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# Impacts of COVID-19 on bike-sharing usages in Seoul, South Korea

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## ABSTRACT

The COVID-19 pandemic and social distancing restrictions have had a significant impact on urban mobility. As micro mobility offers less contact with other people, docked or dockless e-scooters and bike-sharing have emerged as alternative urban mobility solutions. However, little empirical research has been conducted to investigate how COVID-19 might affect micro mobility usage, especially in a major Asian city. This research aims to study how COVID-19 and other related factors have affected bike-sharing ridership in Seoul, South Korea. Using detailed urban telecommunication data, this study explored the spatial-temporal patterns of a docked bike-sharing system in Seoul. Stepwise negative binomial panel regressions were conducted to find out how COVID-19 and various built environments might affect bike-sharing ridership in the city. Our results showed that open space areas and green infrastructure had statistically significant positive impacts on bike-sharing usage. Compared to registered population factors, real-time telecommunication floating population had a significant positive relationship with both bike trip count and trip duration. The model showed that telecommunication floating population has a significant positive impact on bike-sharing trip counts and trip duration. These findings could offer useful guidelines for emerging shared mobility planning during and after the COVID-19 pandemic.

## 1. Introduction

In 2020, the COVID-19 pandemic affected cities around the world, and both COVID-19 cases and deaths continued to increase rapidly worldwide in the later months of the year. By the end of November 2020, >63,000,000 cases and 1,400,000 deaths due to COVID-19 had been reported globally. The implications of this pandemic are not only related to public health issues, it also impacts every aspect of peoples' activities in cities. In order to prevent COVID-19 infection, many cities ordered social distancing measures and issued stay-at-home or lockdown orders. The strict lockdown in Wuhan, China forced people not to leave their residential areas and suspended public transportation within the city. Also, a nationwide lockdown in Italy and stay-at-home policies in the many US cities have been issued (Huang & Li, 2022; Qian & Hanser, 2021). The lockdown policies at the different timings and different degrees of mobility control have resulted in varying outcomes. Germany, New Zealand, Canada, and Norway adopted the lockdown policy at the early in the pandemic and these countries have lower death rates compared to Spain, France, Italy, the U.K., and the U.S. that adopted delayed lockdown (Gargoum & Gargoum, 2021). Unlike other countries, South Korea has kept COVID-19 at bay without a strict

lockdown since the first outbreaks of COVID-19 in January 2020.

The COVID-19 pandemic and social distancing restrictions changed the patterns of how people moved in many cities. For example, many schools and businesses shut down, causing a long-term shift toward remote learning and working at home. As urban movement declined dramatically, the pandemic also had significant impacts on daily public transportation ridership (Jenelius & Cebecauer, 2020). Since it is difficult for passengers to keep a safe distance from each other, conventional public transportation use (buses, subways, and trains) is considered to carry risks of COVID-19 contagion. As a result of social distancing and lockdown orders, many public transportation operators around the world face challenges due to reduced services and higher safety and sanitation standards. However, micro mobility modes such as docked or dockless e-scooters and bike-sharing are considered as effective public transportation alternatives during the COVID-19 pandemic because these modes ensure less contact with other people.

Despite previous studies on the benefits of micro mobility and the impact of COVID-19 on other public transportation services, little empirical research on the relationship between diverse factors in urban environments and micro mobility ridership during the pandemic has been conducted. As people in South Korea have the relatively normal life

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during the pandemic compared to other countries affected by the strict lockdown, how micro mobility modes work for people during the pandemic can be analyzed with sufficient micro mobility usage data. In recent years, data collections of real-time dynamic spatial information (telecommunication floating population, metro, bus, and micro mobility ridership) have become possible in a few cities and have gained attention in smart mobility research. However, there is a lack of research on how real-time spatial-temporal movements of the population affect micro mobility ridership in the pandemic. As Seoul as one of leading smart cities collects data related to urban mobility services – usages of bus ridership, metro ridership, and micro mobility at each station level – in addition to mobile phone-based floating population data and provides them as open data (Joo, 2021; Lee et al., 2018; Lim et al., 2018), the changes of micro mobility usages in response to COVID-19 and the role of micro mobility in post-COVID can be accessed. To address these gaps and the importance of micro mobility as an alternative public transportation solution during and after COVID-19 in urban areas, this research aims to study how COVID-19 affects bike-sharing services and how other factors impact bike-sharing ridership in Seoul without nationwide lockdown during the pandemic. To the best of our knowledge, our research is the first real-time data-driven study to a megacity with a population of 10-million people. Our study addresses a comprehensive study the impacts of COVID-19 on micro mobility including the next contributions:

- We investigated the spatial-temporal patterns of a docked bike-sharing service in Seoul, South Korea utilizing daily urban big datasets between March 1, 2019 and June 30, 2020.
- We provided an extensive analysis of usages of bike-sharing ridership changes – the number of trips and the duration - due to COVID-19 and find important different patterns of pre and post-COVID 19.
- We performed a statistical analysis of a negative binomial panel regression model to study how COVID-19 and other key factors including real-time floating population data in megacity affect bike-sharing usage.

This paper consists of five sections. After the introduction, Section 2 reviews relevant previous literature. Section 3 explains the study area, data collection, and data analysis strategy. Section 4 presents the key findings of our spatial-temporal analysis, descriptive statistics, and regression analysis. Finally, Section 5 concludes this empirical research by explaining the contribution of this study, discussing its limitations and suggesting future research.

## 2. Literature review

### 2.1. The effects of COVID-19 on bike-sharing

The National Association of City Transportation Officials (NACTO) recently reported the rapid growth and adoption of shared micro mobility (bike share, e-bike share and scooter share) in the United States (NACTO, 2020). Their report explained that >136 million trips on shared bikes, e-bikes, and scooters were generated in major cities in the United States in 2019. Compared to 84 million trips in 2018, this marked a 60 % increase in trips on shared micro mobility. Car-centric transportation systems in urban areas have contributed to environmental issues such as traffic congestion, air pollution, and climate change. Shared micro mobility as a sustainable mobility intervention has been widely promoted in recent years (Nikitas, 2019; Nikitas et al., 2016). The possible benefits of bike sharing have been studied in previous research and include serving as the first and last mile travel solution for congested urban areas, reducing car dependency, reducing emissions, and promoting physical activity (Griffin & Jiao, 2019; Shaheen et al., 2010; Shaheen & Chan, 2016; Wang & Zhou, 2017). The implementation of sharing economy platforms along with the growth of mobile phone access has resulted in a rapid increase of shared mobility ridership

(Jiao, 2018). However, the COVID-19 pandemic has significantly impacted urban travel patterns. The shared mobility ridership in India during the pandemic decreased by 35 % compared to usage prior to COVID-19 while people's preferences shifted toward private mobility modes – cars, bicycles, and e-scooters (Campisi et al., 2020; Meena, 2020). In contrast, some cities in the United States show a strong rise in bike-share program usage during the COVID-19 period. Schwedhelm et al. (2020) describe a 67 % increase in the demand for New York's bike-sharing program and a doubling of ridership in Chicago's bike-sharing program, compared to 2019. A survey-based study to assess the impact of COVID-19 on bike-sharing usage in Greece showed that bike-sharing is more likely to be promoted as a preferable mobility option for people during the pandemic (Nikiforiadis et al., 2020). A multiscale geospatial network analysis using New York bike-sharing data showed that the riding flow and its spatiotemporal distribution pattern changed significantly along with the development of the pandemic (Xin et al., 2022).

### 2.2. The effects of COVID-19 on people's daily lives

COVID-19 pandemic also has changed people's daily lives, lifestyles, and behavior. Some studies explain that COVID-19 has detrimental effects on people's daily lives as they stay at home to prevent infection. This isolation leads to health problems such as psychological distress and fear, and decreases life satisfaction (Ahorsu et al., 2020; Hermassi et al., 2021; Park et al., 2021). Research on impacts of the COVID-19 on the lifestyle, mental health, and quality of life shows prominent declines in physical activities of people's daily living, leisure, social activity, and education (Park et al., 2021). The sudden shift to 'New Normal' with Stay Home orders resulted in greater risk to the disabled left unsupported (Goggin & Ellis, 2020). Another analysis of the impact of COVID-19 on every travel behavior regarding activity-related travel patterns explains less frequent in-store shopping and increase in online shopping can be seen. COVID-19 also affected people's travel behavior related to leisure and daily errands, and young adults (17 to 24 years old) appeared to be more active than all other age groups in the Pandemic (Kolarova et al., 2021; Shamshiripout et al., 2020). A comprehensive survey set associated with individual's travel behaviors, habits, and perceptions before and during the pandemic in Chicago to investigate how COVID-19 reshapes activity-travel behavior reveals significant changes in various aspects of people's behavior such as people's mobility style toward tele-activities – online shopping, online meeting, and working from home (Shamshiripout et al., 2020).

Also, the economic concerns in vulnerable population with lower socioeconomic status arose during COVID-19 (Hu et al., 2021; Hu & Chen, 2021). Marginalized population of the poor, working-class, immigrants, and people of color are struggling with an unbalanced share of the burdens of the pandemic (Kasinitz, 2020). Pase et al. (2020) have found by using New York City Bike data that wealthier neighborhood in Manhattan had more socially distance than more impoverished areas with socio-economically vulnerable population. While people craving for parks and open space during the pandemic, well-managed parks and amenities predominantly are planned in white neighborhoods (Hoover & Lim, 2021).

