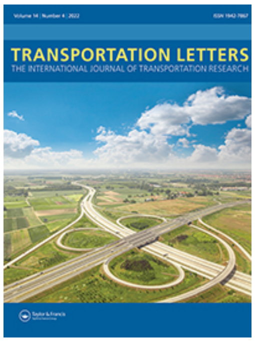


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# Modeling the competitiveness of a bike-sharing system using bicycle GPS and transit smartcard data

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**ABSTRACT**
Competitiveness is an important factor for the sustainable mobility of an integrated multimodal system. In this study, we explore and answer the question concerning what makes bike-sharing trips more competitive than bus trips. The empirical analysis is conducted using transit smartcard and bike-sharing GPS data collected in Seoul, and logistic regression models were developed to understand the factors contributing to the bike-sharing being more competitive than buses. The findings demonstrate that bike-sharing is not only a complementary mode but could also be competing with buses at certain extents. The results indicate that bike-sharing trips can be more competitive than bus trips with longer detours or when the speed of the bus is reduced, such as peak-time periods and short trips. Travel time of bike-sharing is more reliable than bus's during peak times, while the bike lanes contribute to keeping bike-sharing more competitive even during off-peak times.

**KEYWORDS**
Competitiveness; public transport; bike-sharing; logistic regression model; mobility as a service; integrated multimodal transportation system

## Introduction

A well-integrated multimodal urban transport system is the key to sustainable urban mobility due to its great potential for overcoming urban issues related to high automobile demand, such as air pollution, high demand for parking space, and traffic congestion, as a result of the shift from automobile to multimodal transport trips. To achieve this sustainable mobility, however, planners and policymakers must provide multimodal transport systems that are more competitive than automobiles, both at the planning level, by supplying infrastructure and systems that optimally integrate several shared transport modes, such as buses, trains, taxis, bicycles, and walking (Mead, Johnson, and Rose 2016; Weliwitiya, Rose, and Johnson 2019), and at the operational level, using systems such as Intelligent Transport Systems (ITS), or Mobility as service (MaaS) to provide the best intermodal transport alternatives to travelers (Hietanen 2014; MaaS Global 2019; Ambrosino et al. 2016; Giesecke, Surakka, and Hakonen 2016). Therefore, how well different transport modes are integrated together to provide a better or comparable level of services than private vehicles are the key to a successful sustainable urban mobility. However, this integration has always been challenging, especially between motorized modes (e.g. buses, subways, trains, taxis) and non-motorized modes (e.g. walking and biking) (Mead, Johnson, and Rose 2016; Weliwitiya, Rose, and Johnson 2019). Public bike-sharing systems, for instance, are among the emerging active transport and shared mobility options that are being introduced in many cities. Despite the advantages of these systems, the shift from motorized modes to cycling has always been a challenge.

Several planning methods and tools have been proposed to increase the use of cycling. Some of the popular methods include bicycle-transit integration strategies (Mead, Johnson, and Rose 2016; Weliwitiya, Rose, and Johnson 2019), bicycle route choice models (Hood, Sall, and Charlton 2011; Segadilha and Sanches 2014; Kapuku et al. 2019), social equity (Gavin et al. 2016), and the promotion of users' adoption behavior of bike-sharing (Huang et al. 2019). However, these methods do not explicitly consider the competitiveness of cycling trips compared to their competitors (e.g. buses, cars, and subways). As a result, where and how competitive bike-sharing systems could be compared to other modes are still unclear in current planning methods. Other studies have also highlighted the need and importance of clarifying the role of bike-sharing compared to other modes in the planning and operation of multimodal urban transport systems and services, especially with the multitude of travel options that are being provided in emerging services, such as MaaS (Frei, Hyland, and Mahmassani 2017; Utriainen and Markus 2018).

The questions of increasing cycling rates and understanding and clarifying the role of bike-sharing compared to other modes implicitly imply assessing the competitiveness of cycling versus other modes. Knowing where, when, and why bike-sharing could be more competitive than other modes will allow planners to understand and clearly define its role, and properly quantify its benefits.

