, and spatial data are increasingly available. Recent research further cautions that schedule-based accessibility can diverge from realizable accessibility under actual operating conditions [7], while uncertainty in public transport travel time can materially affect dynamic accessibility estimates [8].

Corresponding Author: Senthilal Kumaran, Selangor State, Choa Chua Kang City, No. 1 Taylor Road, Lake Campus of Taylor University, Subang Jaya, Malaysia, 47500, SenthilaKumaran@outlook.com

This paper asks how a transport-equity analysis can preserve the interpretability of a supply–demand framework while becoming sensitive to the timing of observed use. It develops an equity-pressure surface at the station-complex $\times$ hour level. The framework does not claim to calculate full door-to-door opportunity accessibility, crowding, latent need, or causal injustice. Instead, it provides a carefully delimited diagnostic: at which locations and hours does observed entry demand appear high relative to a transparent scheduled-service proxy, after optionally elevating locations with a higher share of Fair Fare entries? The analysis demonstrates the framework using official open data for the New York City Subway on one ordinary Tuesday covered by the contemporaneous GTFS schedule.

The empirical setting is useful for three reasons. First, the subway is a dense, multi-borough network in which a daily mean can obscure pronounced temporal variation. Second, the MTA publishes station-complex-level hourly entry estimates with fare-class information, allowing the demand side to move beyond residential proximity. Third, its GTFS feed provides stop-times from which a reproducible hourly schedule proxy can be derived. The intention is not to rank New York City in a universal transport-equity league table. Rather, it is to demonstrate a portable analytical design that can be adapted when an agency provides equivalent data layers.

The paper addresses three research questions:

RQ1: How can public schedule, hourly ridership, spatial reference, and fare-category data be integrated into a transparent station-hour indicator of supply–demand mismatch?

RQ2: To what extent does a dynamic equity-pressure indicator identify different priority locations from a static daily mismatch indicator?

RQ3: Are priority rankings robust to plausible changes in the weight assigned to the demand-side equity signal?

The paper makes four contributions. It first distinguishes static reachability from an explicitly temporal measure of service–demand alignment. Second, it describes a reproducible data-concordance procedure that matches station-complex ridership records to scheduled platform events. Third, it compares dynamic and static priority classifications rather than assuming that the former merely restates the latter. Finally, it communicates the framework’s normative and measurement limits, including the fact that Fair Fare entries are an observed fare-category signal rather than a residential demographic profile. Section 2 reviews the relevant literature. Sections 3 and 4 present the framework, data, and analytical protocol. Section 5 reports the results. Section 6 interprets the findings, and Section 7 concludes.

II. RELATED WORK AND CONCEPTUAL FOUNDATIONS

A. Accessibility, equity, and the limits of proximity

Accessibility concerns the feasible relation between people, transport systems, time, and opportunities. In socially oriented assessments, it is not reducible to mobility speed or network supply; it is a means through which individuals can participate in valued activities. This orientation matters because ostensibly neutral service metrics can favour places and groups that already have more resources, more flexible schedules, or better alternatives. Recent scholarship emphasises that an equity assessment must make its

population group, outcome, and distributive principle explicit; it also distinguishes accessibility inequality from accessibility poverty and cautions that transport-equity measures embed normative choices about need, benefit, and acceptable service [1].

Proximity remains a valuable starting point. A station, stop, or protected walking connection can be mapped, audited, and improved. Yet the presence of a nearby boarding point does not guarantee that a rider can use it at a relevant time, transfer with reasonable uncertainty, afford the trip, or arrive before an opportunity closes. Empirical work has shown that socially vulnerable populations do not experience walkable and transit-accessible environments uniformly across metropolitan areas [9], while spatial mismatch in transport access can be systematically associated with socioeconomic disadvantage [10]. The implication is not that every study must model every social mechanism. It is that a policy-facing indicator should avoid equating a static resource count with a complete measure of equitable access.

A common response is to construct a composite supply or supply–demand index, combining frequency, connectivity, flexibility, generalized travel cost, or other service attributes with an indicator of population need. Transit-desert research provides a clear example, with classifications based on the relationship between transit provision and demand. Recent work has also demonstrated how interactive dashboards and predictive approaches can extend such assessments beyond one-off static coverage maps [11]. These approaches materially improve on simple proximity measures. However, even sophisticated composites can blur the temporal pattern that converts a potential transport resource into a practical one.

B. From temporal accessibility to realised and reliable access

Time-dependent accessibility research demonstrates why a single daily number can be misleading. Raza et al. applied time-dependent accessibility together with distributional tools such as Lorenz curves and Gini coefficients to examine inequalities in public transport access [2]. Li et al. showed that public-transport-based health-care accessibility and its equity vary across the day and that local accessibility conditions depend on temporal service patterns [3]. Lindner et al. identify a modifiable temporal unit problem, demonstrating that the choice of time window and temporal aggregation method can materially affect accessibility results [4]. These studies establish that time is not merely an index attached to a map; it is a dimension that changes the meaning and distribution of accessibility.

A second body of work moves from scheduled potential toward realised or reliable accessibility. Liu et al. distinguish schedule-based accessibility from accessibility that can actually be realised under observed operating conditions, illustrating the limitations of relying solely on published timetables [7]. Zhang, Zhang, and He demonstrate how large-scale transit data can support more behaviourally grounded measurement of public transport accessibility [12]. GPS-based approaches further allow observed travel patterns to be connected to accessibility measures [13]. Other studies incorporate actual transit operations [14] or explicitly represent joint space–time constraints and travel-time uncertainty [15]. Research based on smart-card data also shows that uncertainty in metro travel time can alter estimates of dynamic accessibility [8]. Together, these studies suggest a

hierarchy of evidence: static schedules describe planned provision; real-time and historical operations describe delivered provision; and observed transactions or trajectories provide evidence about realised demand and travel behaviour.

