

Understanding changing public transit travel patterns of urban visitors during COVID-19: A multi-stage study

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ABSTRACT

COVID-19 has caused huge disruptions to urban travel and mobility. As a critical transportation mode in cities, public transit was hit hardest. In this study, we analyze public transit usage of urban visitors with a nearly two-year smart card dataset collected in Jeju, South Korea – a major tourism city in the Asia Pacific. The dataset captures transit usage behavior of millions of domestic visitors who traveled to Jeju between January 1, 2019 and September 30, 2020. By identifying a few key pandemic stages based on COVID-19 timeline, we employ ridge regression models to investigate the impact of pandemic severity on transit ridership. We then derive a set of mobility indicators – from perspectives of trip frequency, spatial diversity, and travel range – to quantify how individual visitors used the transit system during their stay in Jeju. By further employing time series decomposition, we extract the trend component for each mobility indicator to study long-term dynamics of visitors' mobility behavior. According to the regression analysis, the pandemic had a dampening effect on public transit ridership. The overall ridership was jointly affected by national and local pandemic situations. The time series decomposition result reveals a long-term decay of individual transit usage, hinting that visitors in Jeju tended to use the transit system more conservatively as the pandemic endured. The study provides critical insights into urban visitors' transit usage behavior during the pandemic and sheds light on how to restore tourism, public transit usage, and overall urban vibrancy with some policy suggestions.

1. Introduction

The sudden outbreak of the coronavirus disease 2019 (COVID-19) at the end of 2019 quickly swept the world. The pandemic has caused considerable disruptions to various aspects of people's daily lives (Guzman et al., 2021). One important aspect that has been significantly affected is human mobility, especially in public transit (Pan and He, 2022; Zhang et al., 2021; Pawar et al., 2021). For example, during the early pandemic stage, the usage of public transit declined by 80%-90% in the major cities in China, Iran, and the United States. For some operators in the UK, the drop was as much as 70% (Batsas et al., 2020). A number of scholars have endeavored to assess the impact of the COVID-19 pandemic on public transit. Studies revealed that not only the total ridership but also the daily distance traveling with public transit dropped dramatically (Molloy et al., 2021). Moreover, the reduction in the usage of public transit tends to vary across different areas. Some studies

found that the reductions of public transit usage were more pronounced in metropolitan and central cities, while the rural areas have seen less decline (Eisenmann et al., 2021).

Although existing studies have generated numerous insights regarding the impact of COVID-19 on public transit usage, most of them are drawn upon residents. How the pandemic impacted the public transit usage of other population groups, such as tourists and visitors, remains unexplored. Tourists and visitors (hereafter referred to as visitors in this paper) are very important groups to study. Firstly, visitor users of public transit are a different group from resident users (Le-Klaehn et al., 2014). Thompson argued that visitors are different from residents in travel motivation and behavior (Thompson, 2004). Kinsella and Caulfield found that, in terms of public transit, the residents in Dublin are concerned more about the service quality and safety, while the newcomers in Dublin are concerned about the provision of information and the reliability (Kinsella and Caulfield, 2011). By providing

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free public transit passes and personalized travel information to encourage visitors to use public transit, Bamberg claimed that attracting visitors to use public transit is easier than changing the habit of residents (Bamberg, 2006). Secondly, improving the knowledge of visitors' travel behavior on public transit is the basis for the development of sustainable tourism. For many tourist cities, tourism often leads to various environmental and traffic problems, such as pollution, congestion, etc (Le-Klaehn et al., 2014). As a sustainable and efficient mode, public transit is considered a potential replacement for private cars. Attracting more visitors to use public transit is an effective solution to reducing the environmental and traffic impacts of tourism. To prompt visitors to become public transit users, it is essential to investigate visitors' travel behavior on public transit. Thirdly, understanding the impact of COVID-19 on visitors' public transit usage is essential to the recovery of public transit. During the COVID-19 pandemic, public transit was hit hard and suffered a huge economic loss because of the crowded and enclosed environment. According to Paddison and Mandeno, attracting more visitors to use public transit will increase revenue and attract more investments (Paddison, 1993; Mandeno, 2012). To attract visitors to use public transit and recover public transit, uncovering how visitors' travel behavior on public transit changed during the COVID-19 pandemic can promote more appropriate and effective strategies. As such, an in-depth investigation on how urban visitors used public transit systems during the pandemic would provide meaningful behavioral insights, which may further inform policymakers and local authorities to develop responsive strategies to promote public transit recovery and sustainable tourism.

The dampening effect of COVID-19 on the public transit usage of visitors might be due to different reasons. During the COVID-19 pandemic, visitors may avoid traveling to reduce the risk of contracting the disease (Cahyanto et al., 2016). Thus, firstly, the pandemic may affect visitors' willingness to travel to the city. The reduction in the number of inbound visitors would directly contribute to the reduction of total transit ridership, if the modal shift in transport is not considered. However, if the pandemic also causes a modal shift – for example, by partially shifting visitors from transit to other alternative modes (e.g., private car), this will lead to a further reduction of the transit ridership. Besides these two reasons, it is also possible that individual transit use behavior could change during the pandemic. For example, a more conservative usage of the transit system by visitors (e.g., a lower usage frequency per visitor) would also lead to a reduction in the overall transit ridership.

