All Ridership Is Local: Accessibility, Competition, and Stop-Level Determinants of Daily Bus Boardings in Portland, Oregon

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ABSTRACT

Research on accessibility, a measure of ease of reaching potential opportunities, has advanced significantly, but the adoption of these measures by public transport agencies has lagged. One explanation may be that research has been conducted at different spatial scales from the stop level typically used by agencies. To address this gap, this study examines the relationship between accessibility to jobs and average daily bus boardings at the bus-stop level of analysis in Portland, Oregon. Our models show that daily boardings could increase by 1.8% to 2.1% for every 10% increase in accessibility, measured as the number of jobs reachable in 30 minutes from the bus stop by public transport. This finding supports the argument that accessibility-focused service improvements have the potential to bolster stop-level ridership since network adjustments and new services like bus-rapid-transit often yield considerable increases in accessibility. At the same time, inter-stop competition reduces an individual stop's ridership. This study conveys the benefits of planning for accessibility at a regional scale and links regional decisions back to stop-level ridership, the context most familiar to public transport agencies, in the hope that this will accelerate and extend the adoption of accessibility in practice.

Keywords: accessibility, stop-level ridership, bus boardings, public transport

1. INTRODUCTION

Accessibility, a measure of the ease of reaching desirable destinations (Hansen, 1959), is one of the regional variables that has shown to positively influence public- transport use at different scales (Cui et al., 2020; Wu et al., 2019a). Accessibility can be interpreted in two ways: accessibility to public transport (how easy it is for people to access public-transport services) and accessibility by public transport (how easy it is to reach opportunities by public transport). Public transport operators directly influence accessibility through the location of services (i.e., where stops are located), as well as the type of network that can maximize the number of opportunities that can be reached within the service area. By maximizing the opportunities that can be reasonably reached from a location, the pool of potential users interested in reaching these destinations increases, which should result in increased ridership.

However, the use of accessibility in planning practice has not grown to the degree of scholarly research (Siddiq and Taylor, 2021). One study of transport planners in the UK showed that practitioners have difficulty creating useful measures of accessibility, even as they view accessibility as a desirable planning goal (Curl et al., 2011). These findings conform with other research that accessibility is only rarely considered as part of performance measures (Handy and Neimeier, 1997). By examining how accessibility influence stop-level boardings, we aim to speed up the translation of rapidly advancing accessibility research (Cui et al., 2019; Handy, 2020; Levine et al., 2019; Levinson and King, 2020; Levinson and Wu, 2020) into practice (Siddiq and Taylor, 2021).

The present research will help answer the following question: What is the influence of regional accessibility to jobs on stop-level boardings? We answer this question with a series of linear-regression models using data obtained from TriMet, the main public transport operator in Portland, Oregon. Recognizing the complex role local environments play in stop-level ridership, our model design draws upon previous research to include competition between stops (Kimpel et al., 2007), service attributes (Chakour and Eluru, 2016), and socio-demographics (Frei and Mahmassani, 2013) that have been shown to influence passenger activity at the stop level. Results of our model point to a significant and positive relationship between accessibility to jobs provided by the stop and boardings at the stop. In addition, there is evidence that the presence of other attractive stops, in the sense that they provide the same and even additional job accessibility, may further suppress stop-level boardings at a particular location.

2. BACKGROUND

2.1 Determinants of Ridership

A large body of research examines the factors that influence public transport use at various scales, including the system (Boisjoly et al., 2018; Taylor et al., 2009), route (Chakrabarti and Giuliano, 2015; Diab et al., 2020; Tang and Thakuriah, 2012), and stop or station levels (Chan and Miranda-Moreno, 2013; Chu, 2004; Fan et al., 2016; Kerkman et al., 2015; Lagune-Reutler et al., 2016). The stop or station is the building block that drives ridership and is one of the most used units of analysis in public transport planning and operation. The dynamics around stop-level ridership are complex and affected by local and regional operating as well as built environment characteristics.

Taylor et al. (2009) conducted a cross sectional analysis on public transport ridership in the US and found that external factors—those that are exogenous to the system and largely out of the operators' control—play a significant role in explaining variation in ridership. This is not to say that public transport policies are ineffective, as the researchers found that about 26 percent of the observed variation in per capita ridership is explained by variations in frequency and fare levels once urban size is controlled for. Boisjoly et al. (2018) conducted a longitudinal study on ridership in North America finding that fare elasticity and revenue vehicle kilometers from bus operations are major determinants of ridership at the system level. While these macroscopic studies are useful in identifying trends in ridership across regions, their usefulness for operators and planners is limited as they do not point the way toward specific service-improvement strategies.

Several recent studies were conducted at the census-tract level to highlight the relationship between accessibility and mode choice (Cui et al., 2020; Foth et al., 2014). Accessibility to jobs was consistently found to influence ridership positively at this level of analysis (Chow et al., 2006; Foth et al., 2014; Wu et al., 2019b). Owen and Levinson (2015) found this to be true at the block-group-level in the Minneapolis-Saint Paul region in the United States. The limitations of these studies are that the results, available at the aggregated census unit, are not easily translatable to potential service changes.

Few studies have examined the influence of accessibility at the route-level. Instead, route-level studies have principally focused on answering research questions related to more specific interventions, e.g. the impact of bicycle-sharing system (Campbell and Brakewood, 2017) or a real-time information system (Tang and Thakuriah, 2012) on route-level ridership. The exception is Diab et al. (2020), where the researchers did find a positive relationship between accessibility and ridership at the route-level. However, analysis concerning ridership at the route has shown some shortcomings as sociodemographic variables are not uniform at the route level of analysis making it harder to generalize (Diab et al., 2020).