The present study occupies an intermediate position in that hierarchy. It joins scheduled supply with observed hourly entries. This is intentionally narrower than a full reliability or origin–destination accessibility analysis. It therefore does not infer a passenger’s destination, walking path, wait, transfer, vehicle occupancy, or successful arrival. Its value lies in making a simple but often hidden relationship observable: the hour-by-hour pressure between entry demand and a comparable schedule-frequency proxy. The choice is pragmatic as well as conceptual. Static GTFS is widely available, and hourly station entries are increasingly published by agencies, whereas capacity and comprehensive origin–destination data are not always open.

C. Demand, social disadvantage, and the ethics of weighting

Demand should not be confused with ridership. High observed entries may result from employment concentration, network centrality, tourism, transfers, or special events. Low observed entries may reflect low population, strong alternatives, suppressed travel, or barriers that discourage transit use. Likewise, a fare-program category does not reveal every relevant dimension of disadvantage. These distinctions are important because equity indicators can inadvertently reify administrative categories as identities.

At the same time, demand-side signals are necessary if an equity assessment is to move beyond geographically uniform standards. Kar et al. show that reductions in public transit service can compound social vulnerability across U.S. cities [16]. Sansone et al. demonstrate the value of incorporating social-vulnerability variables when measuring accessibility to essential and safety-net opportunities [17]. Choi and Jiao further demonstrate that transit-desert analysis can incorporate disaggregated demand information and predictive dashboard tools rather than remaining a purely retrospective mapping exercise [11]. The methodological implication is to treat a vulnerability factor as a transparent and contestable component of an indicator rather than as a hidden adjustment.

This study uses the local share of entries classified as Fair Fare as such a component. It is interpreted conservatively as a station-level affordability-related demand-side equity signal, not as a measure of the income, home location, or demographic identity of each rider. Consequently, it offers a proof of concept for incorporating an observed affordability-related signal while requiring strong caveats about representativeness. The model reports results with a baseline weight and tests alternatives. This design is consistent with recommendations that normative choices in transportation-equity measurement should be made explicit and subjected to sensitivity analysis rather than embedded invisibly within a composite indicator [1].

D. Research gap

Existing work establishes the importance of time-dependent accessibility, demand-sensitive transit analysis, observed travel data, and explicit equity principles. A remaining gap is a simple, replicable framework that uses synchronised public data to contrast static daily mismatch with hour-specific service–demand pressure at an operationally legible unit. The contribution required is not

another opaque composite score. It is an auditable sequence: identify data provenance; harmonise spatial units; construct a supply proxy; define demand and the optional equity term; compare static and dynamic classifications; and then test whether conclusions depend on a chosen social weight. Figure 1 summarises this logic.

Methodologically, the framework also sits within a broader movement toward reproducible and multimodal accessibility analysis. Open-source routing tools such as r5r support reproducible time-sensitive travel-time and opportunity matrices [18]. Multimodal spatial-availability measures broaden accessibility analysis beyond single-mode assumptions [19]. Dynamic accessibility studies further show that changing traffic conditions can materially alter measured access to essential destinations [20]. Research on out-of-vehicle time similarly demonstrates that waiting, access, and transfer components can affect public-transport accessibility [21].

At the same time, calculated accessibility does not always correspond to experienced accessibility, which cautions against treating modelled indicators as complete representations of lived access [22]. Observed ridership data have also been used to examine spatial inequalities in transit use [23], while research links urban accessibility to human mobility patterns [24] and shows how mobility data can capture changing travel behaviour associated with work-from-home practices [25].

For policy translation, composite indicators and city dashboards can support place-based intervention and screening [26], but causal claims about transport interventions require research designs distinct from descriptive diagnostics [27]. More broadly, open-data and open-source approaches strengthen the transparency and transferability of urban spatial indicators [28], while dedicated open software environments can make spatial accessibility metrics more reproducible and accessible to analysts [29].

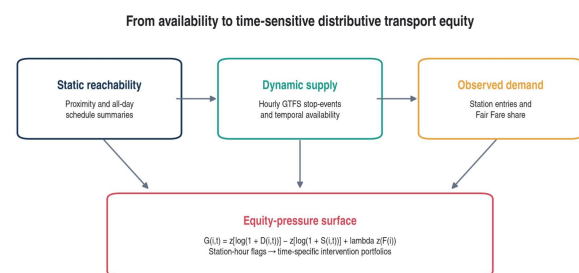


Fig. 1. Conceptual framework from static reachability to a time-sensitive equity-pressure surface.

III. METHODOLOGY

A. Research design and analytical unit

The study follows a model–concordance–comparison design. First, schedule and ridership records were converted to a common station-complex × hour structure. Second, planned stop-events were spatially matched to MTA station-complex centroids. Third, a dynamic mismatch score was calculated for every matched station complex and operating hour. Fourth, the maximum dynamic score for each station complex was compared with an all-day static analogue. Finally, a sensitivity analysis varied the equity weight.

The analytical unit is a station complex i in hour t . A station complex is appropriate because the hourly MTA dataset is published at that level and because large interchanges may encompass several GTFS platforms or lines. The operational time window was 06:00–22:00 local time. This restriction focuses on periods with sustained service and demand, avoids giving disproportionate influence to overnight zero or near-zero values, and creates 17 observable hours per matched complex. It does not imply that overnight equity is unimportant; a future application should evaluate it with an appropriate night-service model.

The case date was Tuesday, 15 September 2026. This date fell within the feed validity interval of the official MTA static GTFS file (26 May–31 October 2026). Restricting analysis to one weekday is deliberate. It allows exact temporal alignment between the schedule and hourly entry data but limits the generalisation of the resulting rankings. The empirical results should thus be interpreted as an illustrative day-specific screening analysis, not as a permanent service-performance score.

B. Data architecture and provenance

Table I documents the four principal data components. The raw entry dataset contained 54,389 records for the case date across 428 station complexes and fare classes. The GTFS feed supplied 992 physical platform stops, 8,497 active weekday trips, stop times, service calendars, and spatial coordinates. The GTFS standard distinguishes the route, trip, stop, and stop-time records needed to derive scheduled service events [20]. MTA developer documentation identifies the subway static feed as the normal published schedule and distinguishes it from the time-limited supplemented feed and GTFS-Realtime products [22]. These distinctions are central: this study measures planned scheduled supply, not real-time service delivery.

