공학석사 학위논문

Factors Affecting Extra Journey Time of Public Bike

공공자전거 이용시간에 영향을 미치는 요인

2020년 8월

서울대학교 대학원

건설환경공학부

정 종 우

ABSTRACT

Considering the severe issue of environmental pollution, the government has attempted low carbon green growth by encouraging the use of the green transportation mode. As the green transportation mode, the revitalization of bike usage attracts remarkable public attention. However, for the acquirement of the effective outcome, the comprehensive analysis of bike usage characteristics should be arranged first. Since the characteristics of public bike usage depend on the journey times, it is necessary to expand the utilization rate considering the journey times. Existing researchers considered the number of usages or utilization rates as a dependent variable when analyzing factors affecting the usage of the public bike. This study aims to analyze the factors that affect the difference between the actual journey times and KAKAO Maps estimated journey times. These journey times from KAKAO Maps were compared with the actual journey times recorded in the dataset to create a new variable called Extra Journey Time. This study was conducted on Yeongdeungpo-gu, a residential-business center district in Seoul. As a results, Trips to and from stations that had a large number of shops within 100 m distance were also found to be likely predictors of the trips with lowest Extra Journey Time. The stations with bike priority road and leisure/cultural facilities are associated with larger Extra Journey Time. This study is helpful to understand the characteristics of public bike by analyzing the effects on journey time, not the effects on the demand for use conducted by previous study.

Keywords: Public bike, Usage, Location, Weather Factors, Cluster analysis, Logistic regression model

Student Number : 2018-28306

Contents

List of Tables

List of Figures

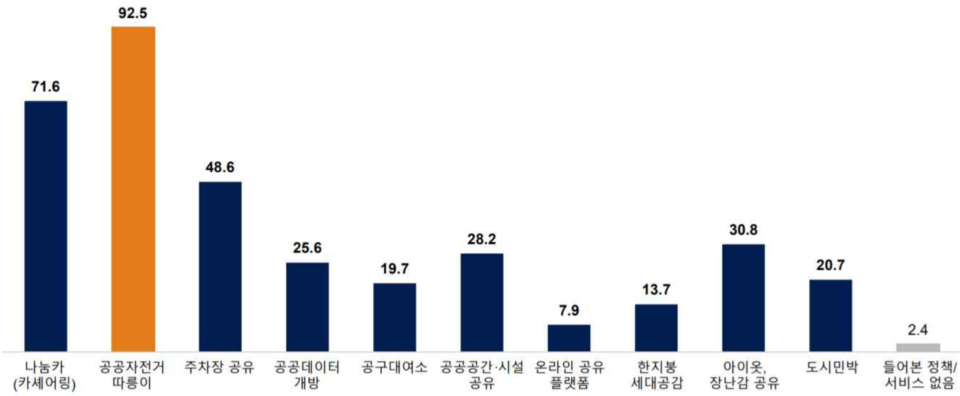
1. INTRODUCTION

1.1 Research background

The vehicle centered city derived from modern urban planning theory has caused not only urban sprawl but also environmental problems such as climate change and energy depletion worldwide. Therefore, from the 1990s, studies on sustainability have been started in various ways along with criticism of existing urbanization. The public bike, which operates in about 300 cities worldwide are considered a means of responding to climate change and energy crises and implementing sustainable transportation systems.

Recently in Korea, the government has been promoting policies to reduce vehicle traffic and encourage the use of bikes as a green transportation method. In December 2019, restrictions on the operation of grade 5th vehicles causing pollution in the “Green Traffic Area” in the area inside of four main gates of Seoul began. Under these circumstances, public bikes, a representative means of green transportation, are paying attention. The 'Fully Unmanned Public Bike Rental Service in Seoul City', introduced in October 2015, is part of an effort to shift the paradigm of transportation policy from vehicle-oriented to human-oriented.

As of 2018, Seoul public bike service has approximately 20,000 public bikes in 1,560 rental locations, which is the most recognized and satisfied among the city's shared policies and services. As the public bike service expands and stabilizes, the number of members exceeds 600,000 and continues to increase, so it is necessary to increase the efficiency of the operation of it. Since the usage type of public bike is different from that of cars or public transportation, various factors affecting the usage of public bikes should be considered.



<Fig. 1> Satisfaction of policy and service for sharing in Seoul City

(Source: www.seoul.go.kr)

1.2 Research purpose

Most of the prior studies on the usage of public bike focused on specific factors, such as use or location, that affect demand. The usage of the public bike is affected by a variety of factors, so it should be studied comprehensively. In addition, the public bike has different types of usage depending on the time of use, so it is necessary to prepare for the expansion of service operation in consideration of it.

Therefore, this study conducted an empirical analysis in consideration of various physical environmental factors that can affect the usage of public bike and intends to provide basic data to prepare an effective expansion and operation plan in consideration of increasing usage. To this end, it is tried to check the usage characteristics of the public bikes by comparing the estimated usage time based on OD (Origin Destination) with the actual rental history data. And also, it was intended to empirically analyze the factors that affect the journey time by comprehensively considering the usage, location, and weather characteristics.

2. LITERATURE REVIEW

2.1 Public bike in Seoul

Public bike system was designed convenient as possible for anyone to use it anytime, anywhere, anywhere (Shin et al., 2012). In other words, this means public transportation as a system in which the state or local governments lend bikes to citizens[1], and it can be used for commuting, exercising, or leisure. Public bike operates in more than 300 cities around the world, and have been concerned as short-distance transportation that can replace cars within the city.

Since public bike has great advantages in many aspects, such as low initial construction costs, eco-friendly and maintaining physical health, Seoul is seeking ways to boost their use. The ultimate goal of Seoul public bike is to operate 20 bikes per 10,000 people and deploy stations within six minutes of walking. (Seoul Facilities Corporation, 2018).

---

1) According to the Seoul <Ordinance on the Promotion of the Use of Bieks> (Article 2, Clause 5), "Public bike service is bikes managed by the Seoul and are provided for the use of citizens for free or at a cost."

2.2 External factor influences

Studies have recently begun to take into account the impact of the social, economic, and physical characteristics of the users on the usage of bikes. While there are many studies on the effects of the physical environment on walking, there is a lack of research on the effects on bike usage. In particular, research focused on infrastructure such as bike priority road and ramps as a physical characteristic factor affecting bike usage (Puello et al., 2015). Due to limitations of infrastructure, the public bike was not actively used as a means of living transportation due to higher entry barriers compared to other public transportation. Based on the fact that the Seoul public bike service has been steadily used by citizens and settled down as a means of living transportation, the study focused on objective analysis of the physical characteristics factors through the survey.