### 2.3. The determinants of bike-sharing usage

Depending on the urban determinants of cities, bike-sharing usage patterns are affected differently. Several studies have investigated the determinants of bike sharing ridership utilizing historical trip data (Younes et al., 2020; Noland et al., 2016; Shaheen et al., 2010; An et al., 2019; El-Assi et al., 2017; Gebhart & Noland, 2014; Caufield et al., 2017). As weather conditions are considered to be significant factors on bike usage, their relationship to bike sharing ridership has been studied by incorporating weather datasets in analysis. Controlling for demographic and built environment characteristics in Toronto, Canada,

weather conditions were found to have a large influence on docked bike-sharing (El-Assi et al., 2017). Air quality has also been found to affect bike sharing usage. Kim (2020) examined seasonal impacts of particulate matter (PM) levels on bike sharing, explaining that PM levels act as a driving factor, in addition to other climate variables, on bike sharing usage in Seoul. Demographic, socio-economic, and built environment factors (i.e. land use classifications, and transportation infrastructure) were considered as key factors that affect shared e-scooter usage in Austin, TX and Minneapolis, MN (Bai & Jiao, 2020; Jiao & Bai, 2020). The results of this study found that the presence of public transit stations, areas with good street connectivity, and places with more compact land use patterns related to an increase in e-scooter usage. Analysis on bike-share ridership for origin-destination pairs to find effects of public transit route characteristics and land-use patterns showed that bike-share ridership has a complementary relationship with the metro, and it has a competitive relationship with bus transit in non-residential areas (Kim & Cho, 2021). Survey-based research on the relationship between perceived built environment and active travel, before and after the COVID-19 in Shiraz city, Iran showed that a people-friendly environment with mixed, diverse, dense and accessible land uses, as well as the presence of bike riding infrastructure had major effects on the mobility in the pandemic. Also, this study found the importance of the existence of alternatives and resilient modes to maintain the social interactions during COVID-19 (Share et al., 2021).

#### 2.4. The importance of real-time datasets on assessment of bike-sharing usage

As bike-sharing programs are relatively new and a wide range of real-time datasets of urban environments are not available, there is little empirical research on how COVID-19 and other urban factors might affect bike-sharing ridership. The production of real-time datasets containing telecommunication floating population have become possible with the development of information and communication technologies (ICT), and studies on mobile-based floating population data have emerged to evaluate spatial-temporal patterns of population (Jo et al., 2020; Lee et al., 2018). Public bike-sharing services have customers use their phones to pay fees or scan QR codes to activate bikes. Thus, taking mobile phone signal-based population into account is important to better understand bike-sharing usage. Several studies have pointed out that although census-based population data is the most meaningful representation of the social and economic status of people, it is hard to reflect dynamic spatial-temporal patterns of people from this data alone. Specifically, the census-based population represents the number of people who are registered in a given district, and it is difficult to capture the human dynamics that can be reflected by mobile-based population patterns (Baker et al., 2017; Yun et al., 2020). Also, static census-based populations are collected every 5 to 10 years, whereas mobile-based population information captures real-time information. Mobile phone-based population data was considered to analyze actual demands for public facilities, and the human dynamics of the spatial-temporal characteristics of people (Jung & Nam, 2019; Jo et al., 2020; Yun et al., 2020). Gender information from mobile-based floating population data was used to analyze gender equality with regard to the use of urban space in Seoul (Jo et al., 2020). Yun et al. (2020) explained that using mobile phone-based data allowed researchers to consider both active and inactive real-time floating population for analysis. They argued that using only census data for accessibility analysis had limitations and could lead to certain errors. The results showed that mobile-based population data could represent real-world characteristics, and could be used to help solve urban issues particularly in the field of primary medical care. Lee et al. (2018) utilized mobile phone-based floating population data to measure the spatial accessibility of public transportation. Areas with less spatial accessibility to public transportation were identified based on spatial-temporal mobile-based population data. They compared the floating population-based accessibility with

the census population data, and the results emphasized that mobile-based floating population provides reliable and fine-grained results to supplement static census data. Urban dynamics during the COVID-19 pandemic based on mobile phone data was accessed and it showed that mobile phone data have a great potential for analyzing how the population in activity areas increased. This study found that it was possible to identify areas with more or less activity during the COVID-19 lockdown (Romanillos et al., 2021). However, real-time public transportation passenger flows and telecommunication floating data on bike-sharing have not been empirically studied specifically with regard to the COVID-19 pandemic. The availability of real-time data on various urban factors in Seoul, South Korea has made it possible to study spatial-temporal analysis of determinants of which previous studies have not empirically analyzed. Therefore, the purpose of this study was to address the importance of bike-sharing as an alternative transportation solution during and post COVID-19 in urban areas by statistically analyzing the impacts of COVID-19 on key factors of bike-sharing ridership in Seoul.

In the light of these existing literature, our study can contribute with a greater understanding of spatial-temporal changes of bike-sharing ridership in the pandemic and providing empirical evidence for proactive strategies of micro mobility planning in post-COVID 19. First, this study provides understanding of how bike sharing works in the relatively normal life during the pandemic compared to other countries affected by the total lockdown. Second, this study presents the effects of real-time dynamic population on bike-sharing ridership, which was not considered for in previous literature. Finally, many previous bike-sharing studies were accessed in Western cities. This study investigates spatial-temporal patterns of bike-sharing and the determinants of bike-sharing usages in Seoul, one of the leading smart cities. Therefore, the result of this study will expand knowledge of bike-sharing in Asian smart city. Geographic knowledge and policy implications gained from studying these cities might be helpful for creative transportation policies.

### 3. Research methods

#### 3.1. Study area

Seoul (37.34° N and 126.59° E) is both the capital of South Korea and the most populous city in the country. It is considered a megacity with a population of more than ten million people (Seoul Metropolitan Government, 2020). The total land area of Seoul is 605 km<sup>2</sup>, and consists of twenty-five districts (or *gu* in local terminology). According to the Korea Meteorological Administration, the city has a clear seasonal climate pattern with an annual mean temperature of 12.5 °C. There are four distinct seasons, with summer and winter mean temperatures of 25.7 °C and -2.4 °C, respectively. The city struggles with air quality issues due to high levels of airborne fine dust concentrations.

In October 2015, the Seoul Metropolitan Government launched a docked-based bike-sharing service, called Ddareungi (Seoul Institute, 2018). There were 450 bike stations when the docked-based bike-sharing service first launched. As of July 2020, the 'Seoul Public Bike Station Location Information' dataset provided by the Seoul Metropolitan Government shows that there are now a total of 2083 bike stations in the city. The number of bike-sharing stations in each district ranges between 54 and 133 (Fig. 1). The bike-sharing service is comprised of bicycle stations with either LCD-based or QR-based user interfaces. The bicycle stations with LCD-based interfaces are expected to be replaced by stations with QR-based interfaces by 2022. The newer QR-based bicycle stations have a QR codes printed on the bikes with a smart lock based on IoT (Internet of Things) technology. People are able to use these bicycles by scanning the QR code with their mobile phones. According to the Seoul Facilities Management Corporation, micro mobility ridership had increased rapidly from 2015 to 2019, during which total bike-sharing ridership increased almost ten times from 1,725,339 to 18,192,716 trips (Fig. 2). For five years, the expansion of bike-sharing

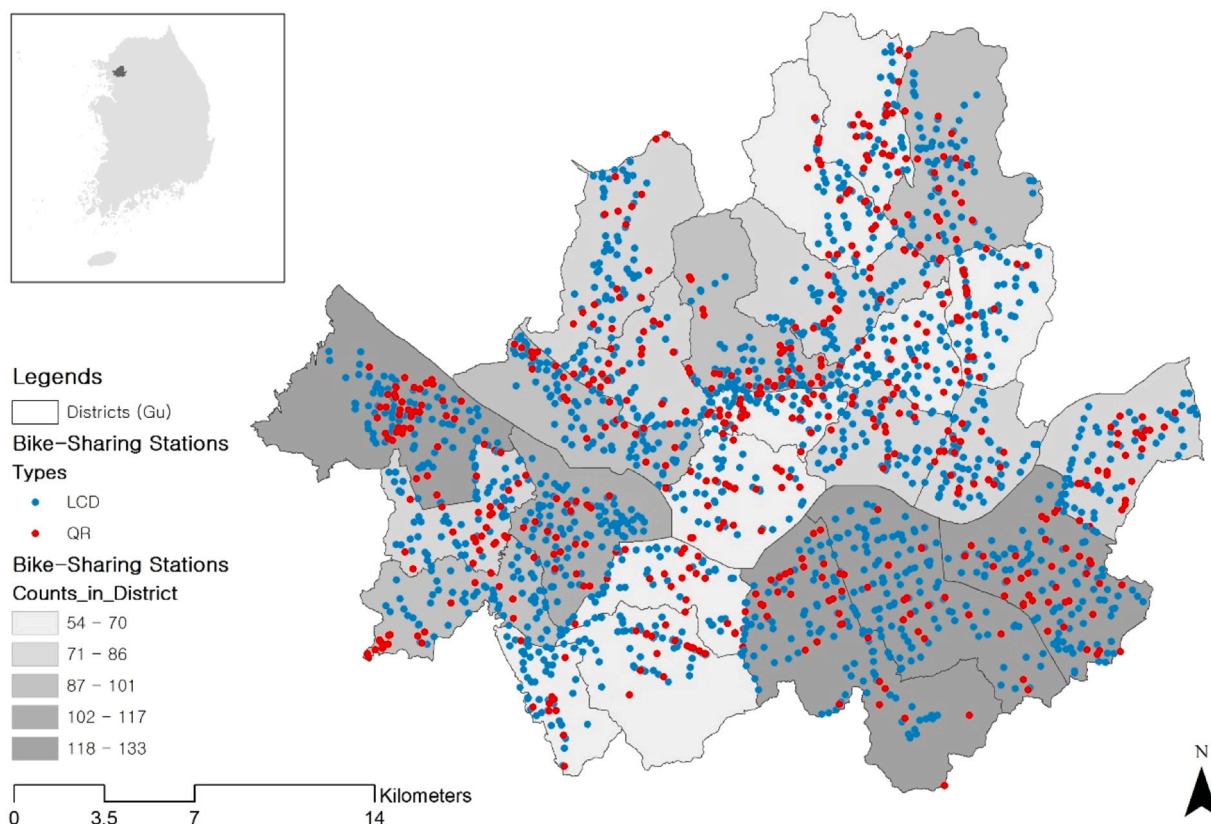


Fig. 1. Study area and bike-sharing stations in Seoul.