TABLE I. MULTI-SOURCE DATA ARCHITECTURE AND ANALYTICAL ROLE

Component	Primary source and temporal scope	Spatial unit	Analytical role	Principal limitation
Hourly ridership	MTA Subway Hourly Ridership; 15 September 2026, 00:00–23:00	Station complex $\times$ hour $\times$ fare class	Observed entry-demand proxy; Fair Fare share	Entries are not origins, destinations, or unique persons
Scheduled service	Official MTA static GTFS; valid 26 May–31 October 2026	Platform stop $\times$ scheduled departure hour	Planned supply proxy via stop-events	Does not represent cancellations, crowding, capacity, or reliability

Spatial concordance	MTA station-complex coordinates and GTFS stop coordinates	Station complex / platform	Assign platform events to complex within 250 m	Complex geometry and entrances are simplified to centroid catchments
Equity signal	Fair Fare category in hourly ridership	Station complex, daily share	Observed affordability-related demand weighting	Not a residential poverty, race, age, or disability measure

The MTA hourly ridership dataset reports estimated entries by hour, station complex, payment method, and fare-class category, with location fields. Its granularity makes it suitable for measuring entry-side temporal demand, but it does not provide the full trip chain. The MTA's origin–destination product is constructed from inferred destinations and has different privacy-protective aggregation assumptions; it was not used here because the objective was station-entry pressure rather than destination accessibility. The decision to retain the entry interpretation avoids a common analytical error: treating fare-gate transactions as residential origins or completed journeys.

C. Spatial concordance and scheduled supply

The spatial-concordance procedure had three steps. First, the nearest GTFS platform to each MTA station-complex centroid was identified. Second, station complexes whose closest physical platform was farther than 250 m were excluded. Third, all physical GTFS platforms located within the same 250-m radius were assigned to that complex. This allowance captures multi-platform and multi-line interchanges without relying on a brittle string-name join. Of the 428 observed station complexes, 427 matched at least one GTFS platform. The median distance to the nearest matched platform was 0.27 m, which indicates that the published coordinates were usually coincident or near-coincident even though the 250-m rule was retained for reproducibility.

Let $N(i)$ denote the set of GTFS platforms within 250 m of station complex i . For each platform p and hour t , the number of scheduled departures in `stop_times.txt` was counted. Planned service supply is then:

$$S(i,t) = \sum_{p \in N(i)} E(p,t) \quad (1)$$

where $E(p,t)$ is the count of scheduled platform stop-events. This is a frequency-like availability proxy. It is not a train-capacity measure because it does not encode vehicle length, passenger load, dwell time, or crowding. It also does not estimate destination reachability because it does not route passengers through the network. It is nevertheless transparent,

directly reproducible from GTFS, and temporally aligned with entry demand. Open-source routing frameworks such as r5r can extend this logic to time-window origin – destination matrices when travel-time and opportunity inputs are available [18].

D. Demand, equity signal, and dynamic mismatch score

Observed demand is represented by the total MTA entry count $D(i,t)$ for a station complex in hour t , summed over payment methods and fare classes. To reduce domination by very large central complexes, demand and supply are transformed with $\log(1 + x)$ and standardised across the complete 7,249-row station-hour panel. The unweighted dynamic pressure score is:

$$M(i,t) = z[\log(1+D(i,t))] - z[\log(1+S(i,t))] \quad (2)$$

A higher value indicates that hourly entries are high relative to scheduled stop-events in the observed panel. It does not prove a service shortage or passenger harm. Rather, it flags a location-hour combination for further operational and community review.

The equity signal $F(i)$ is the station-complex share of observed daily entries in the Fair Fare category. It is held constant across hours because the source data provide fare class by hour but the station-level daily share offers a less volatile, interpretable signal. The baseline equity-pressure score applies a modest weight $\lambda = 0.25$:

$$G(i,t;\lambda) = M(i,t) + \lambda z[F(i)] \quad (3)$$

This additive specification makes the normative choice visible. A higher Fair Fare share increases the priority score only after the relative demand – supply relation is measured. It does not cause an otherwise low-pressure station to become a high-pressure station by definition. The main analysis uses $\lambda = 0.25$. Sensitivity tests use $\lambda = 0$ and $\lambda = 0.50$, representing no affordability-related adjustment and a stronger adjustment, respectively.

For a station-level screening indicator, the maximum value across the operating window is retained:

$$P(i;\lambda) = \max_{t \in T} G(i,t;\lambda) \quad (4)$$

The maximum asks a deliberate policy question: what is the most acute observable station-hour pressure during the defined service day? A different policy question could use a mean, median, percentile, or duration-above-threshold statistic. Lindner et al. show why such temporal aggregation decisions should not be treated as innocuous [4]. The present paper reports the maximum because the aim is to identify time-specific intervention candidates; it also reports the within-station standard deviation as descriptive context.

E. Static comparator and priority classification

The static comparator retains the same transformations but aggregates first. Daily observed entries from 06:00 – 22:00 were compared with total scheduled stop-events over that interval, standardised across station complexes, and differenced to produce $H(i)$. This comparator is intentionally simple. It represents the kind of daily service – demand comparison that may be used when temporal detail is ignored. A station is classified as a priority in either model when its

score lies in the upper quartile of the corresponding station distribution.

Three groups are then possible: (1) both-indicator priorities, flagged by static and dynamic measures; (2) dynamic-only priorities, flagged only when temporal mismatch and the equity signal are considered; and (3) static-only priorities, flagged by the daily index but not by the dynamic maximum. The comparison does not seek a causal ground truth. It assesses information loss: how many potential priorities would be omitted or added if the analysis used daily aggregation alone.

F. Evaluation and robustness protocol

Evaluation has four components. First, descriptive statistics document the observed scale and variation of entries, scheduled events, and the Fair Fare share. Second, Spearman's rank correlation quantifies monotonic agreement between static and dynamic station scores. Third, set overlap describes agreement in upper-quartile priority classifications. Fourth, the sensitivity analysis compares rankings under $\lambda = 0, 0.25$, and 0.50 . Spearman's correlation with the baseline and top-decile overlap are reported for each alternative. This is not a statistical validation of fairness. It is a robustness check of the analyst-controlled equity weight.