Lee et al. (2014) analyzed spatial urban environment characteristics affecting the use of the public bike in Changwon city. As a result of the analysis, it was confirmed that the usage of public bikes increased in rental places in areas where is high ratios of public housing or commercial facilities, and public transportation density and demand for usage showed negative (-) impact.

Lee et al. (2016) analyzed the effect of weather conditions and location characteristics on the usage of the public bike in Goyang city. According to the analysis, the usage of public bike decreases when precipitation is more than 10 mm, the temperature is higher than 29 °c, or wind speed is more than 7 m/s.

Jang et al. (2016) analyzed a total of six months of data from October 2015 to March 2016 in Yeouido and Sangam districts, which are residential complex areas, for the public bike in Seoul. According to the analysis, public bike usage was found for work and transfer purposes in residential complex areas, and the proportion of bike traffic was high in places where bus usage was relatively small.

Sa & Lee (2018) studied the use of rental and return of public bike rental places and the physical environment and analyzed the impact of the physical environment within the 100m area around the public bike station. According to the analysis, the floor area of neighborhood living facilities and office facilities and the traffic volume of adjacent roads had a positive (+) impact on the usage of public bike, and the closer the distance to subway stations and bike priority road, the higher the use of the public bike.

Pucher et al. (1999) analyzed urban weather conditions and bike usage in relation to bike activation in North American cities. According to the analysis, bike usage rate has been confirmed to be high in cities where mild weather and rainfall are not high, while low in cities where the weather is very hot or humid. Even if the rate of bike usage in North American cities continues to rise, it is expected to be lower than in northern European cities, as North American cities have car-oriented transportation systems, limiting bike use to leisure purposes.

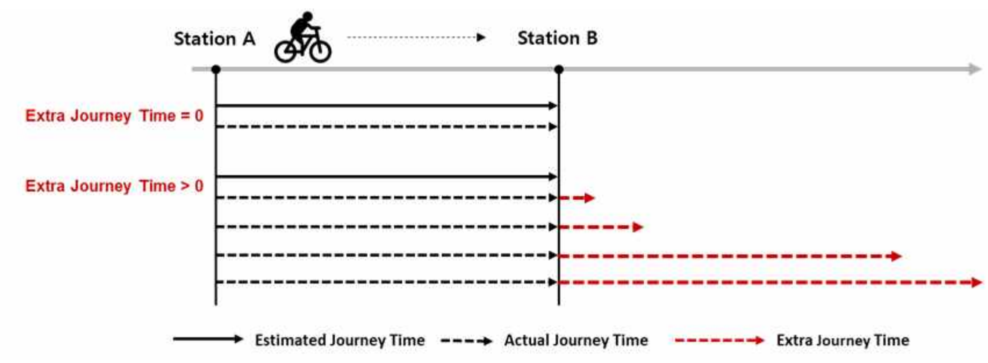
Kim et al. (2012) examined the total area of residential and commercial areas, parks, schools, subway stations, etc. within the influence area of the rental station and also considered usage of weekend and rainfall status as an influencing factor on the usage of the public bike.

Faghih-Imani et al. (2014) identified the determinants of public bike BIXI demand in Montreal, Canada. According to the analysis, the demand for public bikes increased with good weather and decreased on the weekend.

Corcoran et al. (2014) analyzed the temporal and spatial changes to utilization rates about the public bike system in Brisbane, Australia. According to the analysis, rainstorms and strong winds have reduced the usage of public bikes, affecting both leisure and commuting. The temperature did not have a statistically significant effect, which is thought to be related to Brisbane's subtropical climate. Holidays had no significant effect independently, but it was found to have a significant effect on the usage of the public bike when modeling with other influence factors. In particular, it was analyzed that the impact on the use of the public bike in traffic related to central business areas was significant.

Zaho et al. (2014) aimed to examine what influences the effectiveness of public bike systems in Chinese cities by considering the data of 69 different public bike systems. Ridership in these systems and turnover rate seemed to be influenced by external factors such as population density, government expenditure and the number of bike stations. Interestingly, they also found that the adoption of integrated travel cards that could be used for public bikes in addition to other transportation systems can significantly increase public bike usage due to ease of use.

McBain and Caulfield (2018) is most relevant to this study. In their study, the difference between actual journey times and estimated GOOGLE Map based journey times was created with a new variable Extra Journey Time. And the quartile of Extra Journey Time was identified as a dependent variable to determine the effect of the physical environmental factors. Extra Journey Time means that the smaller the quartile, the faster it moved to the destination, and the bigger the quartile, the slower it moved. According to the analysis, the usage of fast movement in areas that are within a five minute walking distance, have fewer stores, and have good access to public transportation has been identified. And those who used public bikes less than seven times in two years showed a long Extra Journey Time.



<Fig. 2> Extra Journey Time as defined in McBain and Caulfield (2018)

