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Assessing and Predicting Mobility Improvement of Integrating Bike-Sharing into Multimodal Public Transport Systems

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Abstract

New shared mobility services have become increasingly common in many cities and shown potential to address urban transportation challenges. This study aims to analyze the mobility performance of integrating bike-sharing into multimodal transport systems and develop a machine learning model to predict the performance of intermodal trips with bike-sharing compared with those without bike-sharing for a given trip using transit smart card data and bike-sharing GPS data from the city of Seoul. The results suggest that using bike-sharing in the intermodal trips where it performs better than buses could enhance the mobility performance by providing up to 34% savings in travel time per trip compared with the scenarios in which bus is used exclusively for the trips and up to 33% savings when bike-sharing trips are used exclusively. The results of the machine learning models suggest that the random forest classifier outperformed three other classifiers with an accuracy of 90% in predicting the performance of bike-sharing and intermodal transit trips. Further analysis and applications of the mobility performance of bike-sharing in Seoul are presented and discussed.

Keywords

bicycle transportation, bikesharing, modeling and forecasting, pedestrians, bicycles, human factors, planning and policy

The core of the new multimodal urban mobility concept is to combine public transport with other motorized and non-motorized transport as well as new mobility services. This use of different and optimally combined transport modes within a trip is one of the key approaches for providing greater sustainability in urban transport (*1*). The integration of these new mobility services into existing multimodal transport systems may significantly affect the city's mobility, such as increasing public transit attractiveness, reducing demands for automobiles and parking space, and reducing air pollution and traffic congestion.

Bike-sharing systems are among the non-motorized shared mobility services that are being introduced in many cities. These systems are the focus of this study.

Many studies have demonstrated the advantages of integrating cycling with public transportation modes, such as trains and buses (*2*, *3*). However, the extent to which integrating bike-sharing systems into a multimodal transport system could improve the mobility of the city compared with other existing transport modes is still unexplored. Moreover, with the multitude of travel options provided by the existing urban transport system, the role and contribution of bike-sharing should be assessed. For example, in many cities, bus networks are typically designed to penetrate residential areas to the extent that bus stops usually are within walking distance of the vast majority of destinations. Feeder bus services are designed to pick up passengers and take them to a transfer point where they can transfer to one of the trunk

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services, such as subways or trains. With these multimodal public transport services that are already available, it is necessary to understand the contribution that integrating bike-sharing with the existing systems makes to the overall mobility to justify and prioritize investments in such systems. This implicitly implies assessing the competitiveness of multimodal alternatives that include bike-sharing systems versus existing alternatives. Knowing where, when, and to what extent integrating bike-sharing with the existing public transport system could provide higher mobility performance and allow planners to plan for high-performing integrated multimodal transport systems. However, the provision of such systems is problematic without an understanding of the related factors and because of the lack of reliable tools that can be used to evaluate the performances of integrating these new mobility services into multimodal alternatives.

The terms "intermodality," "multimodality," and "monomodality" are often used in multimodal transport studies. It is essential to define them to understand their use in this study. According to Chlond and Manz, the term "monomodality" can be defined as the exclusive use of one transportation mode for all travel within a specific time period (*4*, *5*). The term "multimodality" is the flexible use of various transportation modes for travel within a specific time period (typically 1 week). "Intermodality," however, is a subset of multimodality that refers to combining various modes of transportation in the course of one trip. The multimodal transport concept used in our study is consistent with the definition of "intermodality." Although the data used in our study were collected over several months, the time period or travel unit in this study is single trips because our objective was to assess and compare different intermodal trips to determine the best-performing alternative for a given trip.

We propose a method in this paper for analyzing the mobility performance of integrating bike-sharing into multimodal transport systems. To test the proposed approach, we used transit smart card data, bike-sharing GPS data, and transit-bike-sharing transfer data from the city of Seoul to develop an algorithm to extract intermodal alternatives. The various features that may affect the choice probability were extracted from these alternatives were ranked and selected using the ReliefF algorithm. Using the selected features, we built a machine learning model to predict potential bus itineraries in the multimodal system, in which bike-sharing can provide more efficient or competitive services.

