The Multimodal Connectivity at Bus Rapid Transit (BRT) Stations and the Impact on Ridership

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A multimodality index (MI) is developed to evaluate the accessibility and convenience of transit use by investigating the connectivity of a Bus Rapid Transit (BRT) with other modes of travel. Better connected stations increase transit system ridership, resulting in environmental and social equity gains. The integration of the Orange Line BRT system in Los Angeles with other travel modes, including bicycles, pedestrians, regular buses, and private automobiles, was analyzed using field observations and LA Metro data to create a multimodality index (MI). While multimodal connectivity of the Orange Line BRT system varies across stations, a positive relationship exists between ridership and the MI, indicating that the MI is a reliable predictor of transit ridership and a useful tool for transit planning.

INTRODUCTION

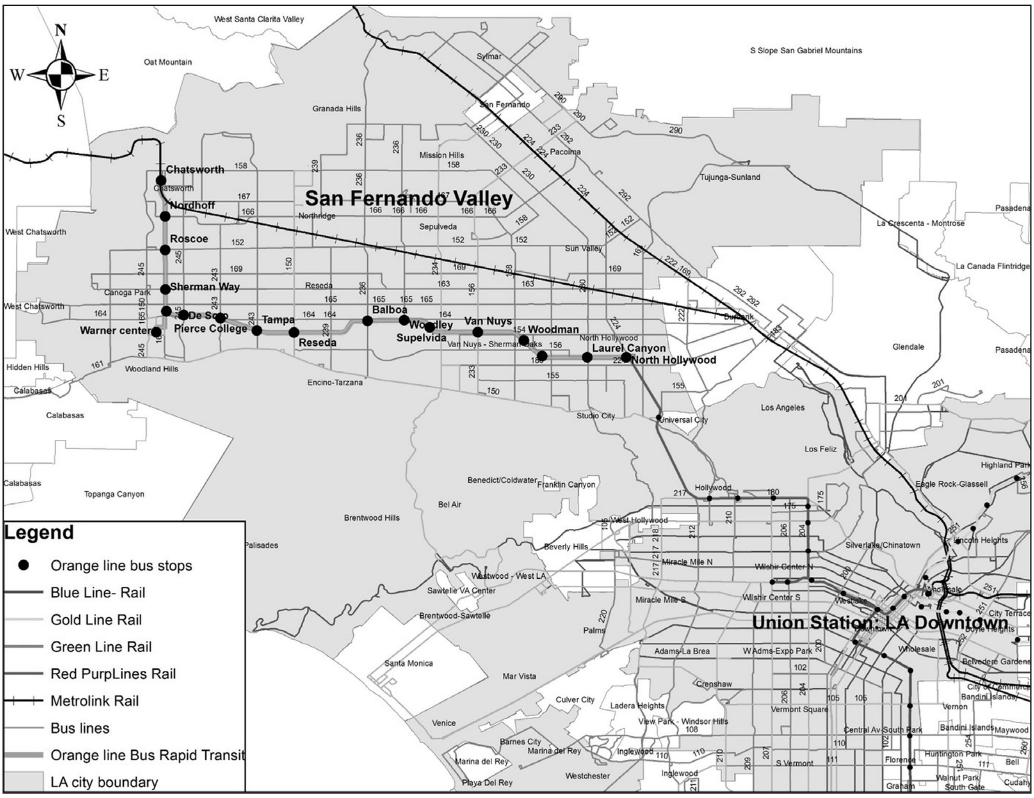
Urban residents frequently utilize multiple transportation modes to travel across the city, making their trips multimodal (Keshkamat et al. 2009; Liu 2011). Multimodal transportation is the use of two or more modes to move people or goods from an origin to a destination (DeWitt and Clinger 2000); and a multimodal transportation system is a system that elegantly integrates multiple travel modes across an urbanized area (Bielli et al. 2006). Public transit, especially Bus Rapid Transit (BRT), is an important part of a multimodal system. Dill et al. (2013) found that BRT ridership depends on several station-level factors, including multimodal connectivity. BRT is considered an ideal form of public transportation because its flexibility, affordability, and accessibility provide overall positive environmental and social benefits (Cain et al. 2007; Hidalgo and Carrigan 2010; Vincent and Jerram 2006; Wright and Fulton 2005; Cervero 2013). So, increasing multimodal connectivity to BRT increases accessibility and reduces traffic congestion, roadway costs, and energy consumption.

