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Analysis on bike-share ridership for origin-destination pairs: Effects of public transit route characteristics and land-use patterns

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ABSTRACT

Studies on bike-share programs have dramatically increased during the past decades. While numerous studies have examined various factors affecting bike-share demand at the station-level, few attempts have been made to understand bike-share ridership at the origin-destination (OD) level due to technical difficulties. The objective of this study is to examine whether existing public transit characteristics affect bike-share ridership at OD-level. We combined three datasets: (1) bike-share ridership data, (2) land-use and bike-transit infrastructure, and (3) bike-transit route characteristics between OD pairs of bike stations. Zero-inflated negative binomial (ZINB) regression models were used for the analysis. Our results showed that the travel distance between OD bike stations, land-use compositions, and the existence of bike-friendly infrastructures were significant factors determining bike-share ridership at the OD-level. In particular, a longer duration of public transit trips than bike-share, and more transit transfers, were associated with bike-share ridership. Further, this study showed that bike-share and public transit might compete with or promote each other, even within the city. The study's findings suggest that the relative efficiency of bike-share compared to public transit is highly associated with bike-share demand and help to increase the utility of bike-share system in response to several limitations of existing public transit networks.

1. Introduction

As concerns about global motorization and climate change have been growing over the past decades, bike-share has emerged as one of the alternative transportation modes that is environment-friendly and sustainable (Shaheen et al., 2010). As of 2017, more than 1200 cities across 63 countries are operating a bike-share program, with around 2 million public bikes in use worldwide (Meddin and Demaio, 2017). Convenience and low travel costs are some significant benefits of bike-share programs that have contributed to their rapid growth (Fishman et al., 2013; Fishman, 2016).

With the rapid rise of the bike-share program, there has also been an increasing number of studies that addressed bike-share's opportunities as a novel mode of the urban transportation system. Above all, recent studies have highlighted that bike-share can serve as an alternative to several limitations of public transit. Public transit has been regarded as a sustainable mode of the urban transportation system, as it can accommodate greater travel demands compared to private vehicles and thus alleviate several traffic problems such as congestions and air pollutions (Murray, 2003). However, the benefits of public transit also have caused inevitable inconveniences for users, such as the inefficient travel routes or transferring (Guo and Wilson, 2011). The "first-last mile" problem of accessibility has also been considered an obstacle to vitalizing public transit use (Boarnet et al., 2017). Despite efforts to optimize the systems, public transit still does not guarantee the most efficient travel between users' origin and destination (OD) due to limited budgets and urban infrastructure (Braz et al., 2018).

Meanwhile, the introduction of the bike-share program may improve the accessibility to public transit and further replace the inefficient public transit network itself. In particular, previous studies have suggested that bike-share can replace short-term public transit trips by connecting users' OD pairs through the shortest path (Khatri et al., 2016). It suggests that bike-share's relative efficiency to public transit can be a significant factor that affects the mode choice between them. Despite this, most previous studies have examined the station-level associations between the surrounding built-environment on bike-share ridership while neglecting the effects of bike-transit route characteristics between OD bike-share stations. The lack of relevant studies is mainly due to insufficient data available on the travel routes between OD pairs of bike-share ridership (Romanillos et al., 2018). While some

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studies have utilized GPS trajectories of actual trips between OD pairs of bike-share stations (Wergin and Buehler, 2017; Lu et al., 2018), most researchers have limited access to specific bike-share trip information due to several practical difficulties, including budget and privacy issues.

Our study investigated one of the persistent questions regarding the relationship between bike-share and public transit. We hypothesized that ridership of bike-share might be dependent on the characteristics of existing public transit routes. More specifically, we assumed that the bike-share system might substitute public transit when the existing public transit route that connects a pair of OD bike stations is much inefficient than the bike route. To this end, we obtained bike and public transit route information between OD bike-share stations from online map APIs and derived important route characteristic variables. To our knowledge, no study has applied this approach to analyzing public transit routes. Also, we utilized the OD-level ridership data of Seoul Bike and several built environment variables within bike-share station service areas.

In this paper, following Section 2 covers the review of previous studies. And the study sites, data preparation, and statistical methodologies are described in Section 3. Section 4 presents the results of a descriptive and spatio-temporal OD-level bike-share ridership patterns. We also developed zero-inflated negative binomial (ZINB) regression models to estimate bike-share ridership at OD-level. The final section further discusses the findings of the study and identifies potential implications for future research.

2. Literature review

With the global popularity of bike-share programs, the number of relevant studies dramatically increased in the 2010s. Much research has examined various factors that affect bike-share demand at the station level (Faghih-Imani et al., 2014). While factors vary in importance depending on a study's site and methodologies, researchers have found bike-share ridership is closely associated with (1) the surrounding built environment, (2) weather and temporal variations, and (3) public transit accessibility (Mattson and Godavarthy, 2017).

Findings have shown that land-use diversity (Bachand-Marleau et al., 2012; El-Assi et al., 2017; Fuller et al., 2013), population and job density (Rixey, 2013; Wang et al., 2015), and proximity to bike infrastructure and points of interest (Buck and Buehler, 2012; Faghih-Imani et al., 2014; Fishman et al., 2015) within the service area of bike-share stations are positively associated with its ridership. Not surprisingly, weather and temporal variations are other main factors that determine bike-share ridership. Previous studies have found that warm and dry weather encourages bike-share use (Heinen et al., 2011; Thomas et al., 2013), while hot and cold, rain, high wind speeds, and humid atmospheres negatively impact ridership (El-Assi et al., 2017; Gebhart and Noland, 2013; Nosal and Miranda-Moreno, 2014). These studies have commonly found that weekdays have higher bike-share demand than weekends, especially in the morning and evening peak hours (Faghih-Imani et al., 2014; Murphy and Usher, 2015; O'Brien et al., 2014).

Meanwhile, the influence of public transit accessibility on bike-share ridership is mixed, with both complementary and competitive relationships between public transit and bike-share (Fishman et al., 2013; Martin and Shaheen, 2014; Wang and Liu, 2013). Some researchers have shown that the spatial proximity between public transit and a bike-share station could facilitate transfers from one to another, promoting public transit and bike-share and reducing overall car use (Fishman et al., 2014; Jäppinen et al., 2013; Rixey, 2013; Sato et al., 2015). Meanwhile, several studies reported that bike-share might reduce public transit use by serving as an alternative means of transportation and competing with bus and rail transit (Fuller et al., 2013; Shaheen et al., 2012; Tang et al., 2011). A few researchers have pointed out that those opposite relationships can coexist within a city. The study conducted in Washington DC and Minneapolis (Martin and Shaheen, 2014) showed that complementary relationships can be strengthened in the urban periphery, while competitive relationships tend to occur in a dense urban core. More recently, Kong et al. (2020) proposed three typologies of relationships between bike-share and public transit - modal substitution, modal integration, and modal complementation, and showed that bike-share users' travel characteristics rather than their physical location determines their relationships with public transit.

While most previous studies have examined various factors affecting bike-share demand at the station-level, there have only been several attempts to understand bike-share ridership at the origin-destination (OD) level. That paucity of relevant studies is mainly due to the lack of available data on the travel routes between OD pairs of bike-share trips (Romanillos et al., 2018). To analyze bike-share ridership at the OD-level, researchers must consider route characteristics between OD bike-share stations. However, acquiring trip route information on the actual bike-share trips from bike-share program authorities is not feasible due to privacy issues.

To overcome this limitation, researchers have attempted to obtain direct or indirect route information for bike-share trips. First, a few studies have obtained the GPS trajectories of actual bike-share trips directly from the bike-share program authorities. By analyzing existing bike-share travel routes, some studies have found that bike-share users prefer the shortest path through a bike-friendly infrastructure with fewer turns and intersections between OD stations (Khatri et al., 2016; Lu et al., 2018; Wergin and Buehler, 2017).