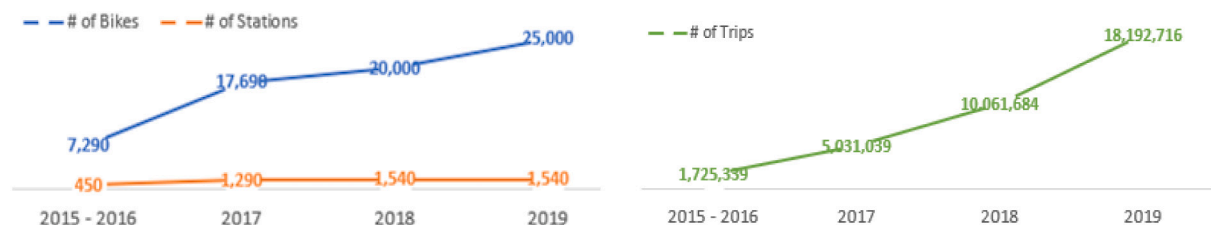


Fig. 2. Changes of bike-sharing 2015–2019.

stations, bikes, and ridership have been dramatically rapid. According to Seoul Transportation in 2020 Data, average daily ridership of bus, metro, taxi, and shared bike in 2020 are 3,940,151, 4,473,224, 781,331, and 64,768, respectively (Seoul Metropolitan Government, 2020). The mode share of transportation in Seoul has been analyzed specifically by assessing ridership of public transportation including bus and metro, private vehicle, taxi, and others (motorcycle and truck only). The most recent data of mode shares in 2019 explains mode shares of public transportation, private vehicle, taxi, and others are 65.6 %, 24.5 %, 5.7 %, and 4.2 %, respectively. As Seoul government has not included the share of bike-sharing ridership for total mode share of transportation, it is not able to compare its significance of bike-sharing ridership directly to other traffic mode shares. However, Seoul government reported that significant increase of bike-sharing ridership was identified between 2019 and 2020, which is 24 % growth. Considering the 34 % decrease of public transportation ridership of bus and metro between 2019 and 2020, the mode share of bike-sharing is getting more importance during COVID-19 pandemic. Some studies argue that public bike-sharing services have limited impacts on commute travel in Seoul, as mode share of the bike-sharing is not prominent yet in Seoul. However, Seoul government analyzed the bike-sharing usages patterns in 2020 and

emphasized that the total usages of the bike-sharing on weekdays present higher ridership compared to weekends. Its statistics analyzed by Seoul government shows that 59.6 % of total ridership in 2020 used the bike-sharing for <4 km and 42.5 % of total ridership used <20 min. Also, 54 % of daily usages are concentrated especially in morning and evening rush hours (7 to 10 am, 5 to 11 pm), and it can be linked to the people's use of bike-sharing for commute trips and the bike-sharing as the first and last mile mobility in Seoul. Also, Seoul Transport Operation and Information Services describe that the percentage of the public bike-sharing usage in evening peak hour reached 9.5 %, which is relatively similar to the usages of metro, 11.3 %. This indicates that Ddareungi is likely to be used as not only to serve leisure purposes but also used as an alternative transportation mode. Due to the small percentages of the mode share of Ddareungi, impacts of bike-sharing may not be as large as anticipated. However, during COVID-19 the total number of usages have increased significantly by 24 % in 2020 compared to 2019, whereas other public transportation usages decreased >30 %. It can be explained that the bike-sharing program is getting more attention as a mode of micro mobility and has potential to grow as an alternative mean of public transportation.

In Seoul, the very first COVID-19 patient was first reported on

January 24, 2020, and since then different levels of social distancing measures have been taking place. By the end of November 2020, the total number of confirmed COVID-19 patients in Seoul was 8811. Although the number of confirmed COVID-19 patients continues to increase, unlike many other countries and cities affected by COVID-19 a national or city level lockdown measure has not been issued in Seoul.

### 3.2. Conceptual methods

#### 3.2.1. Dependent variables – Seoul public bike trip count & trip duration

Seoul public bike-sharing usage data was provided for each trip included in our analysis. The dataset for each individual trip included date and time information as well as the latitude and longitude information of both check-out and return locations. Also, the dataset provided the total duration and distance of each trip. Since the Seoul Metropolitan Government provides a monthly dataset without district information for each trip, data preprocessing was done before further analysis.

Data preprocessing consisted of three steps. First, using the Seoul public bike station location information with latitude and longitude coordinates, each bike station was geocoded and spatially joined with its respective district using ArcGIS. Second, the original public bike usage data was imported using Python, and district information was merged based on each trip's checking-out station code. Each trip's date and time of usage were individually extracted. Third, the preprocessed data was grouped by 'year', 'month', 'day', and 'district', and trip count, trip duration, and trip distance were calculated using Python. Daily total trip duration and trip distance were calculated for each district by aggregating information from each bike-sharing trip. However, since there were many missing values for trip distance, two variables – total trip count and trip duration – were considered as dependent variables for this study. For this study, the time period of analysis ranged from March 1, 2019 to June 30, 2020, which consists of 488 days in total. The unit of analysis is city district level. There are 25 districts in Seoul and it makes the total number of observations for this study 12,200. The total number of samples for this study consists of 12,200.

#### 3.2.2. Independent variables

For this study, we included five factors of independent variables which affect Seoul bike-sharing ridership in our analysis: climate, transportation, land use, population, and COVID-19 factors. For the seasonal climate factors in Seoul, daily mean temperature, wind speed, precipitation, and Particulate Matter (PM) 2.5 from an AirKorea dataset were considered. AirKorea gathers climate data from various weather stations across Seoul. To preprocess the dataset, we geocoded each weather station in ArcGIS and performed a spatial join to gather district information. Then, the daily average of climate factors was analyzed for each district.

The location of public transportation infrastructure, metro stations, bus stations, and bike infrastructure, were obtained from the Seoul Metropolitan Government. The number of metro stations and bus stations per square kilometer for each district were considered as transportation factors. To calculate public transportation ridership, X and Y coordinates of each station were geocoded in ArcGIS to obtain their district information. Then, we were able to aggregate passengers who checked in and checked out of metros or bus stations per district. For metro passengers' inflow and outflow, we first aggregated the passenger count of each station, then preprocessed the aggregated results at the district level. For land use factors, the number of open spaces per square kilometer was included to represent the density of open space in each district. The green infrastructure ratio explains different spatial patterns of green infrastructure in each district. In addition to the open space and green infrastructure variables, six sub-divided land cover classifications – residential, commercial, industrial, cultural, transportation, and public land covers – from the Korea Ministry of Environment (Environmental Geographic Information Service, EGIS) were utilized to measure land

use entropy. According to Song et al. (2013), the land use entropy index ranges between 0 and 1 representing the distribution of different types of land use in the study area. A larger land use entropy index represents a more diverse land use distribution, whereas a value of 0 means there is only one land use type. The land use entropy index is calculated using the following equation:

$$ENT = \frac{-\left[\sum_{j=1}^k P^j \ln(P^j)\right]}{\ln(k)}$$

where *ENT*: the land use entropy index; *P<sup>j</sup>*: the percentage of land use "j" within the study area; and *k*: the total number of land use types within the study area.

For population factors, telecommunication records were obtained from SK Telecom's (SKT) Big Data Hub. SK Telecom is one of the major telecommunication companies in South Korea with nearly 50 % of the market share. Real-time floating population is collected based on the signal transmission information of mobile phones at SK Telecom stations. Phone-based spatial location data can be classified as either passive or active. Passive spatial location data is collected when people engage in communication activities such as phone calls and text messages. Active spatial location data is collected even when people turn on, but do not engage in phone calls or text messages (Song et al., 2010; Becker et al., 2013; Xu et al., 2015; Xu et al., 2016; Lee et al., 2018). The telecommunication floating population factor for this study is based on active data, since it is better for generating dynamic spatial-temporal information than passive data. The data is updated monthly and contains floating population information by district, time zone, gender, and age. We aggregated the raw floating populations and preprocessed them for each district and day for the study.

For the social factor, we looked into the registered population, gender ratio, and relative youth ratio of each district in Seoul (2019). The gender ratio is calculated by dividing the registered male residents by female residents. Youth ratio is calculated by dividing the registered population under age 24 by the total number of registered residents. The COVID-19 confirmed patient counts were obtained from the Seoul Metropolitan Government's COVID-19 dashboard. The Seoul Metropolitan Government updates the number of confirmed patients by district based on each confirmed patient's residence address on a daily basis. For this study, we considered the number of confirmed COVID-19 patients for each day and each district in Seoul. A dummy variable for COVID-19 is also considered for the COVID-19 factor. A COVID-19 factor of zero is assigned to dates before the first confirmed COVID-19 patient was reported in Seoul, and a COVID-19 factor of 1 is assigned to dates on and after the first confirmed case.

### 3.3. Data analysis

The data in this study was analyzed in two phases. First, we investigated the spatial-temporal patterns of bike-sharing ridership for 25 districts in Seoul using descriptive statistics. Second, we conducted a stepwise negative binomial (NB) fixed panel regression model that tested the consequences of 1) climate factors, 2) transportation factors, 3) land use factors, 4) social factors, and 5) COVID-19 factors on the two key indicators of bike-sharing ridership - total number of ridership and total time duration of ridership - for 488 days between March 1, 2019 and June 30, 2020. The multicollinearity issue among variables was tested by running a pairwise correlation test and variance inflation factor (VIF) after conducting a least square regression model with the same variables.

A Poisson regression model or negative binomial model are generally preferred (Ki & Lee, 2019; Sohrabi et al., 2020) for analyzing count data. A Poisson model is employed when the mean and the variance are approximately equal, whereas negative binomial model is used when variance exceeds the mean. Count variables are often overdispersed, as a

variance is greater than the mean. Therefore, a dispersion test is performed to find the overdispersion to identify a statistical model (Chen et al., 2018). For this research, the negative binomial model is preferable over a Poisson regression model when we tested variance and mean values of each dependent variable and the results showed the variables are overdispersed. Negative binomial regression fitted more reliably to model over-dispersion count data (Fig. 3).

#### 4. Results

##### 4.1. Descriptive statistics

This study first analyzed the daily total trip counts and trip duration in minutes. Figs. 4 and 5 display the descriptive statistics of daily bike-sharing ridership for each of the 25 districts from January 1, 2018 to June 30, 2020. Although the time period for this study starts from March 1, 2019, in order to see whether there were any seasonal patterns of bike-sharing ridership in Seoul we also included a daily-based dataset between January 1, 2018 and February 28, 2019. In both 2018 and 2019, for both the temporal patterns of trip count and trip duration, the ridership increased starting in March and started to decrease in November.