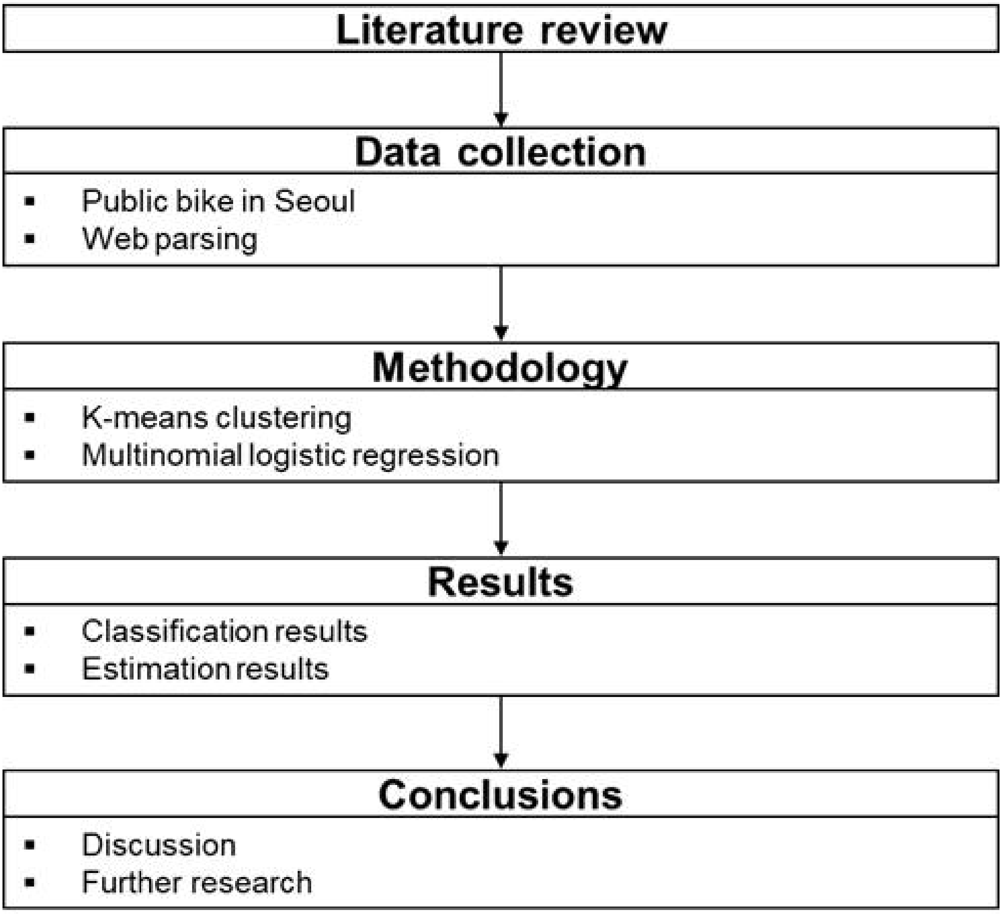
2.3 Contributions

After reviewing each of the journal articles, it has been discovered that there has been little focus on the journey times in public bike systems, which is why this research has been undertaken. Except for McBain and Caulfield (2018), there has been no investigation into how journey times differ due to different factors. This research will, therefore, contribute to the sub-topic of public bike usage, by examining how usage, location, and weather affects the Extra Journey Time of the public bike.

The concept of Extra Journey Time created by McBain and Caulfield (2018) does not reflect the characteristics of usage of the public bike in a short or long period. In this study, the actual journey time and the estimated journey time were compared based on the ratio, not the difference in the time as the previous study. The problem with prior studies is that there is no basis for setting the number of categories due to continuous data categorization, and the similarity of categories classified is unclear because the entire data divided equally. In this study, by categorizing it through K-means clustering, it was classified as a more similar cluster and confirmed that the performance aspect of the model is improved compared to the prior studies.

3. METHODOLOGY

The flow of this study is <Fig. 3>. After cluster analysis using Extra Journey Time, statistical analysis was conducted based on the clustering results.



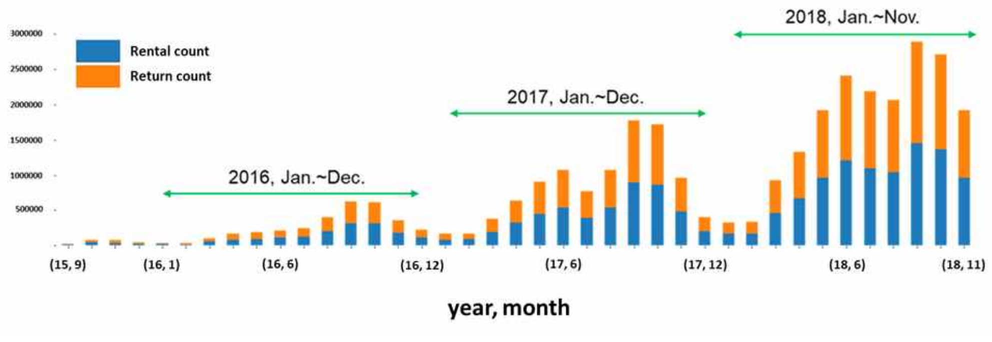
<Fig. 3> Research methodology

3.1 Data collection

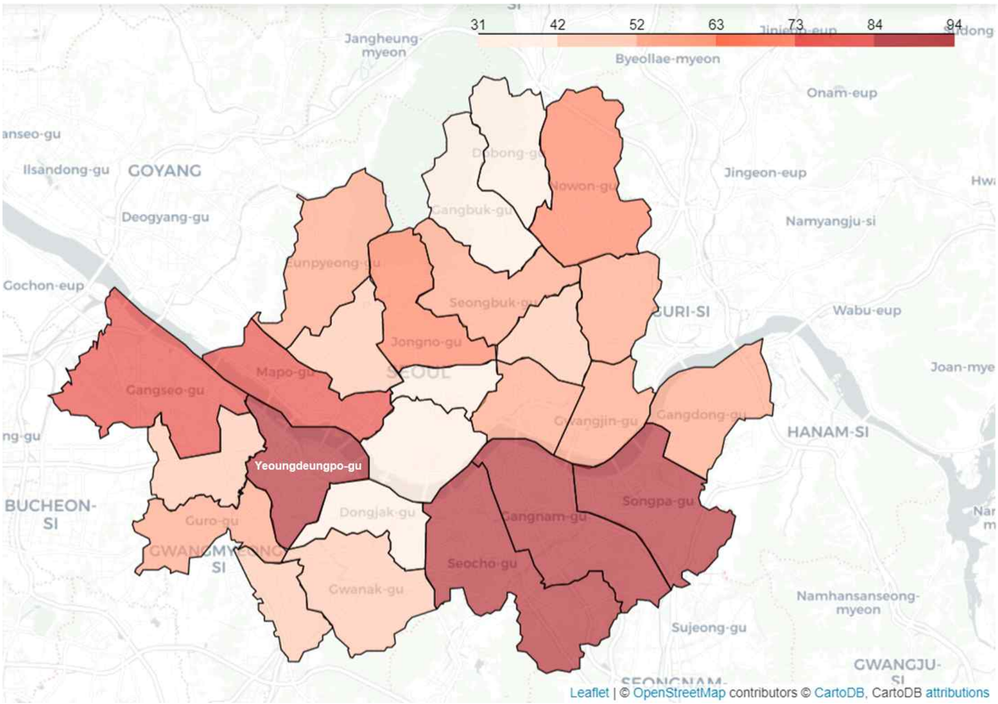
3.1.1 Public bike in Seoul

An analysis of the annual and monthly usage of public bike confirmed that the use increased in May, September, and October before and after summer, and that the use decreased in hot summer and cold winters. This basically revealed the need to analyze the usage patterns of public bike on a one-year basis. Therefore, the temporal scope of this study was set as the data for public bike for one year from January to December 2018.