This study aims to uncover the impact of COVID-19 on public transit usage contributed by urban visitors. The urban visitors are identified from a smart card dataset collected in Jeju, South Korea - a major tourism destination in the Asia Pacific. This nearly two-year dataset tracks millions of domestic visitors' public transit transaction records from January 1, 2019, to September 30, 2020. To uncover the impact mechanism from different perspectives, the change in public transit use of visitors is analyzed from three levels, namely, the collective level, individual level, and spatial level. At the collective level, to uncover the impact of the pandemic severity on transit ridership, we identify some key pandemic stages in South Korea based on the COVID-19 timeline (1st wave, stable period, 2nd wave). Then, we model the relationship between daily transit ridership and different COVID-19 indicators, such as daily new cases and accumulative cases within the past several days during each pandemic stage. The collective analysis uncovers the impact of COVID-19 on public transit usage from a macro perspective. To further uncover the change in individual transit use behavior, we employ the time series decomposition approach to detect the long-term trends of individual travel frequency, spatial diversity, and activity range by public transit. Finally, we conduct a spatial analysis to uncover the spatial pattern of the change in public transit usage by visitors in Jeju.

2. Literature Review

Since the outbreak of the COVID-19 pandemic in 2019, many scholars have investigated the impact of COVID-19 on people's mobility with different travel modes, e.g., bicycle, public transit, private vehicle, taxi, and ride-sharing services (Chen et al., 2022; Tirachini and Cats, 2020; Wang et al., 2021; Parr et al., 2021; Zheng et al., 2021; Wang et al., 2022). Interested readers on the influence of COVID-19 on human mobility are referred to the systematic review by Benita (Benita, 2021). This study mainly focuses on the behavior changes of visitors in public transit use before and after COVID-19, so we will review the related work from the following two aspects, i.e., the impacts of COVID-19 on public transit, and the impacts of COVID-19 on tourism.

2.1. Impact of COVID-19 pandemic on public transit

For the enclosed and overcrowded environment, public transit is a key mediate in the transmission of influenza-like illness (Goscé and Johansson, 2018). During the COVID-19 pandemic, many scholars also found that the spread of SARS-CoV-2 coronavirus, as a kind of influenza-like virus, was associated with the use of public transit (Musselwhite et al., 2020; Mo et al., 2021; Müller et al., 2020). Fathi-Kazerooni et al. (2020) revealed that there was a strong correlation between the ridership of public transit and the number of COVID-19 cases and deaths. Therefore, people became distrustful of public transit (Przybylowski et al., 2021); meanwhile, governments around the world proposed some recommendations to make people reduce the use of public transit, which led to a dramatical reduction in the usage of public transit (Bucsky, 2020; Sahraei et al., 2021). For example, Budd and Ison found that in some cities in Europe, the number of public transit passengers decreased by 80% (Budd and Ison, 2020). By analyzing the data from Google COVID-19 Community Mobility Reports, Wielechowski et al. (2020) observed that the number of public transit users in Poland declined by 77%. Other scholars also found that the reduction of public transit usage varied with different groups of people (Almlöf et al., 2020). Assessing public transit use by different income groups, Parker et al. (2021) revealed that compared with the use of public transit by higher-income riders, lower-income riders had a conspicuously smaller reduction in it. Parker et al. (2021) illustrated that the most affected groups using public transit during the COVID-19 pandemic are pupils and students, children, and seniors, with 89.3%, 85.7%, and 80.0% reduction in public transit demand, respectively. According to Aloi et al. (2020) and Tiikkaja and Viri (2021), the change in public transit mobility was relevant to the land use and demographics. Eisenmann et al. (2021) demonstrated that the metropolises and center cities declined more than rural areas, while Bian et al. (2021) uncovered that work areas had a more significant drop compared to residential areas. However, most of these studies focused on the change in the public transit usage of residents. Few studies were conducted on visitors' use of public transit due to the lack of access to this kind of data. Therefore, this study will analyze the change in the travel behavior of visitors who used public transit during the COVID-19 pandemic.

2.2. Impact of COVID-19 pandemic on tourism travel

A health crisis always brings a devastating impact on tourism. For example, the SARS, which occurred in 2002, hit tourism all around the world disruptively (Wen et al., 2005). The outbreak of Avian flu, foot-and-mouth disease, and swine flu all had a destructive effect on tourism (Blake et al., 2003; McAleer et al., 2010; Page et al., 2012). Similarly, the worldwide pandemic, COVID-19, which occurred in 2019, also brought an unprecedented impact on tourism, which is one of the hardest-hit sectors (Yang et al., 2020; Zhang et al., 2020). Sigala showed that the number of visitors and their transactions dropped sharply due to COVID-19, which caused a large number of tourism job cuts and substantial economic losses (Sigala, 2020). Many firms faced financial

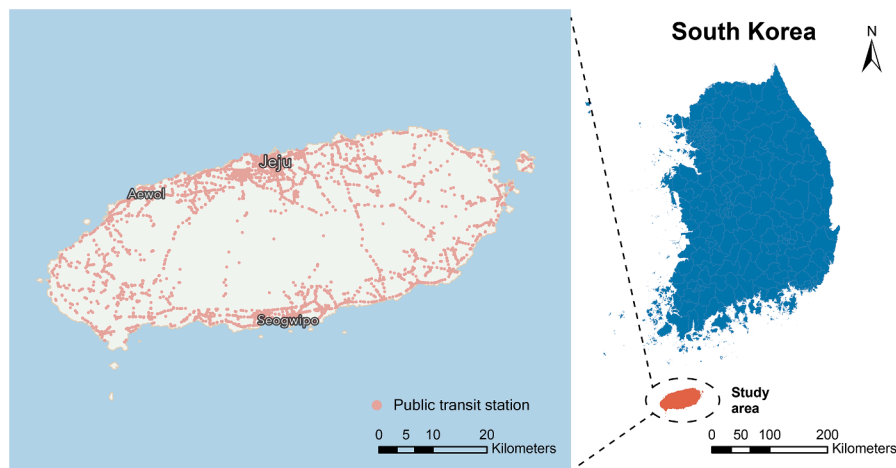


Fig. 1. The study area of Jeju, South Korea.

distress during this period, and the small-sized firms even were more vulnerable to this pandemic (Crespi-Cladera et al., 2021; Hu et al., 2021).