The remainder of this paper is organized as follows. The next section provides a literature review of earlier studies and positions our research. This is followed by descriptions of the data, variables, and modeling methods. Then, the results of the model and their possible implications are presented and discussed. Recommendations for future research are presented in the Conclusions.

Literature Review

Early studies on multimodality in transportation were dedicated primarily to the interactions between automobiles and public transport to understand multimodal behavior. (*6–10*). Although being multimodal does not necessarily result in less car use, indicators of the relationship between multimodality and more sustainable transport could be found from the literature. For instance, some studies revealed that individuals with more multimodal travel behavior patterns are more likely to change their travel behavior over time (*10–12*). Such behavioral change could allow an easier transition to sustainable transport if the right conditions are provided (*12*). It has also been found that a higher level of multimodality may lead to reducing CO_2 emissions under the condition that travel distance remains constant (*13*).

The existing studies on bicycle intermodality with transit have been dedicated primarily to special forms of integrating bicycles with transit. For instance, a study found that most passengers chose walking, bicycling, and public transport to get to or from rail stations (*14*). A study in the U.S. also found that walking was the primary means of transit access and egress, followed by transit and automobiles. Bicycle access and egress trips combined with other modes accounted for only 2.2% and 2.6%, respectively (*15*). Ultimately, all of the studies on the access to transit using bicycles fall into this category, even if they do not refer to intermodality, because the underlying hypothesis is that improved bicycle access to transit may improve their intermodality with transit (*2*, *3*, *16–19*).

Some other studies have compared the mobility performance of bicycles and motorized modes based mainly on the descriptive analysis (*20–22*). Many other studies on shared mobility services have posited that shared mobility services have the potential to fundamentally reshape urban mobility by enhancing public transit, decreasing car ownership, and decreasing the overall transportation cost (*23*).

A few studies are currently emerging to study the impact of shared mobility on the transportation system. For example, Jiao et al. used the 2017 National Household Travel Survey to assess the association between shared mobility services, including ride-hailing services, bike-sharing services, and car-sharing services, and individuals' trip making behaviors (*24*). Henrik et al. conducted a joint simulation of car-sharing, bike-sharing, and ride-hailing for a city-scale transport system, using MATSim to assess the welfare impacts of shared mobility and mobility as a service (MaaS) (*25*).

Despite the intense discussion about the potential benefits and disadvantages of shared mobility, little research has attempted to conduct empirical assessments of their effects on existing systems. This is primarily because of the lack of high-quality data, as many of these services are operated by private companies reluctant to share data (*26*). As a result, there has been little research done on assessing the contribution of cycling as a shared mobility service in a multimodal transport system, although this need has been acknowledged in the literature (*1*, *26–28*).

This paper aims to fill this gap by making the following contributions: (1) We propose a method for assessing the city-wide mobility performance of bike-sharing in the multimodal urban transport system using the available city-wide revealed preference data; (2) We develop a machine learning model for predicting the performance of multimodal alternatives that include bike-sharing in the multimodal transport network; (3) We propose a method for extracting competing multimodal alternatives from the dataset; (4) The proposed model can be used both in the planning and operation stages to suggest high-performing intermodal itineraries for transit and bike-sharing users.

Model Specification

Data Description

The city of Seoul in South Korea was the study area in this research. In 2017, Seoul covered more than 605 km^2, and its estimated population was slightly greater than ten million. Seoul has a well-developed transportation network with significant modes, including cars, taxies, buses, subways, trains, bicycles, and walking. These transport modes are integrated through advanced intelligent transport systems (ITSs)and several trip planner application services that offer real-time information to travelers.

This study used several datasets to reconstitute intermodal trips and their environments to analyze and compare their mobility performance and extract their features to build models. Figure 1 shows the main modeling steps of this study. The first stage involved constructing a database for the analysis. The primary datasets used were as follows: (1) the public transit smartcard data, (2) bike-sharing GPS data, (3) public transit and bike-sharing transfer data, and (4) the multimodal transport network. The public transit smartcard data provided travel information for more than 90% of the passengers using Seoul's public transportation system, including buses and subways. The dataset included over 7.5 million bus transactions collected in real time on 20 June, 2017. The information recorded included trip chains, travel time, travel distance, boarding, alighting

