

Factors Influencing Travel Behaviors in Bikesharing

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1 ABSTRACT

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Over 100 cities around the globe currently operate robust, bikesharing systems. While much research in bikesharing is duly taking place, there have been hardly any studies on the factors influencing travel behavior in bikesharing. This study has taken five variables that may significantly influence bikesharing—the floor area of nearby residential and commercial buildings, parks, schools, and subway stations—and performed regression analyses to determine their impact on the frequency of bikesharing usage. In particular, the study separately analyzes conditions which are expected to render different behaviors, including weekdays vs. weekends; precipitation; and departure point and destination. As a result of the analysis, the total area around residential and commercial buildings, parks, schools, and subway stations were shown to have a positive influence on bikesharing usage, although the extent of such influence was shown to vary depending on the model. Commercial buildings were shown to promote public bicycle usage more than residential buildings; and parks were shown to encourage bikesharing usage 3 to 5 times more than schools or subway stations. A difference between weekday and weekend travel behavior was also identified, with the latter seeing twice the amount of bikesharing traffic volume than the former. Rainfall was generally shown to decrease bikesharing usage as is presumed. The results of this study can be used in estimating the appropriate scale of new bikesharing stations at various venues, and are also applicable to building strategies for maximizing the efficiency of bicycle redistribution.

1 INTRODUCTION

2 It is widely accepted that today's automobile-centric transportation system suffers not only from inherent
3 problems such as traffic and lack of parking, but also leads to secondary issues such as climate change,
4 due to the combustion of fossil fuel and emission of greenhouse gases. Mitchell et al.[1], meanwhile,
5 view today's transportation system in a different light, saying that the automobiles of the 20th century, as
6 adept as they were at quickly transporting many people across long distances, are not as appropriate for
7 servicing the transportation needs of an individual residing in a city, like many do in the present day.
8 Mitchell et al. also suggest that urban automobiles of the future will be closely associated with
9 environmentalism and smart technology, making driving a truly enjoyable experience. Mitchell et al.
10 present some ideas regarding futuristic automobiles, which are centered on a vehicle sharing system
11 utilizing small electric cars. The proposal essentially calls for smaller, publically shared vehicles as a
12 means of providing short-distance transportation services in the congested urban traffic grid. Although
13 there remain a number of issues that must be addressed to realize such ideas, the proposal by Mitchell et
14 al. is expected to become reality in the future.

15 Bikesharing has already been implemented in various regions for varying purposes and
16 circumstances. Bikesharing in the context of Mitchell et al.[1] reveals that bikesharing stations at the
17 current level of technology can be a less costly alternative to public electric cars while yielding a similar
18 effect. In South Korea, there are six cities that operate bikesharing stations, starting with Changwon in
19 2008. Around the world, it is estimated that over 100 cities are operating bikesharing systems[2]. Bicycles
20 are environment friendly, require no artificial source of energy and emit no greenhouse gases. They also
21 take up much less space for movement and parking than automobiles. Furthermore, bikesharing systems
22 would increase the efficiency of utilization as many would share a given amount of resources. With the
23 recent challenges of climate change and energy depletion, bicycle sharing stands out as a highly desirable
24 transportation policy.

25 However, the actual implementation of bikesharing policy has revealed many limitations. In
26 terms of operations, there have been difficulties associated with maintaining and managing the bicycles.
27 While the most severe problem is theft, such problems are increasingly mitigated thanks to new
28 technology such as GPS equipment. Logistical issues, however, remain a primary concern, with great
29 difficulty in selecting the appropriate size and location of the stations. Redistribution of the bicycles at the
30 stations to optimize supply and demand remains a task driven by trial and error.

31 In order to maximize the usage of the bikesharing, costs must be lowered, convenience enhanced,
32 and operations made more efficient. While such accomplishment would require significant analysis on the
33 factors affecting bikesharing usage, the lack of data prevents much needed research. Fortunately, the
34 bikesharing systems in Korea have been accumulating data on their operations, which has enabled
35 analysis in bikesharing system.

36 This study will analyze factors of bikesharing usage based on the data collected in Goyang City.
37 In particular, it will examine various factors that may affect bikesharing usage, such as: certain facilities
38 such as: proximity of schools, parks, and subway stations; the characteristics of land use around the
39 bikesharing stations; and weather conditions.

40 The rest of the paper is organized as follows: Chapter 2 examines previous research on
41 bikesharing systems and on factors affecting bicycle usage in order to determine the factors affecting
42 bikesharing to be analyzed in this study. Chapter 3 takes a closer look at the characteristics of data used in
43 models. Chapter 4 builds regression models for the volume of usage per station and the factors
44 influencing each station, in order to interpret key findings discovered using the coefficient values of each
45 factor estimated in the model. Lastly, Chapter 5 provides the conclusion of this study.

47 LITERATURE REVIEW

48 Weather plays the greatest role in bicycle usage. While in Northern Europe one may often see bicycles in
49 use even on rainy days, the same remains a rare sight in North America or Asia. Although the effect of

1 weather on bicycle usage is often taken for granted, there have not been many empirical studies done on
2 such impact of weather. As increasing data on bicycle usage is compiled, analytical research on the
3 impact of weather on bicycle use has been vitalized as of late. The most recent study by Miranda-Moreno
4 et.al [3] analyzed the influence of weather on bicycle traffic in Montreal by setting up loop detectors on
5 five bicycle roads. The study revealed that temperature, humidity, and presence of heavy rainfall
6 impacted bicycle usage in Canada, with precipitation in the morning and three hours before the travel
7 time having a particularly significant influence over bicycle traffic.