Moreover, many scholars found that the COVID-19 pandemic had a considerable influence on the travel behavior of visitors, on account of the perception of risk (Villacé-Molinero et al., 2021), preparation for potential financial difficulties (Im et al., 2021), and effect of social media (Gössling et al., 2020; Yu et al., 2021), etc. In terms of travel destination, Zenker et al. revealed that visitors might prefer domestic destinations to foreign destinations (Zenker and Kock, 2020), and Hong et al. claimed that compared with urban areas, visitors would be more concerned with natural areas after COVID-19 (Hong et al., 2020). For travel patterns, Zheng et al. illustrated that more visitors would be inclined to choose self-driving tours within the province due to the threat of COVID-19 (Zheng et al., 2021). Meanwhile, scholars also showed that the impact of COVID-19 on visitors varied with their different socio-economic characteristics, experiences, and psyche, etc. Neuburger et al. demonstrated that the willingness to change their traveling plans went up with age (Neuburger and Egger, 2021), while Kim et al. found that young people became more sensitive to the crowding because of COVID-19 (Kim and Kang, 2021). Craig claimed that visitors who had travel experiences prior to COVID-19 were more likely to continue the same experiences after the outbreak (Craig, 2020). By online survey, Park et al. uncovered that the impact of COVID-19 on visitors' avoidance of crowding was negatively related to sensation seeking tendency and the need for uniqueness of visitors (Park et al., 2021).

Although there are many studies investigating the impact of the COVID-19 pandemic on tourism, studies on changes of travel mobility and public transit usage are limited. There are also some literature on understanding changes of travel behaviors during pandemics, however, they mainly conducted descriptive analysis and focused on individual perceptions rather than actual behaviors (Park et al., 2021). In addition, the relevant studies have not fully excluded the effects of restrictions introduced by governments in estimating the influence of COVID-19 on travel demand/behaviors (Yang et al., 2020). In order to address these issues, we will uncover the individual travel behavior change of visitors who used public transit during COVID-19 in Jeju Island, South Korea, which has never announced any lockdown or inter-city travel bans.

3. Research design

3.1. Study area and dataset

Jeju Island is one of the most popular travel destinations in the Asia Pacific (as shown in Fig. 1). The area of Jeju is 1,846 km². It is home to over 600,000 population. According to the Planning and Coordination

Office of Jeju¹, over 15 million visitors came to Jeju in 2019. This number had continuously increased before the outbreak of COVID-19. In terms of travel types in Jeju Island, about 96% and 83% of domestic and international travelers, respectively, are independent travelers who can be regarded as potential users of public transit during their trips². Indeed, bus is the only public transit and plays an important role as a travel mode in Jeju, including City Bus, Tourists Shuttle Bus, Airport Bus, etc. There is no metro facility on this island. During the COVID-19 pandemic, the South Korean government has never introduced any strict lockdown policies. Instead, people in South Korea can have domestic inter-city travel freely. This gives us an opportunity to study the public transit usage of urban visitors during the pandemic period without lockdown.

This study analyzed a large-scale smart card dataset in Jeju, South Korea. The smart card is primarily used to collect public transit fares, while it also contains a large number of travel records (Zhong et al., 2015). This dataset captures 84 million records of 2,585,507 unique users during the period between January 1, 2019 and September 30, 2020. Each record tracks the unique user ID, departure time and date, alighting station ID, user types, etc. Before the outbreak of COVID-19 in South Korea, the users include local residents and inbound visitors (domestic and international). During COVID-19, for the notable drop in international visitors, the inbound visitors in Jeju mainly referred to the domestic visitors.

3.2. Identify visitors from smart card dataset

In this study, we aim to uncover the change in the public transit usage of urban visitors. However, the smart card data does not label whether a user is a local resident or an urban visitor (Egu and Bonnel, 2020). According to 2019 Jeju Visitors Survey³, 96.1% of the visitors to Jeju stayed for no more than five days. 98.9% stayed for no more than one week, while 99.4% stayed for no more than two weeks. Thus, many visitors can be identified with a two-week time span in Jeju as a constraint. In the tourism field, visitors can be divided into two categories, namely, one-time visitors and repeat visitors (Litvin and Ling, 2001). One-time visitors refer to visitors who have been to the destination just once during a specific period of time. Repeat visitors are those who have been to the destination multiple times during a specific period. The public transit use by repeat visitors is similar to that of some residents, e.g., the residents who use public transit less frequently. It is

