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Research Article

Waiting Conditions and Bus Ridership: Stop-Level Evidence from Boston

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ABSTRACT: Bus stops vary widely in the conditions they provide to waiting passengers, yet ridership analysis rarely considers these differences alongside service performance. This study examines how stop-level amenities relate to bus ridership, conditional on service frequency and schedule deviation. Using bus stop amenity inventories, operational data, and stop-level boarding figures from Boston, USA, we have estimated a structural equation path model for a sample of continuously operated, AVL-equipped timepoint stops. The model uses observed composite scores for physical amenities at the stop level and accounts for headway and schedule deviation. The results indicate that greater provision of basic amenities is consistently linked to higher ridership, and during peak periods both amenity and service reliability measures show stronger associations. Further, spatial clustering analysis shows that poor waiting conditions are geographically concentrated rather than being randomly distributed. Taken together, the findings show how passenger waiting environments and service performance jointly influence ridership and point to opportunities for targeted investment strategies.

KEYWORDS: Bus ridership; bus stops; waiting environment; stop amenities; travel satisfaction

1 Introduction

Since the outbreak of COVID-19, U.S. public transit ridership has struggled to return to pre-pandemic levels (Smith et al., 2025). The disruption has sped up the move to working from home and led to greater use of micro-mobility options such as bikeshare and e-scooters (Wang and Noland, 2021; Kong et al., 2022). In this context, traditional bus services have continued to suffer from a poor image. People have seen them as outdated, unreliable and unsafe, undermining efforts to attract riders back (Stradling et al., 2007). Although action is needed in many areas, improving the rider experience offers a particularly practical opportunity to rebuild transit demand (Hosseini et al., 2025; Asgharpour et al., 2025).

Travelers' decisions to use public transportation depend on their perceptions of safety, comfort, and convenience (Han et al., 2018; Sheng and Zhang, 2022; Ranjan and Sinha, 2025). Numerous studies show that the experience outside the vehicle affects overall satisfaction more than the conditions inside the vehicle (Hansson et al., 2019). Nevertheless, the environment that passengers experience while waiting differs greatly from one stop to another. Shelters and benches help protect against the weather and can reduce the sense of discomfort associated with waiting (Briant et al., 2025; Fan et al., 2016), while being close to vehicle traffic and being exposed to poor air quality can increase discomfort and cause passengers to think that they have been waiting longer than they actually have (Lagune-Reutler et al., 2016). Variation in stop quality is not random. Communities long neglected tend to have stops with fewer amenities, weaker pedestrian infrastructure, and less reliable service—exacerbating the disadvantages that affect people who depend most on public transit (Lubitow et al., 2017; Giuliano, 2005; Moran, 2022).

Riders' priorities also change depending on the current state of the service. If the service is unreliable or infrequent, passengers mainly care about punctuality. However, as the quality of the service improves, a broader range of factors, such as physical comfort and cleanliness, become important (Ramos et al., 2019; Sinha et al., 2020). These priorities differ depending on the type of rider: those who have access to private vehicles place more emphasis on reliability. On the other hand, people who rely on public transit tend to place more importance on comfort and the physical conditions at the stops (Asgharpour et al., 2025). Despite this evidence, stop-level waiting conditions are still largely missing from the official transit performance evaluation frameworks. Most transport agencies use on-time performance and schedule adherence as the main measures of system quality and therefore do not reflect the actual environment that passengers experience (Ghasedi et al., 2025; Moran, 2022; Kim et al., 2020). Because of these gaps, an empirical approach is needed one that looks at stop infrastructure and service reliability together in relation to actual ridership.

Previous research has shown a positive link between stop-level amenities and ridership, and has also separately confirmed the importance of service frequency and reliability. However, few studies have combined these factors into a single modeling approach (Iseki and Smart, 2012; Dai et al., 2025). Much of the existing evidence on waiting conditions comes from stated-preference surveys, which show what passengers say they value but do not directly link physical infrastructure and operational features to actual ridership outcomes (Yoh et al., 2011; Hsieh, 2023). It is therefore still unclear whether amenities and service reliability each independently influence ridership, or whether one affects the other.

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This study examines three hypotheses, each based on a different mechanism. H1: Physical amenities reduce both the perceived and actual burden of waiting, lowering the trip cost from the rider's point of view. Therefore, holding service frequency and schedule deviation constant, providing basic amenities should be positively related to ridership. H2: The make-up of riders changes throughout the day, so the same stop conditions do not always have the same impact at all times of day. The associations of amenities and service characteristics with ridership are stronger during periods of high demand. H3: Since both capital investment and service allocation are generally coordinated at the corridor level, stop-level attributes are unlikely to be distributed independently of each other. Basic amenities, transfer opportunities, and service frequency should therefore cluster geographically rather than vary independently across the network.

We test these hypotheses using a structural equation model (SEM) fitted to stop-level boardings, the MBTA amenity inventory, and observed measures of headway, schedule deviation, and transfer opportunity, all estimated for continuously operated timepoint stops where AVL equipment makes those service measures available. We then supplement the model-based analysis with spatial clustering methods applied to all stops that have recorded amenity data in order to assess whether differences in stop environments are geographically concentrated.