8 Rose [4] also analyzed the impact of weather on bicycle usage in Oregon, Portland and
9 Melbourne, Australia. The study revealed that higher temperatures and less rainfall led to increased
10 bicycle traffic in both cities. However, the coefficients of the temperature variable were 0.3 to 0.6 in one
11 city, and 0.2 in the other, showing that the extent of the effect temperature has on bike travel may differ in
12 each city. In the research regarding bicycle commuting [5], university students became the subjects for an
13 attempt to determine the influence of weather and seasonal changes on bicycle commuting, which turned
14 out to be smaller than expected.

15 Lewin [6] analyzed the impact of weather and temperature on bicycle usage in two key roads with
16 large bicycle traffic in Boulder, Colorado, over a span of five years. Summer was shown to have the
17 greatest transportation demand for bicycles, while spring and autumn had 2/3 of bicycle traffic compared
18 to the summer, and winter having 1/3 of summer's bike traffic volume. The temperature was shown to
19 have a positive linear relationship with bike usage, peaking and turning around at 90 degrees Fahrenheit.

20 As both Miranda-Moreno et al.[3] and Rose et al.[4] suggested, there have not been very many
21 studies conducted regarding the impact of weather on bicycle usage because it has often been an intuitive
22 assumption that did not necessitate a great deal of analytical requirements. However, empirical research
23 would be necessary to determine the extent of the impact of weather on bicycle usage, and particularly
24 essential to the efficient operation of 24-hour bikesharing systems.

25 Shaheen et al.[2] created a comprehensive approach to the bikesharing policy, reviewing the
26 current status of bikesharing in use and their developmental history. The research examined the evolution
27 of bikesharing policy from the first generation to the fourth, along with its social, economic and
28 environmental effects. Based on the history of the operations of bikesharing stations thus far, the study
29 argues that theft, redistribution, information system, insurance, and initial establishment are key factors of
30 vitalizing bikesharing.

31 Amoruso et. al.[7] proposed a methodology to analyze the efficiency of bikesharing system by
32 calculating an indicator to describe the state of the system. The suggested indicator can be used as one of
33 the measurements to evaluate bikesharing system and to compare different systems.

34 Froehlich et al.[8] examined the temporal and spatiotemporal pattern of station usage of
35 Barcelona's Bicing, to predict future bicycling station usage behavior. The research suggested four
36 models, including a Bayesian network model, which had the smallest average error, to predict the
37 availability of bicycles at each station.

38 The most recent study conducted on bikesharing systems, the research by Tang et al.[9], analyzes
39 the impact of bikesharing on travel in Beijing, Shanghai and Hangzhou. The three Chinese cities were the
40 first to implement third-generation bikesharing, with the main users belonging to white collar workers
41 between the ages 20 and 39. The study categorized the system according to the managerial authority, such
42 as 'government-Led Model', 'Manufacturing Company-Led, Government Aid Model', and 'Private
43 Company-Led Model,' in order to analyze the transportation demands for bikesharing.

44 Morency et al.[10] examined the station usage volume and patterns of Montreal's bikesharing
45 system, and calculated a balancing factor in consideration of the usage rates along with OD patterns
46 between the stations.

47 Voguel and Mattfeld[11] adopted a nonlinear clearing function in order to model the probability
48 of successful rentals under a certain number of requesting users because a issue observed in bikesharing
49 system is imbalance in the spatial distribution of bikes over time. The imbalance is caused by one-way
50 use and short hiring times of bikes. Therefore, repositioning activities which are followed by travel
51 behaviors in bikesharing were the main focus of the research.

1 Because third generation bikesharing systems, which is applied recent IT such as smartcard or
 2 GPS, were only recently implemented on a large scale, research in bikesharing has been taking place
 3 robustly in the most recent years [2]. However, most studies focus on the analysis and effect of the status
 4 of bikesharing usage, while there are still no previous studies involving a detailed analysis on the travel
 5 behavior affected by each station's characteristics. It is therefore difficult to find literature that includes
 6 empirical examinations on how station usage varies depending on the characteristics of the surrounding
 7 properties and facilities. Such lack of previous analysis can be attributed to the limitations in data
 8 collection. Furthermore, there is virtually no collected data on the characteristics of the surrounding area
 9 or facilities, which rendered the analysis thereof virtually impossible until this point. This study thus
 10 attempts to exploit data on the usage volume of the bikesharing station in Goyang City in order to build a
 11 database on characteristics of land use and facilities surrounding the station, and determine the influence
 12 of the characteristics on bikesharing travel behavior.
 13

14 DATA DESCRIPTIONS

15 Site Selection

16 Table 1 indicates that six cities in Korea currently operate bikesharing systems. Among them, Changwon
 17 and Goyang are the only cities that fully operate more than 100 stations. As new cities, the two cities
 18 possess terrain that is appropriate for bicycles. As a coastal industrial city in the south, Changwon shows
 19 a clear volume of bicycle commutes between the residential area and the industrial complex, while travel
 20 to other areas is not as active.

21 In contrast, Goyang is a satellite city of Seoul, with a population of 950,000 and only 30km away
 22 from the metropolitan area. It features a subway connection to Seoul, artificial lake and park, an
 23 international exhibition hall named KINTEX, along with other diverse facilities and land uses. This study
 24 has thus selected Goyang as its subject location in order to determine the impact of nearby land use on
 25 bicycle stations.