2.2 Determinants of Stop-level Ridership

Stop-level ridership has been studied extensively (Bree et al., 2020; Chakour and Eluru, 2016; Dill et al., 2013; Kerkman et al., 2015; Kimpel et al., 2007). Factors that influence passenger activity at the stop level can be categorized as those related to the built environment and sociodemographic characteristics of areas adjacent to stops, and transit supply, expressed as the level of transit service offered at the stop. Importantly, accessibility has rarely been used in previous research on stop-level ridership. To our knowledge, only two studies (Chu, 2004; Dill et al., 2013) explored this relationship, finding a positive relationship between accessibility and stop level ridership, yet the generation of accessibility measures was not as advanced as today, especially when it relates to the calculation of travel time matrices.

Existing demand in stop-level models has been expressed as the number of people or dwellings that can access a stop, or from the stop's perspective: how many people or dwellings can a stop access? Studies have shown that a decay function is the most appropriate to express the relationship between demand and distance from the stop. Various decay functions have been developed such as the negative exponential (Zhao et al., 2003) and negative logistic decays (Kimpel et al., 2007). The influence of transit demand is always positive regardless how it is calculated (Dill et al., 2013; Kerkman et al., 2015; Kimpel et al., 2007).

Land use has shown to influence passenger activity at the stop-level. In North Carolina, an increase in residential land use area was found to be associated with a decrease in boardings (Pulugurtha and Agurla, 2012) while the opposite was found in Portland (Dill et al., 2013) and in the Netherlands (Kerkman et al., 2015). Other studies found a positive impact of the composite variables that combine both the mixture of land use around a stop and the ease of walking to destinations (Bree et al., 2020; Frei and Mahmassani, 2013).

Certain sociodemographic variables have been found to influence stop-level ridership negatively, such as higher median income (Diab et al., 2020; Kerkman et al., 2015; Pulugurtha and Agurla, 2012; Rahman et al., 2021; Ryan and Frank, 2009) and higher percentage of white population (Berrebi and Watkins, 2020; Chu, 2004; Dill et al., 2013; Ryan and Frank, 2009). Some studies found that higher concentrations of elderly residents are associated with lower daily passenger activity (Berrebi and Watkins, 2020; Kerkman et al., 2015; Rahman et al., 2021) whereas other studies found statistically insignificant relationships (Dill et al., 2013; Johnson, 2003; Somenahalli, 2011). The percentage of households with no vehicles was found to influence ridership positively in some studies (Berrebi and Watkins, 2020; Chu, 2004; Ryan and Frank, 2009) and negatively in others (Dill et al., 2013). Such differences may be related to model specifications and correlations with other variables included in the studies.

The level of service provided at the stop plays an important role in ridership. Stops with more frequent bus service are associated with higher boardings (Chakour and Eluru, 2016; Dill et al., 2013; Frei and Mahmassani, 2013; Kerkman et al., 2015; Rahman et al., 2021). Other significant supply variables that impact ridership positively include whether the stop is a transfer one and average number of other stops on routes served by the stop (Kerkman et al., 2015). Dill et al. (2013) also considered the number of Light Rail Transit (LRT) stations in the stop service area and found that it was negatively correlated with boardings at the stop.

2.3 Competition Effects Between Stops

One consideration in the development of stop-level ridership models is the effect of competition between bus stops. An approach that has been used to address inter-stop competition is to include, the number of other stops in the stop in question's service area as an explanatory variable (Chakour and Eluru, 2016; Chu, 2004; Dill et al., 2013). Inconsistent findings have been found from these studies whereby Dill et al. (2013) and Chu (2004) found a negative correlation between the number of other stops in the stop in question's service area with boardings whereas Chakour and Eluru (2016) identified a positive one. This inconsistency in results reveals the weakness of this simplistic variable when used to represent the effect of competition as not all other stops may be competitive with the stop in question. Our understanding is there could be two ways that stops can be competitive to each other: 1) when the stops are near each other and are served by the same routes, or 2) when the other stops provide access to the same set of opportunities as the stop in question but through the same or other routes. While we found one study (Mucci and Erhardt, 2018) that considered the impact of close-by stops that serve the same route separately from the other stops in the stop's service area, we did not find additional studies that attempt to address competition between stops in terms of overlap in opportunities that can be accessed at the system level.

2.4 Accessibility

Accessibility, the ease of reaching destinations with a specific mode of transport (Hansen, 1959) is one of the most comprehensive land use and transport performance measures (Vickerman, 1974). Cumulative opportunities measure of accessibility counts the number of opportunities that can be reached from a given location within a specified travel duration or distance when using a particular travel mode (Geurs and van Wee, 2004). Such measure is widely used due to its simplicity and ease of communication when compared to other measures such as gravity based or utility based measures (Ben-Akiva and Lerman, 1979). The gravity-based measure of accessibility is derived from discounting the attractiveness of the destinations by a travel or distance decay function derived from travel behavior surveys (Geurs and van Wee, 2004; Handy, 1994; Hansen, 1959; Owen and Levinson, 2014; Vickerman, 1974). Gravity based and cumulative opportunities measures of accessibility are highly correlated, allowing their interchangeable use in planning practice (El-Geneidy et al., 2011; El-Geneidy and Levinson, 2006). Developing accessibility measures requires the knowledge of travel time between all points in the region using the specified mode of transport (public transport) and the availability of destination data to be used in the calculations (jobs). This calculation can be done for morning peak or for different times in the day, while previous research has shown that using morning peak can be a reliable representation of accessibility and its impacts on travel behavior (Boisjoly and El-Geneidy, 2016a).