The competitiveness of cycling has been reported in the previous research based mainly on the descriptive analysis (Ellison and Greaves 2011; Newman 2005). For example, a study conducted in Sydney found that cycling was very competitive with public transport on the basis of travel time, with more than 90% of trips shorter than 5 km being faster by bicycle than by public transportation (Ellison and Greaves 2011). Another study in London found that the disruption in public transportation increased the total number of bike-sharing trips by 85%, the duration of trips, and the connectivity of the network of bike-sharing trips by 88% (Saberi et al. 2018).

In the literature, several research gaps can be identified. First, assessing the competitiveness of bike-sharing compared to its competitors in the multimodal transport system seemed to be the first step toward understanding and clearly defining its roles and benefits. Second, there is some lack of statistical models that could provide guidance in planning by assessing the importance of multiple factors that could make cycling more competitive compared to other modes.

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To fill these research gaps, the aim of this research is to develop models to help in understanding the factors that influence the competitiveness of bike-sharing compared to buses. To achieve this purpose, we use public transit smartcard data and bike-sharing GPS data collected in Seoul city to construct sample data of competing trips of buses and bike-sharing with their associated attributes. Then, we develop models to understand the factors that influence the competitiveness of bike-sharing trips over bus trips.

The contributions of this paper are as follows: (1) It provides a practical case that demonstrates the competitiveness of bike-sharing over buses; (2) It proposes a framework for modeling this competitiveness to help understanding critical factors to consider in the planning of competitive bike-sharing systems and services. (3) Empirical models are established considering observed behaviors and revealed preferences.

The remainder of this paper is organized as follows: Section 2 presents the research methodology. Section 3 summarizes the model results. The results are discussed in Section 4, followed by conclusions and recommendations.

## Method

This study is focused on the megacity city of Seoul, in South Korea. Seoul covers an area of 605 km$^2$ with an estimated population of 10,178,395 in 2017. The primary data sets are used in this study include:

(1) The public transport smartcard data, which was used to construct bus travel time origin-destination (OD) matrices, and bus trip characteristics. These data included travel information of over 7.5 million bus transactions made in Seoul, on June 21 2017, selected as a typical day (weekday and clear weather). The travel information included trip chains, travel time, travel distance, boarding and alighting information, card ID, and travel mode information. Over 6 million bus trips were available after data processing. (2) Bike-sharing GPS data consisted of trip information of Seoul Bike users (the Seoul's largest public bike-sharing system) for the year 2017, such as OD stations, GPS trip trajectories, travel distance, and travel time. Since the bike-sharing trips per day were very few compared to bus trips, one-year data set was used to gather more bike OD trips that better matching with bus OD trips in terms of the number of trips, stations/stops proximity, and travel time. Over 2 million trips were initially available after data processing. (3) Another data was constructed, such as the networks of the road, bicycle lanes, and public transportation including bus stops and lines, bike-sharing stations, and information about bicycle road links. The data were used to represent the components of the multimodal transportation system accurately, which then can be matched with observations to generate the OD matrices and attributes of trips.

The second stage consisted of developing an algorithm to identify and extract competing for OD trips for buses and bike-sharing from the observed trips. The initial OD pairs for the bike-sharing consisted of 187,412 observed OD pairs with over two million trips compared to 473,319 OD pairs with about seven million trips for buses. We defined competing trips as trips that are directly comparable to the competing modes (bike-sharing and bus). Comparable here means that the origin and destination bike stations and bus stops of trips being compared must be close to each other (within a walking distance of 400 m) and must have at least one observed OD trip for both modes. The main task of the algorithm was to find a sample of bus OD pairs in the OD pairs present in smart card data that can be comparable to their corresponding bike-sharing OD pairs, using trip travel times already present in the data set.

Figure 1 shows the four major steps that are required to perform the proposed algorithm. Each step is performed as follows:

STEP 1: In this step, the locations of bike-sharing OD stations were used as reference points. Bike-sharing OD pairs with no trips were filtered and discarded. To keep only direct bike trips, trips with a distance >2.5 × shortest travel distance between the OD pair were removed to eliminate circuitous tours with no likely destination to a specific place (Khatri et al. 2016). The observed OD pairs resulted in 70,164 non-empty OD pairs with direct bike-sharing trips.