26 The transportation network of Goyang is characterized by a central road lying across a two-way,
 27 8-lane road in the heart of the city. Line 3 of the subway sits along the central road. The bicycle path
 28 extends 165km [12]. The 1,034,000 m² artificial lake in the southern part of the city also features a 5km
 29 bicycle path. In terms of land use, shopping centers, commercial buildings and offices are focused around
 30 the subway station. As it was designed as a satellite city to Seoul, Goyang features a great number of
 31 high-density apartment blocks. The average amount of precipitation in 2009 amounted to 1,426mm. The
 32 average temperature in 2009 was 11.0°C [13].
 33
 34

TABLE 1 Bikesharing Systems in South Korea

City	Area (km ²)	Population (in 1000's)	Name	No. of Bicycles	No. of Stations	Starting Year
Changwon	292.72	500	Nubija	3,000	163	2008
Goyang	267.31	940	Fifteen	3,000	125	2010
Daejeon	539.86	1,500	Tashu	200	22	2009
Suncheon	905.15	270	Onnuri	100	11	2009
Seoul	605.33	10,310	Seoul Bike	400	43	2010
Busan	765.94	3,560	U-Bike	300	15	2010

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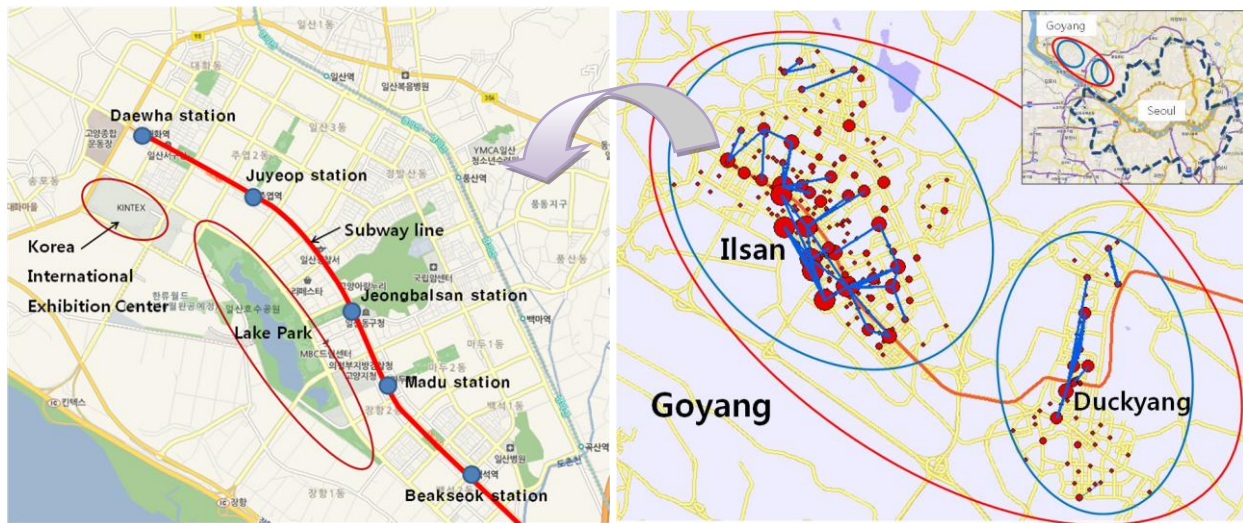


FIGURE 1 Site Map of Ilsan-gu, Goyang city

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Fifteen Data

Dubbed “Fifteen,” the bikesharing system of Goyang city was established in June 2010 [14]. Fifteen indicates the average speed of bike, 15km/h. Since then, it has expanded its fleet to around 3,000 bicycles as of July 2011. It is operated by a special purpose company, Ecobike, comprised of four institutions: Goyang City, Hanhwa S&C, Samchuly Bicycle, and Innodesign.

Fifteen is open to the entire public for an annual fee of 60,000 KRW (\$60 USD). The first 40 minutes are free, with 500 KRW (\$0.50 cents) per additional 30 minutes. Non-members may use the bikes upon authenticating their identity with their personal mobile phones. Non-members are charged 1,000 KRW (\$1 USD) for the first 40 minutes, and 1,000KRW (\$1 USD) per additional 30 minutes thereafter.

This study used the data from June to September 2010 for Fifteen’s service usage. Analyzed data excludes incomplete records that lack return stations or travel time, and travel time under one minute. Structure of the Fifteen data set is shown in Table 2.