3. METHODS

Our approach to answering the research question relies on a series of linear regression models and ensemble machine learning (ML) models with boardings as the dependent variable and accessibility to jobs as the main explanatory variable of interest. Ensemble models can be used for both forecast and analysis roles (Wu and Levinson, 2021a), here we apply ensemble models to analyze the importance of each contributing factor in stop level boarding. The first set of models controls for sociodemographic and service characteristics at the stop level that have been found to be significant in existing stop-level ridership research. Prior to moving forward with additional models, different measures of accessibility are tested and the one providing the best model fit and meets ours needs is retained for subsequent models.

Across the region, bus stops vie for ridership from among the same pool of potential users. In Portland, many bus-stop service areas overlap, reducing walking distance to transit and creating necessary redundancy in the system. This overlap, however, also may give rise to competition between stops that must be accounted for to more accurately predict stop-level boardings. The second set of models incorporated metrics of inter-stop competition, which is largely missing from the existing literature. In the final set of models, we refine the variable related to competing accessibility to examine specifically the influence of overlapping accessibility offered by stops on different routes. Furthermore, additional jobs rendered accessible by other stops in the service area may also have influence the boardings at the stop in question as this may make the other stops more attractive to riders. We examine this as well in the final set of models.

3.1 Data

3.1.1 Stop-level boardings

Information about stop-level boardings was obtained from Automatic Vehicle Location/Automatic Passenger Counting (AVL/APC) data provided by TriMet for the period from August 2018 to November 2019. To align with other available data, including census data and a consistent set of transit schedules for TriMet and all nearby agencies, we selected a study period from Oct. 16, 2018, to Oct. 27, 2018. After cleaning the data to remove trips with faulty AVL/APC recordings and readings from final trip stops where passengers could not board, we tallied daily boardings for each stop location for each weekday in our study period and then averaged across the two weeks.

3.1.2 Service-area characteristics

The service area associated with each stop was generated using a street network analysis applying a threshold of ¼ mile (about 400 meters), which has been found to be an acceptable catchment area for bus stops in North America for planning purposes (Guerra et al., 2012). An OpenStreetMap (OSM) road network for the Portland metro region was downloaded and a layer representing the walkable network was created by removing roads that are inaccessible to pedestrians (including motorways, roads that are tagged as not accessible to the public or not accessible by foot). OSM has been tested by previous research and was found to be a reliable source to obtain street network compared to other street networks (Ciepłuch et al., 2010). To illustrate the influence of local accessibility to services on stop-level ridership, the Walk Score at the stop was obtained from the Walkscore.com using an application interface (API) for each stop location.

We obtained sociodemographic data that has been shown in past research to influence stop-level ridership from the 2014-2018 cycle of the American Community Survey (ACS) and the 2010 Decennial Survey. We wanted to work with the smallest census unit possible so for source variables that were available at the block level only from the more outdated Decennial Survey—population, ethnic makeup, and age groups—we updated the information using the more recent ACS by calculating growth rates for the associated block groups. For variables not available at the block level, such as median household income and household vehicle ownership, we directly downscaled the information from the ACS to the blocks that fall within each block group. Intensive areal weighted interpolation was then used to arrive at an average value for each stop service-area for spatially intensive sociodemographic characteristics. The total population within a stop's service area was generated through extensive areal interpolation where the sum is used rather than the average. An extra step was taken before the areal interpolation process to discount the population by walking distance from the stop using the negative exponential decay function ($1.0126e^{-0.0013x}$, where x is distance in feet) derived by Zhao et al. (2003) until the service area threshold of 400 meters, which is comparable to recent decay curves derived from similar North

American context regarding to the use of a decay curve (El-Geneidy et al., 2014; Kimpel et al., 2007).

3.1.3 Transit service and network characteristics

Information about the available stop-level transit service came from General Transit Feed Specification (GTFS) data obtained from transitfeeds.com for Wednesday, Oct. 17, 2018, which falls within the period for which the AVL/APC data was available. The GTFS data were obtained for all agencies serving the Portland metro region and accessible from TriMet stops within 60 minutes. Information for these non-TriMet agencies was needed for the sole purpose of generating accessibility to capture jobs outside of the TriMet service area that could be reached from TriMet stops through connecting to the other agencies' transit system.

Using the GTFS data for TriMet, which provides information about stop locations, routes serving each stop and daily trips at the stop, we derived the number of daily bus departures from the stop to represent service frequency at the stop and whether there is a MAX light-rail station which could influence bus stop ridership nearby. To capture the impact of competing stops as a result of being physically located closely to each other, we used the GTFS data to generate a variable for the number of other stops in the service area serving the same routes.

3.1.4 Jobs

Like population, the number of jobs associated with each stop was generated by extensive areal interpolation of the block-level jobs, discounted first by distance from the stop (using the same decay function from Zhao et al. (2003)), that fall within the service area. The job data at the blocks for 2018 was obtained from the Workplace Area Characteristics (WAC) table of the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES), enumerated by the 2010 census blocks (U.S. Census Bureau, 2021). The WAC table provides the number of employees working in each census block, which is a proxy for the number of jobs available in each block.