On the other hand, researchers have recently tried to utilize indirect bike route information provided by online map services such as Google Maps (El-Assi et al., 2017), as it generates the bike paths by minimizing travel distance and the proportion of bike lanes along a route (Google Maps, 2014). By assuming that utilitarian bike-share users are likely to follow Google-driven bike paths, the study examined their spatio-temporal travel patterns and found that the distance and proportion of bike-friendly infrastructures between OD stations is positively associated with bike-share ridership.

3. Methodology

3.1. Study site: Seoul Bike ('Ttareungyi')

Seoul Bike, also called "Ttareungyi," is a station-based public bike-share program that has been operated by Seoul Metropolitan Government since September 2015. With the city's enormous population and densely-built environment, Seoul Bike has experienced rapid growth over the past few years. Monthly bike-share ridership increased from 10,863 in the first month of operation to 2,221,800 in May 2019 (Fig. 1). One of the dominant features of bike-sharing is its dependency on climate conditions. The number of Seoul Bike trips tends to increase in mild seasons (Apr, May, Jun, Sep, Oct), while it sharply decreases in cold seasons (Dec, Jan, Feb). During the summer periods (Jul, Aug), there was a slight decrease in the bike-share ridership but still high. This seasonal variability of bike-share ridership may explain that bike users are more sensitive to cold weather than hot (Liu et al., 2015).

As of May 2019, Seoul Bike operates 1530 bike-share stations with approximately 25,000 bikes around the city (Fig. 2). The number of Seoul Bike stations per square mile is about 6.5, which is lower than Velib in Paris (33) and Citi Bike in New York (23), but higher than CaBi in Washington (4) and Nice Ride in Minneapolis (4) (Bergren, 2015). Seoul Bike stations are evenly distributed throughout the city and are located near collector roads, parks, and river banks, which are usually occupied by a large number of floating populations. Seoul has 590 road sections with bike lanes, totaling 940.6 km. Among them, 250 and 340 sections are used by bike-only lanes and bike-pedestrian lanes, respectively.

Seoul has an extensive public transportation network, with more than 300 subway stations across ten lines and approximately 8000 bus stops (Hong et al., 2019). As of 2019, the daily average public transit ridership is about 10.3 million (bus: 5.2 million, subway: 5.1 million)

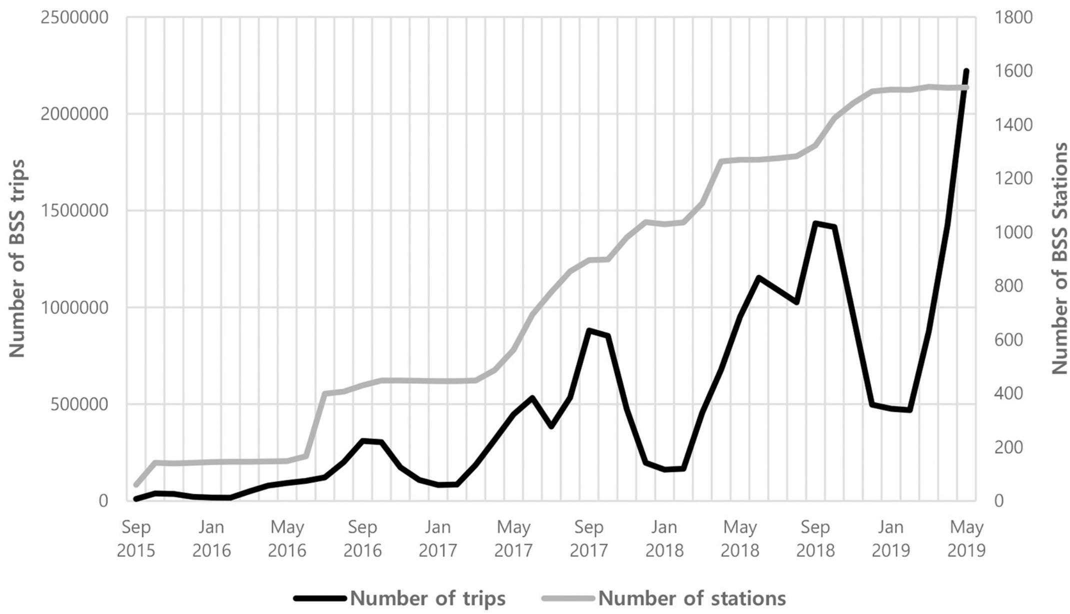

Fig. 1. Monthly trend of Seoul Bike stations and uses (2015.09–2019.05).

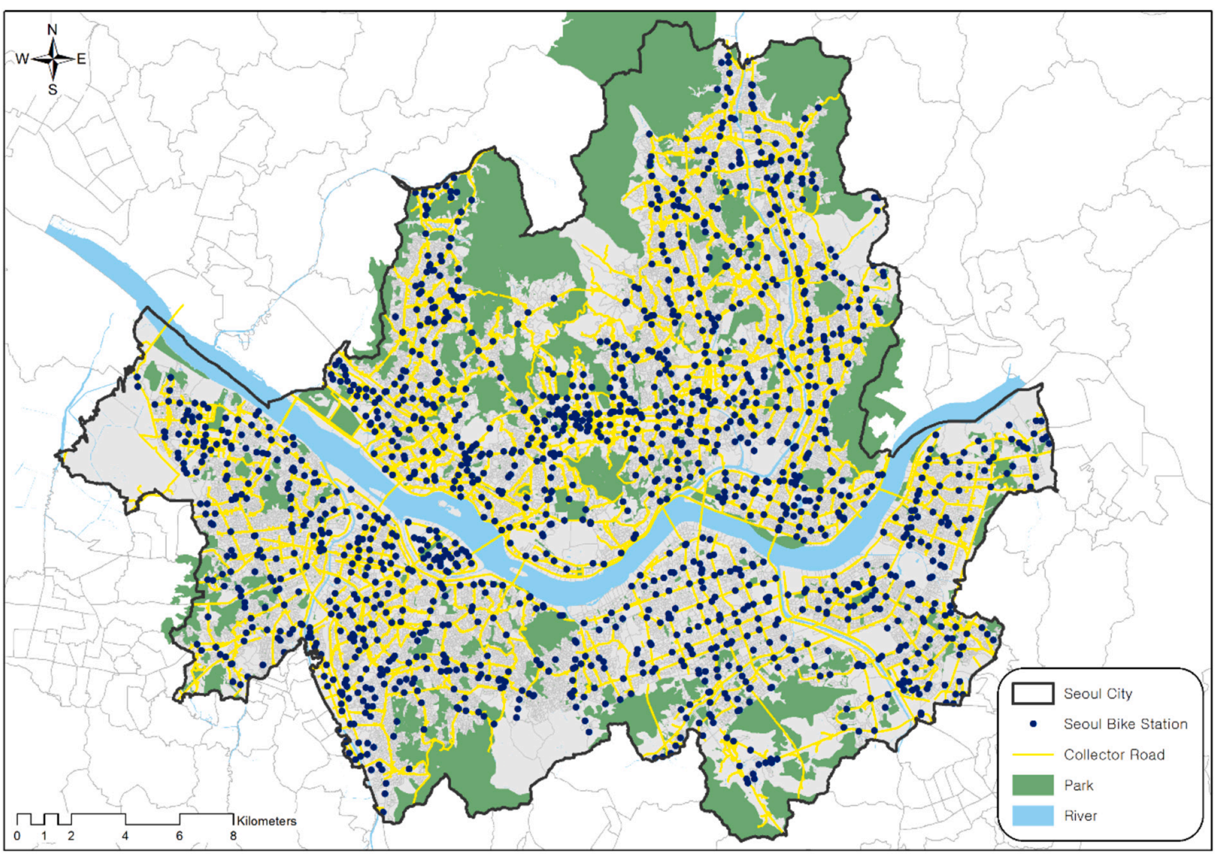

Fig. 2. Geographical location of Seoul Bike stations (May, 2019)

(https://news.seoul.go.kr/traffic/archives/31616). Basic bus and subway fares were 1.02 and 1.07 USD, respectively. Public transit users can transfer between two modes multiple times with discounted fares using the integrated smart card. For Seoul Bike, the price of daily tickets was 0.85 USD, and the price of monthly tickets was 4.26 USD. In 2020, Seoul expanded the transfer mileage service between public transit and Seoul Bike to encourage connections between the two systems (https://www.bikeseoul.com/).