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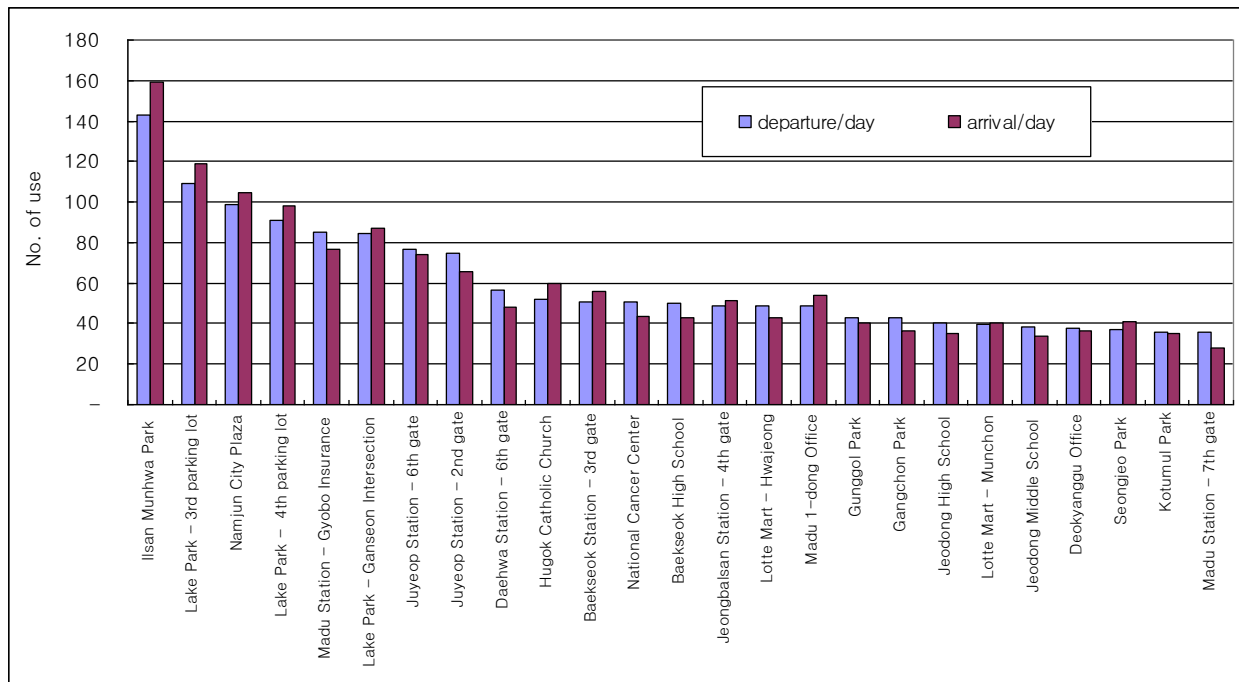
TABLE 2 Fifteen data

date	member id	Departure time	Departure station	Lot number	Arrival time	Arrival station	Lot number	Riding time (min)	Riding distance (meter)
2010-07-25	K****	2010-07-25 12:57:43	STA11	7	2010-07-25 13:01:10	STA29	15	00:04	366
2010-07-25	G****	2010-07-25 15:46:36	STA29	22	2010-07-25 15:59:56	STA85	10	00:13	1,382
2010-07-25	Y****	2010-07-25 22:47:45	STA21	7	2010-07-25 23:16:37	STA61	7	00:29	3,440
2010-07-25	W****	2010-07-25 15:58:26	STA18	3	2010-07-25 16:12:44	STA49	6	00:14	1,587
...

As Figure 2 illustrates, out of the stations with the largest traffic flow, the stations located near the Lake Park and the subway stations showed higher usage patterns than others. This highlights how nearby land use such as the Lake Park or the subway station have significant impact over bikesharing usage. Public transportation points near the subway, travel between and residential areas, and travel to the Lake Park area showed the largest volume of traffic. In particular, the Lake Park area showed a large

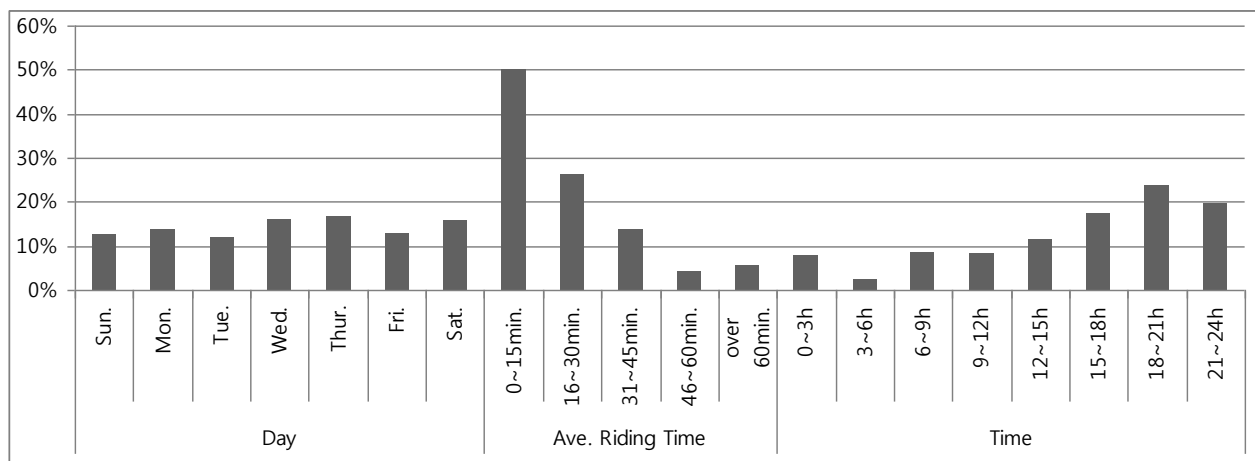
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1 number of departures and arrivals, as well as great volume of traffic to points surrounding the lake. Note
 2 that Figure 2 shows selected stations with frequent usage.
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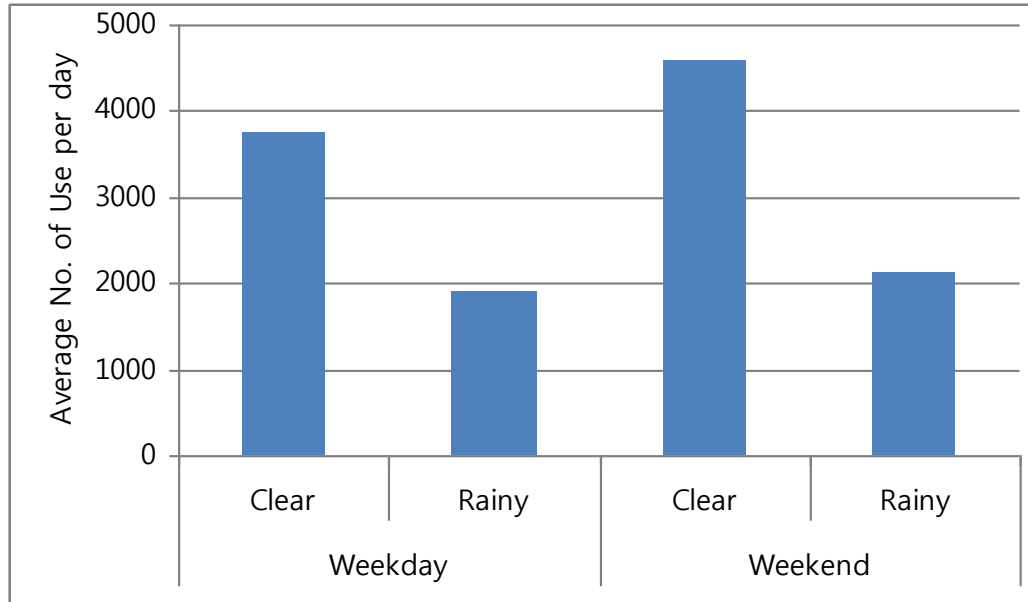
4 **FIGURE 2 Fifteen: Daily Uses per Station**