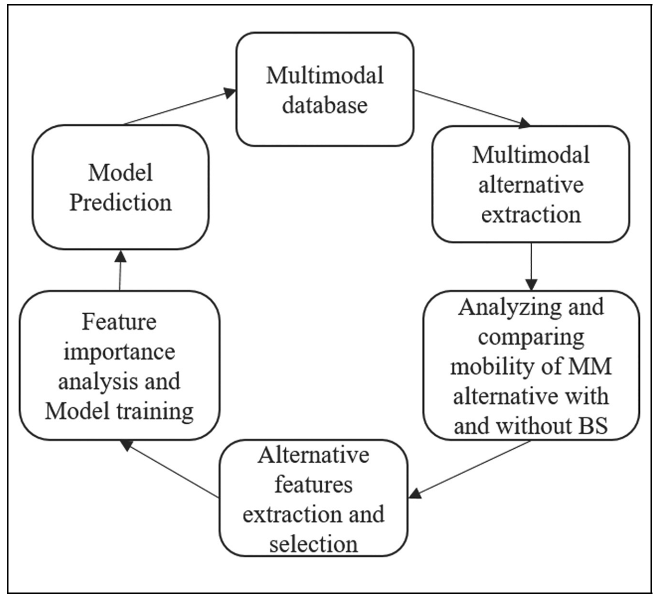

Figure 1. Modeling steps.

information, card ID, and travel mode information. These data were matched with bike-sharing data to obtain similar intermodal trips and extract trip features such as the observed travel time, distance, speed, and bus line detours.

Bike-sharing GPS data were collected from Seoul's most extensive public bike-sharing system, known as "Seoul Bike," which began its operation in 2015. The system records users' routes from the origin to the destination in real time. The data provide GPS routes, origin–destination (OD) stations, travel distance, travel time, gender, age, and trip ID. Trips in this data are the same trips recorded in the transit-bike-sharing transfer data. Both data can be matched using the trip ID. The data were matched with the transit-bike-sharing transfer data to obtain more accurate information about the trips.

Public transit and bike-sharing transfer data were the main datasets used in this study. These data were used mainly to extract trips that combined bike-sharing and public transit. The data provide information on bike-sharing trips in which the travelers transferred to buses or subways in Seoul. Some important information used in this study includes bike-sharing OD station ID, bike-sharing travel time, transit transfer mode, and transit travel time. These data were matched with bike-sharing GPS data to obtain more information about the trips. We used data from September 2016 to June 2017 and from September 2017 to December 2018, including 95,740 Public transit and bike-sharing transfer trips. Finally, additional important data were transportation networks. They included the road network, bus network, subway network, bike cycle network, and bike-sharing stations. A GIS database was used to construct a

Comparable alternatives extraction algorithm:
Inputs: For both bike-sharing and buses: stop/station id and geo-coordinates, travel time of trips, bus lines from smartcard data.
For all bike-sharing intermodal trips
1) Find the k nearest bus stops at origins and destination stations of bike-sharing trips using KNN
(k = 4).
2) Construct an "empty" 4 × 4 bus OD matrix using these bus stop IDs.
3) Search for each of these ODs in the smart card database.
4) If an OD matches with at least one trip, then associate the OD to the current bike-sharing trip; otherwise, remove ODs that do not match any trip in the smartcard data.
5) From the matched bus alternatives, select the bus trip with the least travel time as the competing alternative.
end for

multimodal database used to match the trips with their environment to extract similar trips and their characteristics or features.

Trip characteristics that may affect the choice probability were extracted to be used as features in the model. This study focused on features related to travel time, travel distance and travel speed, and bicycle infrastructure. Table 1 presents a list of the selected variables and features and their descriptive statistics. We used the ReliefF algorithm (*29*) to rank and select important features, particularly for its independence on heuristics, noise-tolerance, and robustness, to feature interactions.

Data Preprocessing

After constructing the database, the next step was to identify and extract multimodal alternatives to be analyzed. We were interested in analyzing and comparing the mobility performances of multimodal alternatives that use bike-sharing as access/egress to those that use buses to connect to the subway or other buses. Figure 2 shows the intermodal scenario of interest in this study. Two different intermodal alternatives were compared: The trips combining bike-sharing and public transit (bike-sharing–transit alternatives) were compared with trips that combined buses and another public transit (bus–transit alternatives) that can be either a subway or another bus. However, the transit–bike-sharing transfer data only provide information on the intermodal trips of bike-sharing users, that is, bike-sharing to bus and bike-sharing to subway trips. Intermodal trips that use buses to connect to other transit modes are in the smart card dataset. Therefore, we developed an algorithm that uses these two datasets to extract comparable and competing intermodal alternatives that used bike-sharing or buses to connect to other transit modes.