3.2. Data

This study combined three datasets to examine factors affecting bike-share ridership at OD-level - (1) bike-share ridership data, (2) land-use and bike-transit infrastructure, and (3) bike-transit route information between OD pairs of bike-share stations. Fig. 3 depicts the process of building the database.

As a first step, to calculate bike-share ridership at the OD-level, we utilized bike-share usage data provided by the Seoul Open Data Platform (www.data.seoul.go.kr). The monthly updated database includes unique identification numbers for the origin and destination stations and rental/return timestamps for each bike-share trip. For this study, we used one month of bike-share usage data collected in May of 2019. Because the number of available bike-share stations and their OD pairs vary from month to month (Fig. 1), combining bike-share usage data for several months is a difficult task. Since the opening of Seoul Bike service, the highest monthly usage (2,221,800 trips) was recorded in May 2019.

We collected land-use and bike-transit infrastructures data within the bike station service areas. The radius of the bike station service areas used in the previous studies varied from 200 to 400 m, depending on the density of the stations (El-Assi et al., 2017; Zhang et al., 2017). We employed a 300 m radius buffer because the distance between two adjacent Seoul Bike stations is often less than 300 m (Fig. 2). Regarding land-use factors, we calculated the average total floor area of residential, commercial, business, and university buildings within a 300 m radius of 1537 Seoul Bike stations. Building use information was derived from the National Geographic Information Institute (https://www.ngii.go.kr). For identifying characteristics of bike-transit infrastructure, this study counted the number of docks, alternative bike-share, bus stops, and subway stations within a 300 m radius around a bike-share station. The Seoul Open Data Platform and ArcGIS 10.4.1 were used to calculate the variables. Although bike availability, which refers to the chance of finding available bicycles at stations, has been recently regarded as an influencing factor that measures the robustness of bike-share system (Faghih-Imani et al., 2017; Kabra et al., 2020), this study did not account for the availability due to limited access to the data.

We constructed bike-transit route characteristics between OD pairs of bike-share stations utilizing Naver Maps API (https://www.ncloud.com/product/applicationService/maps), which is one of the most popular map services in Korea. Naver Maps provides vehicle, public transit, bicycle, and walking travel routes between trip start and endpoints. Although Naver Maps does not release its specific pathfinding algorithms to the public, a few studies (Kim and Kim, 2016; Lee et al., 2015) have found that bike paths recorded on the platform minimize travel distance/time and maximize the proportion of bike lanes, while public transit paths are generated to reduce travel distance/time, number of transfers, and walking distances. Using Python scripts, we extracted the most recommended bike and public transit travel routes from the API.

Travel routes between OD pairs of bike-share stations are formulated in a series of short phrases (see Fig. 4). For identifying route characteristics, we extracted keywords from these phrases, including 'distance/duration,' 'bike lane,' 'crosswalk,' and 'turns' for bike routes and 'distance/duration (average speed),' 'bus,' 'subway,' and 'transfer' for public transit routes. By utilizing these keywords, we derived the distance/duration of bike trips, the proportion of bike lanes, and the number of crosswalks and turns between OD stations. Distance and duration variables for bike and public transit routes were constructed using the stated phrases, and we counted the number of occurrences of 'crosswalk,' 'turn,' and 'transfer' within the phrases to derive the number of crosswalks, turns, and transfers between OD bike-share stations. To calculate the proportion of bike lanes, we first added up the lengths of all sections with bike lanes, and then divide by the total bike distance. Transit distance/duration, number of transfers, and type of public transit between OD bike-share stations were calculated to identify public transit route characteristics.

We tested this approach's reliability from two different perspectives: (1) whether the bike-paths reported from online maps produce empirically probable results, and (2) whether the variables derived from the extraction method provide the same route information phrased in the online platform. We repeated the test and update process several times, and the methods we used in the paper showed close to 100% reliability for both perspectives.

Figs. 5 and 6 show two exemplary cases that compare bike and public transit routes. Fig. 5 represents a case when a transit route (solid blue line) is much longer than a bike route (red dotted line), while Fig. 6 illustrates a case in which they are nearly identical. For each case, the ratio of transit duration to bike duration were estimated at 3.7 and 1.8, respectively.

From 2,362,369 OD pairs (1537 stations $\times$ 1537 stations) in May 2019, 2,235,552 travel routes (94.6% of total) were generated, excluding trips with the same OD (round trips) and those with no route information in Naver Maps.

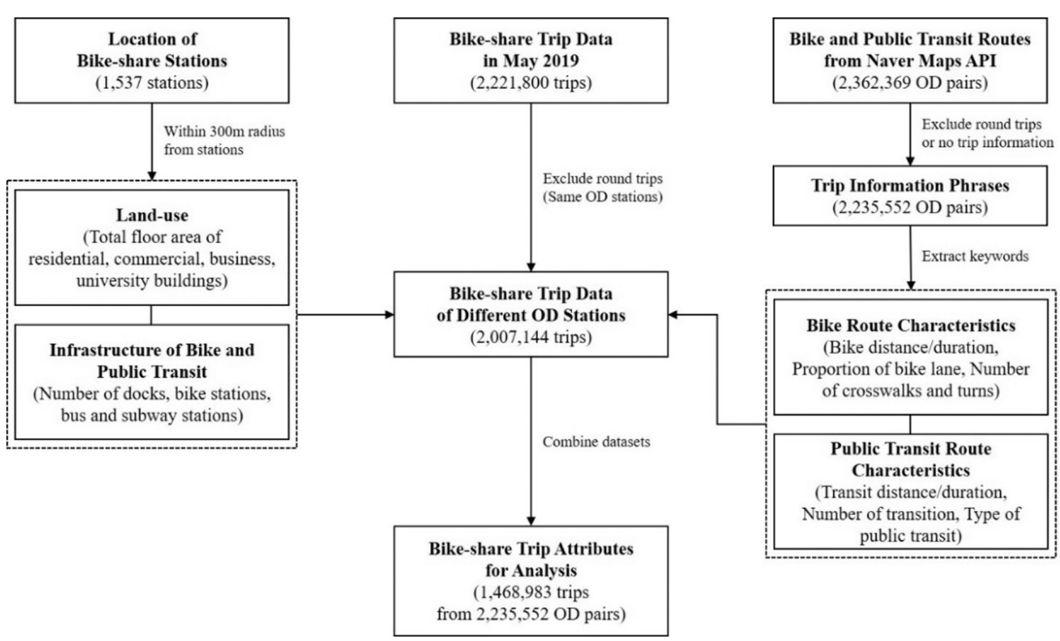

Fig. 3. Data processing for analysis.