STEP 2: The k-nearest neighbor (KNN) algorithm was used to select bus stops closest to both the origin and destination stations of the bike-sharing trips. However, in an urban area, such as the city of Seoul, bus stops of different lines may be very close to each other at certain locations, which may lead to selecting a wrong bus stop, which if connected to its trip end stop (origin or destination) may include, at best, a long detour or, at worst, a non-feasible route. To avoid these behaviors, the top four nearest bus stops were selected at each bike-sharing trip end instead of selecting only one nearest stop. A maximum distance of 400 m (which corresponds to the average distance between bus stops of the same line) was used as the distance constraint. Bike-sharing stations for which corresponding bus OD pairs did not have any observed trips were discarded. Only 10,541 bike-sharing OD pairs matched these conditions. The remaining bike-sharing OD pairs either were not within 400 m of bus stops and/or did not match any observed bus trip.

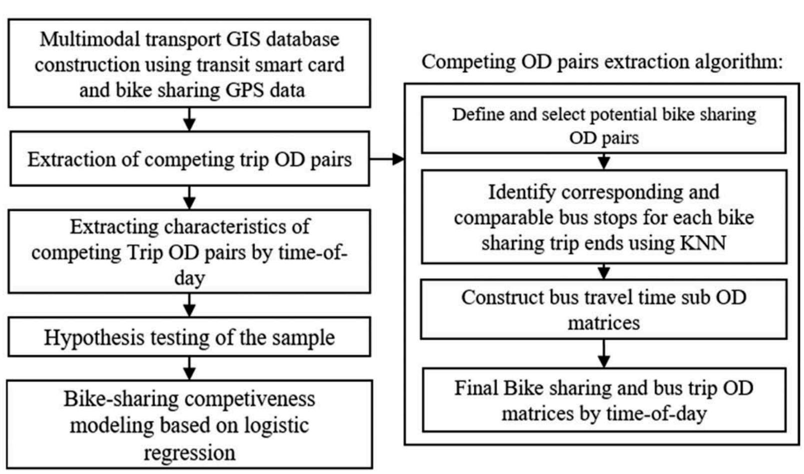



Figure 1. Major steps of the modeling process.

STEP 3: The 4 × 4 bus OD matrices were constructed for each 10,541 OD pairs of bike-sharing. For the bus matrices, the OD pair with the least travel time in the 4 × 4 matrices was selected, making 10,541 bus OD pairs with one OD corresponding to each bike-sharing OD. Of these OD pairs, 342,178 trips were for bus OD trips and 325,575 trips for bike-sharing OD trips.

STEP 4: In the final step, the travel time for each OD of both bike-sharing and bus matrices was estimated by averaging the travel times of the observed trips in these OD pairs. To allow time-of-day analysis, OD matrices were constructed for each time of day including the A.M. peak (7:00 A.M. – 9:00 A.M.), P.M. peak (5:00 P.M. – 8:00 P.M.), and the off-peak.

Many OD pairs of both modes were found not to be comparable since the number of bike-sharing trips was relatively low compared to bus trips. We used the available dataset to match more competitive OD pairs of bus and bike-sharing. The derived sample of 10,541 matched OD pairs of bike-sharing and bus were found to be comparable and were used in the final analysis. This final sample was compared to model the competitiveness of bike-sharing. The descriptive statistics of this final sample are provided in Table 1.

In the third stage, trip attributes that are meant to influence the competitiveness of bike-sharing travel time were extracted to be used as explanatory variables in the model to understand their impacts and relative contributions. The variables were also estimated as the average of trip attributes in the ODs. The Selected variables are listed and described in Table 1. The fourth stage consisted of verifying the hypothesis of the existence of bike-sharing trips that are significantly more competitive than bus trips. A sample of observations in which travel time of bike-sharing was observed to be less than that of the bus for the competing trips was drawn to confirm whether these bike-sharing trips were significantly more competitive than their corresponding bus trips. We employed Mann Whitney's two-tailed and one-tailed t-test statistics to compare the mean travel time of the bike-sharing and bus.