In addition to overall spatial and temporal analysis of bike-sharing ridership changes, Figs. 6 and 7 show a comparison between the daily bike-sharing ridership before COVID-19 and after COVID-19 explains how people's bike-sharing usages have been changed in depth. The total bike ridership between the same period of January to June in 2019 and 2020 shows a prominent increase of bike-sharing usages in 2020. Overall average bike trip duration in the same periods between 2019 and 2020 also shows that people used more minutes on the shared bike. Despite overall increase in bike-sharing ridership, decreased daily bike-sharing ridership was identified between middle of May to the end of June in 2020 when compared to the numbers in 2019. It can be explained that bike-sharing usages were affected by the strict social distancing measure by South Korea Government, which was effective right after big surge of COVID-19 new cases during consecutive national holidays in May 2020.

To better understand temporal patterns of bike-sharing ridership in Seoul before and after COVID-19, bike-sharing trip durations of short or long trips in the same period of January to June in 2019 and 2020 were analyzed. To differentiate short trip from long trip of bike-sharing, a report by National Association of City Transportation Officials (NACTO, 2020) was considered. NACTO mentioned that micro mobility systems are filling important gaps in transportation networks and playing as a solution for first and last mile problems in cities. As NACTO analysis emphasized that shared micro mobility trips are short, averaged between 11 and 12 min in terms of trip duration, we used 12 min as a breakpoint. Our analysis of two types of bike-sharing trip duration

depicted in Figs. 8 and 9 showed that overall long trips in 2020 increased more compared to the same period after COVID-19. These patterns can be explained that due to high risk of getting infected from contacting other people, people spent more times on the bike-sharing when they used it in Seoul.

Since the average winter temperature in Seoul is  $-2.4\text{ }^{\circ}\text{C}$ , this climate condition links to less ridership of bike-sharing between November to March. Also, every year in South Korea there is a heavy rain season in the summer. Increased instances of heavy rain may affect peoples' usage patterns of the bike-sharing service and are related to big drops of ridership between July and August for each year. Among the 25 districts, Yeongdeungpo-gu, one of the major business districts in Seoul which has good access points to the Han river open space, had the highest trip count and trip duration. Comparably, Geumcheon-gu had the lowest trip count and trip duration. After the first COVID-19 confirmed patient in January 2020, similar temporal and spatial patterns are observed for trip count and trip duration variables compared to the previous two years. Surprisingly, a higher number of trip counts and longer trip durations for some districts presented after the COVID-19 pandemic.

In addition to the spatial and temporal patterns of bike-sharing, Table 1 shows descriptive statistics of the dependent and independent variables of this study. The mean daily bike-sharing trip count was 2162 trips per day, and the maximum recorded trip count in a single day was 8881. The daily average duration of total bike-share trips was about 60,710 min and the maximum duration of all trips in a single day was 446,686 min. The average travel time of a single bike-share trip was 27.1 min, whereas the minimum and maximum trip durations were 9 min and 62 min, respectively. For climate factors, the minimum mean temperature was  $-10.2\text{ }^{\circ}\text{C}$ , and maximum mean temperature was  $33.3\text{ }^{\circ}\text{C}$ . Mean wind speed ranged from zero to 10.45 m/s, and mean precipitation ranged from zero to 9.2 mm. Also, the minimum level of mean particulate matter 2.5 was  $1\text{ }\mu\text{g}/\text{m}^3$ , and the maximum level was  $153\text{ }\mu\text{g}/\text{m}^3$ . For context, the Seoul Metropolitan Government issues fine particulate matter (PM-2.5) warnings if the average PM-2.5 concentration exceeds  $150\text{ }\mu\text{g}/\text{m}^3$  per hour at the urban air quality monitoring stations for more than two hours.

For transportation factors, bus infrastructure offered better access compared to metro infrastructure. Since the area of each district ranged from  $9.96\text{ km}^2$  to  $46.8\text{ km}^2$ , the total number of either mode's stations was divided by the area of the corresponding district. The number of metro stations per square kilometer for each district ranged from 0.1 to 2.4, whereas the same variable for bus stations ranged from 12.9 to 27.7. On average, bus infrastructure had 27 times as many stations per square kilometer as did metro infrastructure. The descriptive statistics of public transportation passenger volume variables show that the average metro trip counts of inflow and outflow was 412,682.8 per day, while the average bus trip counts inflow and outflow were 358,289.6 per day. The

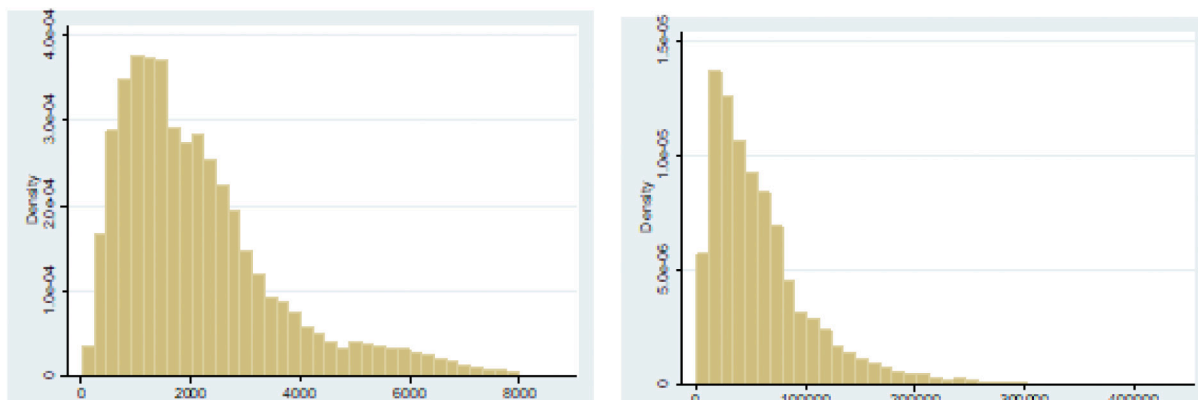


Fig. 3. Histograms of dependent variables.

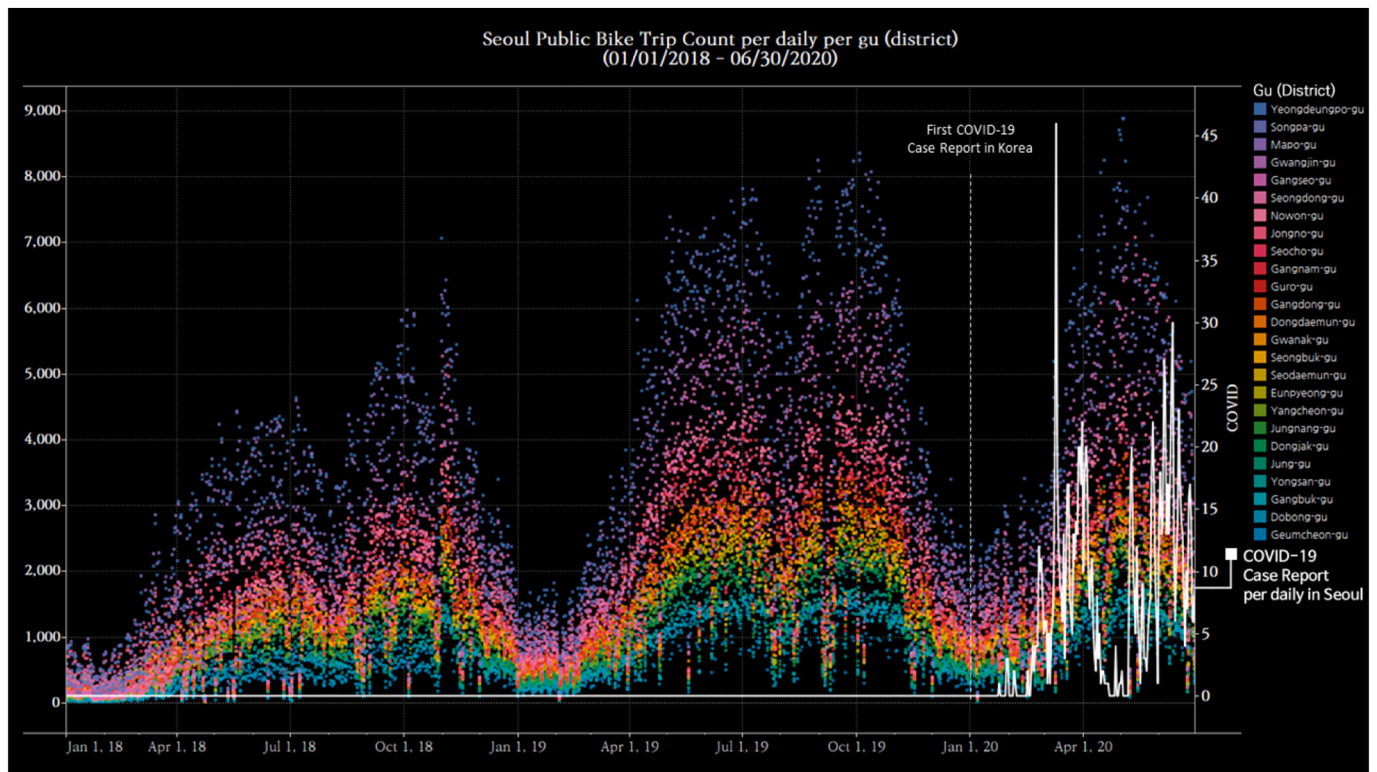


Fig. 4. Spatial and temporal analysis of the bike-sharing trip count in Seoul.