¹ <https://www.jeju.go.kr/stats/stats/indicator.htm>

² <https://ijto.or.kr/korean/>

³ <https://ijto.or.kr/korean/>

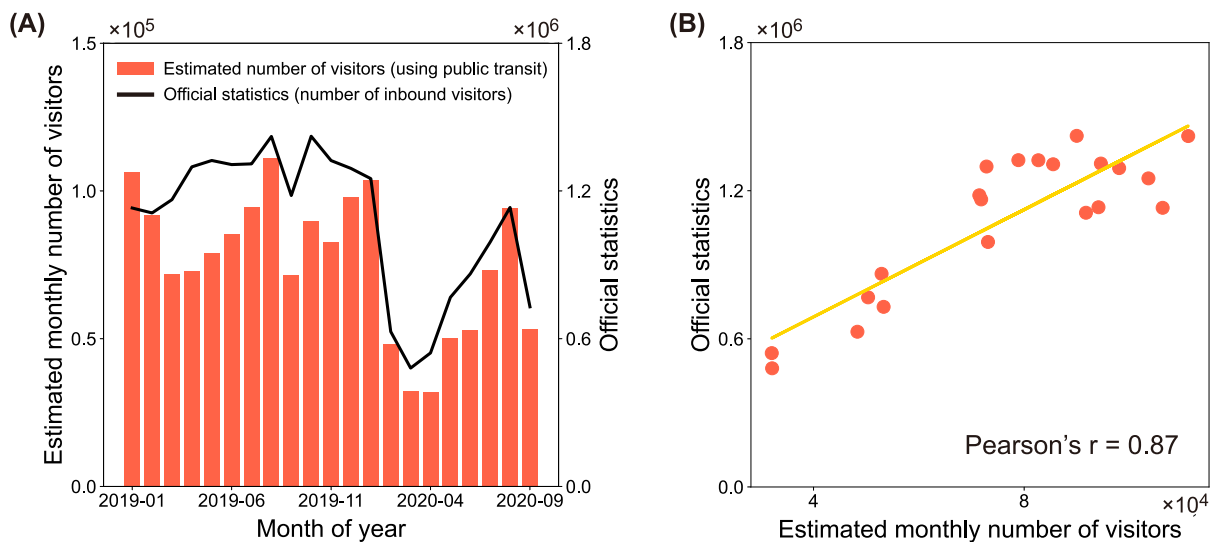


Fig. 2. (A) Official statistics and monthly number of visitors estimated from smart card data and (B) their correlation.

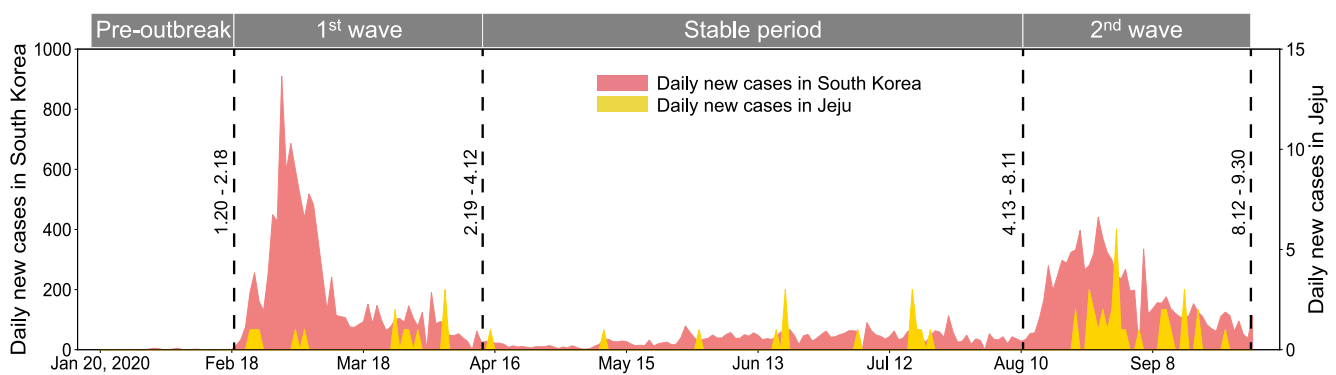


Fig. 3. Four pandemic stages identified during the study period.

difficult to distinguish between repeat visitors and some residents. Therefore, in this study, we focus on identifying one-time visitors during the study period. As such, we identify the one-time visitors with the timespan of his/her first and last records no more than 14 days. This results in a subset of 1,610,097 visitors. Due to the international travel bans during the COVID-19 pandemic, the visitors identified in 2020 correspond to domestic visitors. In order to verify the robustness of our findings, we also identify visitors with five days and seven days as constraints, respectively, to conduct the same analysis as the visitors identified by a two-week constraint (shown in Appendix B).

To evaluate the effectiveness of our visitor identification method, we aggregate the identified visitors by month and compare them to the official statistics, which are the monthly number of inbound visitors recorded on the official website of the Planning and Coordinate Office of Jeju (Fig. 2A). Notably, the official statistics record the total number of visitors traveling to Jeju, while the estimated results are identified the visitors who used public transit during his/her stay in Jeju. According to correlation analysis, the Pearson coefficient between the estimated monthly number of visitors and official statistics is 0.87 (Fig. 2B). The strong correlation between the estimated results and the official statistics reflects the effectiveness of our method.

3.3. Quantify impact of pandemic severity on public transit ridership

Fig. 3 shows the timeline of COVID-19 in South Korea and Jeju from January 20, 2020 to September 30, 2020. The first case in South Korea was reported on January 20, 2020. During the following four weeks, the

confirmed cases per day ranged from 0 to 5. On February 19, the confirmed cases increased by 20 due to a religious gathering in Daegu, and this number rapidly grew up during the following period. On February 29, it peaked at 909 cases. In response, the South Korean government introduced many associated measures to inhibit the spread of the virus, including stay-at-home, international travel restrictions and gathering bans, etc. Until mid-April, the number of confirmed cases was under control, and it was under 50 each day. During this stable period, the restrictions introduced by governments were relaxed. In mid-August, the pandemic became severe again due to another religious gathering at Sarang Jeil Church in Seoul. The daily confirmed cases went up and peaked at 441 on August 27. Until September 20, this number was below 100. The first case in Jeju was reported on February 22, 2020. During the following period, the confirmed cases were between 0 to 3 each day. Until August 31, this number peaked at 6. During the period from January 20, 2020 to September 30, 2020, the number of total confirmed cases in Jeju was 59. Most of the cases were imported, and there was no large-scale outbreak of pandemics in Jeju. Based on the timeline of COVID-19 in South Korea, we divide the whole time horizon from January 20, 2020 to September 30, 2020 into four periods, including pre-outbreak (from January 20, 2020 to February 18, 2020), 1st wave (from February 19, 2020 to April 12, 2020), stable period (from April 13, 2020 to August 11, 2020) and 2nd wave (from August 12 to September 30).