Figure 2 depicts the end-to-end pipeline. Every computational input is traceable to a public source, and every transformation is described in the code accompanying the manuscript. GTFS-Realtime and archived vehicle-location data would provide a further improvement by allowing scheduled events to be replaced with delivered departures and reliability measures [7,14]. Their absence is treated as a limitation rather than silently ignored.

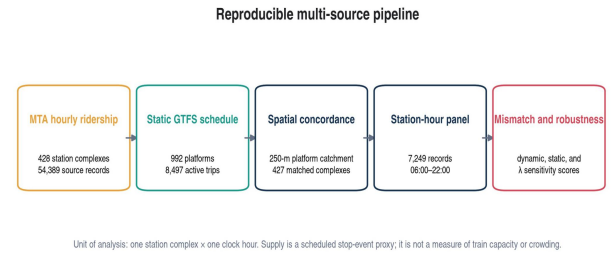


Fig. 2. Reproducible multi-source workflow for dynamic transport-equity screening.

IV. DATA PREPARATION AND DESCRIPTIVE PROFILE

The raw MTA file contained no missing values for ridership or station coordinates on the case date. After grouping across fare classes, 428 station complexes had observed entries. One complex did not meet the 250-m platform-match rule; the final analysis therefore used 427 complexes and 7,249 station-hour observations. The spatial match was exact or near exact for most records because the MTA complex-centroid and GTFS platform coordinates frequently represent the same physical facility. Still, the catchment approach is preferable to an exact-coordinate join because it can tolerate small differences in publication geometry and includes multiple platforms at a complex.

Table II provides descriptive statistics for the analytical panel and station-level summaries. The typical station-hour recorded 288 entries and 24 scheduled stop-events, while the

arithmetic means were higher because central interchange stations create a right-skewed distribution. At the station level, the median complex recorded 5,395 entries between 06:00 and 22:00 and 26 scheduled stop-events per hour. The Fair Fare share had a median of 4.9%, with an interquartile range of 3.4% – 6.9%. These values should not be interpreted as neighbourhood poverty rates. They describe the share of observed entries in an administrative fare-class category at a station complex during the particular day.

TABLE II. DESCRIPTIVE STATISTICS FOR THE MATCHED ANALYTICAL SAMPLE

Measure	Unit / level	Mean	Standard deviation	Median	Interquartile range	Minimum–maximum
Observed entries	Station-hour	605.3	1,084.50	288	120.0–608.0	0–21,283
Scheduled stop-events	Station-hour	35.1	34.3	24	14.0–43.0	0–204
Total observed entries	Station complex, 06:00–22:00	10,275.60	14,787.80	5,395.00	3,216.0–11,334.0	192–150,835
Mean scheduled stop-events	Station complex-hour	35	33.2	26	16.5–34.5	4.4–284.9
Fair Fare entry share	Station complex	5.20 %	2.3 pp	4.90 %	3.4%–6.9%	1.1%–11.3%
Maximum dynamic equity pressure	Station complex	0.886	0.834	1.016	0.400–1.495	–2.687–2.761

The aggregate profiles in Figure 3 show the empirical motivation for temporal analysis. Normalised observed entries exhibit a pronounced morning peak and a second, later afternoon-evening increase. The scheduled stop-event profile also varies, but its relative shape is not identical. This divergence is expected: a large network schedules service in response to many operational constraints, while entry totals reflect the overlapping activities of residents, workers, students, visitors, and transfer passengers. The key point is not that the curves should perfectly coincide. It is that a daily total cannot identify the hours in which their relative relation is most strained.

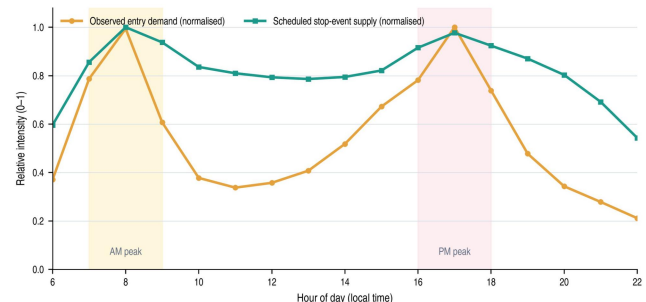


Fig. 3. Aggregate temporal profiles of observed entry demand and scheduled stop-event supply, 15 September 2026. Both series are independently normalised to their 06:00 – 22:00 maximum.

The borough distribution further illustrates why a system-wide mean should not be used as a proxy for local conditions. The matched sample comprised 156 complexes in Brooklyn, 122 in Manhattan, 79 in Queens, 68 in the Bronx, and 2 on Staten Island. In the baseline dynamic classification, 45 Brooklyn complexes, 23 Queens complexes, 23 Bronx complexes, 15 Manhattan complexes, and 1 Staten Island complex fell in the top quartile. Counts should be read against the denominator in each borough: for example, 33.8% of Bronx complexes and 29.1% of Queens complexes were dynamic priorities, compared with 12.3% in Manhattan. The result does not establish that one borough is more just or unjust than another. It indicates where this specific station-hour pressure measure concentrated on the case day.

V. RESULTS

A. Dynamic pressure reveals a distinct priority geography

The baseline dynamic equity-pressure score varied from – 2.687 to 2.761 across station complexes. The upper-quartile threshold was 1.495, which classified 107 of 427 complexes as dynamic priorities. Figure 4 maps the maximum dynamic score, while bubble area represents total observed entries. Priority locations occurred across the network rather than only at the highest-volume Manhattan interchanges. This is substantively important. A demand – supply score based on standardised logarithms does not simply reproduce ridership volume; it identifies unusually high entries relative to the scheduled platform-event baseline, then applies a modest affordability-related adjustment.