The final stage involved developing statistical models to understand the factors that influence the competitiveness of the bike-sharing over bus trips. We formulated the logistic regression problem, which consists of explaining the probability that bike-sharing will be more competitive than buses. The travel time of OD pairs was used as the competitiveness unit. Therefore, the travel time of the competing bus and bike-sharing OD trips was used to describe the dependent variables represented by a binary indicator variable ($Indicator_{bi}$) coded as 1, if bike-sharing travel time was less than the bus travel time, or 0 otherwise. The functional form of the model is as follows in Equation (1):

$$P_i = \frac{EXP\left[\beta_0 + \beta_1 X_{1,I} + \beta_2 X_{2,I} + \ldots + \beta_k X_{k,I}\right]}{1 + EXP\left[\beta_0 + \beta_1 X_{1,I} + \beta_2 X_{2,I} + \ldots + \beta_k X_{k,I}\right]} \quad (1)$$

where $P_i$ is the probability that bike-sharing will be faster than the bus, $\beta_0$ is the model constant, and $\beta_1, \cdots, \beta_k$ are the unknown parameters corresponding with the explanatory variables ($X_k$, $k = 1, \ldots, K$ the set of independent variables). The model goodness-of-fit was assessed using the Akaike information criterion (AIC) and Rho-squared ($\rho^2$).

## Results

The result provided a comparison of the travel time difference between bike-sharing and bus OD pairs in Figure 2(a). The points below zero were ODs in which travel time of bike-sharing is shorter (more competitive) than that of the bus and represents nearly 43% of the total OD pairs. Points above zero represented ODs in which buses are more competitive. It could be observed that the competitiveness of bike-sharing decreases with distance. Moreover, the majority of competitive bicycle OD trips were less than 7 km of travel distance. Figure 2(b,c) showed an example of the competing bike-sharing and bus trips from the sample. It could be observed that bus routes made long detours compared to bike-sharing due to operational constraints, in that they have to visit each stop, while the bike-sharing users took the shorter route and were faster than buses.

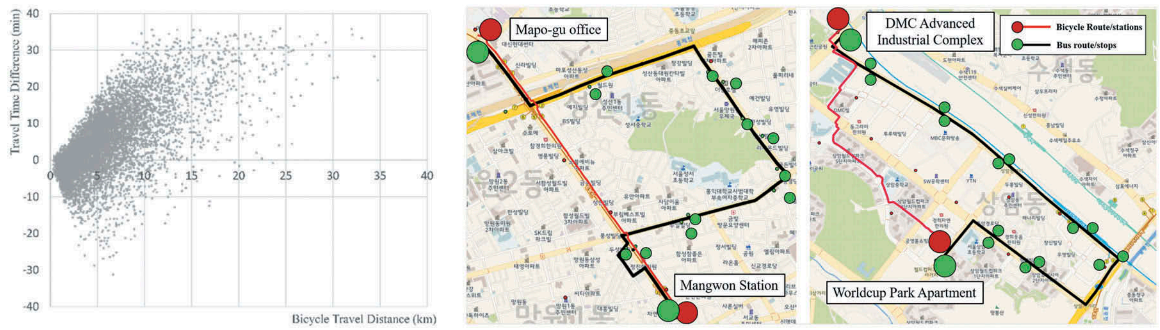
The results of the two-tailed and one-tailed t-test were suggested that the null hypothesis was rejected with the 95% confidence level. This result implied that the sample means are significantly different and the bike-sharing travel time is significantly less than bus travel time. Based on this result, we confirmed that many trips exist in Seoul, in which bike-sharing can be more competitive than buses considering travel time. Table 2 presents the estimates of the model with factors explaining this competitiveness. Four final models were presented, i.e., the full day, off-peak time, A.M. peak time and P.M. peak time models. The goodness-of-fits of all models were relatively good; and all variables were statistically significant at the 95% confidence level with expected signs. In the following sections, the odds ratio was used to interpret the results of models as the relative amount by which the odds of an outcome increases (if positive) or decreases (if negative), when the value of the corresponding independent variable increased by 1 unit.