2 Data and Methods

2.1. Data

The analysis draws on several datasets assembled from the Massachusetts Bay Transportation Authority (MBTA) and other public sources. The MBTA provided the bus stop amenity inventory directly under a data-use agreement. All operational data refer to Fall 2024 (August 25 to December 15, 2024), the latest period available when the analysis was carried out. The records of vehicle arrivals and departures were acquired from the MBTA's Automatic Vehicle Location (AVL) system, which uses Global Positioning System (GPS) receivers fitted on each bus to provide real-time positional data. The system logs timestamps each time a vehicle arrives at or departs from a stop. These records were then used to calculate the average daily service headway at each stop and the proportion of bus arrivals that failed to adhere to their published schedules.

Information about stop amenities came from the MBTA's system-wide bus stop inventory, which agency staff keeps up to date through manual audits and reviews of onboard video footage for maintenance purposes. The inventory records whether each physical amenity is present or absent at a given stop, covering benches, shelters, and trash cans. We encoded each feature as a binary variable (1 = present, 0 = absent).

We obtained ridership data from the MBTA's Automatic Passenger Counter (APC) system. The APC equipment uses infrared sensors mounted at the vehicle doors to record the number of passengers getting on and off at each stop, differentiating between the two types of movement by direction of travel. The counts are associated with stop locations via GPS and are made available through MBTA's Open Data Portal at the stop level, broken down by trip, route, day type, and time of day (for example, morning peak, midday, evening peak). Although APC records are subject to some measurement error—including occasional missed boardings—aggregating counts to the stop level helps reduce this noise.

The analysis is limited to weekday service and includes only stops that operate continuously from early morning through late night. Of the 6,350 bus stops in the MBTA network, 5,870 have recorded amenity data (SI A1); of these, 1,200 are designated timepoints equipped with AVL instrumentation, and 520 satisfy the continuous-operation criterion, which together carry 36% of all weekday bus boardings. Focusing on this subset ensures service-hour differences do not confound ridership comparisons, though it concentrates the analysis on the more intensively served segments of the network.

Transfer opportunities were measured by counting heavy rail stations, light rail stations, and bikeshare stations within a 300-meter radius of each bus stop—a buffer distance grounded in established literature on pedestrian walking distances to transit (Lam and Morrall, 1982; El-Geneidy et al., 2014). Local activity density was measured using points of interest (POIs) drawn from OpenStreetMap, encompassing all features tagged as amenities, shops, or leisure facilities within 300 meters of each stop. We log-transformed the raw POI count as log(1 + POIs) to address right-skewness.

Table 1: Variable Definitions and Measurement Levels for Structural Equation Model

Variable	Type	Description
Endogenous Outcome		
Ridership	Observed	Avg. boardings per bus
Composite Variables		
Basic Amenity Provision	Continuous	Physical infrastructure for waiting passengers
Transfer Opportunity	Continuous	Nearby multimodal mobility options
Components for Basic Amenity Provision		
bench	Binary	Bench present (1 = yes)
shelter	Binary	Shelter present (1 = yes)
trash	Binary	Trash can present (1 = yes)
Components for Transfer Opportunity		
heavy rail	Continuous	Heavy rail stations within 300 m
bike	Continuous	Bikeshare stations within 300 m
light rail	Continuous	Light rail stations within 300 m
Exogenous Predictors		
headway	Continuous	Avg. observed service headway
sched. dev.	Continuous	Share of arrivals deviating from schedule
POI	Continuous	POIs within 300 m
pop_density	Continuous	Residential population within 300 m (per km^2)
emp_density	Continuous	Employment within 300 m (per km^2)

To account for the spatial co-location of stop infrastructure, transit service, and neighborhood demand, we also developed

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indicators of residential and employment density within a 300-meter radius of each stop. We obtained residential population estimates from the American Community Survey 2018–2022 five-year series at the block-group level, and employment figures from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LEHD-LODES) 2022 Workplace Area Characteristics, also at the block-group level. We converted both population and employment figures into density terms (residents per km² and jobs per km²) and then log-transformed them before including them in the model. Table 1 summarizes all model variables. Full descriptive statistics for the 520 stops in the analysis sample are provided in SI A2.

2.2. Structural Equation Modeling Framework

To examine the relationship between stop-level amenities, transfer opportunities, schedule deviation, and bus ridership, we use structural equation modeling (SEM). More specifically, we estimate a path model in which composite scores (obtained by summing the observed indicator variables) serve as inputs, enabling a simultaneous evaluation of both the direct and indirect associations between stop characteristics and ridership outcomes.

Estimating these relationships within a path analysis framework delivers several benefits over sequential regression approaches. First, it estimates multiple endogenous equations—those relating to ridership, amenity provision, and transfer opportunity—simultaneously within one covariance-based model, so it accounts for shared variance among stop infrastructure, multimodal access, service frequency, and land use when estimating any single conditional association. Second, the framework lets the residual covariance between amenity provision and transfer opportunity be modeled explicitly, capturing the tendency for stops with greater physical infrastructure also to be embedded in more multimodally accessible locations beyond what their common predictors explain. Third, SEM yields global fit indices that evaluate whether the full hypothesized pattern of relationships is consistent with the covariance structure observed in the data—assessing the model as a complete system rather than through individual path coefficients alone. However, with seven degrees of freedom, the global indices place few constraints on the specification. They are correspondingly uninformative about theoretical validity so the substantive evidence rests on the path coefficients.