Based on the distribution of public bike rental places by district, Yeongdeungpo-gu, which has various location characteristics such as the central business district, park district, and residential district, was selected as the spatial scope of this study. In addition, considering the characteristics of public bike, this study excluded usage data with an average driving speed of more than 30 km/h. As a result, a total of 432,795 cases of public bike operation data were used in the analysis.



<Fig. 4> Analysis of the annual&monthly usage of public bike in Seoul



<Fig. 5> Distribution of public bike rental places by district

(Source: data.seoul.go.kr)

The data sources of the analysis variables used in this study are as shown in <Table 1>. Dependent variable was established through the Seoul public bike rental history information and the estimated journey time of KAKAO Map from January to December 2018. Independent variables were established by utilizing data such as Seoul public bike rental history (2018), Seoul open data plaza (2018), Business information DB (2018), and Weather information DB (2018).

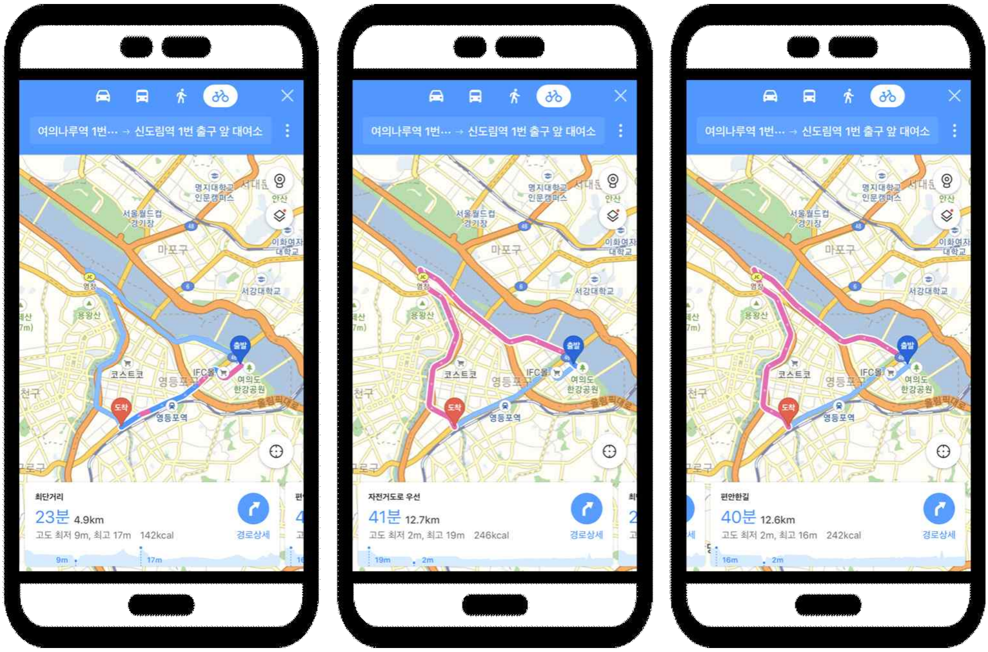
<Table 1> Variables and data source

Variables		Description	Source
Usage factors	Station size Start/End	Number of rental/return station stands	Seoul public bike rental history (2018)
	OD pairs station distance	Straight distance in latitude and longitude to rental/return station	
	Usage distance	User's actual distance to the rental/return station	
	Velocity	Average riding speed of the bike to the rental/return station	
	Day	Time of use of public bike in rental stations (weekdays/weekend)	
	TOD (Time of Day)	AM peak(7am-10am) PM peak(18pm-21pm) Inter peak(11am-17pm) Off peak(22pm-6am)	
Location factors	Bike priority road	Bike priority road within a 100m radius of the rental station	Seoul open data plaza (2018)
	Nearest subway dist. Start/End	Distance from rental/return station to nearest subway station	
	Restaurants Start/End	Number of restaurants within 100 meters of the rental/return station	Business information DB (2018)
	Leisure Start/End	The number of tour/entertainment/leisure shops within 100 meters of the rental/return station	
Weather factors	Temperature	Temperatures by time zone in Yeongdeungpo-gu, Seoul(°c)	Weather information DB (2018)
	Rainfall	Rainfall by time zone in Yeongdeungpo-gu, Seoul(mm)	
	Fine dust	Daily average fine dust in Yeongdeungpo-gu, Seoul PM10($\mu g/m^3$)	

※ Start means Rental station, End means Return station

3.1.2 Web parsing

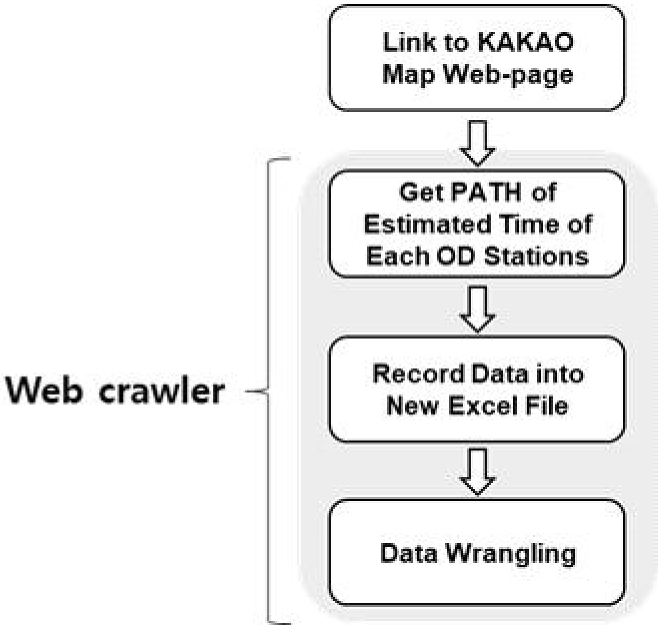
The route finding function of the KAKAO Map was used to established the estimated journey time. KAKAO Map route finding function provides information on the distance, estimated journey time, and routes depending on the means of use, such as cars, public transportation, bikes, and walking to the destination desired by the user. In particular, the bike path finding function provides three paths: the shortest distance, a bike priority road, and a comfortable path. This study established the estimated journey time based on OD (Origin Destination) according to the shortest path of the KAKAO Map bike path finding function.