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 7 Figure 3 shows that Saturdays (15.9%) and Sundays (12.5%) had similar amounts of users to
 8 weekdays, which is believed to be attributed to the increased leisure activities at the Lake Park on the
 9 weekends. The mode travel time was shown to be 15 minutes at 50.2%, followed by 15 to 30 minutes at
 10 26%. Although this may reflect the fact that the first 40 minutes are free, short-distance travel clearly
 11 takes up most of the bikesharing usage. As for the hours of usage, 18:00 to 21:00 took up 23.8% of total
 12 bike usage, while 06:00 to 09:00 saw relatively low usage at 8.6%. Furthermore, 15:00 to midnight saw
 13 61.1% of bikesharing travel, proving that bikesharing are most often used in the afternoon and evening
 14 for commuting back home from school or work, or for shopping and leisure activities.
 15



16 **FIGURE 3 Fifteen: Ratio of Usage by Day, Riding Time, and Time Zone (%)**

1 Regarding the impact of precipitation, daily usage on rainy days has been compared with non-
 2 rainy days. While average rides for dry days on weekdays stood at 3,767 trips, rainy days showed lower
 3 usage at 1,904, merely 50% of the usage in dry days. For the weekends, it was shown to be at a level
 4 similar to that of weekdays, with 4,592 trips on dry days and 2,136 on rainy days.
 5



6
 7 **FIGURE 4 Average Daily Uses Depending on Precipitation**
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10 ANALYSIS OF RESULTS

11 Model Estimation

12
 13 Factors influencing the use of public bike are various, including socio economic condition, geographic
 14 location, cultural trait, land-use and transportation system, and climate condition. The site of this study is
 15 a New Town located in Goyang city, which was developed in 1990s. New Town is geographically even,
 16 planned similarly throughout the area, and remote from the rest parts of the Goyang city having little
 17 inter-regional bike traffic.

18 In order to determine the impact of land use and facilities surrounding bikesharing stations on the
 19 travel behavior of bikesharing, because characteristics and densities of facilities cause to use more
 20 bicycles, variables representing land use and facilities were set as independent variables, while daily
 21 usage per station has been set as dependent variables for this regression model (1):
 22

$$23 \quad bikeusage = a + b_1 \cdot residence + b_2 \cdot commercial + b_3 \cdot park + b_4 \cdot school + b_5 \cdot subway \quad (1)$$

24
 25 where, bikeusage: daily usage of bikesharing at each station (usage/day),
 26 residence: square area of residential buildings (1,000 m²),
 27 commercial: square area of commercial buildings (1,000 m²),
 28 park: park dummy,
 29 school: school dummy,
 30 subway: subway dummy.
 31

1 Gross square areas of residential and commercial buildings were used as variables representing
 2 the characteristics of land use. The greater the number of residential and commercial buildings around the
 3 bikesharing stations the greater traffic and arrivals, and is therefore expected to increase the usage of
 4 bikesharing system. To examine current land use, existing facilities, and the use of public transport within
 5 a 300m radius of Fifteen stations, we used a buffer analysis function of ArcGIS. To prevent a double
 6 counting error which can be caused within a less than 300m inter-Fifteen distances, we create Thiessen
 7 polygons other than a 300m buffer.

8 In order to determine the impact of characteristics of nearby facilities, the presence of schools,
 9 parks, and subway stations around the bikesharing stations have been set as dummy variables. Since
 10 students are likely to make frequent usage of bicycles, the school dummy variable is expected to have a
 11 positive impact on bikesharing usage.

12 Note that spatial random effects are not considered to capture unobserved effects because
 13 research site is believed as uniform as referred above. Therefore, Ordinary Least Square (OLS) estimation
 14 was performed.

15 The Lake Park in Goyang has a robust network of bicycle paths and enjoys a considerable volume
 16 of leisure traffic. As confirmed by the data analysis, the Lake Park area is shown to attract a large volume
 17 of bikesharing rides, particularly on the weekends. As subways are significantly linked to bicycles as a
 18 means of transportation, bicycle stations around the subway stops were also shown to have frequent usage.
 19



20
 21
 22 **FIGURE 5 Bikesharing Stations in Analysis Site(Ilsan new-city in Goyang)(left) and its Analysis**
 23 **Buffer(right)**
 24
 25

26 In order to determine the specific impact of weather on bicycle usage, four models were created
 27 with varying categories for weather and weekday or weekend (dry weekday, dry weekend, rainy weekday,
 28 and rainy weekend). 1682, 547, 782, and 519 instances of data were used for each category, respectively,
 29 to a total of 3,530 entries. The total number of the entries, or 3,530, was collected from 29 Fifteen stations
 30 during 122 days, and 8 entries considered as errors were excluded.