Basic amenity provision and transfer opportunity are represented through composite observed scores. These are additive composites rather than reflective latent factors: all indicators are directly observed, and the component amenities are sited semi-independently rather than driven by a common underlying cause. Because no measurement model is estimated, factor loadings, reliability statistics, and indicator residuals are not defined for these measures and are accordingly not reported.

Basic amenity provision is operationalized as the integer sum of three binary indicators—bench, shelter, and trash can—yielding scores ranging from 0 to 3. This measure captures a limited but consistently recorded group of fundamental physical features and does not cover the full range of stop characteristics that could affect the waiting experience, for example real-time information displays, lighting, accessibility features, or separation from nearby traffic. The three indicators used in this case represent the amenity dimensions most consistently inventoried across the MBTA network and are among the most widely studied features in the transit amenity literature (Fan et al., 2016; Moran, 2022). Transfer opportunity is operationalized as the sum of heavy rail stations, light rail stations, and Bluebikes bikeshare stations within 300 meters of each stop. The coefficient on this composite should therefore reflect a stop's broader accessibility and demand context rather than the isolated effect of multimodal connectivity alone. Exogenous predictors include average observed headway, which represents service frequency—with higher values corresponding to less frequent service—and schedule deviation rate, defined as the share of arrivals deviating from the published timetable by arriving at least one minute early or at least six minutes late, consistent with MBTA's service reliability definitions.

The structural portion of the model specifies ridership as a function of basic amenity provision, transfer opportunity, headway, log(POIs), schedule deviation rate, and two neighborhood-level controls—log(Population Density) and log(Employment Density)—as illustrated in Figure 1. Directed paths in the diagram represent conditional associations, not causal claims. To reduce right-skewness and limit the influence of a small number of very high-ridership stops, the outcome is modeled as log(1 + ridership). The structural equation for stop i takes the form:

$$log(1 + R_i) = \gamma_1\eta_{1i} + \gamma_2\eta_{2i} + \beta_1 H_i + \beta_2 D_i + \beta_3 log(1 + P_i) + \beta_4 log(1 + PD_i) + \beta_5 log(1 + ED_i) + \zeta_i$$

where R_i is average boardings per bus, η_1 and η_2 are the basic amenity provision and transfer opportunity composites respectively, H_i is headway, D_i is schedule deviation rate, P_i is the count of points of interest, PD_i is residential population density, and ED_i is employment density. We estimate parameters via maximum likelihood, identifying values that best reproduce the observed covariance structure.

Because amenities, service, and ridership are not randomly distributed across the network, the model regresses both composite measures on headway, log(POIs), and the two density terms, allows the composites to covary, and permits the exogenous predictors to covary freely among themselves. These specifications help adjust for corridor-level clustering when estimating conditional associations between stop infrastructure, transfer opportunity, and ridership. They should not be read as short-run causal effects of any individual predictor on another. We examine model fit using the chi-square test statistic, the Comparative Fit Index (CFI), the Tucker–Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA).

2.3. Spatial Correlation

To describe how waiting facilities are distributed throughout the network, we created a stop-level summary index using the three binary amenity indicators. The amenity count shows the total number of core waiting amenities present at a given stop—bench, shelter, and trash can—and takes integer values between 0 and 3. We begin by assessing whether stop-level amenity provision exhibits spatial dependence using Global Moran's I, a well-

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established measure of global spatial autocorrelation. This statistic indicates how likely stops with similar amenity levels are to be located near one another. A value of I close to zero implies a randomly distributed pattern over space; positive values mean that similar amenity levels tend to cluster in space, while negative values indicate spatial dispersion, that is, neighboring stops tend to have different amenity levels.

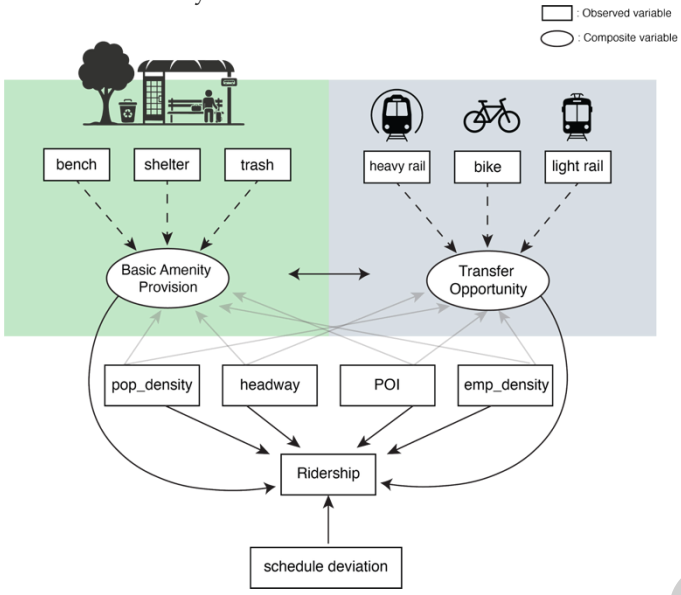


Fig. 1: Structural equation model (SEM) linking stop-level waiting conditions and service performance to bus stop ridership. All variables are observed: the enclosing shapes denote composite indices formed by summing their indicators, and we estimate no measurement model, factor loadings, or indicator residuals. Solid black arrows denote paths in the main ridership equation; solid gray arrows denote auxiliary regressions predicting the composite indices from service and land-use covariates; dashed arrows indicate the observed features summed to form each composite measure.