<Fig. 6> KAKAO Map bike path finding function

(Source: map.kakao.com)

Departure and destination data for estimated journey time could be constructed from Seoul public bike rental history (2018). In this study, it is produced and used a web crawler based on Python 3.7 because it takes too long to construct the estimated usage time by entering the origin and destination of all traffic directly. Web crawler configuration used web driver, the main tool of the Selenium project. The Web crawler executes each factors (PATH) on a web page in a defined way, just as a person behaves. The program used in this study implements the function of collecting the information provided on the web page by running the web driver within a specified time, and the collected data is recorded through the function of being saved as a new excel file.



<Fig. 7> Phase of data deployment with Web crawler

3.2 K-means clustering

In this study, we would like to analyze the factors that affect Extra Journey Time. To this end, K-means cluster analysis was used to classify continuous data Extra Journey Time into clusters with similar characteristics. The K-means clustering method proposed by McQueen (1967) is a type of non-hierarchical cluster analysis that sets the initial seed value and repeats the reassignment of objects in the cluster. The initial cluster allocated by the initial partition is repeated to be allocated to a cluster that is the minimum distance based on the centroid of each cluster. Thus, Euclidean distances are generally used, and each object is reallocated to a cluster close to the center value, modifying the center value of the cluster and ending at a stage where there is no further reassignment.

When the mean of the c th cluster is called $\overline{x_c}$, the squared value of the distance from the i th object to the mean of the c th cluster d_{ic}^2 is shown as the equation (1). (when, $i \in c$)

(1) $d_{ic}^2 = (x_i - \overline{x}_c)^T (x_i - \overline{x}_c)$

As shown in equation (2), sum of squared error E is a method of allocating the i th object to the c th cluster to minimize E to reassign each object to the c th cluster.

(2) $E = \sum_i d_{ic}^2$

In the case of continuous data categorization according to quartile in the previous study, there was no basis for setting the number of categories, and there was a disadvantage in that the similarity of the classified categories is unclear because the quartile divides the entire data equally. Therefore, the categorization of Extra Journey Time was carried out through K-means clustering in this study. As a dependent variable for cluster analysis, Extra Journey Time 432,795 cases were used and the maximum number of iterations was specified at 25 times on average. At this time, the distance of the cluster analysis was euclidean square distance method.

(3) $Extra\,Journey\,Time = \dfrac{Actual\,Journey\,Time}{Estimated\,Journey\,Time}$

<Table 2> Extra Journey Time in this study

	McBain & Caulfield (2018)	This Study
Extra Journey Time	Difference =Actual – Estimated journey time	Ratio =Actual / Estimated Journey time
Classification	Quartile	K-means clustering

3.3 Multinomial Logistic Regression

The Multinomial Logistic Regression model is used when there are three or more alternative for the dependent variables and the dependent variables are independent of each other. The basic principle is the same as the binary logistic model. Multinomial Logistic model, one of the dependent variable is used as a reference group to compare the probability of selecting another alternatives with the probability of selecting a reference group. In this study, it is used to compare the probability of belonging to each cluster of Extra Journey Time classified through K-means clustering.

The Multinomial Logistic model with J alternatives can be expressed as follows.

$$(3)\quad \ln\left[\frac{\mathrm{Pr}ob(y=j)}{\mathrm{Pr}ob(y=J)}\right] = \sum_{k=1}^{K} \beta_{jk} x_k$$

When the J th alternative is called a reference group, the Multinomial logistic model compares the probability of selecting the reference group J against the probability of choosing the alternative j. So that $J-1$ estimates are calculated

In this study, the dependent variable of the Multinomial Logistic model is composed of the clusters of Extra Journey Time classified through K-means clustering. Analysis was performed by setting the cluster with the smallest Extra Journey Time as a reference group. Total 13 independent variables belonging to usage, location and weather factors were used in this model.

Model specification

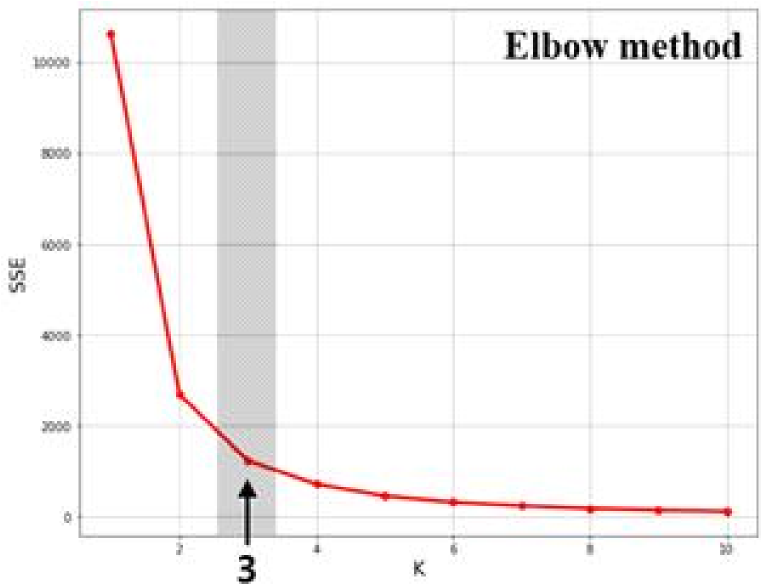
(4) $\ln(\frac{\Pr ob(Y_i)}{\Pr ob(Y_1)}) = const. + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 ... + \beta_{13} X_{13}$

Y_1:	Cluster(Reference category)	Y_i:	K-means clustering results
$const.$:	Model constant	β_i:	Unknown parameters
X_1:	Station size	X_2:	OD pairs station distance
X_3:	Usage distance	X_4:	Velocity
X_5:	Day	X_6:	TOD(Time of Day)
X_7:	Nearest subway dist.	X_8:	Restaurants
X_9:	Leisure	X_{10}:	Bike priority road
X_{11}:	Temperature	X_{12}:	Rainfall
X_{13}:	Fine dust		

4. RESULTS

4.1 Classification results

According to the comparison between the time difference in the previous study and the time ratio in this study, Extra Journey Time was classified by quantile and K-means clustering(k=3)[2], When it was classified in terms of clustering and ratio of time, it was confirmed that the performance of the model was the best.