To reveal how the pandemic severity affected the transit ridership, we conduct a regression analysis between the daily public transit ridership and the COVID-19 indicators, including the daily new cases

and the average daily cases within the past several days at the national and local levels. Considering that the impact of COVID-19 on the ridership varied with the pandemic stages, the regression analysis is conducted for different pandemic stages, which are the 1st wave, stable period, and the 2nd wave (the pre-outbreak period is excluded due to no case in Jeju during this period). We use two variables to denote the public transit ridership, i.e., the daily number of visitors using public transit (N_V) and the daily number of transit trips by visitors (N_T), which are the dependent variables. Typically, calculating the year-over-year (YOY) difference of N_V and N_T is a way to control the seasonal effects. However, the composition of visitors in 2019 is different from that in 2020. Visitors in 2019 include domestic and international visitors, while visitors in 2020 are mainly domestic. The seasonality of domestic and foreign visitors' travel behavior is different. Calculating YOY difference might eliminate some critical information in the dataset. Therefore, we employ a sliding window method to address the seasonal effects. More specifically, for a particular day (say day d), the length of the sliding window is 31 days, namely, from day $d - 15$ to $d + 15$. The reason we set 31 days as the size of the sliding window is to remove the monthly trend of the daily number of visitors and trips. The detailed calculation is shown as follows:

$$N_{V,d} = V_d - \frac{\sum_{i=-15}^{15} V_{d+i}}{31} \tag{1}$$

$$N_{T,d} = T_d - \frac{\sum_{i=-15}^{15} T_{d+i}}{31} \tag{2}$$

where $N_{V,d}$ is the estimated number of visitors using public transit on day d by the sliding window method; V_d denotes the number of visitors using public transit on day d obtained from the smart card data; V_{d+i} is the number of visitors using public transit on day $d+i$ obtained from the smart card data; $N_{T,d}$ indicates the estimated number of transit trips of visitors on day d by the sliding window method; T_d denotes the number of transit trips by visitors on day d obtained from the smart card data; T_{d+i} is the number of transit trips by visitors on day $d+i$ obtained from the smart card data.

The independent variables are the natural log of the daily new cases in South Korea (DNC_{SK}), daily new cases in Jeju (DNC_{Jeju}), average daily cases within the past n days in South Korea (ADC_{SK}^n), and average daily cases within the past n days in Jeju (ADC_{Jeju}^n). The impact of the pandemic severity on public transit usage on the same day can be uncovered by the association between the daily new cases and the daily transit ridership. As the impact of pandemic severity on public transit usage may be lagged, the average daily cases within the past n days at the national and local levels are set as another two independent variables. By varying the value of n , we have different model settings for regression analysis to compare the impact of COVID-19 on public transit use by visitors with different time lags. Based on the incubation period of COVID-19 (Lee et al., 2020; Yang et al., 2020; Cai et al., 2020), we set $n \in \{7, 14\}$. The pandemic severity indicators analyzed in this research are from the Ministry of Health and Welfare, Republic of Korea⁴.

We perform the regression analysis by employing the ridge regression algorithm (Hoerl and Kennard, 1970). According to a multicollinearity test of the independent variables with variance inflation factor (VIF), in each period, there are some of the VIFs > 10 (Table A.1 in Appendix A), which means that the multicollinearity is severe in the regression models. The severe multicollinearity might lead to unreliable regression results. The ridge regression is a general method to address this problem (Gruber, 2017). By adding a penalty function to the estimated coefficients, the ridge regression solves the problem of oversized

coefficients due to multicollinearity. The equations are expressed as follows:

$$Y = \hat{\beta}^T X \tag{3}$$

$$\hat{\beta}^r = (X^T X + \lambda I)^{-1} X^T Y \tag{4}$$

where Y represents N_V or N_T ; $X = \{X_1, X_2, \dots, X_i\}$ indicates the COVID-19 factors; $\hat{\beta}^r$ denote the coefficients in the ridge regression model; I is the penalty matrix; λ , which should be strictly positive, is the coefficient of the penalty matrix, and the optimal λ could be obtained by employing cross validation. Eqs. 3 and 4 are applicable to all the three periods (i.e., 1st wave, stable period, and 2nd wave).

3.4. Characterize long-term dynamics of individual level travel behavior

According to the regression analysis, the impact of COVID-19 on public transit use can be uncovered from a macro perspective. To further uncover the change in transit usage behavior at the individual level, we use four indicators, including the number of active days (N_{day}), the number of trips per active day (N_{trip}), the total number of stations used by a visitor during his/her stay ($N_{station}$), and the radius of gyration (R_g), to describe the spatial and temporal characteristics of individual travel behavior and identify the changes of them. The travel frequency of visitors is indicated by N_{day} and N_{trip} , which are the number of days in which the visitor used public transit and the average number of trips by public transit per active day, respectively. The spatial diversity of individual public transit use is reflected by $N_{station}$, which is the total number of stations visited by the visitor during his/her stay in Jeju. The activity range of visitors is indicated by R_g . The equation of R_g is as follows:

$$R_g = \sqrt{\frac{\sum_{i=1}^n \omega_i (\vec{s}_i - \vec{s}_c)^2}{\sum_{i=1}^n \omega_i}} \tag{5}$$

where \vec{s}_i is a vector denoting the coordinate of station i , ω_i is the times that traveled to station i , $\vec{s}_c = \sum \omega_i \vec{s}_i / \sum_{i=1}^n \omega_i$, and n is the number of stations visited by the visitor during his/her stay. Here, the nearly two-year data (i.e., the data contains public transit transactions from January 1, 2019 to September 30, 2020) is used to perform the analysis, in which the data in 2019 is used as the baseline to reflect the changes in travel behavior more effectively.