To move beyond this general valuation and identify the exact location and nature of spatial clusters, we calculated the Local Indicators of Spatial Association (LISA) for basic amenity provision at the stop level using a k-nearest-neighbors spatial weights matrix with k = 8. Within the LISA approach, each stop falls into one of four cluster categories based on the sign of its standardized amenity value relative to the average standardized amenity value of its eight nearest neighbors. Stops classified as High–High (HH) have amenity levels above average and are surrounded by similarly well-equipped neighbors, creating amenity hotspots. Stops identified as Low–Low (LL) have amenity levels below the average and are located among neighbors who are likewise underserved, giving rise to amenity coldspots. The other two categories indicate spatial outliers: High–Low (HL) stops are well equipped on an individual basis but are situated in areas with lower amenity levels, while Low–High (LH) stops have a relatively small number of amenities even though they are near stops that are better equipped. These two types represent transition zones or boundary cases at the edges of investment corridors and not clear regional patterns. Since the variables being examined were measured on different scales (headway in minutes, schedule deviation as a share of arrivals), we converted the key measures to z-scores prior to the analysis.

3 Results

3.1. Effects of Reliability and Amenities on Ridership

We look at the relationships among stop-level waiting conditions, schedule deviation, and the actual number of bus riders. The model is overidentified by seven degrees of freedom, and the chi-square test does not reject the proposed structure ($\chi^2 = 1.129$, df = 7, p = 0.99). Because the exogenous predictors are allowed to covary freely, few degrees of freedom remain, so the global fit indices provide no useful information about theoretical validity. For this reason, the substantive interpretation is based on the estimated path coefficients and their significance levels rather than on the global fit statistics (Table 2).

Even after controlling for service frequency, schedule deviation, and neighborhood density, stops with higher basic amenity provision are associated with greater average boardings. The estimated coefficient for the amenity composite is positive and significant, indicating a consistent link between stop infrastructure and ridership in the sample. Transfer opportunity is also positively and significantly associated with ridership, though caution is needed in interpreting it: stops with better multimodal access are generally located in areas where transit demand is already high. Therefore, this coefficient shows the broader locational context as well as the direct effect of having nearby alternative modes of transport.

The direct relationship between headway and ridership is statistically significant, but its magnitude is smaller than the total association with the outcome. This is because headway also predicts basic amenity provision, and since this amenity provision is positively linked to ridership, part of the headway-ridership relationship is transmitted indirectly via stop infrastructure. The reduced direct estimate therefore shows the division of variance among the correlated predictors, not evidence that the importance of service frequency has decreased.

When population and employment density are included, the direct effect of log(POIs) becomes small and not statistically significant. Instead, surrounding land use appears to relate to ridership through the two composite variables. In the structural equation, neither residential density nor employment density is directly linked to ridership, but both reliably predict transfer opportunity, and employment density also predicts the level of basic amenities provided. Their impact on ridership therefore appears indirect, operating through stop infrastructure and multimodal access rather than through a direct demand route.

The degree of schedule deviation—defined as the proportion of arrivals that differ from the published timetable—is independently related to the number of riders beyond what stop-level conditions explain. Stops with less reliable schedules have fewer average boardings, showing that operational performance matters in addition to stop-level conditions.

The five exogenous predictors are allowed to covary freely, and the resulting correlations show the expected pattern of co-location at the corridor level. Population density and employment density

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are strongly correlated, as are both with the number of POI entries. In contrast, both density measures are negatively correlated with headway, consistent with more frequently served routes being located in denser, more commercially active areas. By accounting for these correlations, we separate the conditional associations we are interested in from the general spatial relationship between infrastructure and service intensity. The correlations describe co-location, not causal effects of service frequency or land use on amenity provision.

3.2. Ridership Volume and Changing Priorities

To test whether the relationships in the full-sample model differ by time of day, we re-estimated the same structural equation model separately for the peak and late-night travel periods. The peak-period ridership figure includes boardings from the morning peak (7 to 9 am), the midday school period (2 to 4 pm), and the afternoon peak (4 to 7 pm), whereas the late-night model covers the evening through the last scheduled trip (SI A3). Because travelers in these two periods differ systematically in trip purpose and scheduling constraints, we can assess whether the relative importance of amenity provision, service reliability, and

Table 2: Structural Equation Model Results: Infrastructure and Land-Use Effects on Ridership