The algorithm was used to identify alternatives (bus–subway and bus–bus) directly comparable to transit–bike-sharing transfer trips. The algorithm uses the *k*-nearest Neighbor (KNN) algorithm (*30*) to find the nearest alternatives and focuses on the specific part of the intermodal trip. The algorithm can be implemented as follows:

After using this algorithm and processing the data, the final dataset included 120,400 observations of pairs of intermodal trips, with one of the pairs using bike-sharing (60,200 observations) and the other using buses to access other transit modes (60,200 observations). In the next step, after extracting intermodal alternatives and their features, we analyzed and assessed the mobility performance of intermodal trips that included bike-sharing and those without bike-sharing based on travel time. We compared the cases in which less-performing bus trips were replaced by bike-sharing trips that provided better

Table 1. Descriptions and Statistics of the Variables

Variables	Description	Mean	SD
Indicator[a]	One if bike-sharing travel time < Bus travel time; 0 otherwise	NA	NA
Bus_{TT}	Bus trip travel time (min)	7.69	5.28
Bus_{BH}	Bus trip boarding time (hour of the day)	14.13	4.83
Bus_{Speed}	Bus trip travel speed (km/h)	16.38	7.19
Bus_{TD}	Bus trip travel distance (km)	1.85	1.15
Gender	Bike user's gender	NA	NA
Age	Bike user's age (birth date)	1,978.71	24.69
F_{Detour}	Bus detour factor: Bike TD–Bus TD (km)	−638.67	1,128.45
SP_D	The difference in travel speeds between bike-sharing and bus (km/h)	6.04	3.20
BS_{TD}	Bike-sharing trip travel distance (km)	1.21	0.87
BS_{Speed}	Bike-sharing trip speed (km/h)	10.34	3.99
$Bike_{lane}$	The portion of the bike lane in the route (%)	0.34	0.23
$TT_{bike-transit}$	Total travel time for bike–transit intermodal trips (min)	28.73	17.13
$TT_{bus-transit}$	Total travel time for bus–transit intermodal trips (min)	36.42	17.98

Note: Observations 120,400 trips. TD = travel distance; SD = standard deviation; NA = not available.
[a]Used only for defining the binary indicator variable.

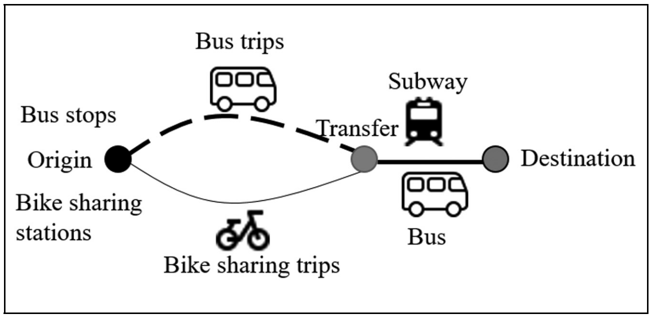

Figure 2. Intermodal travel scenarios.

service in relation to travel time for the access/egress parts of intermodal trips. The *t*-test and Wilcoxon tests were used to make statistical comparisons of the samples for several scenarios.

Machine Learning Model

The aim of the modeling step was to develop a machine learning model capable of predicting the performance of multimodal trip alternatives that include bike-sharing compared with those without bike-sharing. We defined this problem as a binary classification problem that consists of predicting the probability that trips with bike-sharing will be more competitive than trips without bike-sharing, given the selected features of the alternatives. We compared four popular machine learning classifiers to select the model with the best predicting power. These models have either already been successfully used in transportation research or have shown promising results in other fields. These models included logistic regression (LR) (*6*), support vector machine (SVM) (*31*), decision tree (DT) (*32*), and random forest (RF) (*32*).