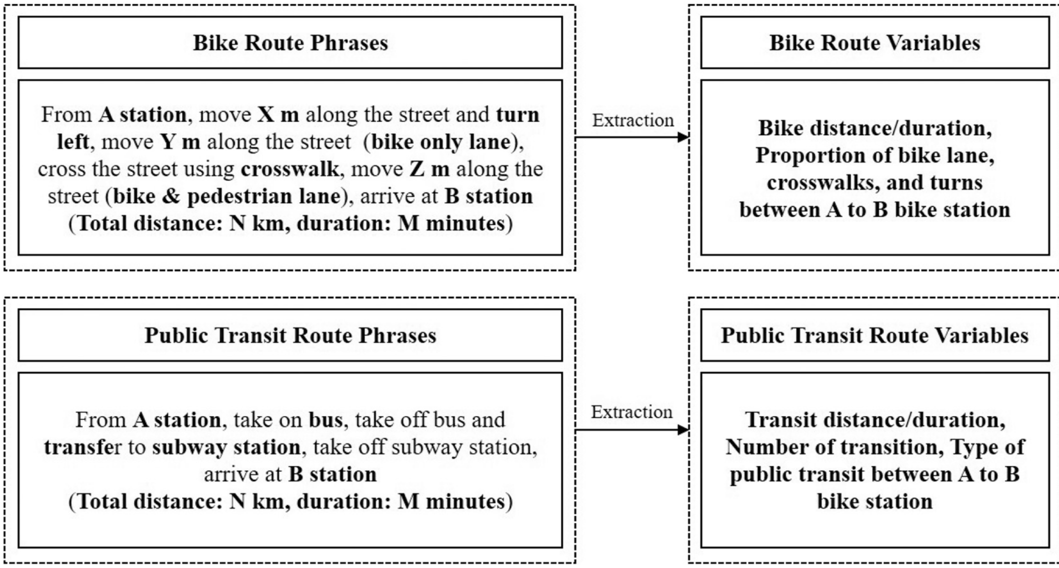

Fig. 4. Extraction of route characteristics of bus and public transit from Naver Maps API.

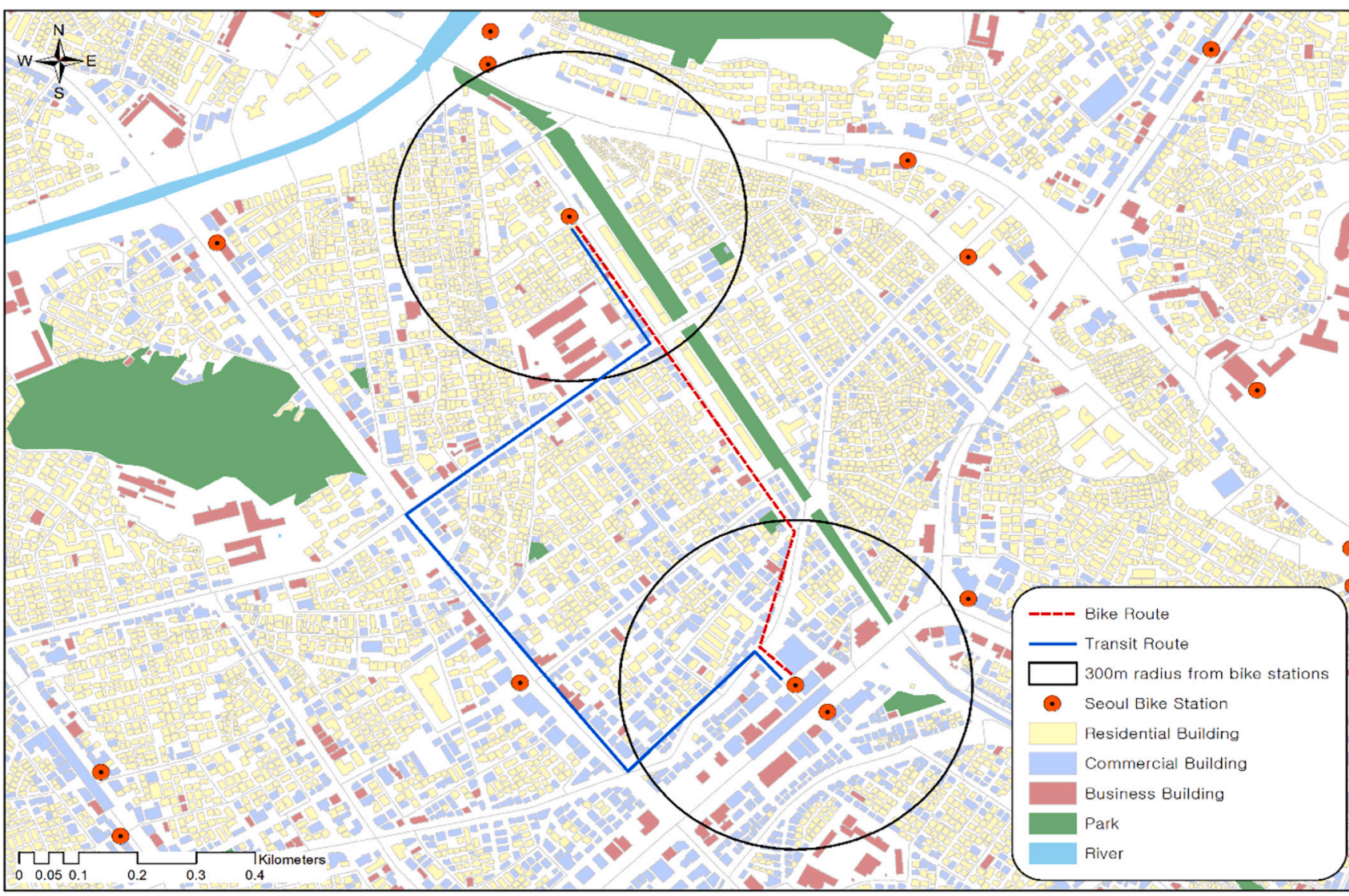

Fig. 5. Example of OD bike station pairs with a high ratio (3.7) of transit to bike duration.

3.3. *Zero-inflated negative binomial (ZINB) regression model*

Previous studies that examine station-level bike-share ridership have generally adopted negative binomial regression model as the number of bike-share trips were non-normal count data (Noland et al., 2016). However, since bike-share ridership values between OD pairs of bike-share stations were non-negative integers with numerous zeros, we used a zero-inflated negative binomial (ZINB) regression model. The dependent variable of the study is bike-share ridership for each pair of OD stations. The independent variables were land use, bike-transit infrastructure, and bike-transit route characteristics within the bike station service area. Table 1 presents a description and the sources of the explanatory variables. The ZINB models produce the outcome from two separate processes: (1) a zero-inflated binary logit model for zero