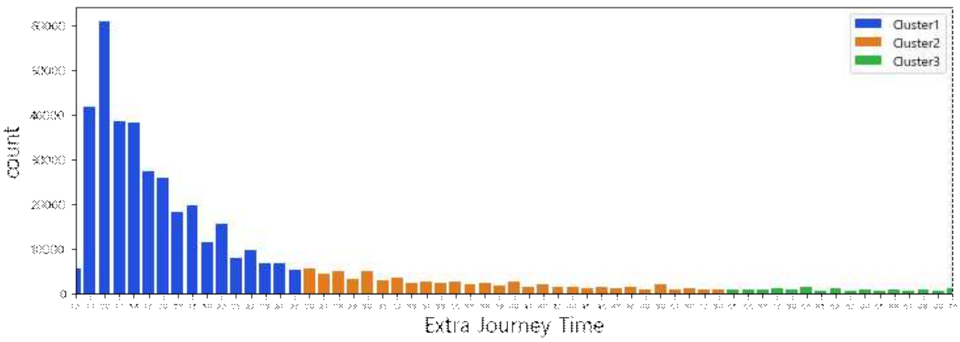
<Fig. 8> Elbow method

2) This study determined that K-means clustering(k=3) was properly clustered using the Elbow method(The place where the number of clusters is sequentially increased and the slope becomes gentle is called the Elbow point, and it is judged that k at this time is an appropriate value).

<Table 3> **Performance of model by methodology**

Extra Journey Time		AIC	BIC
Quantile	Difference	694175	695032
	Ratio	539284	540141
Clustering	Difference	349719	350576
	Ratio	309266	309947

As a result of K-means clustering for the Extra Journey Time of Yeongdeungpo-gu public bike, Extra Journey Time was best classified into three clusters. Cluster 1(2.5≥Extra Journey Time) was the majority of public bike usage with 339,178 cases(78%). Cluster2(2.6≤Extra Journey Time≤5.4) was classified into 65,724 cases(15%), and Cluster3(5.5≤Extra Journey Time ≤10.0), the largest cluster with Extra Journey Time, was classified into 27,893 cases(7%). This study identified three clusters classified as different types of public bike usage. And confirmed the characteristics of each cluster and the factors that affect them.



<Fig. 9> **Extra Journey Time distribution**

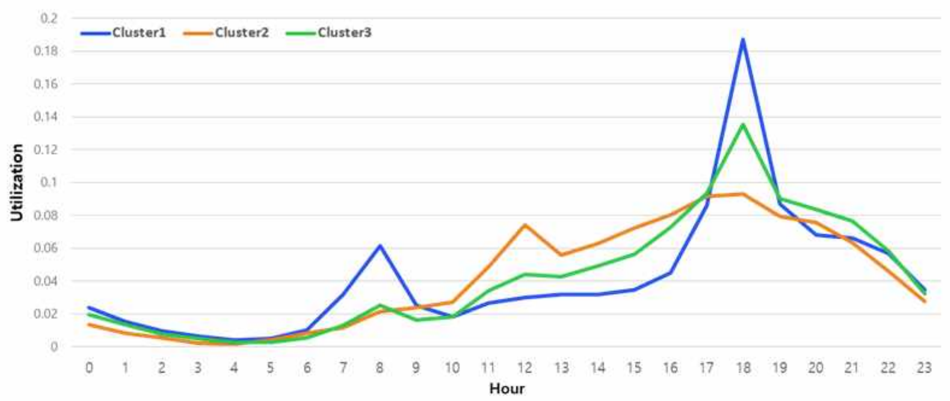
<Table 4> **Classification of Extra Journey Time**

	Cluster 1	Cluster 2	Cluster 3
count	339,178	65,724	27,893
mean	1.5	3.6	7.4
std	0.3	0.8	1.3
min	0.0	2.6	5.5
max	2.5	5.4	10.0

The usage of public bike varies depending on Extra Journey Time. As Cluster1 to Cluster2 and Cluster3, we could see that the demand for weekend traffic increased more than during the weekday. Cluster1, which represents the lower Extra Journey Time, used a public bike during the weekday compared to the weekend and was mostly used during AM&PM peak. As Extra Journey Time increased, Cluster2 and Cluster3 used public bike on weekend compared to weekday, and increased in Inter paek after AM peak.

As the Extra Journey Time increased, the usage distance and usage time on rental history information increased, but OD pairs station distance and OD pairs expected time decreased. That is, if the Extra Journey Time increases, it can be estimated that the public bike is used as a leisure means to move a distance not far away for a long period, rather than a transportation means intended to move.

<Fig. 10> Usage of public bike by day



<Fig. 11> Weekdays public bike usage pattern by time zone

<Table 5> Descriptive statistics

		Cluster1	Cluster2	Cluster3
OD pairs station distance(m)	mean	2728.48	2088.57	1006.62
	std	2422.51	1561.77	651.23
Usage distance(m)	mean	4153.57	5261.67	5167.34
	std	3940.45	4283.70	4109.02
OD pairs expected time(min)	mean	16.31	13.01	7.41
	std	21.21	7.80	3.54
Usage time(min)	mean	24.58	45.07	53.31
	std	19.10	25.68	23.50

※ OD pairs expected time(min): KAKAO Map journey time

4.2 Estimation results

In this chapter, the physical environment factors affecting the Extra Journey Time classified through K-means clustering were analyzed according to the usage, location, and weather characteristics. As the Extra Journey Time decreased, public bike were used for commuting during the AM&PM peak of the weekday as a means of transportation, and as Extra Journey Time increased, it is assumed that is used for other purposes than commuting. Therefore, in this study, the classification according to the Extra Journey Time was treated as an usage characteristics, and a Multinomial Logistic Regression analysis was used to analyze the factors affecting it.

<Table 6> Clustering results

	Frequency	Percent	Cumulative percent	
Cluster1(Y_1)	339178	78.4	78.4	Reference group
Cluster2(Y_2)	65724	15.2	92.6	
Cluster3(Y_3)	27893	6.4	100	
Total	432795	100		

<Table 7> Description of variables

Data			Unit	Criteria	Reference
Dependent variable	Extra Journey Time		ratio	K-means clustering result(Cluster1, 2, 3)	-
Independent variables	Usage factors	Station size Start/End	count	Number of station stands(10 or less, 11-20 or less, 21 or more)	-
		OD pairs station distance	m	Distance quartile on station	-
		Usage distance	m	Bice using distance quartile	-
		Velocity	km/h	Bice speed quartile	-
		Day	-	Weekdays/Weekend	-
		TOD(Time of day)	hour	AM(7-10)&PM(18-21), Inter(11-17), Off peak(22-6)	-
	Location factors	Nearest subway dist. Start/End	m	Primary station area (250m) status	Departmentof Seoul Urban Planning
		Restaurants Start/End	count	Number of shops in the station area(100m) IQR	Department of Public Housing in Seoul
		Leisure Start/End	count	Cultural and leisure facilities in the commercial area(100m) of the station area	Department of Public Housing in Seoul
		Bike priority road	-	Bike priority road of the rental station(100m).	-
	Weather factors	Temperature	°c	Feeling cold(less than 10°c), heat(more than 33°c)	Korea Meteorological Agency, OSHA
		Rainfall	mm	Rainfall(over 10mm)	Korea Meteorological Agency,
		Fine dust	μg/m³	Bad/very bad(over 81)	Korea Meteorological Agency,