Before building our models, we investigated the importance of features of intermodal alternatives that will be used in the models. This paper employs the ReliefF algorithm for feature selection to identify influential subsets of significant predictors. The ReliefF algorithm (*26*) is an extension of the original Relief algorithm (*33*, *34*). Compared with the original Relief algorithm, the ReliefF can deal with multiclass problems and incomplete and noisy data. It also performs well on the feature selection problem that includes interaction among features and local dependencies. Some of the strengths or advantages of the ReliefF algorithm include its independence on heuristics, its low-order polynomial time in computation, and noise-tolerance and robustness to feature interactions (*35*).

Results and Discussion

Multimodality Result

Evaluation of the Comparable Alternatives Extraction Algorithm. The selection of k = 4 as in the KNN algorithm was based on some sensitivity analysis. Figure 3 shows the number of matched observations for each value of k. We found that increasing the number of k also increases the chance of more correct matchings. The main source of mismatching may come from selecting OD pairs that cannot be found in the smartcard, such as OD bus stops of opposite directions because most travelers would travel between bus stops that lead to the same direction toward their destination. Another source of mismatching could come from a selection of wrong bus stops by the algorithm in which trip ends do not match. Either of these k samples can be used for modeling, as they are all observed trips found in the smartcard. We chose k = 4 as it provided more valid matched trips and enough to be used in our model.

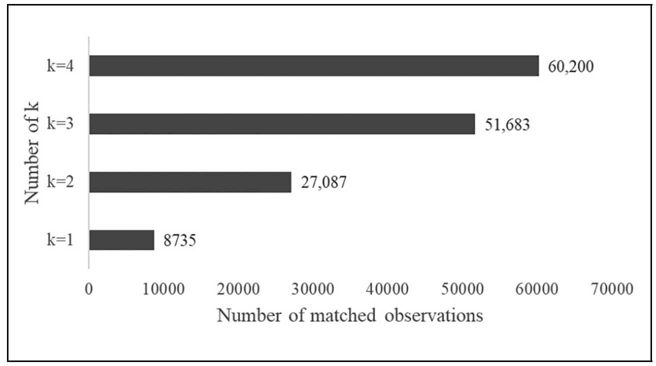

Figure 3. Number of matched trips by selected k in *k*-nearest neighbor.

In general, the trips that were found using the comparable alternatives extraction algorithm were taken by the users, so their related information is accurate. Even so, it is important to validate the results to verify their pragmatism. First, we selected the four nearest bus stops to increase the likelihood of finding at least one OD match with the smartcard data. However, if the distance between the bike-sharing station and the bus stops is too long, travelers might not consider competing or comparable alternatives. To provide more assurance, we analyzed the distances between the selected bike-sharing stations and the bus stops (proximity), and the average distance was found to be 120.4 m with a standard deviation of 84.42 m; the minimum and maximum distances were 2.5 m and 761.7 m, respectively. Thus, we concluded that the bike-sharing stations and the bus stops selected by the algorithm were within acceptable (walking) distances, so they were considered comparable.

Mobility Performance by Scenario. The results of the one-tailed *t*-test confirmed the alternative hypothesis that the travel times of intermodal trips that included bike-sharing were considerably less than the travel times using buses, and this finding was confirmed at the 95% confidence level. These results confirmed that many intermodal itineraries exist in Seoul in which bike-sharing combined with subways or buses can provide better and more competitive services than using buses as the means of access/egress.

To assess the bike-sharing system's potential mobility performance, we compared the cases in which less-performing bus trips were replaced by bike-sharing trips that provided better service in relation to travel time for the access/egress parts of intermodal trips. Three scenarios were evaluated: (1) Bus versus Bike-sharing: In this scenario, we compared to bus and bike-sharing travel times for access/egress trips. The *t*-test and Wilcoxon tests were used to make statistical comparisons of the two samples. The null hypothesis was that the mean of buses' travel times is less than the mean travel time of the bike-sharing sample. (2) Mixed modes versus bus (single mode trips): In this scenario, low-performing bus trips (longer travel time) were replaced by their corresponding bike-sharing trips with better performance (shorter travel time) for the same OD. We called the sample that resulted "mixed modes" (as they include combined bike-sharing and bus trips or bike-sharing and subway trips), and we compared this sample with the sample of travel time that only included buses. The *t*-test and Wilcoxon statistical tests also were conducted to get a statistical comparison of the two samples. The null hypothesis was that the mean of the high-performing mixed modes travel times is less than the bus sample's mean travel time. (3) Mixed-mode versus Bike-sharing: In this scenario, the "mixed mode" sample from the previous scenario was compared with a sample of bike-sharing travel time.