According to the results, each kilometer increase of the bike-sharing travel distance was found to decrease the odds of bike-sharing travel time competitiveness over buses by 40.6% in the full model. The results of the time of day models suggested considerable

**Table 1.** Descriptions and statistics of the variables.

| Variable | Description | Min | Mean | SD | Max |
|---|---|---|---|---|---|
| $Indicator_{bi}$ [a] | If 1 = Bike-sharing TT < Bus TT; 0 otherwise | | | | |
| $Bus_{TT}$ | The average bus OD travel time (min) | 1.0 | 24.5 | 16.2 | 147.1 |
| $BS_{TT}$ | The average bike-sharing OD travel time (min) | 1.0 | 33.5 | 22.8 | 177.2 |
| $BS_{TD}$ | The average bike-sharing OD travel distance (km) | 0.7 | 5.6 | 4.2 | 34.8 |
| $BS_{SP}$ | The average bike-sharing OD speed (km/h) | 6.7 | 10.1 | 3.2 | 40.4 |
| *Detour* | Bus detour compared to bike-sharing (km) | −10.0 | 0.2 | 2.9 | 11.2 |
| *Bike lane* | Average of the proportions of bike lane lengths in the total travel distance for trip routes of the ODs (%) | 0.0 | 0.4 | 0.3 | 1.0 |
| $D_{SP}$ | Speed difference between bike-sharing and bus (km/h) | −25.3 | −4.4 | 5.0 | 21.6 |
| $Bus_{TTR}$ | Bus OD TT reliability (standard deviation in min) | 1.0 | 9.7 | 10.2 | 35.1 |
| $BS_{TTR}$ | Bike-sharing OD TT reliability (standard deviation in min). | 1.0 | 8.0 | 11.9 | 30.8 |
| Bus OD trips | Bus trips by OD (Total trips: 342,178) | 1.0 | 32.5 | 69.6 | 2,529.0 |
| BS OD trips | Bike-sharing trips by OD (Total trips: 325,575) | 1.0 | 30.8 | 52.5 | 693.5 |

[a]Used only for defining the binary indicator variable; TT =Travel Time.




(a) (b) (c)

**Figure 2.** Differences between bike-sharing and public transport (a) travel times for all OD pairs (Bike TT–Bus TT); (b) travel routes between residential and commercial areas; (c) travel routes between industrial and residential areas.

**Table 2.** Modeling results.

| | | Time of Day | | |
|---|---|---|---|---|
| Variables | Full model | Off-peak | AM-peak | PM-peak |
| $BS_{TD}$ (km) | −0.52*** | −0.55*** | −0.49*** | −0.49*** |
| $BS_{SP}$ (km/h) | 0.17*** | 0.26*** | 0.17*** | 0.27*** |
| *Detour* (km) | 1.03*** | 0.86*** | 0.85*** | 1.03*** |
| $D_{SP}$ (km/h) | 0.38*** | 0.34*** | 0.29*** | 0.41*** |
| $Bus_{TTR}$ (min) | 0.02** | 0.02** | 0.03** | 0.06*** |
| $BS_{TTR}$ (min) | −0.04*** | −0.04*** | −0.02*** | −0.03*** |
| *Bikelane* (%) | 0.40*** | 0.35*** | 0.30** | 0.23** |
| AIC | 4,239.3 | 2,286.8 | 1,237.8 | 1,278.8 |
| Rho-squared | 0.69 | 0.65 | 0.64 | 0.67 |
| Number of observations | 10,541 | 5,010 | 2,598 | 2,933 |

Significance: '***' <0.01, '**' <0.05, '*' <0.1.

differences between the off-peak time with 38.4%, 32.6% for A.M. peak and 36.1% for P.M. peak times. This result indicated that, during peak times, the negative impact of the distance on bike-sharing competitiveness over bus decreases. One way to interpret this is that the importance of the distance as a part of the generalized travel cost decreases as the travel time of buses increased due to traffic congestion, causing delays, while at the same travel time of bike-sharing remained constant.