The highest baseline score was recorded at St George (Staten Island Railway), with a maximum equity-pressure value of 2.761 in the 15:00 hour. Ozone Park – Lefferts Boulevard (A) followed with 2.543 at 07:00. The next priority cases were 8 Av (N) in Brooklyn (2.532 at 07:00), Far Rockaway – Mott Av (A) in Queens (2.290 at 06:00), and 86 St (R) in Brooklyn (2.271 at 06:00). These locations are not

presented as definitive failures or investment recommendations. They are high-priority signals requiring investigation of service patterns, connections, platform access, rider destination patterns, and local experience. For example, a maximum at 06:00 may point to early shift travel, a transfer timing issue, or a baseline supply metric that requires calibration—not necessarily to crowding or insufficient line capacity.

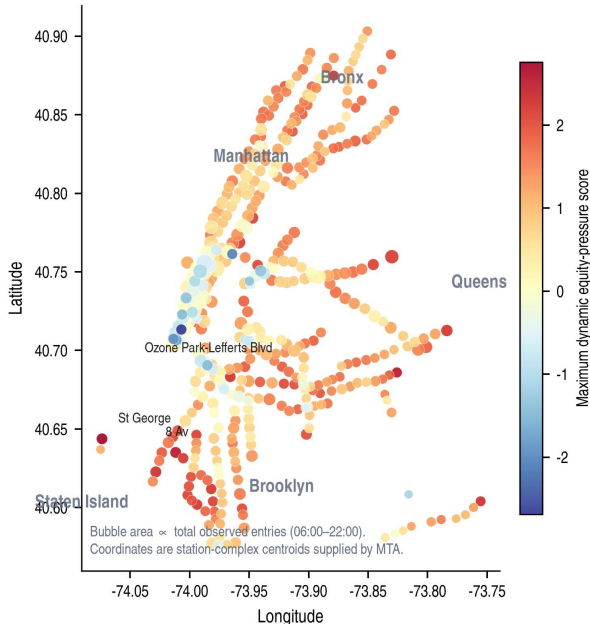


Fig. 4. Geographic distribution of maximum dynamic equity-pressure scores across matched New York City Subway station complexes. Bubble area is proportional to observed entries from 06:00 – 22:00. Scores represent the maximum hourly baseline value ($\lambda = 0.25$).

Table III lists the ten highest-ranked locations. The table separates average service from the service observed at the flagged hour. This distinction makes the dynamic result interpretable. At Ozone Park – Lefferts Boulevard, for instance, the flagged 07:00 hour had 927 entries and 8 planned stop-events despite an average of 8.5 events per hour over the operational window. At 8 Av, the 07:00 hour had 1,065 entries and 15 scheduled stop-events, while the Fair Fare entry share was 11.3%, the highest among the listed cases. The indicator therefore does not treat a high Fair Fare share as equivalent to high demand; it combines the contextual term with a high observed mismatch.

TABLE III. HIGHEST-RANKED STATION COMPLEXES UNDER THE BASELINE DYNAMIC EQUITY-PRESSURE SCORE

Rank	Station complex	Borough	Flagged hour	Entries at flagged hour	Scheduled events at flagged hour	Fair Fare share	Maximum score
1	St George (SIR)	Staten Island	15:00	529	5	5.10 %	2.761

2	Ozone Park–Lefferts Blvd (A)	Queens	7:00	927	8	4.50 %	2.543
3	8 Av (N)	Brooklyn	7:00	1,065	15	11.30 %	2.532
4	Far Rockaway–Mott Av (A)	Queens	6:00	406	8	8.30 %	2.29
5	86 St (R)	Brooklyn	6:00	724	11	7.80 %	2.271
6	Clinton–Washington Avs (C)	Brooklyn	8:00	1,566	12	2.90 %	2.23
7	Jamaica–179 St (F)	Queens	6:00	1,942	15	4.10 %	2.227
8	Norwood–205 St (D)	Bronx	7:00	680	12	8.80 %	2.208
9	Fort Hamilton Pkwy (N)	Brooklyn	8:00	792	14	9.60 %	2.207
10	Bay Pkwy (N)	Brooklyn	8:00	856	14	8.90 %	2.196

B. Static and dynamic classifications agree only partially

The static and dynamic station scores were significantly associated (Spearman's $\rho = 0.708$, $p < 0.001$), indicating that daily aggregation retains meaningful structural information. A high daily mismatch often coexisted with high maximum dynamic pressure. However, the association was far from perfect, and the priority comparison is more consequential than the correlation alone.

Both measures classified 107 stations as upper-quartile priorities. Only 58 complexes appeared in both sets. Forty-nine dynamic priorities were not identified by the static indicator, while 49 static priorities were not in the dynamic top quartile. Thus, 45.8% of dynamic priority stations would have been omitted if screening relied on the daily comparator alone. Figure 5 visualises this partial agreement. Dynamic-only priorities are located above the horizontal threshold but left of the vertical threshold: they have an acute hour-specific equity-pressure signal without being classified as an unusually high daily mismatch.

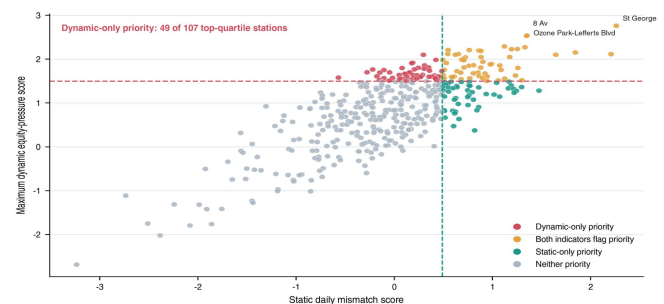


Fig. 5. Comparison between static daily mismatch and maximum dynamic equity-pressure scores. Dashed lines indicate upper-quartile thresholds. Red markers are dynamic-only priorities, gold markers are priorities under both measures, and teal markers are static-only priorities.

This result answers RQ2 directly. The value of the dynamic approach is not that it overturns all static findings; it refines them. Static indicators correctly retain a core set of persistent priority locations. Dynamic analysis adds locations where temporally concentrated pressure matters even though daily totals appear less exceptional. In planning terms, these two categories can prompt different questions. A both-indicator priority may warrant a review of structural service frequency, transfers, and network design. A dynamic-only priority may require timed departures, early-shift adjustments, school-related coordination, or targeted rider engagement before capital investment is considered.