Rickert (2010), Duarte and Rojas (2012), and Dill et al. (2013) found that the connectivity of a BRT with walking, cycling, automobile, and other forms of public transit increases ridership. Higher ridership occurs because patrons know they have a convenient alternative transportation mode to complete their first and last miles of their overall trip. When stations and areas surrounding the stations are designed to integrate alternative travel modes, BRT ridership increases and multimodal patrons have more efficient trips. In 2014, the Institute for Transportation and Development Policy's (ITDP) BRT Standard (2014) identified only four qualified BRT systems: Cleveland, Ohio; Los Angeles Metro Orange Line; Eugene, Oregon; and San Bernardino, California (operational as of April 2014 and not assessed yet). This study will determine the Los Angeles Metro Orange Line station's multimodal connectivity and the effects on ridership.

The Metro Orange Line serves passengers in Los Angeles' suburban San Fernando Valley. Orange Line users can access stations by transferring from commuter rail, subway, and regular bus; biking; walking; driving individual automobiles using park-n-ride facilities, and carpooling and taxis using *kiss-n-ride* (drop off locations where cars can drop off and pick up passengers). The terminus stations have access to larger mass transit systems. At the North Hollywood station, the Orange Line connects to the Red Line subway, which travels through famous population and employment centers including Hollywood, Koreatown, and Downtown Los Angeles. The Orange Line's northwest terminus, the Chatsworth Station, connects passengers to Metrolink (regional) and Amtrak (national) rail service. The Orange Line provides a practical alternative to the automobile, the main mode of transportation in the San Fernando Valley for work, school, shopping, and entertainment trips. The Orange Line began service in October 2005 and was extended from Warner Center to Chatsworth in June 2012. It has quickly exceeded the initial planned ridership levels. Exploring the Orange Line's ridership and multimodal connectivity will allow transit planners to better understand how to make successful BRT systems.

Thus, the infrastructure at and around the Orange Line stations will be analyzed to determine if multimodal connectivity impacts ridership. Pedestrian, cyclist, transit, car, and taxi connections will be examined at each station to determine if ridership is higher at stations with better multimodal connectivity.

Figure 1: The BRT Orange Line in San Fernando Valley



LITERATURE REVIEW

Since World War II, transportation planning in the United States focused on maximizing the efficiency and speed of one mode of transportation (usually the automobile) rather than evaluating and increasing the efficiency of a user's multimodal trip. Building highways was the main priority of transportation legislation until the passage of the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) shifted the focus to multimodal trips (Dilger 1992). In this new era, comprehensive assessments of different travel modes' connectivity were used by metropolitan agencies to develop sustainable transportation systems and to influence local and regional transportation and land use plans (Strate et al. 1997).

Since ISTEA, transportation planning research and transportation modeling techniques account for a wider range of travel options, including walking, biking, carpool, and public transit and evaluate the multimodal system's effect on emissions and land use. This new paradigm recognizes that the ultimate goal is accessibility: people's overall ability to quickly reach desired services and activities

(Litman 2014). Thus, a multimodal transportation system increases the options provided for users to best meet their needs and preferences (Mahrous 2012; Talbott 2011; Cervero and Kockelman 1997; Polat 2012; Nobis 2006; Godefrooij et al. 2009).

While research has focused on the multimodal network at a system level (Bielli et al. 2006; Hochmair 2008), multimodal access at stations has also been studied (Kerman et. al, 2014; Iseki et al. 2007). Kerman et al. (2014) found that transit station design can increase connectivity for pedestrians, bikers, and transit and automobile users. Increased connectivity, with more direct walking routes and better pedestrian facilities, increases the likelihood of transit being incorporated into a multimodal trip (Dill 2004; Moudon et al. 1997; Frank et al. 2005). Dill (2004) identified sidewalk coverage, average block size, and intersection density as three indicators of connectivity. The recommended target for sidewalk coverage, the percent of streets with sidewalks on both sides of the streets within one-half-mile of a station, is 67%. Smaller block sizes increase the station permeability by increasing pedestrian route choices to access transit, with a recommended size of four acres or less. Higher intersection density, the number of four-way intersections per acre, increases the likelihood for more walking routes and increases the ability of a user to take the most direct route (Dill 2004).

Public transit and bicycles are highly compatible modes of transportation (Nelson and Nygaard 2009), so facilitating bicycle access to transit facilities can increase transit ridership. Providing direct, safe routes to stations with dedicated bike lanes and allowing bikes aboard BRT vehicles increases ridership, particularly for routes that carry many riders who travel long distances and collect riders from lower density neighborhoods. Nelson and Nygaard (2009) argue that bike storage at stations and accommodating bicycles aboard BRT vehicles promotes multimodal corridor ridership. Olwert et al. (2015) found that when the Metro Orange Line evening service was increased, stranded cyclists decreased and bicycle ridership increased.

Besides walking and bicycling, other multimodal users arrive by transit and automobile. Evans (2004) found when wait times for BRT customers transferring from local feeder service exceeded 7.5 minutes, ridership decreased. However, when timing of the transfers was optimized and walking connections were minimized, BRT ridership increased (Evans 2004). BRT ridership also increases when more park-n-ride spaces are added. Levinson and Weant (2000) found that ridership increases by 0.74 to 0.77 riders per added parking space with 0.11 to 0.60 of them being new riders.