The increase in cycling travel speed also was found to increase the probability of bike-sharing competitiveness by 19% on average. The Speed difference variable provided more insight. It was found that, on average, and independent of the time of day, each km/h unit increased in the difference between bike-sharing and bus travel speeds increase the likelihood of bike-sharing trips competitiveness by 46%. The proportion of bike lane in the route was found to be the second factor with the most significant effect on bike-sharing competitiveness, especially during the off-peak time with a 42.2% increase in the likelihood of bike-sharing competitiveness. This was important for keeping bike-sharing competitive even during off-peak times, as it has been proven that bike lane provides faster, safer, and more comfortable environment for cycling (Hood, Sall, and Charlton 2011; Segadilha and Sanches 2014; Kapuku et al. 2019).

Each minute increase in the bus travel time standard deviation was found to increase the likelihood of bike-sharing competitiveness by 1.7% in the full day and off-peak, 3% in the AM-peak, and 5.8% in the PM-peak. While at the same times of day, the bike-sharing travel time variance was reduced the likelihood by 3.6%, 4.0%, 1.7%, and 2.8%. This meant that the bus travel time becomes less reliable than bike-sharing travel time during peak times, which increases bike-sharing competitiveness.

The most important variable was the bus detour. For each unit increase of detour in the travel distance of bus compared to that of bike-sharing, the probability of bike-sharing competitiveness increased by 179%. For 500 m of detour, for example, one expected 90% of the likelihood of bike-sharing competitiveness. Detours were common in public transport planning and operation due to the need for maximizing the benefit by meeting the demand as much as possible. However, the detours might be significantly increased travel time due to extra distance, more stops, traffic signals, and many other traffic conditions. In such cases, bike-sharing could be more competitive than buses.

## Discussion and conclusion

This study has provided important findings that can be relevant in the planning and operation of multimodal transport systems and services in many ways.

First, the results of this study confirmed that there exist OD pairs, in which, on average, trips made by bike-sharing were more competitive than those made by bus in Seoul. This finding also demonstrated that bike-sharing is not only a complementary mode but could also be competing with other modes at certain extents and in different times of day. It constituted an opportunity that planners can explore to improve the efficiency of bike-sharing services. Second, the proposed model has helped to understand factors that can make bike-sharing trips more competitive than bus trips. According to the results, bike-sharing trips could be more competitive than bus tips on bus routes with longer detours, and when the speed of the bus is reduced, such as during peak times and for short trips. Moreover, factors such as high variance in bus travel time and bicycle lane also contributed to the increasing competitiveness of bike-sharing systems. These findings also have clarified what the role of bike-sharing systems may be in the multimodal urban transport relative to buses. This role would be to enhance the multimodal transport services in areas where bus services are less efficient due to the factors identified in this study. Third, the travel time benefits that could result from planning bike-sharing systems that are more competitive than motorized modes (e.g. buses) will lead to an increase of cycling rates as a result of the modal shift, allowing planners to better quantify the benefits and justify the investment in such systems. Other important factors that could enforce bike-sharing competitiveness are probably the fare pricing policy. Currently, intermodal transfers between buses and subways are considered and priced as a single trip. Users do not pay separate fees for each mode, which makes it cheaper. However, when transferring from bus or subway to bike-sharing, users must pay the bike-sharing fee separately. This makes intermodal trips that include bike-sharing more expensive and may discourage many riders. Therefore, extending the public transport transfer policy to include bike-sharing may eventually make it even more competitive and attract more riders. Finally, one important observation is that, currently, the bus network in Seoul generates up to 458,413 OD traveled by bus users for a typical day, versus 187,411 OD traveled by bike-sharing users in 1 year (2017). These numbers are the results of current planning which did not explicitly consider the competition between bike-sharing and other modes such as buses. Therefore, the new objective of planners should be to increase these numbers by explicitly considering the competitiveness between competing modes in the planning and operation processes.

Several areas of future research can be investigated to improve the proposed method. First, additional variables can be studied and integrated with these models, such as the monetary cost, and operating conditions such as weather and bus delays, all of which could be useful for real-time operations. The models can then be used to predict and suggest itineraries in ITS or MaaS systems, in which bike-sharing could provide better services than buses. They also can be used for planning new bike-sharing stations and bicycle infrastructure that focus on competitiveness.