Table 2 provides the results of the comparison of the mobility performance of the intermodal trips. All of the statistical tests were significant for both the *t*-test and the Wilcoxon tests. The first scenario result, that is, "Bus versus Bike-sharing," suggests that, on average, bike-sharing and bus trips provide comparable levels of mobility. On average, the difference was very small, that is, only a 1% saving in travel time. For more insight, Figure 4*a* shows a plot of the difference in the travel time for the bike-sharing and bus alternatives. Positive values of Y represent the travel time savings provided by bus trips compared with their bike-sharing alternatives, and the negative values represent the savings in travel time for bike-sharing. The X-axis is the travel distance.

The results of scenario two, that is, "Mixed modes versus bus," suggest that bike-sharing could enhance mobility performance. The results indicated that replacing low-performing bus trips with high-performing bike-sharing trips provided a 34% reduction in travel time. Similarly, the third scenario, that is, "Mixed modes versus Bike-sharing," also suggests that the "Mixed modes" scenario outperformed the scenario in which all trips were made by bike-sharing in a savings travel time of about 33%.

The analysis of the three scenarios provided some insights that could be useful in the planning and policy-making process. The first scenario demonstrated that bike-sharing could provide better mobility than buses used for short distances to access other transit modes in the multimodal transport system. The second and third scenarios demonstrated that integrating bike-sharing in the multimodal transport system can increase mobility performance, especially in areas where bike-sharing can provide better services than buses for the access/egress parts of the intermodal trips. This highlights the need and necessity of developing models for identifying locations, routes, and itineraries in which bike-sharing can provide more competitive services than buses to guide planners in developing such a system. Such models are presented and discussed in the following sections.

Prediction Result

Selected Important Features. Figure 4*b* shows the ranking of the importance of various features provided by the ReliefF algorithm. The features used in the classification models are ranked in the order of their significance in predicting the target. The results of the feature importance show that, for the training set, the detour (F_{Detour}) is the most important feature in predicting the competitiveness of intermodal trips with bike-sharing. This feature, along with Bike lane, speed difference (SP_D), bus boarding hour (Bus_{BH}), and bike-sharing travel distance (BS_{TD}), are the top five features that have the most important effect on whether intermodal alternatives with bike-sharing as an access/egress mode will be more

Table 2. Analysis of the Performance of the Multimodal Trips

Access/egress mode	*t*-Test	Wilcoxon	Mean[1]	Mean[2]	Time saved	Time saved (%)
Bike-sharing[1] versus bus[2]	-4.6^{***}	60^{***}	7.8	7.9	0.1 (min/trip)	1
Mixed modes [1] versus bus[2]	-12.9^{***}	40^{***}	5.2	7.9	2.7 (min/trip)	34
Mixed modes[1] versus bike-sharing[2]	-14.8^{***}	42^{***}	5.2	7.8	2.6 (min/trip)	3

[1]Sample 1; [2]Sample 2; Significance: ***<0.05; mixed mode = combined bike-sharing to bus trip or combined bike-sharing to subway trip.