We reveal the dynamics of visitors' travel behavior in the long run by employing the time series decomposition algorithm. Time series, as a sequence of observations recorded in regular time intervals, is considered as a combination of the base level, trend, seasonality, and error. Thus, it can be split into these four components:

$$Time\ series = Base\ level + Trend + Seasonality + Error \tag{6}$$

Trend is an increasing or decreasing slope observed in time series, whereas seasonality is a repeated pattern observed in time series, caused by month-of-year, day-of-month, or day-of-week. Generally, tourism activity in a city exhibits a significant seasonal pattern. Travel behavior at the individual level could also show seasonality. As such, travel behavior of visitors can be influenced by seasonal and pandemic factors. We use time series decomposition algorithm to eliminate the effect of seasonality on travel behavior. Then, the impact of COVID-19 can be revealed by the trend component.

The whole time horizon from January 1, 2019 to September 28, 2020 is divided into 91 weeks. The visitors are classified into 91 groups by the week that he/she arrived in Jeju. For each group (i.e., week), we obtain the mean of each indicator, expressed as follows:

⁴ <https://www.data.go.kr/>

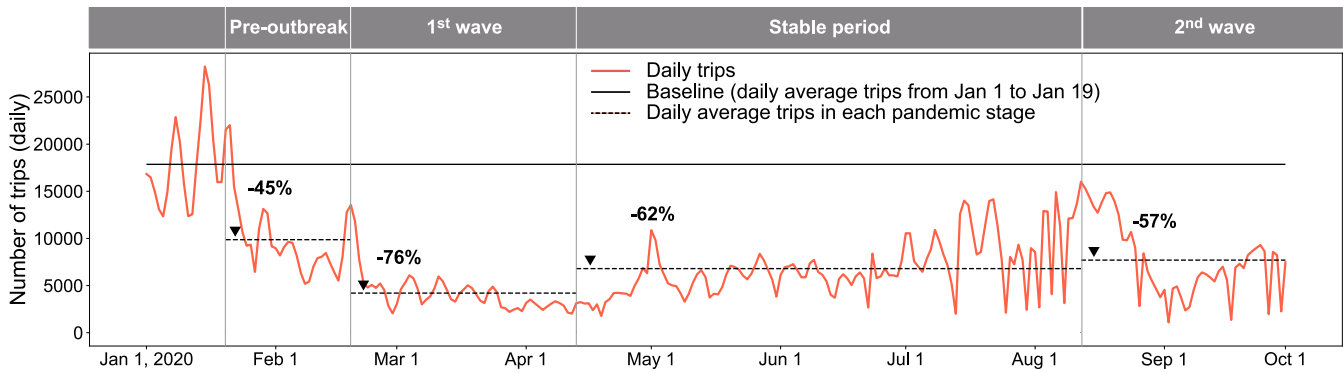


Fig. 4. Daily visitors from January to September, 2020 and changes of average daily visitors during different pandemic stages. The baseline is the average daily visitors from January 1–19, 2020.

$$M_{r,w} = \frac{\sum_{i=1}^n m_i}{n} \tag{7}$$

where $M_{r,w}$ is the mean of indicator r in the week w , m_i is the observation of indicator r for visitor i , and n is total number of visitors arriving in week w . Therefore, we can get a time series for each indicator. Notably, the reason we group visitors by week is to eliminate the influence of day-of-week. With a one-week time span, it not only effectively reflects the dynamics of individual travel behavior, but also removes the effect of some differences between workdays and weekends in travel behavior.

3.5. Uncover spatial-temporal variation of change in public transit ridership

To uncover the spatial distribution of change in ridership and the relationship between the popularity and the change in ridership during different pandemic stages, we employ the hot spot analysis algorithm to identify the hot spots and cold spots of station popularity and change in ridership relative to 2019 during the four stages. The popularity of a station at each stage is represented by the daily number of trips in this station during the corresponding period in 2019. The ridership change at a station during each stage is reflected by the percentage change of the number of trips during the corresponding period in 2020 relative to 2019, expressed as follows:

$$C_{i,p} = \frac{T_{i,p}^{2020} - T_{i,p}^{2019}}{T_{i,p}^{2019}} \tag{8}$$

where $C_{i,p}$ is the percentage change of the number of trips in the station i during period p , $T_{i,p}^{2019}$ and $T_{i,p}^{2020}$ denote the number of trips in the station i during period p in 2019 and 2020, respectively. Although the composition of visitors in 2019 is different from that in 2020 (the visitors in

2019 included domestic and foreign visitors, while the visitors in 2020 mainly referred to domestic visitors), the number of trips in 2019 is defined as the baseline to some extent to reflect the change in public transit usage in different stages of the COVID-19 pandemic. In terms of the hot spot analysis, here, the conceptualization of spatial relationships is a fixed distance band, which works well for point data. The fixed distance is 3,835 meters to ensure that all points have at least one neighbour.

4. Results

4.1. Impact of pandemic severity on public transit ridership

To reflect the dynamics of ridership during the COVID-19 pandemic, Fig. 4 reports the trend in the raw data of the daily trips and changes in the average daily trips during each pandemic stage with the average daily trips before the COVID-19 pandemic (from January 1 to January 19) as the baseline. It illustrates that the changes in the daily trips varied with different periods. During the pre-outbreak period, the trips dropped sharply and had a 45% decline on average. During the 1st wave, when the pandemic was severe, the average daily number of visitors declined by 76%. The number of trips generally increased during the stable period. However, on average, it decreased by 62% in this stage. During the 2nd wave, the number of trips dropped significantly before September, while it slightly went back at the beginning of September. In this stage, the average daily trips had a 57% decline, which was more moderate compared to it during the 1st wave.