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## References

Ambrosino, G., J. D. Nelson, M. Boeroc, and I. Pettinellia. 2016. "Enabling Intermodal Urban Transport through Complementary Services. Developing Inter-modal Transport Systems." *Research in Transportation Economics* 59: 179–184. doi:10.1016/j.retrec.2016.07.015.

Ellison, R. B., and S. Greaves. 2011. "Travel Time Competitiveness of Cycling in Sydney, Australia." *Transportation Research Record* 2247 (1): 99–108. doi:10.3141/2247-12.

Frei, C., M. Hyland, and H. S. Mahmassani. 2017. "Flexing Service Schedules: Assessing the Potential for Demand-adaptive Hybrid Transit via a Stated Preference Approach." *Transportation Research Part C: Emerging Technologies* 76: 71–89. doi:10.1016/j.trc.2016.12.017.

Gavin, K., A. Bennett, A. H. Auchincloss, and A. Katenta. 2016. "A Brief Study Exploring Social Equity within Bicycle Share Programs." *Transportation Letters* 8 (3): 177–180. doi:10.1080/19427867.2015.1126065.

Giesecke, R., T. Surakka, and M. Hakonen. 2016. "Conceptualising Mobility as a Service." *In: 2016 Eleventh International Conference on Ecological Vehicles and Renewable Energies (EVER)*, 1–11. IEEE.

Hietanen, S. 2014. "'Mobility as a Service' – The New Transport Model." *Eurotransport* 12: 2–4.

Hood, J., E. Sall, and B. Charlton. 2011. "A GPS-based Bicycle Route Choice Model for San Francisco, California." *Transportation Letters* 3.1: 63–75. doi:10.3328/TL.2011.03.01.63-75.

Huang, D., Y. Liu, M. Wang, and H. Yang. 2019. "Qiang Huang and Cheng Li "How to Promote Users' Adoption Behavior of Dockless Bike-sharing? an Empirical Study Based on Extended Norms Activation Theory." *Transportation Letters* 1–11.

Kapuku, C., S.-H. Cho, S.-Y. Kho, and D.-K. Kim. 2019. "Bayesian Models with Spatial Autocorrelation for Bike Sharing Ridership Variability Based on Revealed Preference GPS Trajectory Data." *IET Intelligent Transport Systems* 13 (11): 1658–1667. doi:10.1049/iet-its.2019.0159.

Khatri, R., C. R. Cherry, S. S. Nambisan, and L. D. Han. 2016. "Modeling Route Choice of Utilitarian Bikeshare Users with GPS Data." *Transportation Research Record* 2587 (1): 141–149. doi:10.3141/2587-17.

MaaS Global. 2019. Accessed July 18 2019 www.maas.global.com.

Mead, D., M. Johnson, and G. Rose. 2016. "Factors Influencing Variability in the Usage of Secure Bicycle Parking at Railway Stations in Melbourne, Australia." In *Transportation Research Board 95th Annual Meeting*, 16–3283.

Newman, P. 2005. "Urban Design and Transport." *In Search of Sustainability* 123–136.

Saberi, M., M. Ghamami, Y. Gu, M. Hossein, and E. Fishman. 2018. "Understanding the Impacts of A Public Transit Disruption on Bike Sharing Mobility Patterns: A Case of Tube Strike in London." *Journal of Transport Geography* 66: 154–166. doi:10.1016/j.jtrangeo.2017.11.018.

Segadilha, A. B. P., and S. D. P. Sanches. 2014. "Analysis of Bicycle Commuter Routes Using GPS and GIS." *Procedia - Social and Behavioral Sciences* 162: 198–207. doi:10.1016/j.sbspro.2014.12.200.

Utriainen, R., and P. Markus. 2018. "Review on Mobility as a Service in Scientific Publications." *Research in Transportation Business and Management* 27: 15–23. doi:10.1016/j.rtbm.2018.10.005.

Weliwitiya, H., G. Rose, and M. Johnson. 2019. "Bicycle Train Intermodality: Effects of Demography, Station Characteristics and the Built Environment." *Journal of Transportation Geography* 74: 395–404.