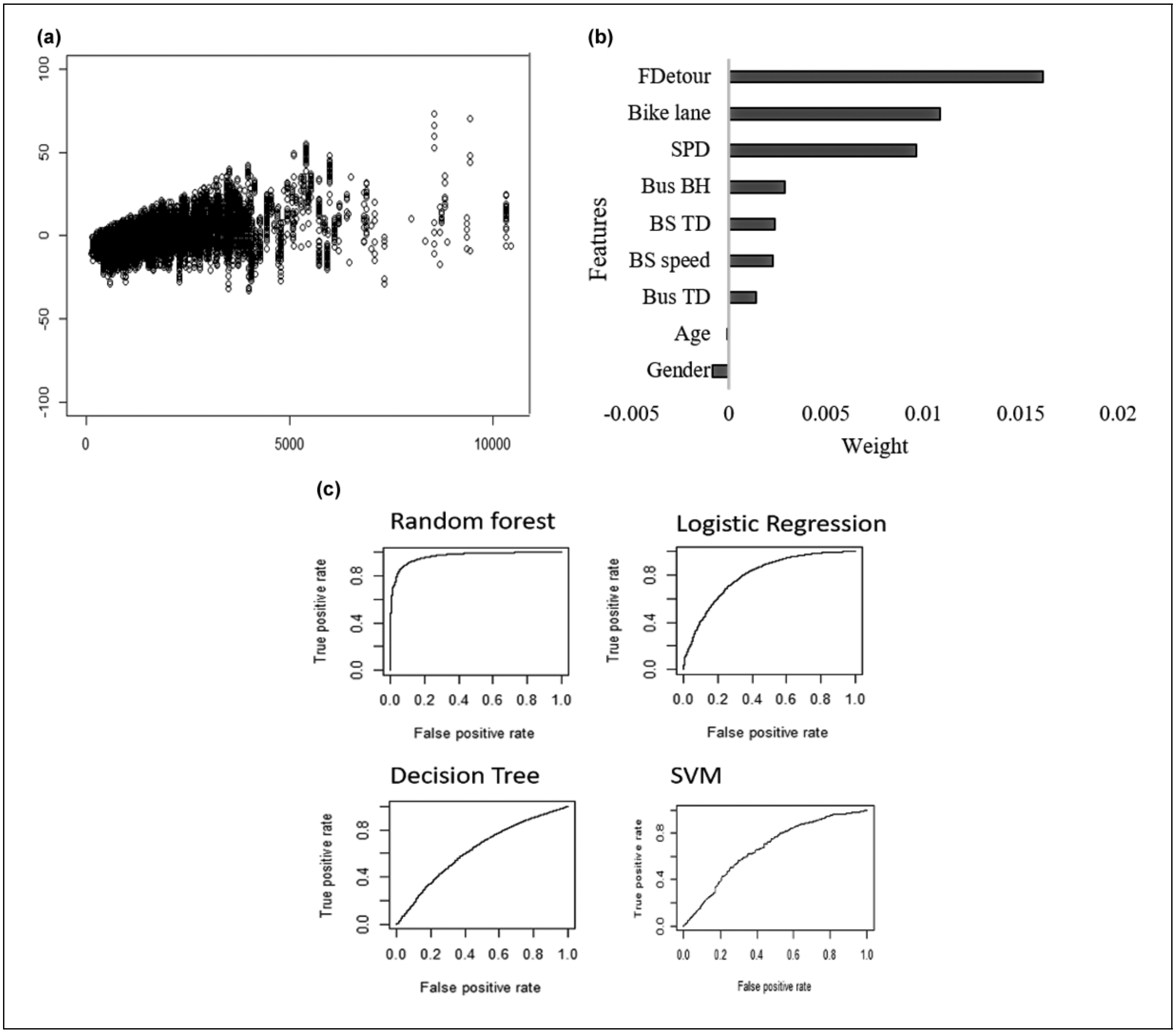

Figure 4. (*a*) Travel time savings by modes for each alternative pair, (*b*) Selected important features, and (*c*) receiver operating characteristic curves of the machine learning models.

efficient or faster than those with buses. The negative ranking indicates noise. Thus, features ranked below zero or at zero do not significantly contribute to the prediction, and they probably should be removed from the data. By considering the features that had positive importance weights, five features were selected for the models, that is, detour (F_{Detour}), bike lane, speed difference (SP_D), bus boarding hour (Bus_{BH}), and bike-sharing travel distance (BS_{TD}).