Multimodal accessibility has been evaluated in several ways: evaluating the immediate area to a transit station, considering the overall transportation system connectivity, and finally, looking at station specific attributes. By looking at the area immediate to a station, researchers have found ways to make recommendations to increase multimodal accessibility at the stations by improvements in an area surrounding the station. Iseki et al. (2007) developed an evaluation tool to assess the quality of transit transfer facilities by focusing on items that improve a passenger's experience: minimal transfer time and distances, and maximum convenience, comfort, safety, and security. Guttenplan and Reynolds (2012) analyzed the level of service (LOS) for connecting modes (automobile, transit, bicycle, and pedestrian) based on the urban street design and operations around the transit stations. The resulting report card evaluates how well streets meet the needs of its different users.

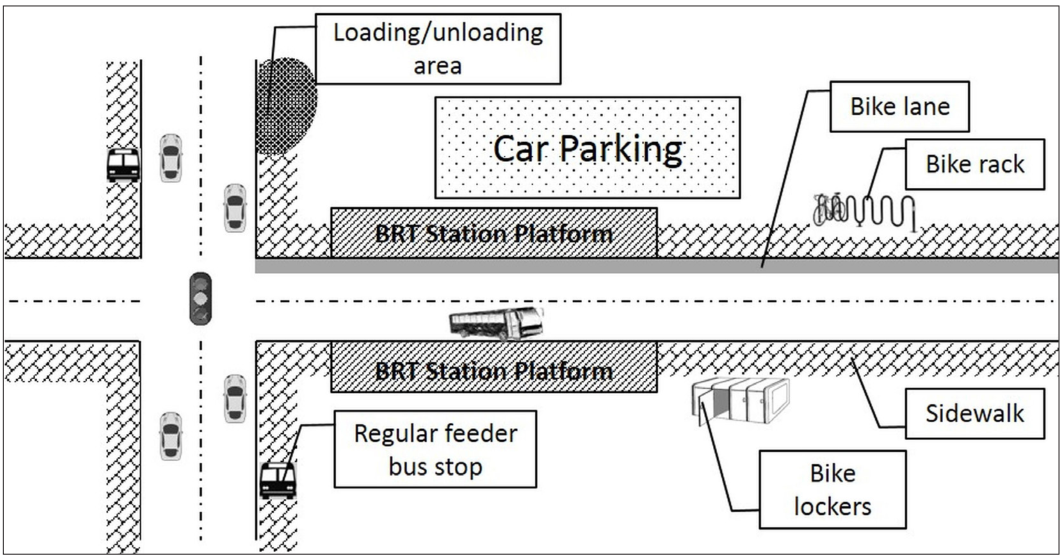
Frank (2008) applied the traditional shortest path algorithms to create integration between different travel modes across the transportation system. Scheurer and Curtis (2008) used spatial network analysis of a multimodal urban transport systems tool (SNAMUTS) to identify and visualize strengths and weaknesses of geographical coverage, network connectivity, competitive speed and service levels to understand the multimodal connectivity of a transportation system. Waddell and Nourzad (2002) used regional accessibility of a neighborhood to assess the multimodal connectivity of the overall transportation system.

Although a system level multimodality analysis is the focus of the above-mentioned studies, some research focuses on station-level connectivity analysis. Martens (2007) analyzed the impact of bicycle infrastructure at stations on ridership and the results indicate that improved bicycle services at stations lead to an increase in public transport ridership and a (small) decrease in car use on specific routes. Duarte and Rojas (2012) evaluated Curitiba and Bogota's BRT stations to determine if different modes of transportation were connected, including sidewalk access, bicycle parking, car parking, and accessibility for the disabled. They found that Bogota's BRT stations had better pedestrian and bicycle access than Curitiba. Neither of the cities had good access for private cars but better access for taxis. Our study further extends the literature on station level connectivity and their influence on ridership.

DATA AND METHODS

The goal of this study is to create a multimodality index (MI) that comprehensively measures a BRT station's connectivity. Station elements that facilitate access by multiple modes were incorporated, including availability and quality of nearby sidewalks, availability of bike infrastructure, availability of parking for cars and bikes, connectivity to regular feeder buses, and presence of kiss-n-ride facilities. Field observations were made within a 100-feet radius for all 18 BRT Orange Line stations using a standardized checklist for all five variable categories included in the MI calculation.