<Table 8> Multinomial Logistic Regression model

			Cluster2	Cluster3
		const.	-4.57***	-8.65
Usage factors	Station size Start	10 ~ 20	0.03**	0.01
		> 21	0.02	0.10***
		(Ref.) < 10		
	Station size End	10 ~ 20	0.16***	0.24***
		> 21	0.22***	0.30***
		(Ref.) < 10		
	OD pairs station distance	881 ~ 1621m	-1.81***	-3.36***
		1621 ~ 3152m	-3.62***	-7.11***
		> 3152m	-5.99***	-12.16***
		(Ref.) < 881m		
	Usage distance	1581 ~ 3120m	2.81***	4.26***
		3120 ~ 6140m	5.37***	8.33***
		> 6140m	8.24***	13.04***
		(Ref.) < 1581m		
	Velocity	< 5km/h	5.14***	8.00***
		5 ~ 10km/h	1.48***	2.66***
		10 ~ 20km/h	-0.28**	0.18
		(Ref.) > 20km/h		
	Day	Weekday	-0.29***	-0.22***
		(Ref.) Weekend		
	TOD(Time of Day)	AM&PM peak	0.05***	0.18***
		Inter peak	0.37***	0.70***
		(Ref.) Off peak		
Location factors	Nearest subway Start	≤ 250m	0.16***	0.16***
		(Ref.) > 250m		
	Nearest subway End	≤ 250m	0.12***	0.06***
		(Ref.) > 250m		
	Restaurants Start	10 ~ 34 shops	-0.42***	-0.35***
		≥ 35 shops	-0.41***	-0.39***
		(Ref.) < 10 shops		
	Restaurants End	10 ~ 34 shops	-0.36***	-0.44***
		≥ 35 shops	-0.38***	-0.44***
		(Ref.) < 10 shops		
	Leisure Start	≥ 1 shop	0.10***	0.11***
		(Ref.) 0		
	Leisure End	≥ 1 shop	0.01	0.04*
		(Ref.) 0		
	Bike priority road	Yes	0.31***	0.56***
		(Ref.) No		
Weather factors	Temperature	≤ 10°c	-0.12***	-0.08***
		≥ 33°c	-0.05*	-0.15***
		(Ref.) 11-32°c		
	Rainfall	≤10mm	0.02	0.03
		> 10mm	-0.59	-2.18**
		(Ref.) 0mm		
	Fine dust	Poor/Very poor	-0.05***	-0.07***
		(Ref.) else		

Model fit statistics
The reference category is: Cluster1
Pseudo R-squared: 0.454 Degrees of Freedom: 60
AIC: 309261 BIC: 309942

(Ref.) is a reference term
* This has a significance p-value<0.10
** This has a significance p-value<0.05
*** This has a significance p-value<0.01

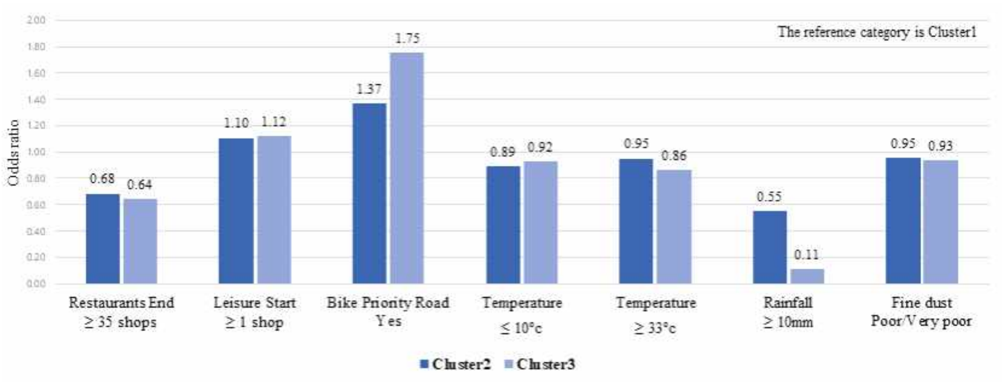
The results of analyzing the factors influencing the Extra Journey Time of public bike are as follows. The model's Pseudo R-squared is 0.454, indicating that the dependent variable has an explanatory power of about 45.4% by the independent variables. According to the results of the covariance between variables, the variance inflation factor(VIF) shows that the value of both temperature and discomfort index exceeded 3 and the discomfort index was excluded from the variables, while all other variables were lower than 3. So multicollinearity was not an issue. Thus, a total of 13 independent variables were considered in this study.

In terms of usage factors, Station size End, OD pairs station distance, Usage distance, Day, and TOD were identified as significant variables. Extra Journey Time increased at stations with large return station sizes. The usage distance increases as the Extra Journey Time increased, but the OD pairs station distance decreased. In the weekend Inter peak compared to the weekday AM&PM peak, Extra Journey time was observed to increased.

In terms of location factors, Restaurants Start/End, Leisure Start/End, and Bike priority road were identified as significant variables. Extra Journey Time was found to have a negative (-) effect on the number of restaurants around the rental place and a positive (+) effect on the number of cultural/leisure facilities. Also Extra Journey Time increased when there was a bike priority road around the rental place.

In terms of weather factors, Temperature and Fine dust were identified as significant variables. The temperature less than 10 °c or above 33 °c was found to have a negative (-) effect on Extra Journey Time. Also the level of Poor/Very poor of fine dust was found to have a negative (-) effects too.

The Odds ratio of the major variables that have a significant effect on the result of the regression model was analyzed. As a result, the Extra Journey Time decreased in return stations with large number of Restaurants. But the Cultural/Leisure facilities and Bike priority road were the increased factors. Also Certain level of Rainfall, Temperature, and Fine dust were found to have a negative (-) effect on Extra Journey Time.