C. Temporal location of maximum pressure

The maximum-pressure hour was not uniformly distributed. Across all station complexes, the median was 07:00, while the interquartile range extended from 07:00 to 15:00. The dispersion of within-station unweighted dynamic pressure had a median standard deviation of 0.511. These statistics confirm that the maximum is not a trivial restatement of all-day conditions: the pressure relationship varied within stations over the service day.

The highest-ranked cases show several temporal regimes. Morning cases—Ozone Park-Lefferts Boulevard, 8 Av, Clinton-Washington Aves, Norwood – 205 St, and Fort Hamilton Parkway—suggest that the morning peak remains a critical equity-sensitive period. Early-morning cases — Far Rockaway – Mott Av, 86 St, and Jamaica – 179 St—illustrate the importance of considering work and care travel before the conventional peak. St George’s mid-afternoon maximum demonstrates that a commuter-focused AM/PM framework is not sufficient for every terminal or ferry-connected location. These observations align with research warning that temporal segmentation and aggregation alter accessibility interpretation [4] and with evidence that time-dependent service conditions shape equity outcomes [3,5].

D. Sensitivity to the Fair Fare weighting term

The baseline results were not driven solely by the selected $\lambda = 0.25$ weight. When λ was set to zero, the station ranking correlated 0.939 with the baseline, and 74.4% of top-decade cases overlapped. When λ increased to 0.50, the correlation was 0.963 and top-decade overlap was 69.8%. Figure 6 presents these results. The modest decline in overlap at the stronger weight is expected: a larger adjustment raises the ranking of stations with a high observed Fair Fare share when their underlying demand – supply pressure is otherwise comparable.

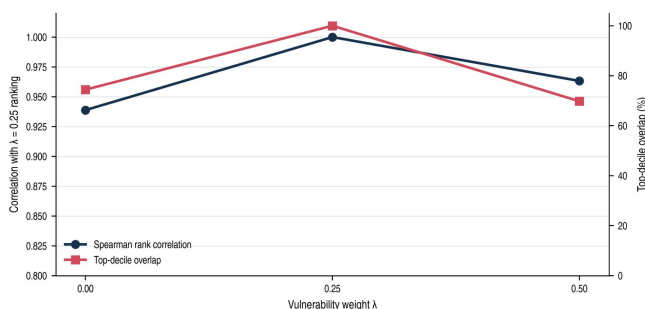


Fig. 6. Sensitivity of station rankings to alternative Fair Fare weights. Rank correlation and top-decade overlap are calculated relative to the baseline $\lambda = 0.25$ ranking.

The sensitivity analysis answers RQ3 in two ways. First, the broad ranking pattern is stable: all rank correlations exceed 0.93. Second, priority membership at the top of the distribution is meaningfully responsive to the equity assumption. This responsiveness is desirable when it is transparent. It tells decision-makers that a choice about how strongly to elevate affordability-related demand can affect which stations receive early scrutiny. Concealing the choice within an opaque composite would be less defensible.

VI. DISCUSSION

A. What is gained by moving from static reachability to dynamic equity?

The principal finding is that daily supply – demand mismatch and time-specific equity pressure overlap, but neither is a substitute for the other. The static indicator captured a substantial persistent core. This is useful because static assessments are often less costly to compute and easier to communicate in strategic planning. However, 49 of 107 dynamic priorities were invisible to the static upper-quartile screen. In a decision process that uses a short list of locations, this omission rate is material. It means that a daily dashboard could direct staff away from stations whose mismatch is concentrated in a particular hour.

This contribution extends prior two-dimensional supply – demand approaches. Ballantyne et al. show the policy value of joining transport supply and mode-specific demand at fine spatial scales [6]. The present framework alters both the temporal resolution and the demand evidence. Rather than comparing area-level mode use with an aggregated supply measure, it relates observed station entries to scheduled events in the same hour. It should not be interpreted as a superior replacement for accessibility to destinations. It measures a different layer: the temporal alignment of boarding demand and planned service provision. The two approaches are complementary. A station can exhibit strong entry pressure while serving poor access to essential destinations, or it can offer substantial scheduled service while residents struggle with first/last-mile barriers.

The framework also clarifies why observed demand should be used carefully. An entry count is an outcome of a network, land-use system, fare policy, and population schedule. It can reveal when riders appear at a station, but it cannot identify people who are excluded from transit altogether. Studies using smart-card, GPS, or mobile data can more closely approximate trip chains and realised opportunity choices [12,13]. Other studies show how to model reliable access when actual operations or uncertainty are available [7,8,14,15]. The present study trades that richer behavioural detail for a highly reproducible data architecture. Its value lies in using commonly available data without overstating what they mean.

B. Implications for planning, design, and governance

The output can support a sequence of decisions rather than a single investment prescription. First, agencies can examine high values of $P(i; \lambda)$ alongside platform layout, crowding measures, service reliability, transfer flows, and rider feedback. Second, they can distinguish recurring morning, early-shift, school-time, and afternoon patterns. Third, they can choose a response matched to the mechanism: departure retiming, frequency adjustment, bus – rail transfer coordination, station-management staffing, wayfinding, fare

outreach, or targeted accessibility improvements. The appropriate action cannot be inferred from the score alone.

The distinction between dynamic-only and both-indicator priorities is particularly actionable. Persistent priorities may be candidates for network-level evaluation because their relative mismatch remains high when supply and demand are aggregated. Dynamic-only priorities, by contrast, suggest that timing is the relevant design material. A service planner may not need a new route; a small change in departure spacing, coordinated connection, platform information, or staffing may be more responsive. This insight is consistent with the broader design principle that systems should be evaluated not only by the infrastructure they contain but also by the temporal experience they enable.

The Fair Fare term offers a narrow example of how administrative records can inform an equity-aware screen. It should be used in partnership with, rather than instead of, community data and civil-rights analysis. Equity cannot be fully read from a fare gate. A robust deployment would join the framework to census-based demographic indicators, disability access audits, pedestrian safety, fare burden, reliability, transfer time, and opportunity access. It would also invite community interpretation of whether the detected hours correspond to work shifts, child-care schedules, schooling, health care, or other forms of essential travel. The indicator supplies a question, not a final answer.