Figure 2: Multimodal Features for Ideal Connectivity

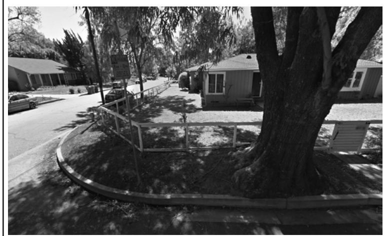


Data for Multimodality Index

Trained field observers assessed the following features: sidewalks, bikeways, parking, bus connections, and taxi and/or kiss-n-ride. This section explains the grading systems and how data for the index calculation were derived.

1. **Sidewalks.** All streets segments within a 100-feet radius of the platform's peripheral point were assigned a grade of 1-5 based on sidewalk availability, quality and compliance with the Americans with Disabilities Act (ADA). A detailed description of the sidewalk grading system is presented in Table 1. The final sidewalk assessment score for each station was calculated as the average sidewalk quality score of all street segments in the station buffer area (an area that covers a 100-foot radius around the platform's peripheral point).

Table 1: Sidewalk Quality Scale

Grade	Description	Picture representation
1	**EXTREMELY POOR QUALITY SIDEWALK:** Unpaved path, sloping, uneven dirt or grass. A score of 1 means that no sidewalk is present: no pavement	
2	**POOR QUALITY SIDEWALK:** Discontinuous paved sidewalk. A grade 2 sidewalk is non-continuous. There are stretches of pavement, but also sections of grass and/or dirt. In Los Angeles, some properties have a paved sidewalk in front of them and others have dirt or grass. Sidewalks of grade 2 are hazardous because they may seem walkable but can easily cause a person to fall because of the varied surfaces.	
3	**FAIR QUALITY SIDEWALK:** Paved sidewalk, with many obstacles: large cracks or bumps that can cause a person to trip or fall. Injuries can occur from falls on the cracks and bumps, especially for children and the elderly.	
4	**VERY GOOD QUALITY SIDEWALK:** Paved level sidewalk with no surface obstacles, *without* ADA-complaint ramps at crossings.	
5	**EXTREMELY GOOD QUALITY SIDEWALK:** Paved level sidewalk with no surface obstacles, *with* ADA compliant ramps at crossings.	

Source of pictures: ©2015 Google Map

2. **Bikeways.** The length of Class I, II, and III bicycle infrastructure within a 100-feet radius of the stations was used to create a bike quality score. The Los Angeles Metropolitan Transportation Authority defines the three classes of bicycle right-of-ways as shown in Table 2. Utilizing field observation, all streets and right-of-ways within the station buffer was classified. GIS was then used to calculate the length of each bicycle right-of-way classification for each BRT station. The data were inputted into the Bikeway Quality equation, presented below, which expresses each station bike score as a ratio weighted by the access quality of each classification.

$$(1)\quad Bikeway\ Quality\ Score = \frac{3l_1 + 2l_2 + l_3}{\sum_{i=1}^{3} l_i}$$

where, l is the length of the road segments of each of the three class types i.

3. **Parking**. Counts of available parking spaces were recorded as continuous variables in three mode categories: 1) car parking spaces, 2) bike lockers, and 3) bike racks
4. **Bus Connections**. Using the Los Angeles Metropolitan Transportation Authority transit line maps, the count of regular, express, and municipal bus connections to each Orange Line BRT station was recorded as continuous variable data. Connections were defined as the number of other transit lines which intersect and stop at an Orange Line BRT station.
5. **Taxi and/or Kiss-n-ride**. The presence of designated taxi and passenger kiss-n-ride zones was recorded as a binary variable (available=1; not available=0). Designated facilities, marked by signage, could be provided as short-term parking spaces, turnout areas, and curbside temporary parking.

Table 2: Classification for Bikeways

Class	Description	Picture representation
Class I	A class I bicycle path is completely separated from automobile traffic. Class I paths are usually found along current transit systems, rivers, parks, and/or former train track corridors.	
Class II	A class II bicycle lane is on-street with painted striping to separate cyclists from moving traffic and parked cars. This is the most common class in Los Angeles.	
Class III	A bike route or a sharrow is not a lane or a path. Markings or signage remind automobile drivers that cyclists may be present.	