31 The reason for having separate categories for weekdays and weekends is because weekdays and
 32 weekends show different travel patterns that can in turn have different impacts on bicycle usage.
 33 Precipitation is another key factor to bicycle usage; this study set 2 mm as the standard amount of rainfall
 34 when categorizing the models for precipitation, as rainfall of less than 2 mm was shown to have a
 35 relatively insignificant effect on bicycle usage according to the usage data. Despite that bikesharing

1 behavior differs at winter season, temperature and snowfall were not taking into account for the analysis
 2 as winter season's usage data was not available.

3 Furthermore, traffic at each station varies depending on departures and arrivals. Thus the four
 4 models were further categorized into eight models that account for departures versus arrivals.

5 Data for rainfall was taken from information provided by Weather I Inc., a meteorological
 6 information institute registered under the Korea Meteorological Administration [15]. Values for the
 7 independent and dummy variables (land use, and presence of schools, parks or subway stations) were set
 8 for each bicycle station using the Gyeonggi Province real estate information [16] and the ArcGIS (ver.
 9 9.3) application. Coefficient values for the regression model were estimated using the statistics program
 10 STATA (ver. 10.0) [17, 18].

11 The variable statistics used for the multiple regression analysis models is shown in Table 3.
 12
 13

TABLE 3 Basic Statistics of the Variables Used in the Model

			Mean	Standard Deviation	Min.	Max.	
Dependent Variables	Departures (instance/ day)	Total	53.92	34.56	1	338	
		Weekday	<2mm	59.95	33.11	1	215
			\geq 2mm	45.54	29.82	3	204
		Weekend	<2mm	62.84	40.53	11	338
	\geq 2mm		37.64	30.55	1	180	
	Arrivals (instance/ day)	Total	46.99	30.98	0	304	
		Weekday	<2mm	52.72	29.76	6	235
			\geq 2mm	39.62	25.97	1	177
		Weekend	<2mm	53.36	36.92	7	304
			\geq 2mm	32.80	27.93	0	184
Independent Variables		Land use	Residential Sq Area (1,000 m ²)	252.84	329.24	27.98	1438.94
	Commercial Sq Area (1,000 m ²)		90.76	158.26	2.02	778.88	
	Facility	Park(dummy)	0(none): 3,408(96.5%), 1(present): 122(3.5%)				
		School(dummy)	0(none): 488(13.8%), 1(present): 3,042(86.2%)				
	Public Transport.	Subway (dummy)	0(none): 2,920(82.7%), 1(present): 610(17.3%)				

16 Findings

17 Table 4 and Table 5 display the coefficient values for the eight models built in the aforementioned steps.
 18 The analysis shows that more active use of land surrounding the location and the presence of schools,
 19 parks, or subway stations are correlated with increased usage of bikesharing usage.
 20

TABLE 4 Results of the Regression Models for Departure

Precipitation		<2mm				≥2mm			
Day		Weekday		Weekend		Weekday		Weekend	
		Coef.	VIF	Coef.	VIF	Coef.	VIF	Coef.	VIF
Land Use	Residential (1,000 m ²)	0.010***	1.08	0.009***	1.08	0.008***	1.08	0.007**	1.08
	Commercial (1,000 m ²)	0.148***	2.07	0.153***	2.07	0.110***	2.07	0.104***	2.07
Facility	Park (dummy)	97.551***	1.59	177.588***	1.59	68.255***	1.59	94.800***	1.59
	School (dummy)	27.006***	2.33	32.153***	2.33	25.093***	2.33	22.031***	2.33
Public Transport.	Subway (dummy)	27.184***	1.26	25.814***	1.26	20.495***	1.26	13.768***	1.26
cons.		12.828		8.239		5.989		1.824	
Num of obs.		1682		547		782		519	
Prob>F		0.0000		0.0000		0.0000		0.0000	
R_squared		0.6683		0.7386		0.4211		0.4228	
Adj R-squared		0.6673		0.7362		0.4174		0.4172	

Note: Significant at *** = 1%; ** = 5%; * = 10%

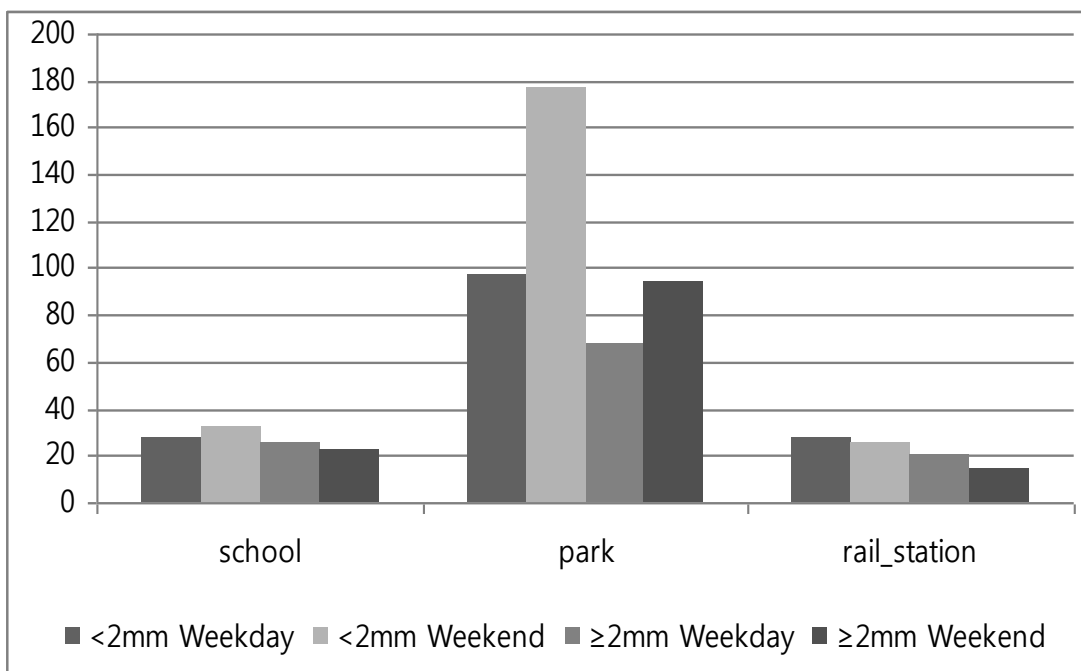
For weekdays without rain, the coefficient value of residential buildings' square area was shown to be 0.010 at the significance level of 1%, while square area of commercial buildings yielded a coefficient value of 0.148 at the significance level of 1%. The coefficient values suggest that commercial land use leads to bikesharing rides 14.8 times that of residential areas.