3.1.5 Accessibility

Both cumulative and gravity measures of accessibility to jobs from stops for the AM peak were generated using r5r, an add-on package for the R statistical software program, that provides convenient access to Conveyal's java-based R5 multi-modal routing engine (Pereira et al., 2021). The Conveyal engine was used previously in evaluating transport plans and was validated by several scholars as a reliable tool for conducting accessibility analysis (Grise et al., 2021). For cumulative measures, various cut-off periods were tested. For gravity accessibility measures, the travel time decay constant previously derived by Chaloux et al. (2018) for public transit was used ($1e^{-0.034x}$ where x is time in minutes). The gravity measure can be thought of as the equivalent number of jobs or people if they were located exactly at the stop. To account for the variability in travel times as a function of departure time, accessibility was calculated at every minute from 7:00 am to 8:30 am on October 17, 2018, to correspond to the peak period defined by TriMet (City of Portland, 2020). The 50th percentile accessibility values were considered in the models. Since our accessibility calculation is conducted at the stop level, it directly incorporates waiting and travel times. Egress time is indirectly incorporated in our calculations through the discounting of jobs using the decay function at every stop destination. Access time is incorporated in our models through the decay of the population in the service area of each stop.

3.1.6 Accessibility Overlap and Additionality

To assess potential competition between closely located stops, we analyzed accessibility overlap and accessibility additionality or complementarity. For overlap, we considered accessibility to specific jobs provided by each stop and the other stops located within its service area. In its simplest application, we successively compared the 30-minute travel time matrices for all stops within a 400 m network radius buffer without regard to the specific routes the nearby stops served. We then divided the mean number of specific overlapping jobs made reachable by other stops in the buffer by the total number of jobs accessible by the target stop.

Figure 1 demonstrates the basic calculation. Here, we consider a hypothetical Stop 1, which provides 30-minute accessibility to 1,600 jobs (the sum of jobs available at destinations B, C, and D). Other stops within Stop 1's service area provide access to at least some of these destinations. For example, Stop 2 can reach Destination B, and its associated 500 jobs. Stop 2 therefore possesses an accessibility overlap ratio with respect to Stop 1 of 500 overlapping jobs/1,600 total jobs accessible from Stop 1, or 31.25 percent. Similarly, Stop 4 has an accessibility overlap ratio of 600/1,600, or 37.5 percent with Stop 1. Stop 3 does not have any overlaps with Stop 1. To prepare an aggregate measure of competition faced by a stop within its service area, we take the mean overlap ratio based on all potentially competing stops ((31.25 + 37.5 + 0)/3). We hypothesize that a higher number of potentially competing stops will result in lower boardings at the target stop. To further refine the metric and better understand the role of potentially competing routes, we created an additional measure that calculated specific overlap from only those nearby stops serving entirely different routes, rather than both the same and different routes considered in the simplest version of this metric.

We also wanted to examine the competitive influence of additional jobs that are made accessible by other stops of different routes. We used the same technique comparing travel time matrices to generate a measure of accessibility additionality. To calculate this measure, we averaged the number of specific additional jobs nearby stops serving different routes made accessible. It is expected that the higher the average additional jobs that nearby stops served by different routes, the lower the boardings as other stops may be more attractive to users because of the additional jobs that can be reached.

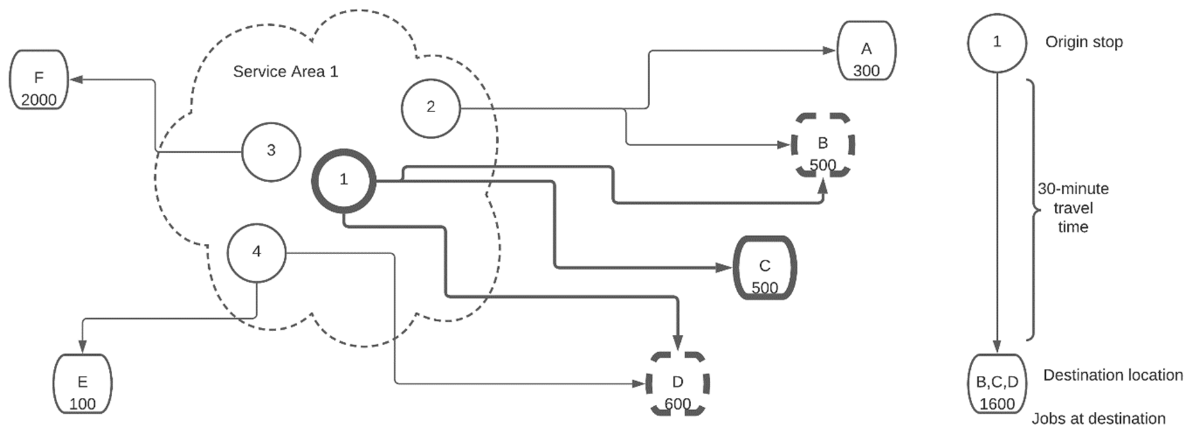

Figure 1 Diagram illustrating the calculation of overlapping accessibility as a measure of inter-stop competition.

3.2 Analysis

To explore accessibility's influence on ridership at the stop level, we first constructed an ordinary-least-squares (OLS) linear regression that controlled for local population, residents' ages, household income, and vehicle ownership, among other things (See Model 1 in

Table 4). All variables were tested for multicollinearity prior to executing the models and highly correlated variables were removed. Variance inflation factor (VIF) was also calculated after running the models to ensure no correlated variables are included in the final models. In our models, we applied a natural-log transformation to both our dependent variable—average daily stop-level boardings—and the primary explanatory variable of interest: stop-level public transport accessibility to jobs, when the average ridership was 0 it was converted to 0.0001, which is a common practice when doing log transformation in statistical modeling with zero values (Crown, 1998). The natural-log transformation allowed us to apply a simple and easily explainable model to what would otherwise be non-normally distributed count data. Simultaneously, transforming the jobs-accessibility variable allowed us to both improve model fit and directly generate elasticities (percent change-to-percent change comparisons). For population within the service area of each stop, we included its squared value to account for the apparently nonlinear relationship between this variable and stop-level boardings.