Source of pictures: ©2015 Google Map

Table 3: BRT Station Amenities Used to Calculate the MI

Stations	Sidewalk quality (out of 5)	Bikeway quality score	Bike rack spaces (count)	Bike locker spaces (count)	Car parking spaces (count)	Kiss-n-ride facility available	Public transit connections (count)	Area characteristics	Multimodality Index (MI)	Total boarding (2014)
Chatsworth	4	2.5	16	16	610	1	9	Terminus	8.14	16,391
Nordhoff	3.38	2.5	12	8	0	0	2	Industrial/ Employment center	-2.77	10,145
Roscoe	4	2.5	12	8	0	0	2	Residential	-0.50	22,437
Sherman Way	3.98	2.5	12	16	207	1	2	Residential	1.91	29,201
Warner Center	4.5	2	6	0	0	0	11	Employment center	3.31	20,937
Canoga	4	1.5	24	32	288	1	2	Employment center/retail	5.29	33,571
De Soto	2.88	1.2	12	8	0	0	4	College	-5.65	14,807
Pierce College	3.25	1.5	12	8	373	1	2	College	-2.98	24,948
Tampa	3.25	1.5	12	8	0	1	1	Residential	-4.55	12,840
Reseda	3.63	2.5	6	16	522	1	2	Residential/retail	0.01	53,463
Balboa	4	2.75	12	20	270	1	5	Residential	4.83	27,121
Woodley	3.17	2.75	8	16	0	0	2	Residential	-3.11	17,876
Sepulveda	4.33	1.5	12	12	1205	1	2	Residential/retail	3.62	37,964
Van Nuys	3.75	2.5	12	8	776	1	8	Employment center/retail	5.16	81,260
Woodman	2.5	2.5	12	8	0	0	3	Residential	-5.35	20,513
Valley College	2.88	2.5	8	8	0	0	5	College	-3.76	21,734
Laurel Canyon	4	2	8	8	0	0	3	Residential	-1.76	29,241
North Hollywood	4	1	8	32	952	1	12	Terminus	8.15	167,514
Mean	*3.64*	*2.09*	*11.33*	*12.89*	*289.06*	*0.56*	*4.28*		0.56	35,664.61
SD	*0.55*	*0.57*	*4.12*	*8.41*	*378.77*	*0.51*	*3.41*		4.59	36,918.99
Min.	*2.5*	*1*	*6*	*0*	*0*	*0*	*1*		-5.65	10,145
Max.	*4.5*	*2.75*	*24*	*32*	*1205*	*1*	*12*		8.15	167,514

Data for Statistical Analysis

Station-level boarding and socio-economic data were collected for each station. Ridership data for the BRT Orange Line wer obtained from the Los Angeles Metropolitan Transportation Authority for the year 2014. Socio-economic data were obtained from several open source databases: the American Community Survey, Zillow, and Great Schools (a non-profit organization which provides nationwide school statistics). The following control variables were obtained for a one-mile radius from each station: density (measured in persons/acre), the distance from downtown (Union Station), the log of household income for the census tracts adjacent to the station, and the number of high schools within a mile radius from the station. The control variables are chosen with the assumption that denser areas have more people closer to stations that can use transit (Kolko 2011); stations closer to downtown are likely to have more ridership due to proximity to residences, shopping, and jobs; richer households are more likely to operate their own personal vehicles and not use transit (Neff 2007); and a larger number of teenagers in the area are expected to increase a population of more mobile residents who are less likely to have their own personal vehicles (Woldeamanuel 2014). The 2014 boarding data were available for both east and west travel, so west boarding was added as a dummy control variable. The data were also available by month (except for incomplete November data that were removed) so March, which had the highest ridership, was used as the reference variable and dummy variables were added for the rest of the months. Metro also collect the data as weekday, Saturday, and Sunday boarding. Because of commuting, higher numbers are expected during the weekdays, so Saturday and Sunday were both added as dummy variables because of expected lower ridership during the weekend.

Table 4: Data for Statistical Analysis

Variables	Mean	Std. Dev.	Min.	Max.
Station Boarding				
Total boarding (2014) per station	35,664.61	36,918.99	10,145	167,514
Westbound boarding (2014) per station	17,601.83	37,972.49	0	167,514
Eastbound boarding (2014) per station	18,062.78	12,047.38	0	54,663
Weekdays boarding (2014) per station	17,402.06	16,888.02	5,618	77,303
Saturday boarding (2014) per station	10,334.44	11,239.88	2,601	50,411
Sunday boarding (2014) per station	7,928.11	8,951.76	1,926	39,800
Control Variables (1-mile radius)				
High Schools (count)	3.44	2.04	0	7
Median Household Income ($)	53,658	9,784	41,910	73,557
Population Density (persons/acre)	16.66	6.31	6.58	26.14
Distance from Union Station (miles)	21.95	6.37	12.7	33

Multimodality Index Calculation

The multimodality index represents the relative ease to transition to or from the BRT line. Since the measurement units for each subcomponent variable used to calculate MI varies significantly (as seen in Table 3), the scores are normalized:

(2) $NS_j = \frac{x_j - \bar{x}_j}{s_j}$

where the normalized score for each attribute j, NS_j, is calculated as the score, S_j , minus the mean, $\bar{x}_j$, and then divided by the standard deviation, s_j. The normalized scores can be directly compared to assess each category's relative impact on the multimodality index.

The attributes, j, include sidewalk scores, bikeway scores, number of parking spaces, number of transit connections, presence of kiss-n-ride, number of bike spaces, and number of bike lockers. The normalized scores for each station are then inputted into the calculation of the multimodality index. As presented below, the MI is calculated as the sum of the normalized scores, NS_j multiplied by their weights, w_j.