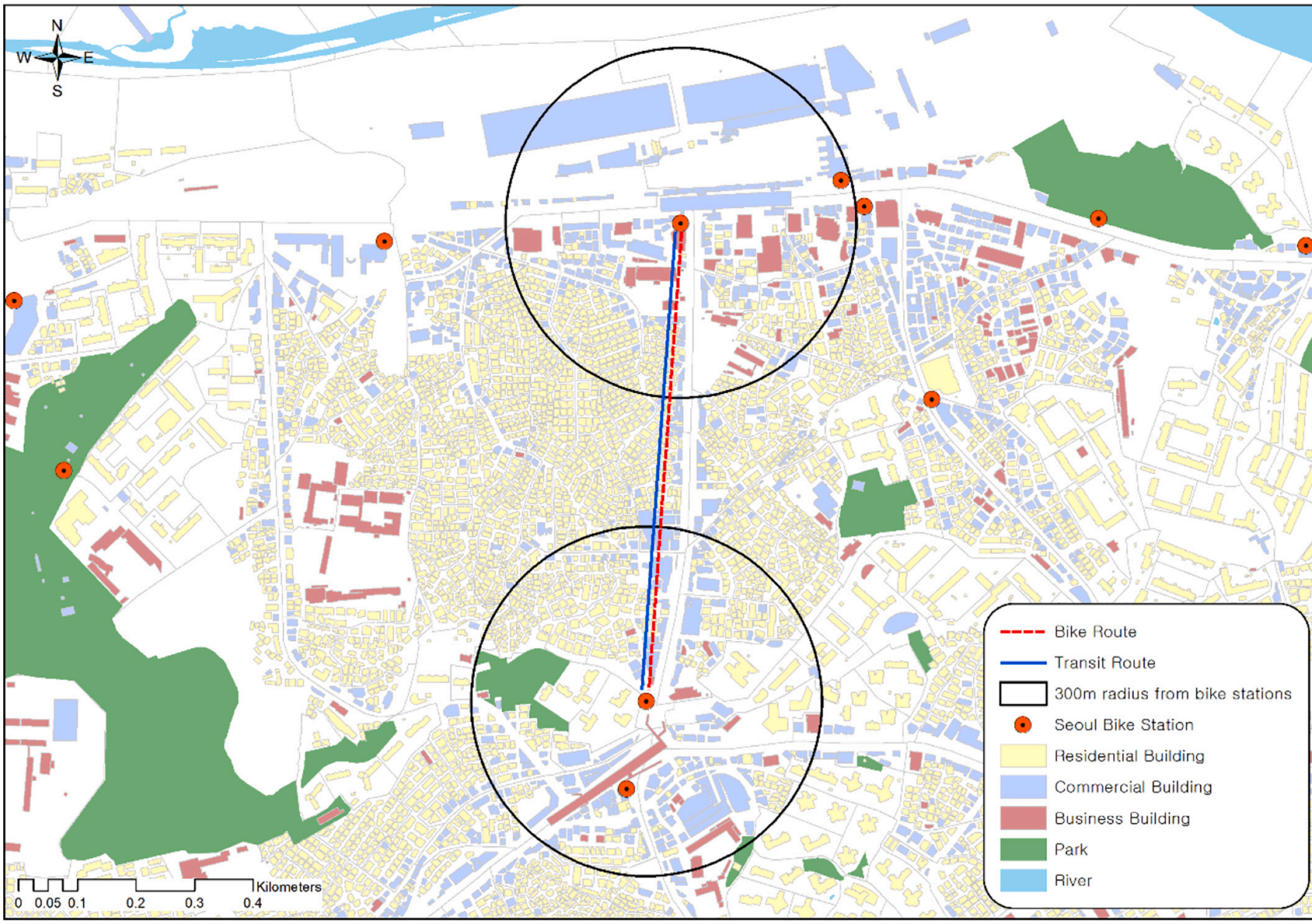

Fig. 6. Example of OD bike station pairs with a low ratio (1.8) of transit to bike duration.

outcomes and (2) a negative binomial model for non-zero outcomes (Cameron and Trivedi, 2013). The probability distribution of variable y_i can be expressed as

$$Pr(y_i = j) = \begin{cases} \pi_i + (1-\pi_i)g(y_i = 0) \ if \ j = 0 \\ (1-\pi_i)g(y_i) \ if \ j > 0 \end{cases} \quad (1)$$

where y_i represents the number of trips between OD pairs of bike-share stations and π_i is the probability of zero bike-share ridership. $g(y_i)$ is negative binomial distribution given by

$$g(y_i) = Pr(Y = y_i \,|\mu_i, \alpha \Big) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(y_i+1)} \left(\frac{1}{1+\alpha\mu_i}\right)^{\alpha^{-1}} \left(\frac{\alpha\mu_i}{1+\alpha\mu_i}\right)^{y_i} \quad (2)$$

where μ_i is the mean bike-share ridership, and α is the over-dispersion parameter.

In our study, the zero-inflated part examines those factors that explain the probability of zero ridership, while the negative binomial part investigates factors associated with the bike ridership numbers for non-zero OD pairs. All land use, bike infrastructure, and bike-transit efficiency variables were used in the negative binomial part. In the zero-inflated part, we used bike infrastructure, including bike distance, proportion of bike lanes, number of crosswalks, and number of turns.

4. Results

4.1. Descriptive analysis

The hourly average bike-share ridership for the entire month of May 2019 was 1974 trips per hour, and those for weekends and weekdays were 2089 and 1707 trips per hour, respectively. A higher number of bike-share trips during weekdays has been consistently reported in previous studies (Faghih-Imani et al., 2014; O'Brien et al., 2014).

Fig. 7 shows the number of average hourly bike-share trips in weekends and weekdays, by time of day, which was into five sectors: dawn (3:00–6:59), morning peak time (7:00–10:59), daytime (10:00–16:59), evening peak time (17:00–19:59), and nighttime (20:00–2:59). In general, hourly bike-share trips in weekdays present a typical urban pattern characterized by two peaks, one in the morning and one in the evening. In weekends, however, there's no peak-time travel patterns of bike-share trips but have more daytime and night-time trips compared to weekdays. Compared with hourly traffic flow variations in Seoul (Seoul Metropolitan Government, 2019), bike-share trips show more considerable hourly variations. In particular, the number of trips is concentrated in the evening peak time.

We classified bike-share stations into either dominant residential and dominant non-residential locations and examined the spatial patterns of bike-share ridership by time and day. Stations at which more than 50% of residential uses occur within a 300 m radius were defined as 'dominant residential'; otherwise, we labeled the station as 'dominant non-residential.' As Fig. 8 shows, average hourly bike-share trips for origins were higher when residential use was dominant, while there were larger

Table 1
Description of explanatory variables for the study.

Variable name		Description (measurement)	Source
Land use	Residential area	Total floor area (km^2) of residential building in 300 m buffer	National Geographic Information Institute
	Commercial area	Total floor area (km^2) of commercial building in 300 m buffer	
	Business area	Total floor area (km^2) of business building in 300 m buffer	
	University area	Total floor area (km^2) of university building in 300 m buffer	
Bike-transit infrastructure	# of docks	# of Docks of bike station	Seoul Open Data Platform
	# of BSS stations	# of Alternative Bike-Share Stations in 300 m buffer	
	# of Bus stops	# of Bus Stops within in 300 m buffer	
	# of subway stations	# of Subway Stations within in 300 m buffer	
Bike-transit route characteristics	Bike distance	Bike Distance (km) throughout the bike route	Naver Maps API
	Bike-only Lane proportion	Bike-Only Lane (km) / Bike Distance (km)	
	Bike-pedestrian Lane proportion	Bike-Pedestrian Lane (km) / Bike Distance (km)	
	# of crosswalks	# of Crosswalks throughout the bike route	
	# of turns	# of Turns throughout the bike route	
	Transit duration/bike duration	Transit Duration (min) / Bike Duration (min)	
	# of transfer	# of Transfer throughout the public transit route	

numbers for destinations when non-residential use was predominant. This pattern was consistent during the weekdays. During the weekends, the ridership in both origin and destination stations was higher when residential uses were dominant. We suppose that bike trip demand for commuting may result in a different pattern during weekends and weekdays.

Table 2 summarizes the descriptive statistics of explanatory variables constructed for the analysis. Within a 300 m radius from a station, 26% of the building floor area is for residential use, and 16.4% is for commercial use, on average. This finding is unsurprising since these two uses are the primary land use type in urban settings (Wang et al., 2015).

Seoul Bike had approximately 12.6 docks per station on average, which is slightly higher than Toronto (10), Chicago (9), Washington (9), and Paris (8), but lower than New York (17) and Hangzhou (25) (Bergen, 2015). The average number of other bike-share stations, bus stops, and subway stations was 2.1, 8.9, and 0.4, respectively. Compared to other cities that operate bike-share programs, the Seoul bike program seems to have a relatively high bike station capacity and a dense transit network.

The average distance between OD pairs of stations was 19.6 km (ranging from 0.7 to 51 km), and 67% and 20% of the length was used for bike-only and bike-pedestrian lane. On average, 1.6 crosswalks and 12 turns existed throughout the bike routes. The average ratio of public transit to bike trip duration was approximately 0.57, which implies that the travel time for public transit is 43% shorter than that of bike-share trips on average.

4.2. *Zero-inflated negative binomial regression model*

Tables 3 and 4 present the parameter estimates from the zero-inflated negative binomial (ZINB) models by distance, day type, and time of day. The total number of OD station pairs was 2,235,552 and 141,639; 6.3% of them had non-zero bike-share ridership. The proportion of non-zero pairs depends on trip distance. The proportion is 26.2% when the trip distance is shorter than 10 km.