We tested equivalent models using am-peak morning boardings and service frequency. These models generated coefficients with identical directionality and similar magnitude but with a lower explanatory power than the daily models. For simplicity, we therefore did not report them here. Initial models also explored other variables that we ultimately discarded in the final runs. For example, we ultimately removed a statistically significant variable related to the ethnic makeup of the service area as we believe that this variable is not useful to planners who should not and could not attempt to influence the ethnic makeup of areas near stops. A variable for the percentage of carless households in the stop service area was found to be correlated with both accessibility and median income and was also removed from the model. In addition, a land-use variable for whether the stop service area is predominately residential and a simple dummy variable for the presence of at least one MAX LRT station, were also excluded from final models as they were not statistically significant after including other variables, such as area population.

We then generated models to explore the impacts of stop-versus-stop competition for riders in locations with overlapping service areas. In Model 2, we tested the influence of the presence of stops serving the same route as well as the accessibility overlap metric for stops serving the same and different routes as the stop in question. In Model 3, we replaced the metric of accessibility overlap from all stops, serving the same and different routes, with the refined metric to consider only the overlapping accessibility of stops serving different routes. In this model, we also incorporated our metric of accessibility additionality to evaluate the impact that additional accessibility provided by other stops can have on the ridership at the stop in question.

Lastly, we evaluated the relative importance of the variables retained in this final model using ensemble machine learning models. The use of ensemble models improves the reliability of analysis results. Both the random forest and gradient boosting machine models include mechanisms for examining the relative importance of variables (Friedman and Meulman, 2003). The importance of each explanatory variable is determined by how much the model prediction error changes with and without certain variables; the more a variable can reduce errors, the more influential it becomes among the set of explanatory variables. The amount of prediction error reduction attributed to each variable is ranked, so that variables with a significant amount of explanatory power can be identified.

4. RESULTS

The study's results are presented in multiple parts. We first discuss general ridership and local-area characteristics, providing an overview. Second, we describe the outputs of our final models, which document the relationship between stop-level ridership and (a) accessibility to jobs by public transport, (b) service-area and transit service characteristics, and (c) competition for riders among stops. Lastly, we present the results of the ensemble ML model which demonstrates the relative importance of the variables retained in the final model.

4.1 Descriptive Statistics

Our analysis of daily stop-level boardings encompassed 6,261 TriMet bus stops, which consisted of passenger-serving locations where boarding is allowed and for which we were able to generate complete ridership and service-area characteristics. The raw AVL/APC data contained 6,770 unique location ids, several hundred of which could not be matched with GTFS data or were located in areas for which census data at the block level was incomplete. The last stop at each bus route and pseudo stops added by TriMet for operations purposes to the AVL/APC data were excluded. On average, 28 passengers boarded TriMet buses at each studied stop per day (

Table 1). During the two-week period we examined, the AVL/APC data recorded zero daily boardings at 340 stops, predominantly located in areas outside central Portland. On the other hand, more than 30 stops registered over 500 daily boardings. These higher-use stops are located principally in Portland's dense downtown core or in the centers of other regional cities within the TriMet service area, such as Beaverton and Gresham.

Table 1 Summary statistics for TriMet bus stops and 400-meter service area.

Variable	Mean	St. Dev.	Min	25th Pctl	75th Pctl.	Max	Source
Average daily boardings at stop	28	72	0	1.56	25.7	1,259	TriMet AVL/APC data
Service-area characteristics							
Household median income in service area ($10k)	7.49	2.92	1.07	5.49	8.93	21.95	U.S. Census
Pop. over 65 years old (%)	14.3	9.23	0.00	8.82	17.44	131.6	U.S. Census
Pop. (100)	2.24	1.71	0.000	1.02	3.25	20.22	U.S. Census
Walk Score (0-100)	62	23	0	47	81	100	Walk Score
Transit service characteristics							
Daily 24-hour departures from stop	51.28	36.64	1	23	72	551	TriMet GTFS
Stops serving same routes	5.543	3.319	0	4	7	42	TriMet GTFS
Accessibility characteristics							
Cumulative 30-min access to jobs (10k)	17.42	33.64	0	1.44	10.63	142.1	U.S. Census - LEHD, PDX-area GTFS
Jobs rendered accessible by stop covered by other stops in service area (all routes) (%)	90.43	10.63	0	87.43	96.89	100	TriMet GTFS, LEHD
Jobs rendered accessible by stop covered by other stops in service area (different routes) (%)	49.5	46.1	0	0	100	100	TriMet GTFS, LEHD
Additional jobs accessible by other stops in service area of different routes (10k)	1.53	4.49	0	0	0.8	71	TriMet GTFS, LEHD

4.2 Accessibility, Service-area, Transit Service Characteristics, and Stop-Level Ridership

A complex array of local-area and transit-service characteristics combine to shape stop-level ridership. Accessibility—measured here by the number of jobs reachable within 30 minutes by public transport from the stop—plays a clear role, even after controlling for local areas' sociodemographic attributes and other transit-service characteristics. Model 1 in Table 4 shows that for every 1 percent increase in 30-minute accessibility, stop-level ridership could be expected to increase by 0.21 percent, all else being equal. The seemingly small elasticity belies a significant aggregate potential to bolster ridership through accessibility-focused service improvements. For example, a well-integrated bus-rapid-transit project—even in the context of an already robust public transport network such as Montreal—could yield localized stop-level accessibility increases on the order of 40 percent or more (Manaugh and El-Geneidy, 2012). An accessibility enhancement of this magnitude could be associated with a stop-level ridership increase of more than 8 percent when all other variables are held constant.