Evaluation of the Models. The models were evaluated by applying them to the test set with known response values compared with the predicted values. Specifically, 70% of the records were randomly selected and used to train the models, and the remaining records were used to test the model. We used ten-fold cross-validation to estimate the accuracy of our models before applying the trained model to the independent test set. The values in Table 3 measured the accuracies of the four models. The results showed that the RF model outperformed the other three models in most performance measures; concerning accuracy, RF achieved the best result (90%), followed by DT (80%), whereas SVM and LR had similar accuracy (72%). Figure 4*c* shows the receiver operating characteristic (ROC) curves of all models. RF also yields a better AUC, which is the area under the ROC curve. AUC measures the discriminating ability of a binary classification model. The larger the AUC, the higher the

Table 3. Performance Measures of Different Machine Learning Classifiers

Measures	RF	DT	SVM	LR
TPR	0.92	0.79	0.76	0.74
TNR	0.88	0.83	0.69	0.70
PPV	0.89	0.86	0.71	0.73
FDR	0.11	0.14	0.29	0.27
FPR	0.12	0.17	0.31	0.30
F-score	0.90	0.82	0.73	0.73
Accuracy	0.90	0.80	0.72	0.72
AUC	0.96	0.63	0.65	0.80

Note: TPR = true positive rate or sensitivity; TNR = true negative rate or specificity; PPV = positive predictive value or precision; FDR = false discovery rate; FPR = false positive rate or fall-out; AUC = the area under the receiver operating characteristic curve; RF = random forest; DT = decision tree; SVM = support vector machine; LR = logistic regression.

likelihood that the actual positive case will be more positive than an actual negative case.

Conclusion and Future Research

This paper analyzed the mobility performance of integrating bike-sharing into the multimodal transport systems based on travel time. We developed machine learning models to identify and predict high-performing intermodal trips that include bike-sharing compared with those without bike-sharing for a given trip. The results suggest that bike-sharing could greatly enhance the mobility performance of the multimodal transport system for many scenarios. More specifically, the results indicated that replacing low-performing bus trips with high-performing bike-sharing trips could provide a 34% reduction in travel time. "Mixed modes" scenario outperformed the scenario in which all trips were made by bike-sharing, resulting in savings in travel time of about 33%.

This study has revealed important findings that could serve in planning and policy-making that aim to improve the mobility performance of multimodal transport systems. First, it has been demonstrated that bike-sharing could provide a comparable or even better mobility level than buses in certain itineraries. System variables such as bus detour, bike lane, speed, and travel distance seem to be the best predictors of mobility performance rather than individual characteristics such as age and gender. From a policy point of view, these results have shown the potential of bike-sharing in multimodal transport systems. They have demonstrated the need to develop sustainable transport policies such as providing more bicycle infrastructure and services to encourage shared cycling as a faster way to connect to other transit systems in multimodal trips, especially in the itineraries in which their benefits are identified. Such policies could provide more environmentally friendly and faster transport options to transit riders, which may minimize the use of automobiles for trips that aim to access main modes in multimodal tours or trips. The substitution of these bike-sharing trips from automobiles could provide great environmental and health benefits, considering that bike-sharing is zero carbon emission compared with automobiles.

The proposed machine learning models can be used at the planning level to identify existing itineraries in which bike-sharing can be introduced to enhance the mobility of multimodal systems for transit and bike-sharing users. For instance, the models can be used to identify intermodal trips in which the bus part of the trip can be replaced by high-performing bike-sharing trips, which may increase the mobility performance of the entire multimodal system. This can be a more efficient way of introducing new bike-sharing services and a good reason for justifying investments in such systems. At the operation level, the proposed models could also be applied within various systems, such as ITS, MaaS, and route planner apps, to suggest intermodal alternatives enhanced by bike-sharing systems. This could increase the number of transit riders through high-performing services, and may also have a positive effect on travelers' behaviors.

This model's application in a practical case study would be a good research topic for future investigations. Currently, the model was trained only on intermodal trips, which are often short for the access/egress part. Future research could include many types of alternative trips, such as mono- and multimodal trips including more than two modes, to provide more findings on the prediction performance. Future research can also improve the model's prediction power by adding new variables and conducting testing in different environmental conditions, such as different seasons, bad weather, and different times of the day. Finally, the transferability of the model both in relation to the nature of the data and the use of proposed approach in other regions remains another area for future studies.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: C. Kapuku, S.-H. Cho, D.-K. Kim; data collection: C. Kapuku, S. -H. Cho; analysis and interpretation of results: C. Kapuku, S.-H. Cho, S. -Y. Kho; draft manuscript preparation: C. Kapuku, S.-H. Cho, S.-Y. Kho, D.-K. Kim. All authors reviewed the results and approved the final version of the manuscript.

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