4.2.1. *Land-use*

One of the most noticeable results was the difference in the effects on the bike-share ridership between residential and non-residential areas near bike-share stations. In general, the size of residential land-use near stations had a positive association with bike-share ridership. Table 4 shows this association varies by time of day and location. During the

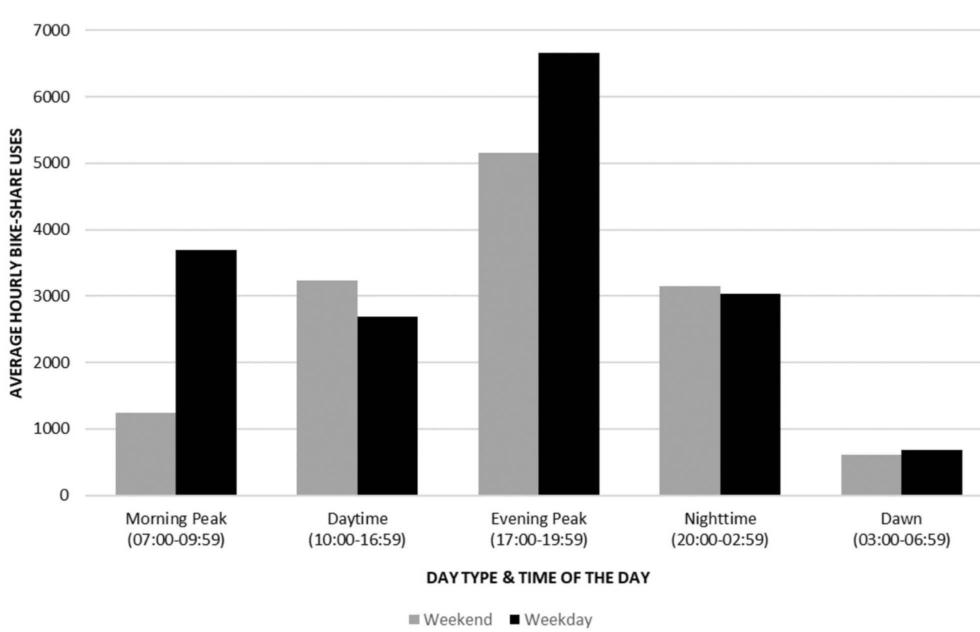

Fig. 7. Mean hourly bike-share trips by day type and time of the day.

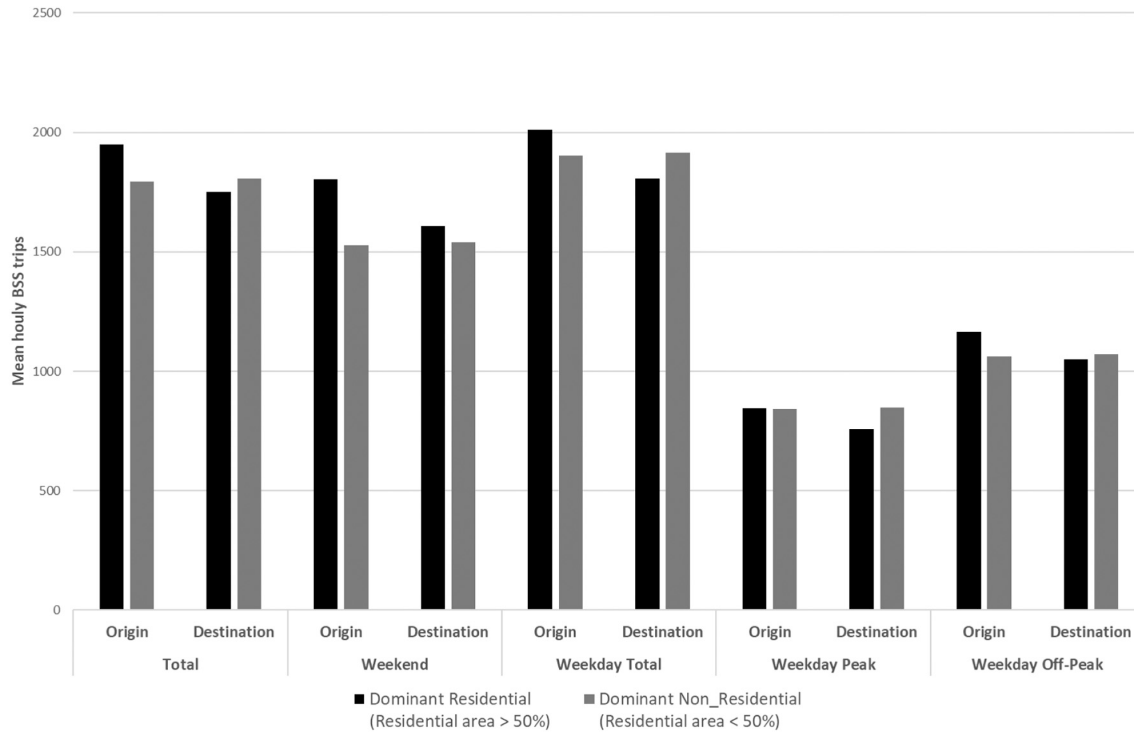

Fig. 8. Mean hourly bike-share trips by land-use types.

Table 2
Descriptive statistics of explanatory variables.

Variable (Obs = 2,235,552 OD pairs)		Mean	Std. Dev.	Min	Max
Land Use	Residential area (km^2)	0.261	0.171	0.000	1.413
	Commercial area (km^2)	0.164	0.195	0.000	1.780
	Business area (km^2)	0.011	0.012	0.000	0.127
	University area (km^2)	0.104	0.172	0.000	1.697
Bike-transit infrastructure	# of docks	12.570	4.567	5.000	40.000
	# of bike-share stations	2.095	1.086	1.000	8.000
	# of bus stops	8.851	4.553	0.000	32.000
	# of subway stations	0.367	0.490	0.000	2.000
Bike-transit route characteristics	Bike distance (km)	19.606	10.314	0.684	51.007
	Bike-only lane proportion	0.670	0.290	0.000	1.000
	Bike-pedestrian lane proportion	0.200	0.233	0.000	1.000
	# of crosswalks	1.614	1.337	0.000	11.000
	# of turns	12.007	5.264	0.000	40.000
	Transit duration/ bike duration	0.569	0.255	0.160	8.169
	# of transfer	1.074	0.794	0.000	5.000

morning peak, residential land-use ridership increased at the origin stations, but it decreased at the destination stations. During the evening peak, ridership decreased at the destination station while it increased at the origins. The size of non-residential land-uses (commercial, business, and university areas) had exactly the opposite of associations with ridership. This result is partly due to the commuting travel demand of bike-share users. Murphy and Usher (2015) also reported that peak hour bike-share demand is generated mainly for home-based commuting purposes. For a similar reason, the amount of business use at both the origin and destination stations had a strong negative association with weekend ridership.

4.2.2. Bike-transit infrastructure

The number of installed docks increased ridership. Users may prefer stations with more docks because of the higher odds of renting a bike-share (El-Assi et al., 2017), or, oppositely, higher bike travel demand at the stations may increase the number of docks. However, the number of alternative bike-share stations within the service areas consistently had a negative relationship with bike-share ridership. It suggests that the presence of other bike-share stations may distribute bike-share demand in the surrounding areas. These two conflicting effects of additional bike-share infrastructure imply that bike-share ridership needs to be analyzed in a larger spatial extent. In other words, bike-share practitioners should consider not only ridership at a particular bike-share station but also general bike-share demands in the corresponding region when they determine the location of additional stations.

Knowing whether bike-share ridership has a positive or negative relationship with other transit stations can provide a way of understanding potential relationships between bike-share and public transit. The number of subway stations had a consistent positive association with the bike share ridership in the models, which implies that proximity to subway transit can encourage bike-share ridership. By providing access to subway stations, bike-share can offer a solution to the “first/last mile” problem (Noland et al., 2016). The number of bus stops showed more complicated results. A higher number of bus stops increased ridership at the origin station during the morning peak but decreased it at the destination. By contrast, during the evening peak, a higher number of bus stops decreased ridership at the origin but increased it at the destination stations. Given that the dominant trip direction of the morning peak is from residential to non-residential land use, while the evening peak is in the opposite direction, we speculate that the presence of bus stops in residential use may be positively associated with bike share ridership. Meanwhile, in non-residential areas, the presence of bus stops showed negative associations with bike-share trips. These findings suggest that the absence of bus stops in

Table 3
Zero-inflated negative binomial regression model (Distance and Day type).