C. Methodological implications

The modelling choices are deliberately separable. The analyst may replace scheduled stop-events with actual vehicle departures, weighted capacity, route diversity, generalized cost, reachability to opportunities, or a reliability-adjusted measure. The demand side may use entry counts, origin – destination estimates, inferred home stations, survey travel diaries, passive location traces, or an explicit population need model. The equity term may use social vulnerability, fare burden, disability access, or participatory weights. Each modification changes the substantive meaning of the indicator and should therefore be recorded in a data and methods appendix.

This modularity also makes comparison possible. For example, an application with GTFS-Realtime can estimate the difference between scheduled and actual supply by hour, as advocated by research on realizable accessibility and retrospective timetables [7,14]. An application with reliable travel-time matrices can model opportunity access over several departure windows [4,18]. An application with richer demographic data can construct multiple vulnerability scenarios rather than relying on a single fare category. In each case, the central question persists: does the transport system provide an adequate and timely match for the people and trips that depend on it?

D. Limitations

Five limitations should govern interpretation. First, the case examines one weekday. It does not capture weekly, seasonal, weather-related, holiday, disruption, or special-event variation. Second, the supply proxy counts planned stop-events, not vehicle capacity, train crowding, dwell time, accessibility outages, cancellations, or delivered frequency. GTFS-Realtime or archived operations should be used where available [7,14]. Third, station entries cannot establish trip origin, destination, transfer purpose, unmet demand, or

successful arrival. The MTA's separate origin – destination estimates offer one possible extension but are themselves modelled and temporally aggregated.

Fourth, the 250-m spatial catchment and the maximum-over-hours aggregation are analytical choices. The former is reasonable for coordinating platform and station-complex records but does not represent actual walking access from residences. The latter identifies acute conditions but does not quantify duration or cumulative exposure. Fifth, Fair Fare share is an administrative fare-category signal. It should never be interpreted as an individual-level socioeconomic attribute or a geographically representative poverty rate. These limitations do not invalidate the screening framework; they delimit it and identify the data needed for a fuller equity assessment.

VII. CONCLUSION

This paper developed and demonstrated an original multi-source framework for moving from static reachability to dynamic transport equity. The approach synchronised official MTA hourly entry records, a valid static GTFS schedule, station-complex geography, and an observed affordability-related fare signal. It produced a transparent station-hour equity-pressure score that compares standardised log demand with standardised log scheduled supply and reports the normative Fair Fare weight explicitly.

The New York City Subway demonstration showed that daily and dynamic indicators partially agree but generate meaningfully different priority sets. Of 107 top-quartile dynamic priorities, 49 were not identified by an otherwise comparable static daily screen. Dynamic pressures appeared in morning, early-morning, and mid-afternoon periods, reinforcing the conclusion that a single daily accessibility or coverage measure cannot fully represent the temporal distribution of transport disadvantage. Rankings were robust to plausible changes in the Fair Fare weight, while top-decile membership remained appropriately sensitive to that equity assumption.

The theoretical contribution is to frame transport equity not only as the spatial distribution of access, but also as the temporal alignment between what a system plans to offer and when riders are observed to need it. The practical contribution is a replicable diagnostic that can be implemented with public data before more resource-intensive reliability, capacity, or opportunity-access studies are undertaken. Future research should repeat the analysis across multiple days and seasons; replace planned events with actual operations and capacity; integrate walking, transfer, and destination opportunities; model unmet demand; and co-design vulnerability weights with affected communities. Used with these safeguards, dynamic supply – demand diagnostics can help agencies shift from generic coverage narratives toward time-specific, evidence-led, and socially accountable transport decisions.

REFERENCES

- [1] Karner A, Pereira RHM, Farber S. Advances and pitfalls in measuring transportation equity. *Transportation*, 2025, 52(4): 1399–1427. DOI: 10.1007/s11116-023-10460-7.
- [2] Raza A, Zhong M, Akuh R, Safdar M. Public transport equity with the concept of time-dependent accessibility using geostatistics methods, Lorenz curves, and Gini coefficients. *Case Studies on Transport Policy*, 2023, 11: 100956. DOI: 10.1016/j.cstp.2023.100956.
- [3] Li X, Yang Z, Guo Y, Xu W, Qian X. Factoring in temporal variations of public transit-based healthcare accessibility and equity. *International*