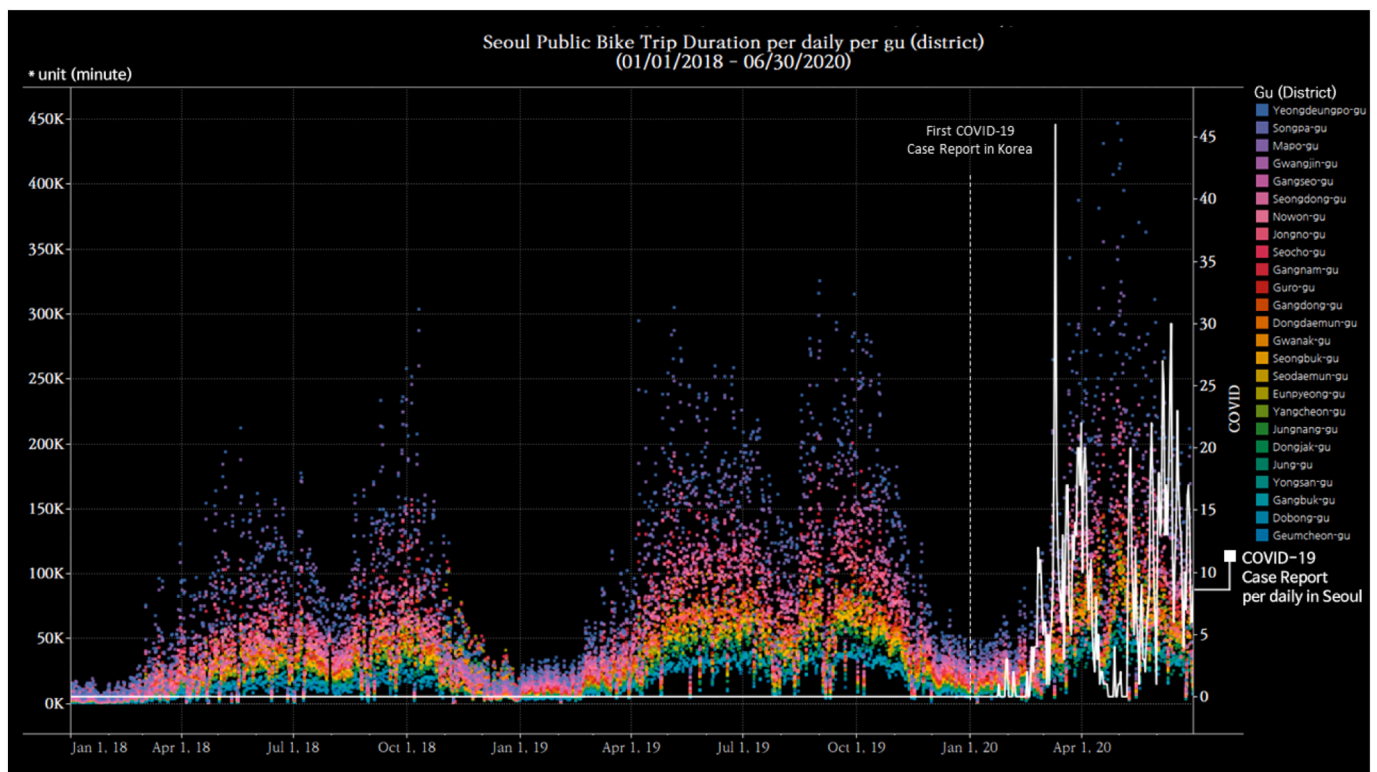


Fig. 5. Spatial and temporal analysis of the bike-sharing trip duration in Seoul.

number of bike-sharing docks per square kilometer in each district ranged from 19 to 51, and the average bike dock density is 34 docks/km<sup>2</sup>. Statistics of land use factors show that land use entropy, which refers how diversely the land uses of each district are distributed, ranged

from 0.59 to 0.80, while the mean land use entropy was 0.68 city-wide. This represents that there was not a dominant single land use for any district, and that multiple different types of land uses are spatially planned in each district in Seoul. However, green infrastructure land use



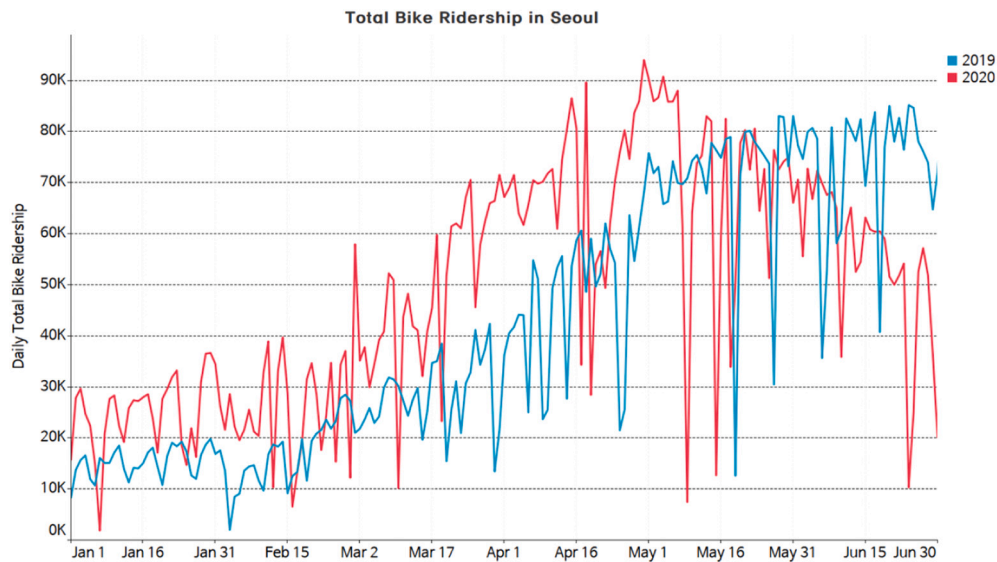


Fig. 6. Bike-sharing trip count changes before COVID-19 and after COVID-19.

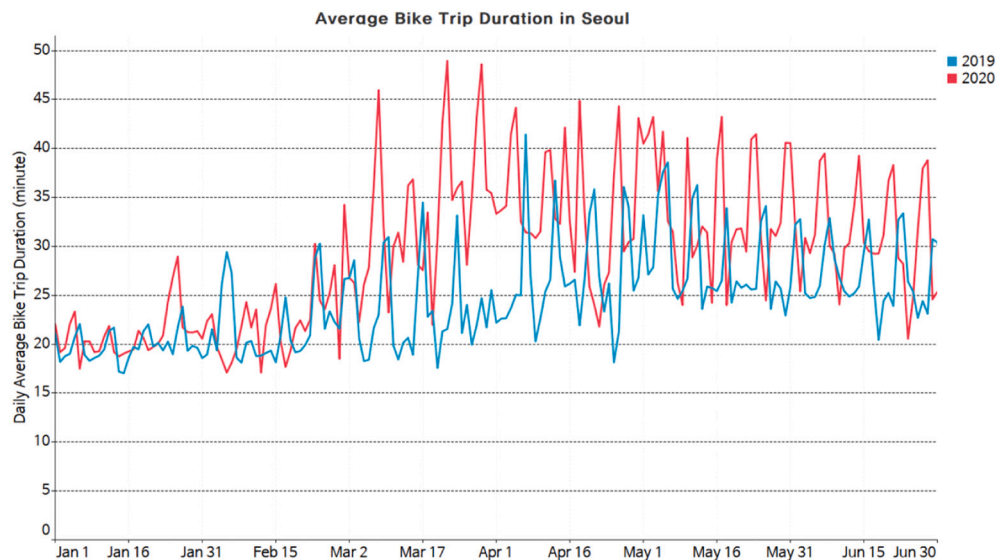


Fig. 7. Bike-sharing trip duration changes before COVID-19 and after COVID-19.

ranged from 0.08 to 0.6, which suggests that some districts lacked green infrastructure, whereas some districts consisted of almost 60 % open space. For population factors, two types of population variables, telecommunication floating population and registered population for each district, were considered, and different patterns were presented. While the registered population density of each district ranged from 6769 to 26,559 people/km<sup>2</sup>, telecommunication floating population, which represents real-time population, ranged from 63,815 to 949,721 people/km<sup>2</sup>. Despite the COVID-19 pandemic, Seoul has not issued any lockdown-level social distancing measures. Therefore, there were substantial differences between the registered population and the real-time floating population during the pandemic. Our COVID-19 factor measuring the total number of COVID-19 confirmed patients per square kilometer in each district ranged from 0 to 0.58.

#### 4.2. Negative binomial panel regression model results

To better understand the impact of COVID-19 and other social and urban environmental factors on bike-sharing ridership in Seoul, we

analyzed the data using a stepwise negative binomial panel regression model with STATA 11.0 software. Five factors of 20 independent variables were considered for this study to find the impacts of these variables on bike-sharing ridership. The same method was used to analyze for two dependent variables – bike trip count and bike duration, separately.

##### 4.2.1. Bike-sharing trip count and COVID-19 and urban environment factors

Among all climate factors, lower wind speed, less precipitation, and less particulate matter 2.5 level held a negative relationship with bike-sharing trip count, whereas higher temperature was positively related to trip count across the five statistical models. This reveals that people used more bike-sharing in Seoul when climate conditions consisted of warm temperatures, less wind, less precipitation, and cleaner air quality. For transportation factors, metro station density, and public transportation passenger volumes had significant impacts on bike-sharing trip count. The higher metro station density was negatively related to bike-sharing trip count, and both metro and bus passenger ridership, including inflow and outflow, held a positive relationship with bike-

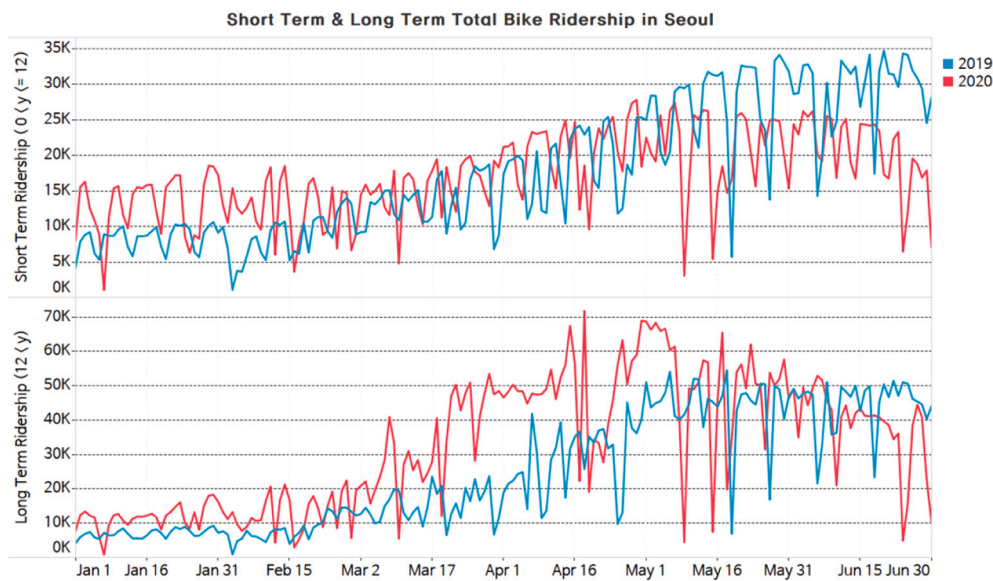


Fig. 8. Short and long trips count changes of bike-sharing before COVID-19 and after COVID-19.