Dep. Var: # of bike-share use per OD in May 2019				Total	Bike distance > 10 km	Bike distance < 10 km	Weekend/holiday (<10 km)	Weekday (<10 km)
# of samples				2,235,552	1,775,085	460,376	460,376	460,376
# of non-zero				141,639	20,945	120,690	73,814	114,460
Negative binomial part	Land use	Residential area	Origin	0.319**	0.150*	0.266**	0.326**	0.247**
			Dest	0.246**	0.611**	0.306**	0.320**	0.312**
		Commercial area	Origin	0.015	0.670**	0.094**	0.075**	0.110**
			Dest	0.033	0.138*	0.101**	0.090**	0.128**
		Business area	Origin	−0.500	−0.835	−0.154	−4.923**	1.378**
			Dest	0.292	−2.288	−0.246	−5.885**	1.652**
		University area	Origin	0.171**	0.531**	0.250**	0.243**	0.280**
			Dest	0.108**	0.165	0.234**	0.152**	0.251**
	Bike-transit infrastructure	# of docks	Origin	0.030**	0.035**	0.029**	0.037**	0.028**
			Dest	0.027**	0.035**	0.026**	0.034**	0.024**
		# of BSS stations	Origin	−0.098**	−0.123**	−0.117**	−0.125**	−0.118**
			Dest	−0.107**	−0.159**	−0.127**	−0.145**	−0.131**
		# of bus stops	Origin	0.005**	−0.008**	−0.001	−0.002	0.0001
			Dest	0.009**	−0.003	0.001	−0.002	0.003**
		# of subway stations	Origin	0.326**	0.324**	0.283**	0.390**	0.267**
			Dest	0.325**	0.332**	0.282**	0.391**	0.265**
	Bike-transit route characteristics	Bike distance		−0.050**	0.037**	−0.451**	−0.434**	−0.437**
		Bike-only lane proportion		0.267**	0.997**	1.485**	1.306**	1.326**
		Bike-pedestrian lane proportion		0.223**	−0.272	0.284**	0.313**	0.280**
		# of crosswalks		−0.072**	−0.003	−0.029**	−0.051**	−0.028**
		# of turns		−0.020**	0.034**	−0.031**	−0.042**	−0.027**
		Transit duration/bike duration (dummy)	~ 1.0	–				
			1.0~2.0	1.156**	0.171	−0.050**	−0.191**	−0.045**
			2.0~	2.011**	–	0.405**	0.171**	0.447**
		# of transfer (dummy)	0 or 1	–				
			2	0.330**	−0.143**	0.126**	0.258**	0.108**
			3~	1.550**	−0.305**	−0.272	−0.712*	−0.156
	Constant			0.579**	−3.122**	2.795**	1.562**	2.429**
Zero-inflated part	Bike distance			0.386**	0.272**	0.559**	0.696**	0.587**
	% of bike-only lane			−2.564**	−4.944**	−2.605**	−3.177**	−2.831**
	% of bike-pedestrian lane			−0.446**	−1.669**	−0.568**	−0.577**	−0.584**
	# of crosswalks			0.036**	0.052**	−0.0003	−0.030**	0.0002
	# of turns			0.097**	0.067**	0.062**	0.066**	0.067**
	Constant			−1.563**	0.957**	−2.156**	−2.285**	−2.350**
LR chi2				54,112.4**	3959.34**	60,778.2**	30,660.6**	53,928.0**
Ln(alpha)				0.749**	1.894**	0.458**	0.500**	0.564**

* Significant at the 90% level.
** Significant at the 95% level.

non-residential areas is more likely to increase commuting bike-share trips. In residential areas, this relationshp was not found.

Compared to bus trips, subway trips are more likely to make longer travel distances that cannot be traversed by bike-share only. Thus, bike share tends to complement with the subway by providing better access to people who previously resided far from subway stations (González et al., 2015; Noland et al., 2016; Ma et al., 2018). Although substantial variations of travel patterns exist, the result implies that bike share has a competitive relationship with bus transit under particular circumstances. The distinction between subway and sub becomes more evident when we compare travel distance. Seoul's 2016 transportation statistics show that the average trip distance for the subway, buses, and bicycles was 9.8, 2.5, and 1.6 km, respectively.

4.2.3. Bike-transit route characteristics

We found that the proportion of bike-only and bike-pedestrian lanes was positively associated with bike-share trips, while the number of crosswalks and turns on the bike routes negatively influenced it. These findings explain that bike-share users seem to prefer bike travel routes with more bike-friendly lanes and fewer obstacles, such as crosswalks and turns (Khatri et al., 2016; Lu et al., 2018; Wergin and Buehler, 2017).

As an indicator to compare bike-share and public transit, we used a ratio of the transit trip duration to bike trip duration. The variable consistently influenced bike-share ridership. For OD pairs within 10 km, the models explain that bike-share ridership increases when the transit trip duration exceeds twice of bike trip duration. Bike share ridership increases where the public transit route does not effectively connect the travel paths of users. We did not find any meaningful effect of this factor on bike-share trips longer than 10 km. Bike-share ridership also increased when the number of public transit transfers exceeded two. The effects of more than three bike-share ridership transfers were not statistically significant, mainly due to an insufficient number of samples.

We discuss the non-linear impact of route characteristics and the potentially confounding effect of travel distance in the next section.

5. Discussion

Understanding the relationships between bike-share and public transit helps explain the effects of bike-shares on existing transportation systems and the resulting behavioral changes in travel mode (Campbell and Brakewood, 2017; Fishman et al., 2014; Wang and Zhou, 2017). Martin and Shaheen (2014) showed that bike-share and public transit may either compete with or promote each other, and these conflicting relationships can coexist within the same city. The findings of our study also suggest that bike-share can have a competitive relationship with bus transit, particularly in non-residential areas, while it can increase connectivity with rail transit regardless of land-use characteristics. In other words, the bike-share system has the potential to directly or indirectly reduce private vehicle usage by improving connectivity with rail transit (Noland et al., 2016). For those who reside in neighborhoods with poor walking accessibility to subway stations, bike-share might be a suitable alternative for travelling from home to stations.

Another contribution of this study lies in its comparison between

Table 4
Zero-inflated negative binomial regression model (Time of the weekday).