Next, we report the regression results. Table 1 shows the regression results of N_V in different model settings. In the model setting 1–1 (ADC_{SK}^7 and ADC_{Jeju}^7), the R^2 were 0.56 ($p = 0.000$), 0.05 ($p = 0.550$), and 0.57 ($p = 0.000$) during the 1st wave, stable period, and 2nd wave, respectively. The results reveal a strong relationship between the daily number of visitors using public transit and COVID-19 indicators when the

Table 1
The regression results of daily number of visitors (N_V).

Model setting	Period	R^2	P	Factors						
				Intercept	DNC_{SK}	DNC_{Jeju}	ADC_{SK}^7	ADC_{Jeju}^7	ADC_{SK}^{14}	ADC_{Jeju}^{14}
1–1	1 st wave	0.56	0.000	1941.41	−105.91	−332.98	−223.76***	−1844.85***		
	Stable period	0.05	0.550	890.28	209.79	55.43	−341.95	73.00		
	2 nd wave	0.57	0.000	3448.60	137.99	−211.40	−601.14	−2023.43***		
1–2	1 st wave	0.36	0.000	1686.92	−152.82*	−297.26			−133.63	−1806.75**
	Stable period	0.04	0.645	365.20	174.75	56.53			−281.65	−146.96
	2 nd wave	0.54	0.000	6317.05	71.84	−211.64			−1202.71*	−929.84
1–3	1 st wave	0.54	0.000	2041.35	−159.60**	−376.34		−2113.57***	−179.13*	
	Stable period	0.04	0.662	402.14	172.84	57.91		55.26	−296.80	
	2 nd wave	0.59	0.000	5899.93	92.33	−153.46		−1524.40*	−895.03*	

Note: * significant at 0.05 level, ** significant at 0.01 level, and *** significant at 0.001 level.

Table 2

The regression results of daily number of trips (N_T).

Model setting	Period	R^2	P	Factors						
				Intercept	DNC_{SK}	DNC_{Jeju}	ADC_{SK}^7	ADC_{Jeju}^7	ADC_{SK}^{14}	ADC_{Jeju}^{14}
2-1	1 st wave	0.51	0.000	4583.54	-237.79	-740.57	-545.24**	-4171.12* **		
	Stable period	0.05	0.549	721.82	524.09	86.87	-756.49	210.61		
2-2	2 nd wave	0.51	0.000	6951.96	277.54	-403.29	-1229.28	-3863.32* **		
	1 st wave	0.32	0.001	3999.62	-347.78 ⁺	-665.06			-342.61	-3904.82 ⁺
2-3	Stable period	0.04	0.607	672.34	455.81	91.71			-652.01	-275.28
	2 nd wave	0.50	0.000	12636.27	146.42	-384.49			-2419.24 ⁺	-1740.61
2-3	1 st wave	0.49	0.000	4836.80	-367.62**	-848.07			-4825.18* **	-439.49**
	Stable period	0.04	0.619	752.87	450.57	97.73			175.22	-684.03
2-3	2 nd wave	0.54	0.000	10082.54	187.96	-273.82			-2795.27 ⁺	-1871.36 ⁺

Note: * significant at 0.05 level, ** significant at 0.01 level, and *** significant at 0.001 level.

pandemic situation was serious. During the stable period, the model does not observe any notable relationship between N_T and COVID-19 indicators. The average daily cases within the past 7 days at the national and local levels are significant, which shows that COVID-19 had a lagged impact on public transit use by visitors. By comparing the significance of ADC_{SK}^7 and ADC_{Jeju}^7 , we find that the impact of ADC_{Jeju}^7 is more significant. The coefficients of all the significant variables are negative. This finding indicates that the pandemic had a dampening impact on public transit use by visitors.

Similarly, the R^2 in the model setting 1-2 (ADC_{SK}^{14} and ADC_{Jeju}^{14}) reveal a significant association between COVID-19 and public transit use by visitors during the 1st wave and 2nd wave. Based on the results of visitors with time span ≤ 7 days and ≤ 5 days (shown in Table B.2 and Table B.4 in Appendix B), we find that compared to ADC_{Jeju}^{14} , ADC_{SK}^{14} had a more notable association with public transit usage by visitors. The regression results in the model settings 1-1 and 1-2 revealed that ADC_{SK}^{14} and ADC_{Jeju}^7 might be a better combination to explain visitors' transit usage. As such, we conduct the regression analysis in the model setting 1-3 (ADC_{SK}^{14} and ADC_{Jeju}^7). Compared to the model settings 1-1 and 1-2, the R^2 of the model setting 1-3 was the highest during the 2nd wave. During the 1st wave, the R^2 of the model setting 1-3 was similar to the R^2 of the model setting 1-1. ADC_{SK}^{14} and ADC_{Jeju}^7 were both significant during the 1st wave and 2nd wave. According to the coefficients of ADC_{SK}^{14} and

ADC_{Jeju}^7 , we observe that 1% increase in ADC_{Jeju}^7 would lead to more reduction in transit ridership. The regression results of model setting 1-3 are the most robust compared to model settings 1-1 and 1-2.