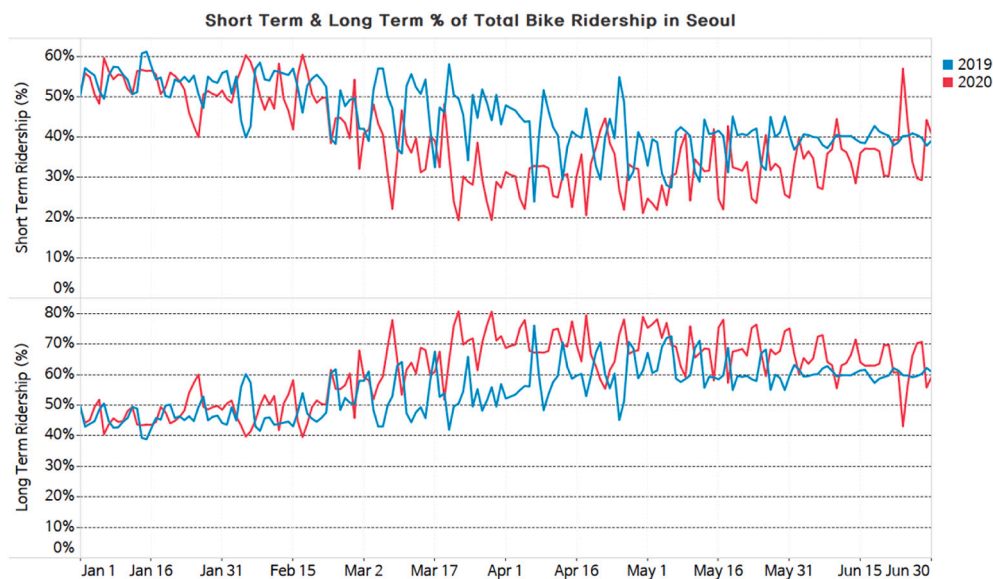


Fig. 9. Short and long trips percentages of bike-sharing before COVID-19 and after COVID-19.

sharing trip count. Fig. 10 shows the results of a buffer analysis of the accessibility from bike-sharing stations to public transportation (bus and metro) stations. It indicates that the coverage of bus stops is much higher compared to metro stations. We analyzed the total number of bike-sharing stations without bus or metro stations within 400 m and 1 km buffers created from each bike-sharing station. The buffer analysis explains that there is a good degree of accessibility from bike-sharing stations to bus stations in Seoul, since almost all bike-sharing stations are located within either 400 m or 1 km distances from bus stations. However, 59.2 % of bike-sharing stations in 400 m buffers and 19.1 % of bike-sharing stations in 1 km buffers are without good accessibility to metro stations. This buffer analysis explains the significant negative relationship between metro station density and bike-sharing trip count. It emphasized that the accessibility to other public transportation from bike-sharing stations is more important than total numbers of bus and metro stations. To potentially play as a solution for first and last mile connectivity with the existing public transportation network, the catchment area of metro stations near bike-sharing stations needs to be

extended (Shaheen & Chan, 2016). This suggests that micro mobility acts as an alternative urban mobility solution and is used as a means to solve first and last mile accessibility and connectivity issues (Alcorn & Jiao, 2019; Ma et al., 2018; Nikitas et al., 2016; Zhao et al., 2019; Wu et al., 2021; Bieliński & Ważna, 2020).

For all land use factors, the land use entropy variable had a significantly positive relationship, except in model 3. In model 4 and model 5, a 1 unit increase in land use entropy would relate to 1.07 times and 1.25 times increases in ridership, respectively. This reveals that more diverse land uses in a district links to higher bike-sharing ridership. Both open space density and green infrastructure ratio also held a significant positive relationship with bike-sharing ridership. A 1 percentage increase of the green infrastructure ratio in a district generates between 80.7 and 124 additional daily bike-sharing trips. From this, it can be explained that if more open space and green infrastructure are planned for urban areas, people will use a bike-sharing program more.

For social factors, telecommunication floating population, which represents real-time population data, had a significant positive

**Table 1**  
Descriptive statistics of variables.

Variables (units)	Mean	S.D.	Min	Max	Sources
<b>Dependent variables</b>					
Bike trip total counts (count)	2161.743	1499.654	16	8881	Seoul metropolitan government
Bike trip mean duration (minute)	60,710.12	50,693.95	131	446,686	
<b>Independent variables</b>					
<b>Climate factors</b>					
Mean temperature (°C)	14.19355	9.013775	-10.16667	33.31667	Air Korea
Mean wind speed (m/s)	1.700615	0.8614617	0	10.45	
Mean precipitation (mm)	0.1099192	0.3833158	0	9.166667	
Mean PM 2.5 (µg/m <sup>3</sup> )	22.9166	15.07294	1	153	
<b>Transportation factors</b>					
Metro station (count/km <sup>2</sup> )	0.7026367	0.4272448	0.135352	2.408969	Seoul metropolitan government
Bus station (count/km <sup>2</sup> )	19.89971	4.647335	12.91951	27.6805	
Metro trips counts in & out	412,682.8	256,487.3	29,067	1,750,457	
Bus trips counts in & Out	358,289.5	140,358.2	69,795	847,197	
Bike dock (count/km <sup>2</sup> )	34.26444	9.876691	19.09591	50.99643	
Bike road (km/km <sup>2</sup> )	1.116062	0.6076595	0.2963889	2.737634	
<b>Land use factors</b>					
Land use entropy (ratio)	0.68372	0.0514115	0.585	0.797	Korea Ministry of Environment (EGIS)
Open space density (count/km <sup>2</sup> )	4.937375	1.073422	3.471984	7.327281	
Green infrastructure (ratio)	0.2634169	0.1412847	0.0812693	0.6072711	
<b>Population factors</b>					
Telecommunication floating population (count/km <sup>2</sup> )	344,164.6	94,985	63,814.65	949,721.1	SKT Big Data Hub
Registered population (count/km <sup>2</sup> )	17,410.12	4714.139	6769	26,559	Seoul metropolitan government
Population male to female (ratio)	0.947628	0.033736	0.8806	1.0362	Seoul metropolitan government
Population under age 24 (%)	21.20037	1.44154	18.42533	24.30377	Seoul metropolitan government
<b>COVID-19 factors</b>					
Covid-19 patients (count/km <sup>2</sup> )	0.0043934	0.0229014	0	0.5804729	Seoul Metropolitan government COVID-19 Dashboard
Covid Dummy <sup>a</sup>	0.3340164	0.4716648	0	1	
<b>Control variable</b>					
Area (km <sup>2</sup> )	24.20961	9.11502	9.962769	46.85598	

Note: Total number of observations = 12,200 (25 districts × 488 days); <sup>a</sup> Covid Dummy(1: After the first COVID-19 Patient, 0: Before the first Covid-19 Patient, The first COVID-19 patient in Seoul was reported on January, 24 2020).

relationship with bike-sharing ridership. The impact of telecommunication floating population suggested that telecommunication floating population has a significant positive impact on bike-sharing services. The docked bike-sharing systems in Seoul are available for cell phone users who can read QR codes or use an application for the service, telecommunication floating population data, which collects cell phone signals, had a positive relationship with bike-sharing ridership. Surprisingly, the population under age 24 had a significantly negative relationship. As only people above age 14 are eligible to use the Seoul bike-sharing system, this requirement may explain the negative impacts of the younger population on bike-sharing in Seoul.

Lastly, COVID-19 factors show some impacts on bicycle-sharing ridership. Although COVID-19 patient density did not have a significant relationship, our COVID-19 dummy variable held a significantly positive relationship with bike-sharing ridership. This suggests that COVID-19 had positive effects on people's usages of bike-sharing in Seoul (Table 2).

#### 4.2.2. Bike-sharing trip duration and COVID-19 and urban environment factors

For all climate factors, we found that lower wind speed, less precipitation, and less particulate matter 2.5 levels held a negative relationship with bike-sharing trip duration, whereas higher temperature is positively related to trip duration across the five statistical models. Our results also suggest that people are willing to use bike-sharing for longer durations in Seoul as weather conditions are warmer, less windy, less rainy, and as the air has less fine particulate matter. For transportation factors, metro station density and public transportation passenger volumes have significant impacts on bike-sharing trip duration. Higher metro station density was negatively related to both bike-sharing trip duration and trip count. However, metro passenger ridership had a positive impact on the trip duration of people's bike-sharing usage, whereas the bus passenger ridership held a negative relationship with bike-sharing trip duration.

For all land use factors, the land use entropy variable had the most

significant negative relationship in model 3. This relationship reveals that more diverse land uses in districts link to lower bike-sharing trip durations. The more types of land use in a district, the more often people used bike-sharing. In contrast, the higher the land use entropy of a district, the lower the average bike-share trip duration. Both open space density and green infrastructure ratio held a significant positive relationship with bike-sharing trip duration, just as they did with bike-sharing trip count. According to our analysis, a 1 percentage increase of green infrastructure in a district generates between 82 and 125 additional bike sharing trip counts. It can be explained that if more open space and green infrastructure are planned for urban areas, people are willing to ride shared bikes longer. For social factors, telecommunication floating population, which represents real-time population data, has a significant positive relationship with bike-sharing trip duration. In model 4, the registered population shows a significantly negative effect on bike-sharing trip duration. Districts with higher registered populations had a negative effect on trip duration. This suggests that people used bike-sharing for fewer minutes to avoid physical contacts with others. Increased amounts of females and young people under age 24 were negatively related to trip duration. For population factors, as telecommunication floating population has significant positive impact on bike-sharing trip duration, more of the floating population were willing to use the bike-sharing service for longer periods of time. It explained that higher floating population captured by telecommunication signal linked to more often and longer bike-sharing usages in Seoul. For COVID-19 factors, although COVID-19 patient density did not have a significant relationship with bike-sharing trip duration, our COVID-19 dummy variable held a significant positive relationship with bike-sharing ridership. This suggests that COVID-19 had a positive impact on people's bike-sharing trip duration in Seoul. For population factors, telecommunication floating population has significant positive impact on bike-sharing trip counts and trip duration. It explained that higher floating population captured by telecommunication signal linked to more often and longer bike-sharing usages in Seoul (Table 3).