(3) $MI = \Sigma_j \, w_j \, NS_j$

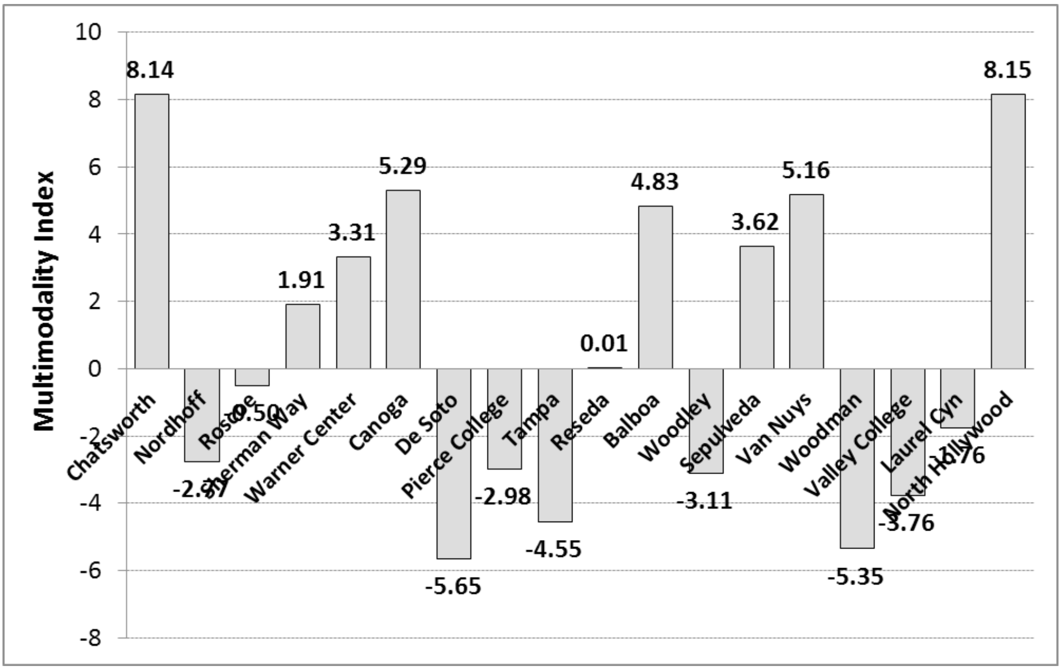
All the weights were set to one, except for the sidewalk quality and public transit connection scores. For these two variables the weight is set to two because they are underrepresented compared with the other modes. Biking has locker, rack, and bikeway quality; auto mode has parking and kiss-n-ride facilities, but walking and transit only have one measure: sidewalk quality and public transit connection scores, respectively. Regression analysis was used to test the effectiveness of the multimodality index as a predictor of ridership while using the control variables shown in Table 4.

ANALYSIS RESULTS

Multimodality Index Results

The multimodality index scores for each Orange Line station are shown in Figure 3. The North Hollywood station has the highest MI, 8.15, indicating the best infrastructure combination to support modal transitions. The De Soto station has the lowest MI, -5.65, because it has neither parking nor kiss-n-ride drop off facilities and has a very low bikeway score. The two terminal stations of the route, Chatsworth and North Hollywood, have the best connectivity (scores of 8.14 and 8.15, respectively), with Metrolink and Red Line subways connections, respectively, and other increased infrastructure. Stations that serve community colleges (Pierce College and Valley College) have low MI scores, so increasing the scores at these stations might increase ridership of a population likely to use transit.

Figure 3: Orange Line Station Multimodality Index Scores



Statistical Analysis: The Effect of Multimodality Index (MI) on Ridership

The Multimodality Index (MI) was designed to assess how multimodal provisions at transit stations influence ridership levels. The index contains several characteristics (subcomponents) of Orange Line BRT stations such as sidewalk quality, overall bikeway quality, bike rack availability, bike locker availability, number of parking spaces, kiss-n-ride availability, and number of regular Metro bus connections. For this study, ridership is defined as boarding at the individual stations for all the months in 2014, except November where data were incomplete, as provided by LA Metro.

To assess the benefits of the MI versus using the individual MI subcomponents, a correlation analysis (including boarding) was conducted. All the subcomponents were statistically significantly correlated with the boarding, but the strongest correlation were with the number of bike lockers, the number of transit connections and the number of parking spaces. The MI was positively and statistically significantly correlated to boarding and all the subcomponents with the higher correlations for sidewalk conditions, the number of parking spaces, and presence of kiss-n-ride (refer Table 5). The MI allows for stations to be designed differently to suit the needs of the surrounding neighborhoods. This creates flexibility for transit operators and the correlation analysis seems to support a strong relationship.