<Fig. 12> Compare Odds Ratio for Factors Affecting Extra Journey Time

5. CONCLUSIONS

This study is meaningful that focuses on the journey time of public bike and examining the relationship with physical environmental factors that affects Extra Journey Time to analyze the usage of public bike and the impact of physical environmental factors that have not been addressed in previous studies. The results of the study will contribute to the preparation of basic data to increase the use of services and to suggest ways to operate the services efficiently according to the public bike usage.

By analyzing the Extra Journey Time at a ratio, we could reflect the characteristics of public bike with a various journey time. Extra Journey Time was classified by K-means clustering, which was more similar than Quantile of prior study and could be classified into a suitable number of clusters.

Extra Journey Time shows increased usage after AM peak of the weekend. When Extra Journey Time increased, OD pairs station distance was decreased but the usage distance getting increased. Also in the location factors, Extra Journey Time decreased when there were many restaurants. Which can be inferred that there are more users for moving purposes than the estimated use of leisure in the shopping quarters when Extra Journey Time increased. On the other hand, in areas where leisure/cultural facilities and bike priority road exist, the usage of leisure activities was found to increase rather than for moving purposes. Finally in weather factors, Extra Journey Time of public bike increased as the average temperature was higher, but decreased when the average temperature was below 10 °c and above 33 °c.

Since the spatial scope of this study is limited to Yeongdeungpo-gu in Seoul, it is expected that follow-up study will allow to analyze the usage of public bike by district to comparing Extra Journey Time with other districts. And factors influencing the usage of public bike should reflect characteristics of users in addition to physical environmental factors such as age, sex, job and income factors.

References

Corcoran, J., Li, T., Rohde, D., Charles-Edwards, E., & Mateo-Babiano, D. (2014). Spatio-temporal patterns of a Public Bicycle Sharing Program: the effect of weather and calendar events. Journal of Transport Geography, 41, 292-305.

Faghih-Imani, A., Eluru, N., El-Geneidy, A. M., Rabbat, M., & Haq, U. (2014). How land-use and urban form impact bicycle flows: evidence from the bicycle-sharing system (BIXI) in Montreal. Journal of Transport Geography, 41, 306-314.

Jang, J. M., Kim, T. H., & Lee, M. Y. (2016). A Study on the Seoul Public Bikes Use Characteristics: A Case of the Districts of Yeouido and Sangam. Seoul Urban Research, 17(4), 77-91.

Kim, D., Shin, H., Im, H., & Park, J. (2012). Factors influencing travel behaviors in bikesharing. In Transportation Research Board 91st Annual Meeting.

Lee, J. H., Jung, K. O., & Shin, H. C. (2016). Impact Analysis of Weather Condition and Locational Characteristics on the Usage of Public Bike Sharing System. Korean Society of Transportation, 34(5), 394-408.

Lee, S. Yi., Shin, E. K., & Kim, S. Y. (2014). Impacts of the Regional Environment Characteristics on the Public Bicycle Use: Analysis of the Spatial Information Using the Public Bicycles OD Flow-data in Changwon-si. Korean Architecture Journal, 30(12), 215-223.

Zhao, J., Deng, W., & Song, Y. (2014). Ridership and effectiveness of bikesharing: The effects of urban features and system characteristics on daily use and turnover rate of public bikes in China. Transport Policy, 35, 253-264.

McBain, C., & Caulfield, B. (2018). An analysis of the factors influencing journey time variation in the cork public bike system. Sustainable cities and society, 42, 641-649.

Pucher, J., Komanoff, C., & Schimek, P. (1999). Bicycling renaissance in North America?: Recent trends and alternative policies to promote bicycling. Transportation Research Part A: Policy and Practice, 33(7-8), 625-654.

Puello, L. L. P., & Geurs, K. (2015). Modelling observed and unobserved factors in cycling to railway stations: application to transit oriented developments in the Netherlands. European journal of transport and infrastructure research, 15(1).

Sa, K. E., & Lee, S. G. (2018). Analysis of Physical Characteristics Affecting the Usage of Public Bike in Seoul, Korea: Focused on the Different Influences of Factors by Distance to Bike Station. Journal of Korea Planning Association-Vol, 53(6), 39-59.

Seoul City (2018). 2018 Shared City Awareness Survey Results Report.

Seoul City Council. (2017). Seoul City Public Bike(Ttaleung-i) Policy evaluation and improvement plan research, D0000032579998

Seoul Facilities Public Bike Operation Center (2018), General conditions for public bicycles

Seoul Institute (2019). Seoul type Mobility as a Service (MaaS) Introduction plan. Policy Report, 1-23.

Shin, H. C., Kim, D. J., & Jang, S. Y. (2012). Impact Analysis on Bike-Sharing and Its Improvement Plan. Korea Transport Institute Basic Research Report, 1-310.

국문초록

공공자전거 이용시간에 영향을 미치는 요인분석

환경오염의 심각성에 따라 정부는 저탄소 녹색성장의 방안으로 친환경 교통수단 활성화에 노력하고 있다. 녹색교통으로서 공공자전거 이용활성화가 사회적으로 큰 조명을 받고 있으나 효과적인 성과를 내기 위해서는 자전거 이용특성에 대한 구체적이고 다양한 분석이 수행되어야 한다.

공공자전거는 단시간, 장시간 이용에 따라 이용특성이 다르므로 이를 고려한 이용률 확대 방안이 필요하다. 기존의 선행연구들은 공공자전거 이용에 영향을 미치는 요인분석의 종속변수로서 이용횟수 혹은 이용률만을 고려하였다. 본 연구는 실제 대비 추정 이용시간의 차이에 영향을 미치는 요인을 분석하였다. 이에 Extra Journey Time은 실제 대비 추정 이용시간의 차이를 비교하기 위한 새로운 변수로서 생성되었다.

본 연구는 서울시 주거업무 중심 지역인 영등포구를 대상으로 연구를 시행하였으며, 그 결과 Extra Journey Time은 주중 대비 주말에 여가/문화 시설이 존재하며 자전거전용도로가 잘 갖춰져 있는 곳에서 증가하였고, 주중 출퇴근 시간대 상점이 많은 곳에서 Extra Journey Time이 감소하였다. 날씨 측면에서 Extra Journey Time은 특정 조건(기온 10°c 이하, 33°c 이상, 미세먼지 나쁨/매우 나쁨 등)에서 감소하는 이용특성을 확인하였다.

주요어: 공공자전거, 이용, 입지, 날씨 특성, 군집분석, 로지스틱 회귀모형
학번: 2018-28306