- Journal of Transportation Science and Technology, 2024, 13: 186–199. DOI: 10.1016/j.ijtst.2024.01.001.
- [4] Lindner A, Kühnel F, Schrömbges M, Kuhnimhof T. When to measure accessibility? Temporal segmentation and aggregation in location-based public transit accessibility. *Urban Science*, 2024, 8(4): 165. DOI: 10.3390/urbansci8040165.
 - [5] Guo J, Brakewood C. Analysis of spatiotemporal transit accessibility and transit inequity of essential services in low-density cities, a case study of Nashville, TN. *Transportation Research Part A: Policy and Practice*, 2024, 179: 103931. DOI: 10.1016/j.tr.2023.103931.
 - [6] Ballantyne P, Filomena G, Rowe F, Singleton A. Developing two-dimensional indicators of transport demand and supply to promote sustainable transportation equity. *Computers, Environment and Urban Systems*, 2024, 113: 102179. DOI: 10.1016/j.compenvurbsys.2024.102179.
 - [7] Liu L, Porr A, Miller HJ. Realizable accessibility: Evaluating the reliability of public transit accessibility using high-resolution real-time data. *Journal of Geographical Systems*, 2023, 25(3): 429–451. DOI: 10.1007/s10109-022-00382-w.
 - [8] Zhang Y, Liang K, Loo BPY. Measuring dynamic accessibility by metro system under travel time uncertainty based on smart card data. *Journal of Transport Geography*, 2025, 127: 104294. DOI: 10.1016/j.jtrangeo.2025.104294.
 - [9] Bereitschaft B. Do socially vulnerable urban populations have access to walkable, transit-accessible neighborhoods? A nationwide analysis of large U.S. metropolitan areas. *Urban Science*, 2023, 7(1): 6. DOI: 10.3390/urbansci7010006.
 - [10] Ermagun A, Janatabadi F, Maharjan S. Inequity analysis of spatial mismatch for low-income socially vulnerable populations across America. *Transportation Research Part D: Transport and Environment*, 2023, 118: 103692. DOI: 10.1016/j.trd.2023.103692.
 - [11] Choi SJ, Jiao J. Developing a transit desert interactive dashboard: Supervised modeling for forecasting transit deserts. *PLOS ONE*, 2024, 19(7): e0306782. DOI: 10.1371/journal.pone.0306782.
 - [12] Zhang T, Zhang W, He Z. Measuring positive public transit accessibility using big transit data. *Geo-spatial Information Science*, 2021, 24(4): 722–741. DOI: 10.1080/10095020.2021.1993754.
 - [13] Haamer M, Aasa A, Poom A. Assessing public transport accessibility using GPS data. *European Transport Research Review*, 2025, 17(1): 36. DOI: 10.1186/s12544-025-00733-w.
 - [14] Sim JW, Cho GH. Dynamic public transit accessibility analysis using actual transit operation data. *International Journal of Urban Sciences*, 2025: 1–23. DOI: 10.1080/12265934.2025.2503727.
 - [15] Fu X, Zuo Y, Zhang S, Liu Z. Measuring joint space-time accessibility in transit network under travel time uncertainty. *Transport Policy*, 2022, 116: 355–368. DOI: 10.1016/j.tranpol.2021.12.018.
 - [16] Kar A, Carrel AL, Miller HJ, Le HTK. Public transit cuts during COVID-19 compound social vulnerability in 22 US cities. *Transportation Research Part D: Transport and Environment*, 2022, 110: 103435. DOI: 10.1016/j.trd.2022.103435.
 - [17] Sansone M, Gohlke D, Zhou Y. Incorporating social vulnerability variables in measures to quantify access to opportunities. *Transportation Research Record: Journal of the Transportation Research Board*, 2024, 2678(12): 2140 – 2155. DOI: 10.1177/03611981231168861.
 - [18] Pereira RHM, Saraiva M, Herszenhut D, Braga CKV, Conway MW. r5r: Rapid realistic routing on multimodal transport networks with R⁵ in R. *Findings*, 2021. DOI: 10.32866/001c.21262.
 - [19] Soukhov A, Tarriño-Ortiz J, Soria-Lara JA, Páez A. Multimodal spatial availability: A singly-constrained measure of accessibility considering multiple modes. *PLOS ONE*, 2024, 19(2): e0299077. DOI: 10.1371/journal.pone.0299077.
 - [20] Zhou X, Yuan L, Wu C, Yu Z, Lei W. Measuring spatiotemporal accessibility to healthcare with multimodal transport modes in the dynamic traffic environment. *Open Geosciences*, 2023, 15(1): 20220461. DOI: 10.1515/geo-2022-0461.
 - [21] Wang Z, Liu D, Li S, Liu S, Li H, Chen N. Analyzing the impact of decreasing out-of-vehicle time of public transportation travel on accessibility to tertiary hospitals. *Sustainability*, 2023, 15(16): 12453. DOI: 10.3390/su151612453.
 - [22] Ryan J, Pereira RHM. What are we missing when we measure accessibility? Comparing calculated and self-reported accounts among older people. *Journal of Transport Geography*, 2021, 93: 103086. DOI: 10.1016/j.jtrangeo.2021.103086.
 - [23] Owen D, Arribas-Bel D, Rowe F. Tracking the transit divide: A multilevel modelling approach of urban inequalities and train ridership disparities in Chicago. *Sustainability*, 2023, 15(11): 8821. DOI: 10.3390/su15118821.
 - [24] Graells-Garrido E, Serra-Burriel F, Rowe F, Cucchiatti FM, Reyes P. A city of cities: Measuring how 15-minutes urban accessibility shapes human mobility in Barcelona. *PLOS ONE*, 2021, 16(5): e0250080. DOI: 10.1371/journal.pone.0250080.
 - [25] Gibbs H, Ballantyne P, Cheshire J, Singleton A, Green MA. Harnessing mobility data to capture changing work from home behaviours between censuses. *The Geographical Journal*, 2024, 190(2): e12555. DOI: 10.1111/geoj.12555.
 - [26] Ballantyne P, Singleton A. Using composite indicators and city dashboards to promote place-based policy interventions. *Cities*, 2024, 154: 105329. DOI: 10.1016/j.cities.2024.105329.
 - [27] Frank LD, Hong A, Ngo VD. Build it and they will cycle: Causal evidence from the downtown Vancouver Comox Greenway. *Transport Policy*, 2021, 105: 1–11. DOI: 10.1016/j.tranpol.2021.02.003.
 - [28] Boeing G, Higgs C, Liu S, Giles-Corti B, Sallis JF, Cerin E, et al. Using open data and open-source software to develop spatial indicators of urban design and transport features for achieving healthy and sustainable cities. *The Lancet Global Health*, 2022, 10(6): e907–e918. DOI: 10.1016/S2214-109X(22)00072-9.
 - [29] Saxon J, Koschinsky J, Acosta K, Anguiano V, Anselin L, Rey S. An open software environment to make spatial access metrics more accessible. *Journal of Computational Social Science*, 2022, 5(1): 265–284. DOI: 10.1007/s42001-021-00126-8.

ACKNOWLEDGEMENTS

The author gratefully acknowledges the public data providers and open-source research community whose openly available transit data and analytical resources supported this study.

FUNDING

None.

AVAILABILITY OF DATA

Not applicable.

AUTHOR CONTRIBUTIONS

Senthilal Kumaran: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review & editing, and Project administration. The author has read and approved the final version of the manuscript.

COMPETING INTERESTS

The authors declare no competing interests.

Publisher's note WEDO remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is published online with Open Access by Green Design Engineering and distributed under the terms of the Creative Commons Attribution Non-Commercial License 4.0 (CC BY-NC 4.0).

© The Author(s) 2026