Path	Estimate	SE	z-value	p-value	
Structural Model					
Basic Amenity Provision → log(Ridership)	0.162	0.018	8.960	<0.001	***
Transfer Opportunity → log(Ridership)	0.038	0.015	2.532	*0.011*	*
Headway → log(Ridership)	−0.042	0.020	−2.047	*0.041*	*
log(POIs) → log(Ridership)	0.014	0.035	0.394	0.694	
Schedule Deviation Rate → log(Ridership)	−0.057	0.023	−2.424	*0.015*	*
log(Population Density) → log(Ridership)	0.016	0.029	0.539	*0.590*	
log(Employment Density) → log(Ridership)	0.027	0.018	1.475	*0.140*	
Covariance					
Basic Amenity Provision ↔ Transfer Opportunity	0.110	0.089	1.235	*0.217*	
Directed Regressions					
Headway → Basic Amenity Provision	−0.235	0.054	−4.374	*<0.001*	***
log(POIs) → Basic Amenity Provision	0.008	0.080	0.099	*0.921*	
log(Pop Density) → Basic Amenity Provision	0.031	0.073	0.426	*0.670*	
log(Emp Density) → Basic Amenity Provision	0.149	0.045	3.296	*<0.001*	***
Headway → Transfer Opportunity	−0.101	0.073	−1.380	0.167	
log(POIs) → Transfer Opportunity	0.783	0.119	6.601	*<0.001*	***
log(Pop Density) → Transfer Opportunity	0.367	0.108	3.384	<0.001	***
log(Emp Density) → Transfer Opportunity	0.473	0.073	6.509	<0.001	***
Model Fit Indices					
Chi-square	1.129 (df = 7)				
CFI	1.000				
TLI	1.028				
RMSEA	0.000				

Notes: N = 520 bus stops.
Significance levels: *** p < 0.001, ** p < 0.01, * p < 0.05

multimodal access changes between high-demand and low-demand periods.

Both the peak and late-night models fit well (CFI = 0.94 and CFI = 0.95, respectively). The negative association between headway and basic amenity provision is statistically significant in both periods and stable in magnitude across models (Figure 2), consistent with long-run spatial coupling of frequent service and physical stop investment along prioritized corridors rather than time-of-day variation in operational resource allocation.

The link between basic amenities and ridership remains important in both demand scenarios but weakens in the late-night model. This difference shows that stop conditions matter most when total demand is highest. At night, ridership instead comes more from people who depend on public transport and have few other options. These riders take the bus no matter how good or bad stop conditions are, which reduces the importance of amenities. On the other hand, the opportunity to transfer is more closely linked to ridership in the late-night hours than during peak times, which is consistent with a shift away from commute travel toward destination-oriented trips that cluster around multimodal hubs as the day's service ends.

During peak times, the direct link between headway and ridership is statistically significant, but during late-night service it is not. Schedule deviation shows the most obvious differences over time: higher deviation rates are strongly linked to fewer boardings in peak hours, since irregular arrivals create real costs for time-sensitive travelers, but this connection is much weaker at night, when ridership is mainly composed of captive riders.

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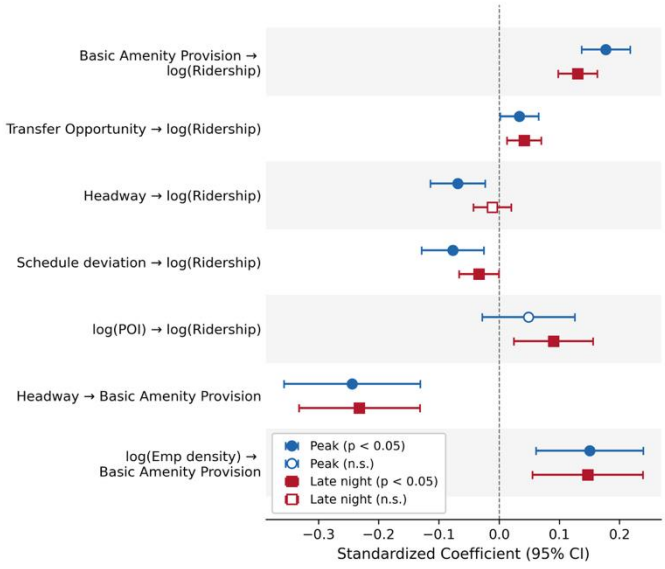


Fig. 2: Time-of-day heterogeneity in SEM path estimates between peak periods (AM/PM peak and school–midday) and late-night periods (evening through end of service). The panel displays estimated structural path coefficients with 95% confidence intervals. Filled markers indicate statistical significance ($p < 0.05$), open markers indicate non-significance.

3.3. Spatial Distribution of Amenities

The SEM results show the relationship between stop-level conditions and ridership after accounting for corridor characteristics, but they do not show whether amenity shortfalls are geographically concentrated in a way that exacerbates disadvantage among neighboring stops. To investigate this, we used both global and local autocorrelation methods to examine the spatial distribution of basic amenity provision. The cluster comparison is limited to a sample of 520 stops because the service and ridership data needed to characterize the cluster types depend on AVL and APC equipment, which is not available for the entire network. For this sample, we identify groups of stops with similar amenity levels and analyze how these groups differ in service conditions and ridership outcomes.