Table 5: Correlation Analysis

	Boarding	MI	Sidewalk	Overall Bike	Bike-rack	Bike locker	No. of space	Kiss-n-ride	Connection
Boarding	1.00								
MI	0.29**	1.00							
Sidewalk	0.15**	0.78**	1.00						
Overall Bike	-0.30**	0.50**	0.20**	1.00					
Bike-rack	-0.22**	0.50**	0.16**	0.63**	1.00				
Bike locker	0.54**	0.43**	0.16**	0.14**	0.11**	1.00			
No. of space	0.39**	0.72**	0.48**	0.12**	0.37**	0.44**	1.00		
Kiss-n-ride	0.21**	0.61**	0.38**	0.17**	0.44**	0.50**	0.74**	1.00	
Connection	0.50**	0.36**	0.27**	-0.24**	-0.32**	0.02*	0.11**	-0.08**	1.00
*(N=1257); *Significance at 0.05 level; **Significance at 0.01 level*									

Multivariable linear regression was performed with the MI or each subcomponent as an independent variable to determine the best predictor of boarding while including control variables (density, distance, income, high school availability, the route direction, and month). Because the subcomponents were correlated to each other causing multicollinearity for the regression analysis (refer Table 5), an overall regression with all the subcomponents cannot be performed. This is an advantage of having the MI, which includes all the subcomponents.

The regression results shown in Table 6 demonstrate that MI is the best explanatory variable of ridership, because the adjusted R-squared value (0.41) is higher than most of the subcomponents. The MI and all the control variables are significant at the 99% confidence level. The results of the first regression (with MI as independent variable, excluding the subcomponent variables) indicate that denser areas and stations with high MI have higher ridership; and stations further from downtown, with more high schools and higher income, have lower ridership The unexpected result of high school presence reducing ridership may be due to the significant amount of land they occupy, reducing the density and usage of the transit system.

All the other regression models were also statistically significant at p = 0.01 level. The subcomponent variable was significant for all the models except the bike racks. Bike locker best explained boarding with an adjusted R-squared value of 0.55. The more bike lockers, the more boarding. The control variables had similar results and were statistically significant. In the other model higher sidewalk quality, high transit connection, increased parking spaces, and the presence of kiss-n-ride led to increased transit boarding as expected but with lower adjusted R-squared values (0.31, 0.44, 0.36, and 0.31, respectively). Bikeway quality has a negative beta value indicating an inverse relationship with ridership. This shows that for BRT riders, the station bicycle infrastructure is more important than bicycle infrastructure along the journey to access BRT. Next to bike locker, the MI is the best predictor of transit ridership. It also includes all the subcomponents, which could not be used together in the estimation due to collinearity issues, and therefore a useful tool for transit planning.

The statistically insignificant subcomponent model included the number of bike racks. The number of bike racks was an insignificant variable probably due to cycling transit users' aversion to using bike racks (Olwert et al. 2015) most likely due to weather and theft exposure. This contrasts with the significant variable of the number of bike lockers, where bikes are protected from exposure to weather and theft.

In all the models, Saturday and Sunday boarding were less than the weekdays and were statistically significant. Westbound boarding was also statistically less significant than eastbound. The months were also used in the models but broadly not statistically significant.