Dummy variables to represent the characteristics of nearby facilities (i.e. presence of schools, parks, and subway stations) were shown to have both a qualitative and quantitative correlation with the volume of usage of bikesharing stations. Coefficient value of the school variable was shown to be 27 at the significance level of 1%, suggesting that 27 rides occur at stations near schools. The park variable was analyzed to have 98 rides at significant level of 1%, which suggests that parks have four times more effect than schools do on promoting bikesharing usage. The subway variable showed a similar degree of impact, with 27 rides at significance level of 1%.

Weekday and weekend usage of bikesharing were shown to have different patterns. Stations near parks and schools show an increase in bikesharing traffic volume on the weekends. While traffic at stations near parks stand at 98 rides on the weekends, it nearly doubles on the weekends to 178 rides. This can be attributed to an increase in leisure activities at the parks on the weekends. Weekend increase in rides at stations near schools is assessed to be due to visits to schools for social activities, leisure, and exercise on the weekends. While gross residential area and subway station were shown to have less bicycle traffic on the weekends, commercial gross area shows greater traffic on the weekends than weekdays; the difference, however, is not significant.

Rainfall is analyzed to decrease the amount of bicycle rides regardless of weekdays or weekends, but more so during the latter. Stations near schools seemed less affected by rain on weekdays, with 27 rides on dry days to 25 rides on rainy days; this can be interpreted as students being captive riders, having to ride their bicycles to school regardless of the weather. Usage around parks and subways is seen to be affected heavily by rainfall, particularly on the weekends.

1 Stations near parks are shown to cause 98 rides on dry weekdays and 178 rides on weekends,
 2 displaying a significantly positive impact on bikesharing rides (Figure 6). Although stations near parks
 3 are shown to have decreased visits on rainy days, they still enjoy 68 and 95 rides on weekdays and
 4 weekends, respectively; parks are therefore analyzed to have 3 to 5 times the positive effect schools or
 5 subways have on bikesharing usage. Although schools and subways were also shown to cause bikesharing
 6 usage, their impact on weekdays and weekends did not significantly differ.



8 **FIGURE 6 Coefficients for Variables Representing Parks, Schools, and Subway in Each Model**

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 12 Station arrivals were also analyzed for four instances categorized as dry weekdays and weekends,
 13 and rainy weekdays and weekends. The school variable was shown to have 50% more departures than
 14 arrivals. This is assessed to be the result of students taking the family vehicle, shuttle, or a bus to school,
 15 while using a bicycle after the school day has finished. In addition, students may have varying
 16 destinations after school, which may include home, academies, or leisure venues. The subway variable
 17 was shown to have similar results, as the final destinations may vary after using the subway. However,
 18 stations near park areas, where traffic is mostly leisure-oriented, are shown to have nearly equal amounts
 19 of arrivals and departures.

20 As for variables on land use, residential gross area was shown to have more impact on arrival
 21 than departure. This can be construed in the same context as how schools and subways cause more
 22 departures than arrivals. Commercial gross areas, on the other hand, showed similar levels of departure
 23 and arrival. Meanwhile, arrivals during rainy weekends or weekdays showed similar patterns as those of
 24 departures, revealing that the weather has no particular effect on determining arrivals or departures.
 25

1 **TABLE 5 Results of the Regression Models for Arrival**

Precipitation		<2mm				≥2mm			
Day		Weekday		Weekend		Weekday		Weekend	
		Coef.	VIF	Coef.	VIF	Coef.	VIF	Coef.	VIF
Land use	Residential (1,000 m ²)	0.015***	1.08	0.015***	1.08	0.013***	1.08	0.011***	1.08
	Commercial (1,000 m ²)	0.133***	2.07	0.132***	2.07	0.093***	2.07	0.089***	2.07
Facility	School (dummy)	18.031***	2.33	21.978***	2.33	16.848***	2.33	15.691***	2.33
	Park (dummy)	93.695***	1.59	171.015***	1.59	65.282***	1.59	92.756***	1.59
Public Transport.	Subway (dummy)	18.950***	1.26	16.990***	1.26	14.897***	1.26	9.694***	1.26
cons.		14.849		9.657		8.566		3.502	
Num of obs.		1682		547		782		519	
Prob>F		0.0000		0.0000		0.0000		0.0000	
R_squared		0.6853		0.7763		0.4235		0.4400	
Adj R-squared		0.6844		0.7742		0.4198		0.4346	

2 Note: Significant at *** = 1%; ** = 5%; * = 10%

3

4 **CONCLUSION**

5 Recently, bikesharing systems have been actively implemented all around the world. Although this trend
 6 has led to a variety of research on public bicycle systems, there have been no previous studies on the
 7 factors influencing the travel behavior using public bicycles. This study has analyzed the impact of land
 8 use and facility factors that are speculated to have significant influence over bikesharing usage. The
 9 factors are gross area of residential buildings around the station; gross area of nearby commercial
 10 buildings; and parks, schools, and subway stations near the bikesharing stations. In addition, eight models
 11 were categorized according to factors that were also expected to yield different riding patterns: weekends
 12 and weekdays; rainy and non-rainy days; and arrivals to and departures from the bike stations.