Daily service frequency—which has the potential to enhance accessibility by reducing waiting time—is itself closely aligned with stop-level ridership. Each additional daily bus departure from a stop is associated with a 2.7 percent increase in passenger boardings. Local accessibility is associated with increased transit usage at the stop level. A higher Walk Score, a measure that reflects the presence of amenities within the immediate vicinity of a location, correlates with increased stop-level ridership. Each one-point increase in the Walk Score at a bus stop's location equates to around 1.8 percent increase in daily boardings.

As expected, larger populations are strongly correlated with increased stop-level ridership up to a point. For every additional 100 residents within a stop's 400-meter service area, boardings could be expected to increase approximately 16.5 percent but this rate is expected to decrease by 1.4 percent with every additional 100 residents, all other variables held constant at their means. After approximately 600 residents in the 400-meter service area, the trend reverses and the number of boardings at a stop begins to decline. This inversion may be due to elevated amenity and job densities in the few areas where such large populations occur within the study region. In these amenity-dense locations, would-be public transport users may instead opt to walk or bike. This would be consistent with other research suggesting that public transport use may actually decline once accessibility exceeds a certain threshold (Cui et al., 2020). This generally occurs only in dense, highly walkable areas.

Greater affluence, as measured by income, is associated with declines in stop-level bus boardings. Every $10,000 increase in median household income within the service area correlates with a 19 percent decline in stop-level ridership, all else being equal. This, too, is consistent with other research on public transport mode share. An elderly population is associated with slightly lower stop-level ridership. Each point increase in the percentage of people over the age of 65 in the service area corresponds to a decline of 1.1 percent in boardings.

4.3 Different Measures of Accessibility

Additional measures of stop-level accessibility were tested to identify the best model fit. These included other cumulative measures with 15-, 45- and 60-minute cut-offs, and a time-decayed gravity measure, as shown in Table 2. Incremental measures of accessibility (e.g. jobs that can be accessed under 15 minutes, between 15 minutes and 30 minutes, etc.), shown in Table 3, were also considered to evaluate the relative influence of jobs that can be accessed with each additional 15 minutes . In each case, we substituted only the accessibility variable and retained all others contained within Model 1.

The magnitude of accessibility's correlation with daily boardings appears greatest when using the time-decayed metric. The best model fit is observed for models using the incremental measures of accessibility ($R^2 = 0.368$) but only minutely when compared to the cumulative measure with a 30-minute travel time threshold ($R^2 = 0.367$). In addition, the insignificance of all the incremental accessibility measures except for accessibility between 15 and 30 minutes illustrates that jobs that can be accessed over very short as well as longer bus travel times (less than 15 minutes or longer than 30 minutes from the origin to the destination stop) do little to influence ridership at the stop level. After retaining the only significant incremental accessibility measure, the model fit remains stable and is comparable to the model using the cumulative 30-min accessibility measure. For the sake of simplicity, we elected to retain the cumulative 30-minute accessibility measure for subsequent models, which is consistent with previous research regarding average travel time in North America (Levinson and Kumar, 1994; Marchetti, 1994).

Table 2 Comparative assessment of stop-level accessibility measures.

	Coefficients for ln(Daily Stop-Level Boardings)	Average accessibility at stop	Model R^2
Accessibility Measures			
ln(time-decayed access to jobs (10,000))	0.230	322,601	0.362
ln(cumulative 15-min access to jobs (10,000))	0.168	23,317	0.363
ln(cumulative 30-min access to jobs (10,000))	0.213	174,203	0.367
ln(cumulative 45-min access to jobs (10,000))	0.122	556,561	0.362
ln(cumulative 60-min access to jobs (10,000))	0.101	1,048,775	0.361

Table 3 Regression results for incremental accessibility measures.

	Dependent variable	
Predictors	**ln(Daily Stop-Level Boardings)**	
	(a)	(b)
ln(0-15min access to jobs (10,000))	0.048	
ln(15-30min access to jobs (10,000))	0.193^{***}	0.201^{***}
ln(30-45min access to jobs (10,000))	-0.029	
ln(45-60min access to jobs (10,000))	0.025	
R^2	0.368	0.367
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.4 Competing Stops and Stop-Level Ridership

In Model 2, we test the presence of stops serving the same route as well as accessibility overlap from stops served by both the same and different routes. For each additional stop on the same route within the buffer, boardings at the stop under consideration are estimated to be 12.3 percent lower, with all other variables held constant at their mean. Similarly, each additional percentage point of average accessibility overlap is associated with a 2 percent decline in stop-level ridership.

After accounting for competition in Model 2, the direction and significance of other variables remained largely stable. The influence of cumulative access declined slightly to a 0.18 percent increase in boardings for every 1 percent increase in the number of jobs reachable by public transport in 30 minutes, all else being equal. Meanwhile, Walk Score's positive correlation with stop-level ridership rose slightly to 2.1 percent in stop-level ridership for each point increase in the measure of local accessibility.