Dep. Var: # of bike-share use per OD in May 2019 (<10 km)				Weekday	Morning peak (07:00–09:59)	Daytime (10:00–16:59)	Evening peak (17:00–19:59)	Nighttime (20:00–02:59)
# of samples				460,376				
# of non-zero				114,460	31,471	61,308	69,288	70,154
Negative binomial part	Land use	Residential area	Origin	0.247**	0.598**	0.045	−0.006	0.407**
			Dest	0.312**	−0.218**	0.195**	0.449**	0.587**
		Commercial area	Origin	0.110**	−0.905**	0.156**	0.555**	0.167**
			Dest	0.128**	0.667**	0.285**	−0.023	−0.408**
		Business area	Origin	1.378**	−9.697**	4.446**	5.776**	−1.041
			Dest	1.652**	17.979**	3.422**	−7.900**	−6.335**
		University area	Origin	0.280**	−0.146	0.166**	0.834**	−0.004
			Dest	0.251**	0.868**	0.065	−0.016	−0.272**
	Bike-transit infrastructure	# of docks	Origin	0.028**	0.013**	0.032**	0.037**	0.028**
			Dest	0.024**	0.026**	0.032**	0.025**	0.018**
		# of BSS stations	Origin	−0.118**	−0.119**	−0.099**	−0.122**	−0.129**
			Dest	−0.131**	−0.112**	−0.130**	−0.151**	−0.166**
		# of bus stops	Origin	0.0001	0.011**	−0.002	−0.010**	0.003**
			Dest	0.003**	−0.017**	0.002	0.009**	0.015**
		# of subway stations	Origin	0.267**	0.099**	0.255**	0.327**	0.415**
			Dest	0.265**	0.174**	0.361**	0.335**	0.272**
	Bike-transit route characteristics	Distance of bike route		−0.437**	−0.254**	−0.440**	−0.357**	−0.426**
		Bike-only lane proportion		1.326**	0.641**	0.882**	1.051**	0.976**
		Bike-pedestrian lane proportion		0.280**	0.242**	0.249**	0.280**	0.267**
		# of crosswalks		−0.028**	−0.031**	−0.040**	−0.046**	−0.023**
		# of turns		−0.027**	−0.003	−0.015**	−0.040**	−0.030**
		Transit duration/bike duration (dummy)	~ 1.0	–				
			1.0 ~ 2.0	−0.045**	−0.049	−0.132**	−0.114**	−0.193**
			2.0 ~	0.447**	0.451**	0.332**	0.334**	0.168**
		# of transfer (dummy)	0 or 1	–				
			2	0.108**	0.040	0.209**	0.147**	0.189**
			3 ~	−0.156	0.606	−1.04*	0.335	−0.573
	Constant			2.429**	0.950**	1.097**	1.024**	1.593**
Zero-inflated part	Bike distance			0.587**	0.794**	0.695**	0.644**	0.643**
	% of bike only lane			−2.831**	−2.755**	−3.252**	−3.337**	−3.034**
	% of bike pedestrian lane			−0.584**	−0.511**	−0.620**	−0.681**	−0.469**
	# of crosswalks			0.0002	−0.024*	−0.020*	−0.010	−0.001
	# of turns			0.067**	0.065**	0.082**	0.071**	0.072**
	Constant			−2.350**	−1.844**	−2.256**	−2.119**	−2.338**
LR chi2				53,928.0**	6380.70**	23,552.2**	24,179.8**	27,612.2**
Ln(alpha)				0.564**	1.408**	0.637**	0.808**	0.689**

* Significant at the 90% level.
** Significant at the 95% level.

public transit and bike-share route characteristics at the OD-level. Existing studies in this field have adopted various methods to examine the competitive bike-transit relationships at the station-level, by utilizing user surveys (Tang et al., 2011; Buck and Buehler, 2012; Fuller et al., 2013; Martin and Shaheen, 2014) or actual ridership data (Brakewood et al., 2015; Campbell and Brakewood, 2017). Findings from those studies have shown that the spatial proximity of bike-share stations and bus stops can strengthen their competition. However, to our knowledge, there has been no existing study that applied the analytical approach of this study, where the relative efficiency of bike-share to public transit was constructed as explanatory variables. Our results showed that longer duration of public transit trips compared to bike-share and a higher number of transit transfers were positively associated with bike-share ridership. This implies that the bike-share system can provide better utility in the districts with poor public transit networks.

Since these two variables have a non-linear relationship with bike-share ridership, we ran a series of ZINB models to test the sensitivity of bike-share ridership to changes in two variables (Table 5). For the ratio of transit trip duration to bike trip duration, compared to less than 0.25 (transit trip duration is shorter than bike trip duration 75% or more), the parameter estimates become statistically significant when the ratio exceeds 1.0 (transit trip duration is equal to bike trip duration). As the ratio increases, the positive influence on bike-share ridership increases, while the marginal effect tends to lessen. For the number of transfers, our models show that bike-share ridership tends to decrease when there were 1 or 2 transfers between OD pairs, and when there were three or more transfers, the ridership started to increase.

Table 5
The ZINB estimates of indicators of relative efficiency between bike-share and public transit.

Threshold ranges		ZINB estimates
Transit duration/bike duration (dummy)	~ 0.25	–
	0.25–0.5	0.796*
	0.5–0.75	0.026
	0.75–1.0	0.427
	1.0–1.25	1.062**
	1.25–1.5	1.579**
	1.5–1.75	1.946**
	1.75–2.0	2.123**
	2.0 ~	2.361**
Number of transfers (dummy)	0	–
	1	−0.765**
	2	−0.434**
	3 ~	0.413**

The confounding effect of travel distance might cause this seemingly counter-intuitive result. Our study's bike travel distance shows a higher than moderate Pearson correlation with the number of transfers ($\rho = 0.471$). Although we controlled bike distance in the models, a higher number of transfers partly explains longer travel distance, which might produce relatively unreliable model estimates for the number of transfers.

The study has a couple of noteworthy methodological limitations. First, we did not directly compare public transit and bike-share ridership due to the lack of trip diaries. Since the ridership database does not contain bike-share users' trip chain records, it was not feasible to thoroughly examine travelers' actual travel behaviors. Another and more important reason is the substantially different scale of public transit and bike-share trips. The ridership of bike-share is steadily increasing, but the average daily bike-share ridership is approximately 48,000 per day, which is not analytically comparable with the bus or subway daily ridership (10.3 million) in Seoul. We suppose that the influence of bike-share on existing transit systems will become more manifest as the patterns of bike-share trips continue to grow in the future. Second, we did not account for personal and social factors that explain bike-share ridership. As Kong et al. (2020) suggested, the relationships between bike-share and public transit can highly depend on users' personal trip features, such as trip time and purpose, rather than surrounding built-environment. However, the Seoul Bike usage dataset does not include personal information of bike-share users. Alternatively, we could include aggregated socio-demographic characteristics—such as average age, income, or proportion of households with a private vehicle—near each station, but this approach may produce misleading implications since bike stations' characteristics do not represent the characteristics near the users' residence.

6. Conclusion

This paper has examined the influence of built-environment factors and public transit characteristics on bike-share ridership. The results of our ZINB models showed that bike-share ridership was associated with land-use, bike infrastructure availability, and existing public transit route characteristics. In particular, we found that the route characteristics of trip duration and number of transfers explained bike-share ridership, which has not been well documented in previous studies. We constructed route characteristic variables using recommended travel route information from online map API and Python scripts and found that this method produced reliable measurements.

While previous research has suggested several optimizing strategies for locating bike-share stations (Chen et al., 2015; Conrow et al., 2018; O'Mahony and Shmoys, 2015), this approach does not concurrently account for both public transit and bike-share. Our result suggests that understanding the complementary or competitive relationship between bike-share and public transit, differentiated by time and context, is important to determining the capacity and locations of bike-share stations. Locating bike-share stations to improve linkage with public transit and supplement lack of transit service may encourage greater use of both bike-share and public transit systems and ultimately reduce dependency on private vehicles.

Our findings may provide some implications for the recent debates on the benefits of the bike-share program, particularly on its social equity issues. Several previous studies, including Chardon's work (de Chardon, 2019), have criticized that bike-share programs have served the privileged urban population such as male, white, higher income, and younger generations while neglecting socially vulnerable groups (Murphy and Usher, 2015; Buck et al., 2013; Goodman and Cheshire, 2014; Hoffmann, 2016; Hosford and Winters, 2018). Their criticism seems reasonable when bike-share is understood as an independent transportation mode.

However, one of the main objectives of the bike-share program is to fill gaps in existing urban transportation networks (Jäppinen et al., 2013; Shaheen et al., 2013). In particular, bike-share has strengthened its benefit by substituting and complementing with public transit system (Fishman et al., 2015; Chen et al., 2020). In this regard, our findings suggest that bike-share improves the city's overall transportation equity as it increases urban mobility for those who isolated from efficient public transit networks. Also, a recent outbreak of the COVID-19 pandemic has led to a further increase in the utility of bike-share users who are not likely to own private vehicles or bikes (Aloi et al., 2020; Tan and Ma, 2020; Przybylowski et al., 2021). In conclusion, bike-share becomes more and more sustainable and resilient transportation modes particularly for people who exist in the blind spots of urban transportation networks.

Further research should examine the influence of social and personal factors on bike-share ridership using individual travel surveys. Investigation of transit ridership changes that result from the introduction of a bike-share system may suggest more implications. Collecting bike route information using actual GPS trajectories would improve the reliability of behavioral data.

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