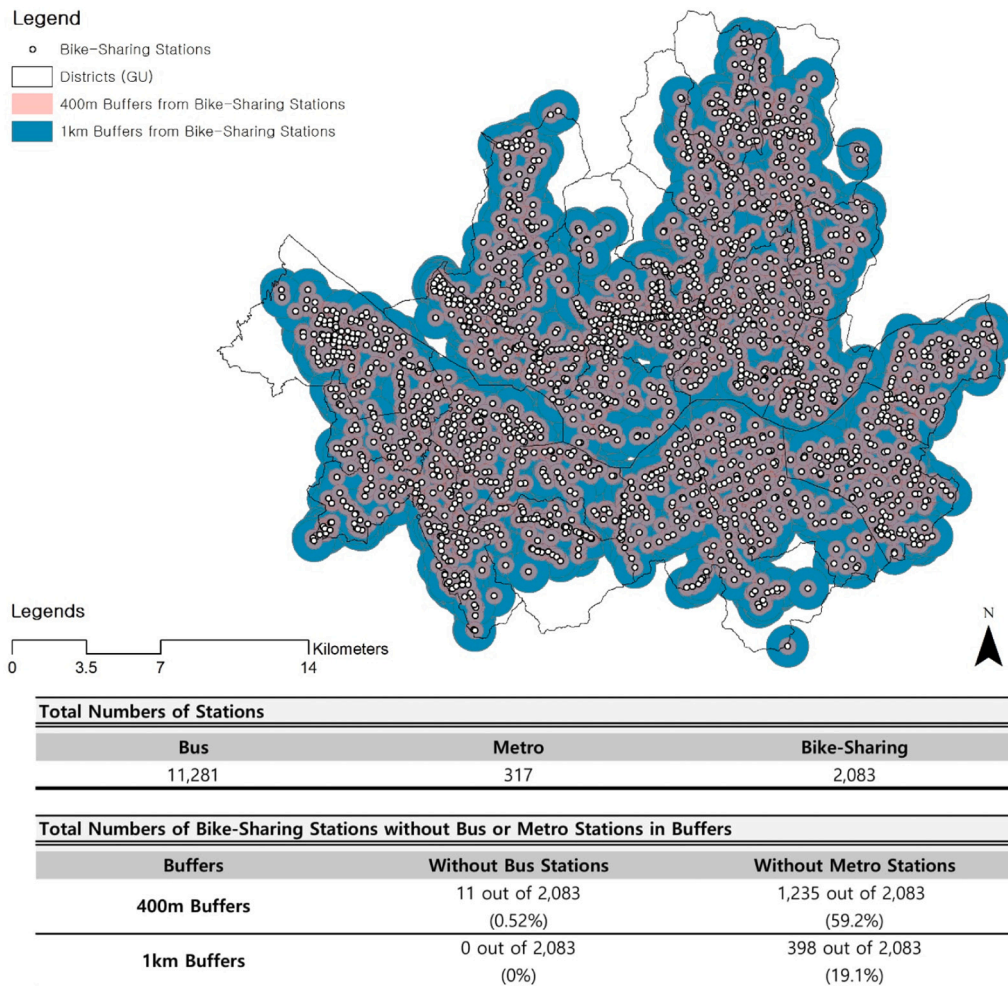


Fig. 10. Buffer analysis of the accessibility from bike-sharing stations to public transportation.

### 5. Discussion and conclusion

This study analyzed 26.3 million bike-sharing trips from March 2019 to June 2020 in Seoul, South Korea. First, this paper investigated the spatial-temporal patterns of docked bike-sharing ridership in Seoul and its 25 districts between January 2019 to June 2020 to determine how COVID-19 impacts micro mobility usage. The descriptive statistics of our spatial-temporal analysis show that, on average, the total count of daily bike-sharing trips is 2162 and the maximum trip count during the study period is 8881. The daily average duration of total trips is about 60,710 min, and the daily maximum trip time is 446,686 min. Due to the distinct weather conditions in Seoul - cold temperatures in the winter and heavy rains in the summer, seasonal patterns of increased active transportation ridership between March to November, and a decrease in ridership between July and August were observed. Despite the unexpected nature of the COVID-19 pandemic, similar seasonal patterns were observed, and some districts showed more active usage of bike-sharing after the first COVID-19 patient was reported in January 2020.

The stepwise negative binomial fixed panel regression models conducted in this study tested the impacts of climate factors, transportation factors, land use factors, social factors, and COVID-19 factors on bike-sharing ridership, total trip count, and total trip duration on a set of 25 districts in Seoul for 488 days. This negative binomial panel regression models showed that climate factors held statistically significant impacts on bike-sharing ridership. Warmer temperatures, less wind, less precipitation, and less fine particulate matter (PM-2.5) were more likely to correlate with more bike-sharing trips and longer trip durations.

Transportation factors of metro station density and public transportation passenger volumes had statistically significant impacts on trip count and trip duration. Metro station density showed significant negative impacts on trip count and trip duration. For the relationship between metro and bus passenger ridership and trip count, the results showed statistically positive impacts. In contrast, metro passenger ridership had a positive impact on bike-sharing trip duration, whereas bus passenger ridership held a negative relationship with bike-sharing trip duration. The number of bike docks per square kilometer and bike path density showed negative relationships with trip count in model 2 and model 3, respectively. These factors were also analyzed in model 2, 3, and 5 for trip duration. From our analysis, it could be explained that other factors besides existing bike infrastructure had statistically significant impacts on bike-sharing ridership. Compared to the results of key factors that affect shared e-scooter usage in Austin, TX and Minneapolis, MN (Bai & Jiao, 2020; Jiao & Bai, 2020), our study explained the significant relationship between public transportation services usage patterns – metro and bus – and bike-sharing ridership. The results of e-scooter usage focused on the presence of public transportation, whereas our research examined more detailed ridership data of metro and bus in Seoul.

For land use factors, our results showed that open space density and green infrastructure had statistically significant positive impacts on both the trip count and trip duration of bike-sharing usage. Our findings emphasize the importance of open space and green infrastructure to increase bike-sharing usage in dense urban areas. Additionally, the land use entropy of districts in Seoul showed positive impacts on trip count,

**Table 2**  
Negative binomial panel regression analysis results – impacts of factors on trip count.

Variables	Model I	Model II	Model III	Model IV	Model V
	Coef.	Coef.	Coef.	Coef.	Coef.
	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)
<b>Climate factors</b>					
Mean temperature	0.032*** (0.000)	0.032*** (0.000)	0.318*** (0.000)	0.032*** (0.000)	0.033*** (0.000)
Mean wind speed	-0.035*** (0.005)	-0.028*** (0.004)	-0.028*** (0.004)	-0.029*** (0.004)	-0.030*** (0.004)
Mean precipitation	-0.802*** (0.017)	-0.796*** (0.016)	-0.800*** (0.016)	-0.803*** (0.016)	-0.800*** (0.016)
Mean PM 2.5	-0.005*** (0.000)	-0.005*** (0.000)	-0.005*** (0.000)	-0.004*** (0.000)	-0.004*** (0.000)
<b>Transportation factors</b>					
Metro station		-0.150*** (0.037)	-0.268*** (0.040)	-0.223*** (0.043)	-0.255*** (0.043)
Bus station		-0.001 (0.005)	-0.008 (0.006)	0.005 (0.007)	0.008 (0.007)
Metro trips counts in & out		2.02e-07*** (4.40e-08)	3.19e-07*** (4.64e-08)	2.30e-07*** (5.14e-08)	3.13e-07*** (5.22e-08)
Bus trips counts in & out		3.71e-07*** (6.29e-08)	2.41e-07*** (6.50e-08)	2.90e-07*** (6.78e-08)	3.69e-07*** (6.82e-08)
Bike dock		-0.005** (0.002)	0.002 (0.002)	-0.001 (0.002)	-0.003 (0.003)
Bike road		-0.040 (0.032)	-0.070* (0.040)	-0.007 (0.046)	0.003 (0.050)
<b>Land use factors</b>					
Land use entropy			0.004 (0.412)	1.065** (0.421)	1.245*** (0.422)
Open space density			0.101*** (0.018)	0.138*** (0.020)	0.160*** (0.020)
Green infrastructure			0.807*** (0.141)	1.171*** (0.159)	1.240*** (0.159)
<b>Population factors</b>					
Telecommunication floating population				8.14e-07*** (8.44e-08)	6.34e-07*** (8.79e-08)
Registered population				-7.08e-06 (4.50e-06)	-5.43e-06 (4.50e-06)
Population male to female				0.466 (0.527)	0.927* (0.529)
Population under age 24				-7.257*** (1.298)	-8.101*** (1.301)
<b>COVID-19 factors</b>					
Covid-19 patients					-0.100 (0.125)
Covid Dummy					0.080*** (0.007)
<b>Control variable</b>					
Area	1.55e-07 (0.001)	-0.011*** (0.002)	-0.008*** (0.002)	-0.003 (0.003)	0.002 (0.003)
Constant	1.923*** (0.037)	2.346*** (0.145)	1.575*** (0.395)	1.042 (0.711)	0.507 (0.713)
Log likelihood	95,109.661	-94,874.516	-94,839.91	-94,776.21	-94,715.965

Model I: Wald chi2(5) = 13,295.75, Prob > chi2 = 0.0000; Model 2: Wald chi2(11) = 14,419.72, Prob > chi2 = 0.0000.

Model 3: Wald chi2(14) = 14,578.46, Prob > chi2 = 0.0000; Model 4: Wald chi2(18) = 14,825.84, Prob > chi2 = 0.0000.

Model 5: Wald chi2(20) = 15,021.92, Prob > chi2 = 0.0000.