Table 6: Regression Analysis Results

	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P
Constant	-	0.00	-	0.00	-	0.00	-	0.00	-	0.00	-	0.00	-	0.00	-	0.00
Distance from Union Station	-0.44	0.00	-0.39	0.00	-0.24	0.00	-0.32	0.00	-0.28	0.00	-0.31	0.00	-0.35	0.00	-0.26	0.00
Log HII	-0.22	0.00	-0.23	0.00	-0.16	0.00	-0.25	0.00	-0.21	0.00	-0.20	0.00	-0.20	0.00	-0.17	0.00
Density	0.25	0.00	0.27	0.00	0.34	0.00	0.30	0.00	0.31	0.00	0.27	0.00	0.31	0.00	0.27	0.00
#of high schools	-0.37	0.00	-0.17	0.00	0.06	0.04	-0.08	0.01	-0.33	0.00	-0.17	0.00	-0.18	0.00	-0.12	0.00
MI	0.45	0.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Sidewalk	-	-	0.18	0.00	-	-	-	-	-	-	-	-	-	-	-	-
Overall Bike	-	-	-	-	-0.32	0.00	-	-	-	-	-	-	-	-	-	-
Bike-rack	-	-	-	-	-	-	-0.04	0.27	-	-	-	-	-	-	-	-
Bike locker	-	-	-	-	-	-	-	-	0.57	0.00	-	-	-	-	-	-
No. of space	-	-	-	-	-	-	-	-	-	-	0.29	0.00	-	-	-	-
Kiss-n-ride	-	-	-	-	-	-	-	-	-	-	-	-	0.19	0.00	-	-
Connection	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.40	0.00
Saturday	-0.17	0.00	-0.17	0.00	-0.17	0.00	-0.17	0.00	-0.17	0.00	-0.17	0.00	-0.17	0.00	-0.17	0.00
Sunday	-0.22	0.00	-0.22	0.00	-0.22	0.00	-0.22	0.00	-0.22	0.00	-0.22	0.00	-0.22	0.00	-0.22	0.00
West	-0.05	0.02	-0.06	0.01	-0.07	0.00	-0.06	0.01	-0.10	0.00	-0.05	0.02	-0.05	0.02	-0.06	0.00
January	-0.02	0.53	-0.02	0.52	-0.03	0.39	-0.02	0.53	-0.01	0.63	-0.01	0.66	-0.01	0.70	-0.03	0.21
February	0.01	0.66	0.01	0.74	0.01	0.87	0.01	0.73	0.02	0.47	0.02	0.56	0.02	0.55	-0.01	0.86
April	0.01	0.77	0.01	0.84	0.00	0.98	0.01	0.83	0.01	0.57	0.01	0.65	0.01	0.64	-0.01	0.75
May	0.01	0.70	0.01	0.77	0.00	0.91	0.01	0.77	0.02	0.50	0.02	0.59	0.02	0.58	-0.01	0.82
June	-0.01	0.85	-0.01	0.81	-0.01	0.66	-0.01	0.82	0.00	0.99	0.00	0.99	0.00	0.99	-0.02	0.41
July	-0.01	0.67	-0.01	0.64	-0.02	0.50	-0.01	0.65	-0.01	0.80	-0.01	0.80	-0.01	0.84	-0.03	0.29
August	-0.01	0.66	-0.01	0.63	-0.02	0.49	-0.01	0.64	-0.01	0.78	-0.01	0.79	-0.01	0.82	-0.03	0.28
September	0.00	0.91	0.00	0.97	0.00	0.88	0.00	0.96	0.01	0.72	0.01	0.78	0.01	0.77	-0.01	0.61
October	0.01	0.83	0.00	0.90	0.00	0.95	0.00	0.89	0.01	0.64	0.01	0.71	0.01	0.70	-0.01	0.68
December	0.00	0.97	0.00	0.97	-0.01	0.83	0.00	0.98	0.01	0.78	0.01	0.84	0.01	0.82	-0.02	0.56
R Square	*0.41*		*0.32*		*0.36*		*0.30*		*0.55*		*0.37*		*0.32*		*0.44*	
Adj. R Square	*0.41*		*0.31*		*0.36*		*0.29*		*0.55*		*0.36*		*0.31*		*0.44*	
F- significance	*0.00*		*0.00*		*0.00*		*0.00*		*0.00*		*0.00*		*0.00*		*0.00*	
Dependent variable: Station boarding for the year 2014. N=1257. Data source: LA Metro																

DISCUSSION AND CONCLUSION

The multimodality index provides objective scores of multimodal access to each Orange Line stations. Because the MI calculations use normalized data, the MI is a relative measure that compares stations in a given study, the Orange Line in this case. By comparing the MI scores across the stations, planners can identify stations on the Orange Line that are potentially underserved and subcomponents that might increase ridership. Increased multimodal accessibility provides convenient alternatives to Los Angeles' primary commute mode: the automobile. The MI identifies stations that have poor access, providing insight to transit agencies.

The correlation and regression analysis supports the MI as a reliable predictor of ridership, but allows transit agencies flexibility in deciding how to increase the MI score. Different combinations of facilities can still produce a similar MI score. A station with abundant parking can have the same MI score as a station with less parking but more biking and pedestrian facilities. Transit planners should increase MI scores by providing facilities that the station types need. A residential station may require more parking while an employment center station may require better pedestrian quality and more transit connections. This has, in fact, been implemented in part along the Orange Line. Terminus stations and stations with industrial and employment activities have higher MI scores because of their better walking and biking facilities and increased transit connections. However, the residential stations that have high MI have abundant parking. Thus, it is recommended that multimodal infrastructure be provided based on the neighborhood characteristics surrounding the station.

The correlation and regression analysis suggests that bike lanes and bike racks, when assessed independently, are not significant in affecting ridership. This contradicts the literature (USDOT-FHWA 1992; Nelson and Nygaard 2009), and may be a result of the short buffer zones used (100 ft). A quarter mile would be recommended as a more reasonable length for similar studies. However, as part of the overall MI, the bicycle components are still important.

The MI could be used to compare individual stations across regions or even between regions. Using a random sample of stations across a large area, the normalization mechanism would allow for comparison of a particular station to the greater population of stations. The MI score for a particular station could be compared with the median MI to provide insight on useful upgrades.

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