When applied to the sample of 520 stops, Global Moran's I gives a value of 0.083 with a z-score of 4.2, showing that there is statistically significant spatial clustering in the provision of stop-level amenities (see Figures 3a–b). This suggests that well-equipped stops tend to be located near other well-equipped stops, and that poorly served stops tend to group together—in line with the logic of corridor-level investment: routes given priority attract coordinated capital spending, while less prioritized areas continue to suffer from disinvestment. A further analysis of all 5,870 stops with amenity data (SI A4) yields a much higher Global Moran's I of 0.268 ($z = 42$, $p < 0.001$), showing that this concentration is a feature of the entire system, not just an artifact of limiting the sample to timepoint stops.

Comparing the High–High (HH) and Low–Low (LL) clusters shows a consistent and systematic difference in service and ridership conditions. The HH stops—those with high amenity levels in areas that are themselves high in amenities—have the highest average ridership in the sample, are served by more frequent routes, and have more nearby opportunities to transfer modes. In contrast, the LL stops show the opposite pattern: lower ridership, longer headways, and fewer nearby multimodal connections. Together, these differences show that passengers at LL stops face a worsening combination of poor physical environments and inadequate service conditions, increasing their disadvantage while waiting. These findings show how the spatial arrangement of transit investment tends to concentrate benefits in corridors that are already relatively well served.

Identifying the geographical locations of the LL clusters provides a practical basis for planners who want to make their amenity investments more equitable. Transport agencies might use a stop's membership of an LL cluster as a data-driven criterion for deciding which stops to audit in the field and for determining the order in which to carry out capital improvements along corridors. Although the analysis is associative, it offers a reproducible and transparent approach to allocating resources to stops where waiting conditions are most deficient.

The local analysis also highlights cases involving a transition—that is, HL and LH stops located at the boundaries between investment zones or where well-served corridors meet underresourced neighborhoods (see Figure 3c–d). These boundary cases are operationally useful because they identify stops whose amenity levels diverge from their immediate surroundings: isolated, well-equipped stops within predominantly low-amenity corridors, or low-amenity stops isolated within otherwise well-served areas. From a planning point of view, this distinction matters because it separates large-scale network inequities—represented by coherent LL regions requiring corridor-level intervention—from localized infrastructure gaps that can be correctable through targeted maintenance investment at individual stops.

LH stops tend to have shorter headways and more nearby transfer opportunities than HL stops, suggesting they are part of corridors whose service priorities are set as a whole, even if infrastructure gaps remain. On the other hand, HL stops are located on corridors that are served less intensively, have longer headways, and offer fewer nearby transfer options, yet still achieve relatively high ridership, indicating that isolated investments in amenities are linked to relatively high ridership even when overall service conditions are poor. Whether these spatial patterns have equity implications depends on the sociodemographic characteristics of riders at the affected stops, which the present analysis does not directly address.

4 Discussion

The study improves understanding of how stop-level waiting environments influence bus ridership through four separate contributions. First, it brings together basic stop amenities, transfer opportunities, and service performance into a single empirical framework, so the way they link to ridership can be estimated and interpreted together rather than treated as separate issues. Second, the stop features are combined into clear composite scores, so no single binary indicator dominates the results and the resulting measures remain directly interpretable. However, these scores include only the main physical aspects. Third, estimating the

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model separately for different times of day reveals that the relationships between stop conditions and ridership differ, highlighting specific demand situations in which waiting environments matter more. Fourth, the spatial clustering analysis extends the stop-level findings to network planning by identifying geographic areas where poor waiting conditions and low ridership co-occur and where targeted infrastructure investment could have the greatest impact.

Taken together, the results indicate that stop-level infrastructure has a strong, independent relationship with observed ridership at these MBTA stops, even after accounting for service frequency and schedule deviation. The waiting environment should be regarded as a significant part of transit performance, and not merely as a secondary consideration alongside operational metrics. Improving the physical conditions at stops is a cheap undertaking and one that passengers can see directly.