Note: dependent variable: bike trip counts; \*\*\*p < 0.01; \*\*p < 0.05; \*p < 0.1; n = 12,200.

and negative impacts on trip duration, respectively. The impact of land use factors was in line with the results in survey-based research on the relationship between perceived built environment and active travel, before and after the COVID-19 in Shiraz city, Iran (Share et al., 2021). Mixed, diverse, dense and accessible land uses with the presence of bike riding infrastructure had positive relationship between bike ridership in the pandemic. Compared to registered population factors, real-time telecommunication floating population had a statistically significant positive relationship with both trip count and trip duration. It explained that higher floating population captured by telecommunication signal linked to more often and longer bike-sharing usages in Seoul. Surprisingly, the ratio of younger population under 24 in a district was negatively related with both total trip count and trip duration. Lastly, observing the impacts of our COVID-19 dummy variable on our model

revealed that despite the COVID-19 pandemic, people were likely to use the bike-sharing service in Seoul more often and for longer durations after the first COVID-19 patient was reported in January 2020. Compared to the previous a multiscale geospatial network analysis using New York bike-sharing data that explained the pandemic has strong negative impact on the stability of the bike-sharing system (Xin et al., 2022), our study showed relevant different results of bike-sharing patterns.

In this study, we conducted a data-driven analysis of impact of COVID-19 on bike-sharing usages in Seoul where people have the relatively normal life compared to other countries affected by the city-wide lockdown. The novelty presented in this study includes a greater understanding of spatial-temporal changes of bike-sharing ridership, and of how micro mobility modes work for people in the pandemic. This

**Table 3**  
Negative binomial panel regression analysis results - impacts of factors on trip duration.

Variables	Model I	Model II	Model III	Model IV	Model V
	Coef.	Coef.	Coef.	Coef.	Coef.
	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)
<b>Climate factors</b>					
Mean temperature	0.037*** (0.000)	0.037*** (0.000)	0.037*** (0.000)	0.038*** (0.000)	0.039*** (0.000)
Mean wind speed	-0.015*** (0.005)	-0.022*** (0.005)	-0.024*** (0.005)	-0.025*** (0.005)	-0.028*** (0.005)
Mean precipitation	-0.932*** (0.022)	-0.954*** (0.022)	-0.957*** (0.022)	-0.963*** (0.022)	-0.962*** (0.022)
Mean PM 2.5	-0.005*** (0.000)	-0.005*** (0.000)	-0.005*** (0.000)	-0.005*** (0.000)	-0.005*** (0.000)
<b>Transportation factors</b>					
Metro station		-0.025 (0.038)	-0.186*** (0.041)	-0.141*** (0.044)	-0.214*** (0.044)
Bus station		0.010** (0.005)	-0.004 (0.006)	0.000 (0.007)	0.003 (0.007)
Metro trips counts in & out		1.89e-07*** (5.44e-08)	4.28e-07*** (5.79e-08)	2.87e-07*** (6.36e-08)	4.78e-07*** (6.39e-08)
Bus trips counts in & out		-8.79e-07*** (7.87e-08)	-1.17e-06*** (8.16e-08)	-1.09e-06*** (8.54e-08)	-9.50e-07*** (8.53e-08)
Bike dock		-0.008*** (0.0021762)	0.000 (0.002)	-0.003 (0.003)	-0.005** (0.003)
Bike road		-0.012 (0.032)	-0.083** (0.039)	0.035 (0.045)	-0.032 (0.045)
<b>Land use factors</b>					
Land use entropy			-1.000** (0.406)	-0.393 (0.414)	-0.093 (0.415)
Open space density			0.128*** (0.018)	0.150*** (0.020)	0.183*** (0.020)
Green infrastructure			0.820*** (0.140)	1.102*** (0.155)	1.249*** (0.154)
<b>Population factors</b>					
Telecommunication floating population				1.05e-06*** (9.45e-08)	6.80e-07*** (1.00e-07)
Registered population				-8.94e-06** (4.43e-06)	-4.78e-06 (4.43e-06)
Population male to female				1.336** (0.528)	2.071*** (0.528)
Population under age 24				-0.026** (0.013)	-0.035** (0.013)
<b>COVID-19 factors</b>					
Covid-19 patients					-0.103 (0.146)
Covid Dummy					0.179*** (0.009)
<b>Control variable</b>					
Area	-0.003** (0.001)	0.000 (0.002)	0.004* (0.002)	0.012*** (0.003)	0.008*** (0.003)
Constant	1.376*** (0.039)	1.683*** (0.139)	1.612*** (0.386)	-0.086 (0.699)	-0.990 (0.070)
Log likelihood	-138,130.4	-137,983.04	-137,922.97	-137,854.57	-137,646.48

Model I: Wald chi2(5) = 10,951.41, Prob > chi2 = 0.0000; Model 2: Wald chi2(11) = 11,492.23, Prob > chi2 = 0.0000.

Model 3: Wald chi2(14) = 11,756.09, Prob > chi2 = 0.0000; Model 4: Wald chi2(18) = 12,026.10, Prob > chi2 = 0.0000.

Model 5: Wald chi2(20) = 12,717.77, Prob > chi2 = 0.0000.

Note: dependent variable: bike trip duration; \*\*\*p < 0.01; \*\*p < 0.05; \*p < 0.1; n = 12,200.

study also enhances understanding of key factors affecting bike-sharing usages in one of the leading smart cities. Especially, the effects of real-time floating population on bike-sharing ridership were assessed, which was rarely considered for in previous research. The result of this study in Seoul provides geographic knowledge and policy implications for better public bike transportation and the role of micro mobility in post-COVID.

The micro mobility modes of docked/dockless e-scooters and bike-sharing have gained more popularity in urban areas in recent years, and these modes are expected to have greater impacts on smart cities in near future. Therefore, the results of this empirical research analyzing urban big data on the relationship between COVID-19, various urban factors and micro mobility ridership are important. Both local and international practice can consider the results of this study for promoting

and enhancing bike-sharing services in many cities. Despite the rapid growth and popularity of micro mobility services serving as first and last mile problem solutions in urban areas, there are many issues such as parking, safety, and inequality that the micro mobility industry faces. Specifically, as micro mobility has emerged as an alternative urban mobility solution during and post COVID-19, the results of this research exploring how COVID-19 affects bike-sharing ridership and how other factors have impacts on bike-sharing usage will be helpful to prepare urban micro mobility guidelines and policy recommendation for both local and international practice in many cities. First recommendation for local practice, this study empirically tested the consequences of the COVID-19 pandemic on bike-sharing ridership. When the passenger volumes of other public transportation modes decreased from the direct impacts of the COVID-19 pandemic, Seoul bike-sharing ridership was

empirically analyzed to show increases during the COVID-19 period. To promote increased bike-sharing usage in Seoul, more areas of mixed land use with diverse types of classifications should be planned. Moreover, open space and green infrastructure strategic planning should be prioritized to develop better urban environments for bike-sharing usage. Especially during COVID-19 and post COVID-19, people are more likely to visit open spaces and prefer green infrastructure in urban areas where there is less close contact with other people and less of a chance of infection. Also, the Seoul Metropolitan Government should provide diverse types of bike-sharing services so that younger people below age 14 can use the micro-mobility safely. Moreover, in order to provide a successful alternative urban mobility solution during COVID-19 and post COVID-19, further research on the relationship between other public transportation modes and bike-sharing programs should be conducted. Thus, cities will be better able to implement regulations and guidelines for the future micro mobility industry in the post COVID-19 era.

In addition to studying the impacts of COVID-19 on how often and how long people use bike-sharing, this study is also significant in that it utilizes real-time telecommunication floating population datasets. Traditional urban planning data analysis usually utilizes census or registered population data which does not represent peoples' actual movements. Registered population data is not enough to explain how people move around or to study direct impacts of spatial and temporal patterns of population on micro mobility ridership. Specifically, because there were not any city-level lockdown social distancing measures in Seoul during COVID-19, consideration of real-time big urban data from telecommunication floating population was utilized to explain the consequence of social factors on bike-sharing ridership in this study. Based on these data-driven analyses, additional bike-sharing planning and budget allocation for the related infrastructure should be addressed to the areas with large numbers of floating population. Based on the results of this study in Seoul, many international smart cities can utilize real-time urban data for enhancing bike-sharing programs and providing better infrastructure. Also, this research considered other big urban datasets to test the consequences of climate factors and transportation factors on bike-sharing usage. Thus, diverse aspects of urban environments that might affect bike-sharing ridership were analyzed in this study, and findings from the empirical analysis can inform guidelines for emerging shared mobility technologies.

In terms of international practice, for cities with popularity in bike-sharing program we suggest them to increase budget allocation for better bike infrastructure so that bike-sharing can work as an important mode of transportation in the pandemic. As this study explained that the increase of bike-sharing ridership in COVID-19, it is suggested to maintain and promote bike-sharing in critical time. Also, more sophisticated transportation planning for bike-sharing stations and routes should be considered based on diverse types of real-time urban data in many global cities.

This study empirically showed the impacts of COVID-19 and other urban factors on bike-sharing in Seoul. However, there are several points that should be considered for further research of the topic. First, this study focused on bike-sharing in Seoul only. In order to generalize the impacts of COVID-19 and other factors on bike-sharing, other cities should be tested. Second, although the results of this study help prepare micro mobility guidelines in urban areas, a diverse range of other dockless bike or e-scooter datasets should be analyzed for better interpretations of spatial and temporal patterns of micro mobility in the post COVID-19 era. Third, despite the significant importance of telecommunication floating population data to our study, SK Telecommunication is not the only major mobile company in South Korea, and the data represent only a portion of the floating population. Further study considering all real-time telecommunication data will provide more insight into the impacts of floating population on bike-sharing in Seoul. Fourth, this study analyzed the impacts of COVID-19 on bike-sharing usages in Seoul considering the remarkable growth of bike-sharing in

Seoul during the pandemic. However, as bike-sharing ridership is relatively small compared to other modes of transportation, there is a potential limitation that the impacts of bike-sharing identified in this study may not be as large as anticipated. Therefore, future research should be conducted to reduce this potential limitation. Finally, this study analyzed datasets between March 2019 and June 2020. Further research considering more recent datasets will be meaningful to analyze the impacts of COVID-19 and other factors on bike-sharing ridership for longer term insights.

#### CRediT authorship contribution statement

**Junfeng Jiao:** Conceptualization, Methodology, Validation, Writing – review & editing.

**Hye Kyung Lee:** Conceptualization, Methodology, Data curation, Spatial Analysis, Statistical Analysis, Writing – original draft.

**Seung Jun Choi:** Data curation, Spatial Analysis, Visualization, Writing – original draft.

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#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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