13 As a result, land use factors (the gross area of nearby residential and commercial buildings) and
 14 facilities (parks, schools, and subway stations) were shown to have positive impact on bikesharing usage.
 15 However, the extent of their impact varied depending on certain variables and models. For non-rainy
 16 weekdays, commercial areas were shown to cause rides 15 times more than residential areas; and parks
 17 were shown to cause 3 to 5 times more rides than subway stations and schools. Parks, which are
 18 frequented mostly by traffic for the purpose of leisure, were shown to enjoy about twice the amount of
 19 traffic on the weekends than weekdays. As expected, bicycle usage was shown to decrease on rainy days
 20 overall.

21 This study is meaningful in that it has empirically analyzed the extent of the impact various
 22 factors have on the travel behavior of bikesharing users. When establishing bikesharing systems, the
 23 appropriate scale of each station must be calculated in consideration of nearby land use and facilities. In
 24 terms of operating bikesharing, an efficient redistribution strategy is also essential. This study may be
 25 used as a foundational reference in estimating the scale of new stations and building redistribution
 26 strategies for bikesharing stations. Afterwards, comprehensive analysis should be done in consideration of
 27 socio economic indicators, climate conditions, and the time of day.

28

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2
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4

5 REFERENCES

- 6
7
8 1. Mitchell, W.J., Borroni-Bird, C.E., Burns, L.D., Reinventing the Automobile-Personal Urban
9 Mobility for the 21st Century, The MIT Press, March 2010.
10 2. Shaheen, S. A., Guzman, S., Zhang, H., “Bikesharing in Europe, the Americas, and Asia Past,
11 Present, and Future,” *Transportation Research Record*, No. 2143, Transportation Research Board of
12 the National Academies, Washington, D.C., 2010, pp. 159-167.
13 3. Miranda-Moreno, L. F., Nosal, T., “Weather or not to Cycle; Whether or not Cyclist Ridership has
14 Grown: a Look at Weather's Impact on Cycling Facilities and Temporal Trends in an Urban
15 Environment,” *Proceedings of 90th Transportation Research Board Annual Meeting*, Washington,
16 D.C., 2011.
17 4. Rose, G., Ahmed, F., Figliozzi, M., Jakob, C., “Quantifying and Comparing the Effects of Weather
18 on Bicycle Demand in Melbourne (Australia) and Portland (USA),” *Proceedings of 90th*
19 *Transportation Research Board Annual Meeting*, Washington, D.C., 2011.
20 5. Nankervis, M., “The Effect of Weather and Climate on Bicycle Commuting,” *Transportation*
21 *Research Part A*, vol. 33, 1998, pp. 417-431.
22 6. Lewin, A., “Temporal and Weather Impacts on Bicycle Volumes,” *Proceedings of 90th*
23 *Transportation Research Board Annual Meeting*, Washington, D.C., 2011.
24 7. Amoruso, P., Binetti, M., Deflorio, F., Requirements analysis of a bike sharing system based on ITS
25 applications, ITS World Congress, 2010
26 8. Jon Froehlich, Joachim Neumann, Nuria Oliver, “Sensing and Predicting the Pulse of the City
27 through Shared Bicycling”, 21st international joint conference on Artificial intelligence, Pasadena,
28 California, USA. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 2009, pp. 1420-1426
29 9. Tang, Y., Pan, H., Shen, Q., “Bike-sharing Systems in Beijing, Shanghai and Hangzhou and Their
30 Impact on Travel Behavior,” *Proceedings of 90th Transportation Research Board Annual Meeting*,
31 Washington, D.C., 2011.
32 10. Morency, C., Trepanier, M., Godefroy, F., “Insights into Montreal's Bikesharing System,”
33 *Proceedings of 90th Transportation Research Board Annual Meeting*, Washington, D.C., 2011.
34 11. Voguel, P., & Mattfeld, D. C., “Modeling of repositioning activities in bike-sharing systems”, 12th
35 WCTR Lisbonne (Portugal). 2010, pp. 1-13
36 12. Goyang city, Masterplan of the Bicycle Facility in Goyang, 2008.
37 13. Goyang city, Goyang Statistical yearbook, 2010.
38 14. Ecobike Corp., Korea, <http://www.fifteenlife.com/>. Accessed October 6, 2010.
39 15. Weatheri Inc., Korea, <http://www.weatheri.co.kr/>. Accessed March 23, 2011.
40 16. Gyeonggi Real Estate Portal, Gyeonggi Provincial Government, Suwon. <http://gris.gg.go.kr/>.
41 Accessed June 3, 2011.
42 17. StataCorp., Stata Statistical Software: Release 10. College Station, TX: StataCorp LP, 2007.
43 18. Stata Base Reference Manual Volume 3: Reference Q-Z. Stata, College Station, Texas, 2007, pp. 79-
44 145.