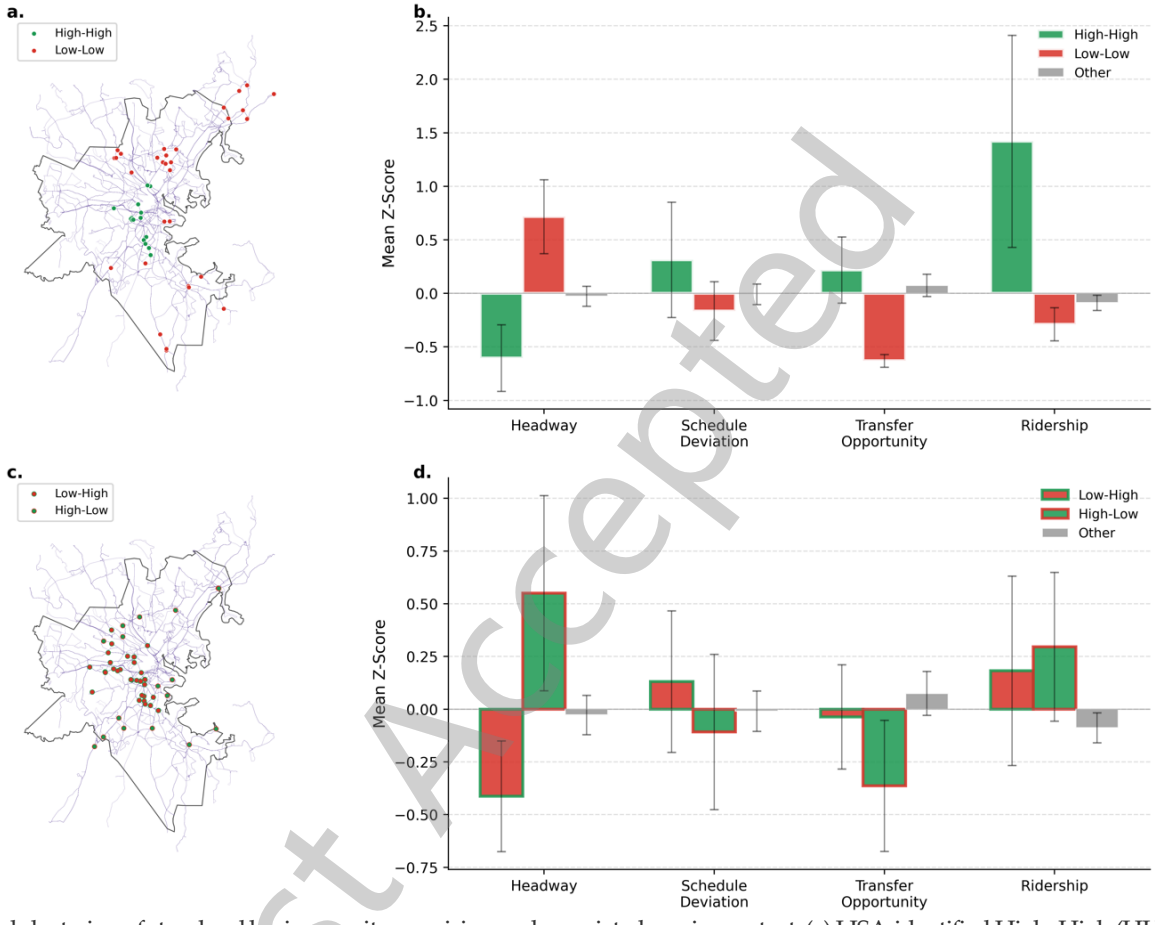


Fig. 3: Spatial clustering of stop-level basic amenity provision and associated service context. (a) LISA-identified High–High (HH) and Low–Low (LL) clusters of basic amenity provision; gray points indicate non-significant stops. (b) Mean standardized (z-score) headway, schedule deviation, transfer opportunity, and ridership for HH, LL, and all other stops. (c) LISA-identified Low–High (LH) and High–Low (HL) clusters of basic amenity provision. (d) Mean standardized service and ridership measures for LH, HL, and other stops. Error bars in (b) and (d) show 95% confidence intervals of cluster means.

The SEM framework allows simultaneous modeling of the relationships between stop amenities, transfer opportunities, service frequency, neighborhood activity, and ridership, but the resulting estimates are associational rather than causal. Establishing causal effects would require quasi-experimental designs—such as before-and-after studies of amenity installations—that more cleanly separate stop-level investment effects from the demand-driven processes shaping where amenities are sited. Ridership is also affected by factors beyond the stop environment, such as local traffic conditions and the overall distribution of trip destinations, factors that proximity-based indicators cannot consider.

By limiting the study to 520 timepoint stops that are continuously operated and equipped with AVL and APC devices, the analysis focuses on the parts of the MBTA network that are better resourced and have higher service frequencies. Within this group, the prevalence of amenities is considerably higher than the overall system figures—42% of the stops in the analysis have benches, compared with 16.5% of the 5,870 stops across the entire network for which amenity data are recorded (SI A1). The stops that have been excluded from the analysis are more likely to have fewer amenities, less frequent service, and passenger populations with more limited transportation options. As a result, the estimated associations between amenities and ridership may differ in both magnitude and statistical significance. Expanding automated passenger counting to a wider section of the network would increase the generalizability of these results and provide the data needed to guide amenity investments to the areas where they are

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most needed.

The amenity indicator includes only benches, shelters, and trash cans; other stop-level features—such as lighting, real-time arrival information, accessibility facilities, and physical separation from surrounding traffic—might also affect the waiting experience and perceived safety but are not included in this study. Lastly, the analysis does not include the sociodemographic features of the populations using the stops, even though these factors might influence how ridership responds to infrastructure conditions, especially in areas with higher numbers of transit-dependent riders. Future studies could extend this approach by obtaining a more comprehensive range of stop-level characteristics from street-view images or systematic on-the-ground audits, and by using longitudinal data to assess how ridership responds to specific capital investments over time.