Model 3 further explores the connection between potentially competing stops by (a) focusing on competition generated by the co-location of stops serving different routes, (b) documenting the nonlinear relationship between the accessibility overlap generated by these specific nearby stops and (c) introducing a measure of accessibility additionality.

As expected, competition from other nearby stops serving different routes while providing access to the same destinations and jobs is associated with a decrease in stop-level boardings, but only after a certain threshold. Initially, accessibility overlap is associated with an increase in stop-level boardings, as demonstrated by the positive coefficient for the regular or non-squared accessibility overlap variable. After approximately 45 percent of overlap, the relationship reverses—as shown by the negative coefficient for the squared term of the nonlinear relationship. This may indicate that in areas of extremely low accessibility overlap, the presence of even a modest amount of service from other routes may simply be associated with higher local transit ridership in absolute terms. Meanwhile, in areas of exceedingly high accessibility overlap, riders may enjoy greater choice in stops and services providing access to the same destinations, thus spreading riders over a wider range of stops and suppressing the number of boardings at any individual stop.

Enhanced or additional accessibility provided by nearby stops—rather than redundant accessibility—also is associated with a decline in stop-level boardings. For each additional 10,000 jobs that cannot be reached from the target stop but that are made accessible by nearby stops, stop-level boardings could be expected to decline by about 1.4 percent, all else being equal. This decline in stop-level boardings could reflect a different type of competition, one based on the enhanced attractiveness of another stop rather than simply the availability of other stops. We did not find a non-linear relationship between this variable and boardings.

In this final model, the direction and magnitude of other variables are mostly stable relative to Models 1 and 2. The influence of cumulative access rose to 0.2 percent after dropping to 0.18 percent in Model 2. In addition, the influence of income dropped slightly in Model 3 with the addition of refined accessibility overlap and additionality variables. The model fit of Model 3 is also the best when compared to Models 1 and 2 (as shown by higher R^2 and lower AIC), implying that the refinement of the accessibility overlap variable and the addition of the accessibility additionality variable were useful to improve the explanatory power of the model.

Table 4 Regression results for predicting average daily boardings (values in parentheses are confidence intervals)

Predictors	***Dependent variable:* ln(daily boardings)**		
	(1)	(2)	(3)
ln(cum. 30-min access to jobs (10,000))	0.213***	0.181***	0.202***
	(0.162, 0.263)	(0.131, 0.230)	(0.151, 0.254)
Pop. (100s) (distance discounted)	0.165***	0.197***	0.193***
	(0.087, 0.243)	(0.120, 0.274)	(0.116, 0.270)
Pop. squared (distance discounted)	-0.014***	-0.015***	-0.013***
	(-0.022, -0.005)	(-0.023, -0.006)	(-0.022, -0.005)
Total daily stop departures	0.027***	0.033***	0.031***
	(0.025, 0.029)	(0.030, 0.035)	(0.029, 0.033)
Walk Score	0.018***	0.021***	0.019***
	(0.013, 0.022)	(0.017, 0.026)	(0.015, 0.023)
Med. household income ($10k)	-0.186***	-0.179***	-0.177***
	(-0.209, -0.163)	(-0.202, -0.156)	(-0.200, -0.154)
Pop. over 65 (%)	-0.011***	-0.008**	-0.008**
	(-0.018, -0.004)	(-0.015, -0.001)	(-0.015, -0.002)
Stops serving same routes		-0.123***	-0.131***
		(-0.144, -0.102)	(-0.152, -0.110)

Jobs rendered accessible by stop that are covered by other stops of same and different routes (%)		-0.020*** (-0.026, -0.014)	
Jobs rendered accessible by stop that are covered by other stops of different routes only (%)			0.0636*** (0.052, 0.075)
Jobs rendered accessible by stop that are covered by other stops of different routes only squared ($\%^2$)			-0.0007*** (-0.001, -0.001)
Additional jobs accessible by other stops of different routes only (10k)			-0.014** (-0.028, -0.001)
Constant	-0.104 (-0.457, 0.249)	1.740*** (1.111, 2.370)	0.066 (-0.281, 0.413)
Observations	6,261	6,261	6,261
R^2	0.367	0.385	0.393
Adjusted R^2	0.366	0.384	0.392
AIC	29,091.1	28,918.6	28,834.6
Residual Std. Error	2.468 (df = 6253)	2.434 (df = 6251)	2.417 (df = 6249)
F Statistic	517.872*** (df = 7; 6253)	434.043*** (df = 9; 6251)	368.081*** (df = 11; 6249)
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.5 Relative importance of variables

The relative importance of variables retained in Model 3 are shown in Table 5 using random forest and gradient boosting ML models. Two additional formulations are developed for each model– one with daily departures as an explanatory variable (Model RF 1 for random forest and GB 1 for gradient boosting) and the other one without (Model RF 2 and GB 2).

In the absence of the daily departures variable, both the random forest and the gradient boosting machine models produced identical rankings in terms of the relative importance of explanatory variables. Accessibility is identified by both models as the most important variable in explaining stop level boarding, followed by median household income, and the Walk Score. In both models, the importance of accessibility variable leads other variables by a notable margin, suggesting the special role of transit accessibility in explaining ridership.