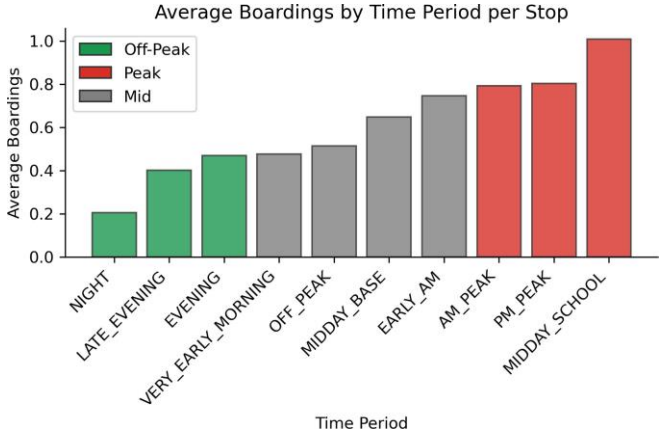
Appendix

A1: Descriptive Statistics of Bus Amenities in MBTA System (N = 5,870)

Variable	Mean	SD	Median	Min	25th	75th	Max
Basic Amenities							
Bench	0.165	0.371	0.000	0.000	0.000	0.000	1.000
Shelter	0.110	0.313	0.000	0.000	0.000	0.000	1.000
Trash Can	0.138	0.345	0.000	0.000	0.000	0.000	1.000

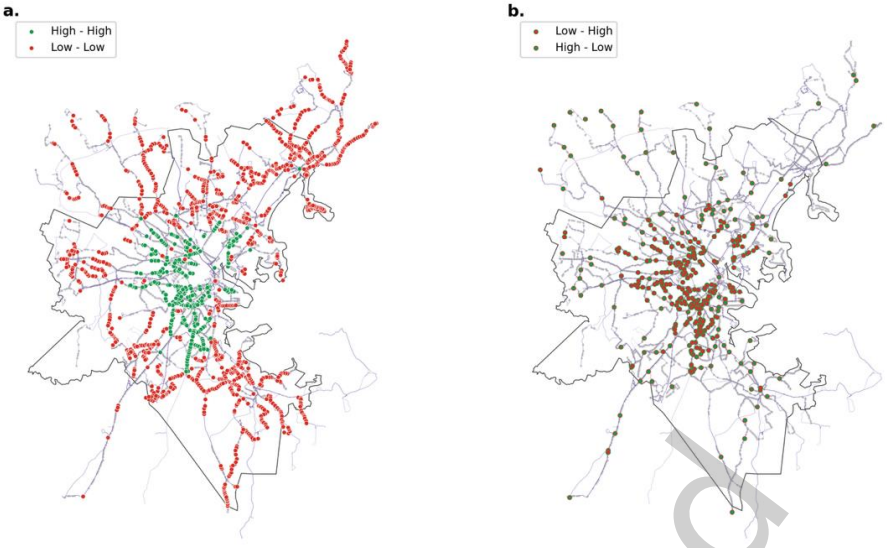
A2: Descriptive Statistics of Study Variables (N = 520)

Variable	Mean	SD	Median	Min	25th	75th	Max
Dependent Variable							
Average Boardings	0.818	1.828	0.280	0.000	0.100	0.817	24.700
Basic Amenities							
Bench	0.421	0.492	0.000	0.000	0.000	1.000	1.000
Shelter	0.314	0.464	0.000	0.000	0.000	1.000	1.000
Trash Can	0.370	0.480	0.000	0.000	0.000	1.000	1.000
Transfer Opportunity							
Heavy Rail Stations	0.149	0.383	0.000	0.000	0.000	0.000	2.000
Light Rail Stations	0.297	0.831	0.000	0.000	0.000	0.000	6.000
Bikeshare Stations	1.256	1.354	1.000	0.000	0.000	2.000	8.000
Service Characteristics							
Headway (min)	31.323	10.769	31.068	6.466	23.460	39.194	58.203
Schedule Deviation (%)	0.395	0.141	0.384	0.042	0.297	0.484	0.859
Land Use							
POI Count	49.618	69.465	18.000	0.000	5.000	61.250	420.000
Population Density	6772.8	4054.8	6473.1	85.9	3559.4	8925.4	22492.2
Employment Density	7321.6	17035.7	2021.6	10.06	813.3	4852.3	137855.6



A3: Average boardings per stop by time period, sorted in ascending order. Time periods are classified as peak (top three), mid, and off-peak (bottom three) based on average ridership volume.

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A4: System-wide spatial clustering of stop-level amenity counts across the 5,870 MBTA bus stops with recorded amenity data. (a) LISA-identified High–High (HH; n = 489) and Low–Low (LL; n = 1854) clusters. (b) Low–High (LH; n = 340) and High–Low (HL; n = 103) spatial outliers. Gray points indicate stops not assigned to a significant cluster ($p \geq 0.05$).

Author contributions

Nail Bashan: Writing – original draft, Methodology, Visualization, Investigation, Formal analysis, Data curation.

Qi Wang: Writing – review & editing, Supervision, Funding acquisition, Resources, Methodology, Investigation, Conceptualization.

Replication and data sharing

The analysis code and a detailed description of the replication workflow is available at https://doi.org/10.26599/ETSD.2026.9190116. The Fall 2024 stop-level bus ridership data are publicly available through the MBTA–MassDOT Open Data Portal (mbta-massdot.opendata.arcgis.com/). Stop locations and schedules are available through MBTA GTFS feeds; bikeshare station data are available through the Bluebikes System Data portal (bluebikes.com/system-data); POI data are available from OpenStreetMap; and population and employment inputs are available from the U.S. Census Bureau. The bus-stop amenity inventory was obtained directly from the MBTA under a special data-use agreement, and the authors cannot redistribute it. Researchers may request the amenity inventory and any restricted operational extracts directly from the MBTA, subject to the agency's data-availability and use policies.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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