Table 5 Relative importance of variables with respect to daily stop-level boardings

Predictors	***Relative importance (%) of predictors on dependent variable:*** **ln(daily boardings)**			
	(RF 1)	(GB 1)	(RF 2)	(GB 2)
Total daily stop departures	30.97	54.03		
ln(cum. 30-min access to jobs (10,000))	16.37	9.02	22.80	39.80
Med. household income ($10k)	12.01	9.84	17.11	18.55
Walk Score	12.08	9.29	16.00	11.36
Pop. (100s) (distance discounted)	8.86	5.80	13.31	8.29
Pop. over 65 (%)	8.80	5.74	11.22	8.23

Stops serving same routes	4.13	2.76	6.24	4.01
Jobs rendered accessible by stop that are covered by other stops of different routes only (%)	3.65	2.40	7.41	6.97
Additional jobs accessible by other stops of different routes only (10k)	3.13	1.11	5.91	2.79

5. CONCLUSION

Transit operators and policymakers have increasingly adopted accessibility as both an overarching goal and a key performance metric because of the concept's unique ability to bridge the divide between transport and land use systems (Boisjoly and El-Geneidy, 2016b; DeWeese and El-Geneidy, 2020; Handy, 2005). Planning for access, as opposed to mobility, focuses on solutions that ensure that users' trip-making needs are adequately met. In this way, accessibility as a performance measure could be used to track the public transport system against each element associated with the triple bottom line of sustainability – economic, environmental as well as social in terms of equity.

Here, we demonstrate that accessibility, usually applied at larger scales, such as the system or route level, has a role to play in furthering operators' and planners' understanding of the determinants of stop-level ridership. Modeling show that accessibility is a significant factor in explaining stop level boarding, and it has a greater impact on ridership than other social demographic variables explored in this paper. By placing accessibility's benefits within the stop-level context most familiar to transit operators, we hope that this paper will further facilitate its adoption in practice.

In the aggregate, bolstering the level of accessibility provided by stops through clever network design, improvements in service reliability and speed, or by offering additional service, may yield significant improvements in ridership. Understanding precisely where and how these ridership increases may occur can help agencies better plan and allocate resources. This understanding necessarily includes a consideration of the competition effects that may arise from the interaction of closely located stop locations and the overlap in their associated services. The models developed in this paper demonstrate that, within a small area, a multiplicity of stops providing access to the same locations and opportunities may cannibalize, rather than bolster, ridership. Similarly, the presence of other attractive stops—those that provide service to both the same locations and additional ones—may further suppress stop-level boardings at a particular location.

The measures of specific accessibility overlap and additionality we apply do not merely fine tune our expectations regarding ridership under different accessibility scenarios. Its application may also assist agencies and planners in identifying opportunities to relocate or even remove stops without compromising overall accessibility. Optimizing stop locations may yield significant benefits for riders and agencies alike in the form of reduced in-vehicle passenger stopping costs (and thus faster trips and greater access), operating efficiencies, or even capital savings (El-Geneidy et al., 2006; Stewart and El-Geneidy, 2016; Wu and Levinson, 2021b).

Taken as a whole, this study underscores and extends the usefulness of accessibility as a concept applied to more fine-grained transport planning analyses and decisions. The development of stop-level accessibility creates an accessibility performance measure for analysis that is typically already undertaken. It also highlights the range of ways in which public transport agencies, planners, and policymakers can more productively and efficiently deploy new and existing resources to promote ridership, helping to achieve critical social and environmental goals.

5.1 Limitations

Several refinements can be done on the models developed in this study. Time-of-departure information, rather than the cumulative daily travel flows available in the LEHD data, might improve our understanding of the true levels of accessibility experienced by actual travelers. Similarly, other accessibility measures accounting for a broader basket of meaningful opportunities might help to better calibrate models of stop-level ridership, as people do not travel solely for work. Destination jobs can serve as a valuable proxy for economic activities that may, in turn, represent desirable nonwork opportunities for others. Those jobs may represent office or industrial workers making a transit commute, retail workers at stores, ticket-takers at cinemas, or librarians at libraries. But there are countless other destinations, including parks or volunteer-operated facilities, that do not appear in the work-related data. The decay curve used in calculating population and jobs around station was derived from previous research, future work can develop more detailed decay curves if access to detailed walking to stops is available in the region.

DATA ACCESSIBILITY STATEMENT

1. The stop-level boardings were generated using cleaned and processed AVL/APC data which were provided directly by TriMet. The agency has agreed for the authors to publish the aggregated average daily stop-level boardings.
2. The road network used to generate accessibility measures using the R5R package in R and subsetted to create the walkable network layer for the creation of stop services area is extracted from OpenStreetMap for the Portland Metro region using the web tool BBBike extracts OpenStreetMap.
3. The 2014-2018 American Community Survey and 2010 Decennial Survey census data provided by the US Census Bureau was obtained using the tidycensus package in R.
4. The GTFS data for all agencies serving the Portland Metro region and accessible from TriMet stops within 60 minutes is publicly available at https://openmobilitydata.org/l/63-oregon-usa (for agencies in Oregon) and https://openmobilitydata.org/p/c-tran/282 (for C-Tran operating in Vancouver, WA). A list of the agencies that were considered in the study are provided in the data repository.
5. Origin-Destination Employment Statistics (LODES) datasets are publicly available and are provided by the Longitudinal Employer-Household Dynamics (LEHD) program at the U.S. Census Bureau. The authors used the grab_lodes package in R to extract the datasets for 2018 used in the study but they are also available online for Oregon at https://lehd.ces.census.gov/data/lodes/LODES7/or/wac/or_wac_S000_JT00_2018.csv.gz; and Washington at https://lehd.ces.census.gov/data/lodes/LODES7/wa/wac/wa_wac_S000_JT00_2018.csv.gz.

6. The final dataset used in the models that were tested for this study as well as the associated R scripts for extracting and organizing the data used and for running the models are included in the data repository set up for this project.

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