We also conduct the regression analysis between the number of daily transit trips (N_T) and COVID-19 indicators in the three model settings. The regression results of N_T are similar to those of N_V . As shown in Table 2, the R^2 shows a notable association between the COVID-19 indicators and transit ridership of visitors during the 1st wave and 2nd wave. The direction and significance of the independent variables indicate that COVID-19 had a lagged and dampening impact on visitors' public transit usage. Similarly, we find that the combination of ADC_{SK}^{14} and ADC_{Jeju}^7 might yield a stronger explanatory power. Thus, we conduct the regression analysis in the model setting 2-3, of which the regression results are most robust compared to model settings 2-1 and 2-2. From the regression analysis of the visitors with time span ≤ 7 days and ≤ 5 days (as shown in Table B.2, Table B.3, Table B.4 and Table B.5 in Appendix B), we find that the results are consistent with the results in Table 1 and Table 2.

4.2. Long-term dynamics of individual travel behavior

To provide a micro view of how individual travel behavior changed during different pandemic stages, we calculate the mean, median, standard deviation (Std), 75th percentile, and 95th percentile of each

Table 3

Descriptive statistics of individual level travel behavior indicators during the four pandemic stages.

Indicators	Period	Statistics					Total visitors
		Mean	Median	Std	75%	95%	
N_{day}	Pre-outbreak	1.95	2.00	1.28	3.00	4.00	67,742
	1 st wave	1.88	1.00	1.29	2.00	4.00	56,742
	Stable period	1.86	1.00	1.30	2.00	4.00	234,654
	2 nd wave	1.82	1.00	1.27	2.00	4.00	126,261
N_{trip}	Pre-outbreak	1.94	1.50	1.16	2.50	4.00	67,742
	1 st wave	1.80	1.50	1.07	2.00	4.00	56,742
	Stable period	1.73	1.33	1.00	2.00	4.00	234,654
	2 nd wave	1.66	1.00	0.94	2.00	3.00	126,261
$N_{station}$	Pre-outbreak	3.83	2.00	3.83	5.00	12.00	67,742
	1 st wave	3.41	2.00	3.49	4.00	11.00	56,742
	Stable period	3.23	2.00	3.32	4.00	10.00	234,654
	2 nd wave	2.96	2.00	3.00	4.00	9.00	126,261
R_g	Pre-outbreak	13.17	4.12	182.97	12.42	21.35	67,742
	1 st wave	9.94	2.76	140.80	11.83	21.67	56,742
	Stable period	9.59	2.32	135.83	11.57	21.36	234,654
	2 nd wave	7.28	1.73	90.15	10.17	20.83	126,261

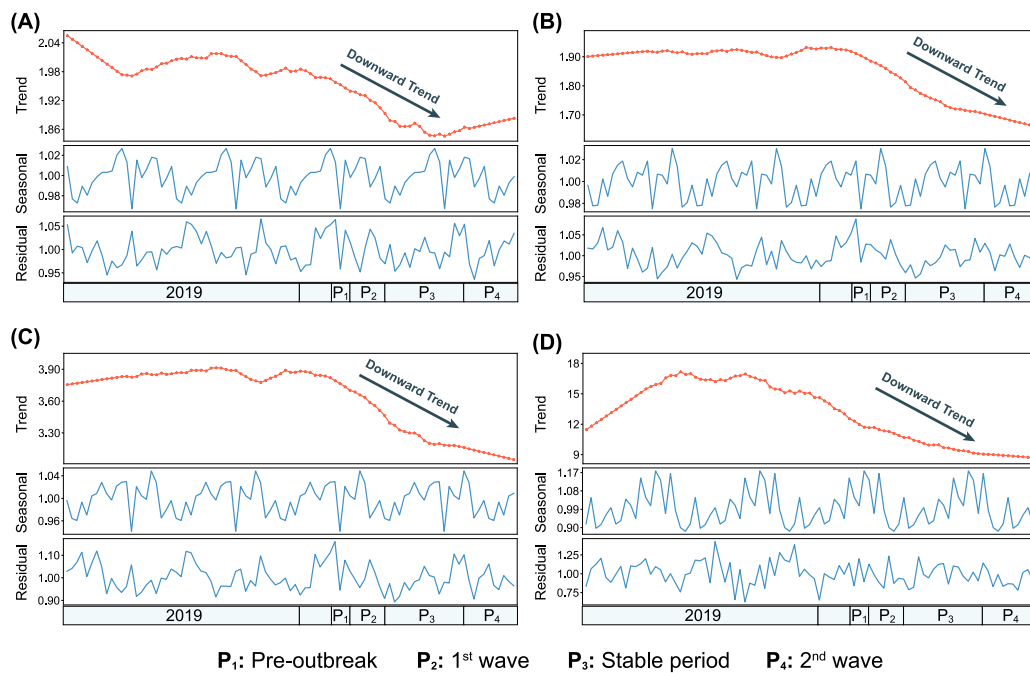


Fig. 5. Time series decomposition result of (A) number of active days, (B) total number of trips per active day, (C) total number of stations used, and (D) radius of gyration of transit usage of individual visitors during their stay in Jeju.

indicator during the four pandemic stages, as shown in Table 3. According to these statistics, we find a long-term decrease in individual behavior of public transit usage during the COVID-19 pandemic. It reflects that the travel frequency, spatial diversity, and activity range of visitors using public transit had been declining throughout the pandemic. By analyzing the standard deviation of all indicators during different pandemic stages, we find that the difference in the travel behavior of public transit use among visitors also decreased during COVID-19.

To account for the effect of seasonal factors, we further combine the data collected in 2019 with that in 2020 to conduct the time series decomposition analysis. Fig. 5 is the decomposition results of N_{day} , N_{trip} , $N_{station}$, and R_g , respectively. The trend component of each indicator shows that individual mobility declined in the long run. According to Fig. 5A, the number of active days decreased by 0.1 during the pandemic period. Fig. 5B shows that the number of trips per active day decreased from 1.90 to 1.66 from the pre-outbreak period to the 2nd wave. As for the trend of $N_{station}$ (Fig. 5C), the number of stations visited by visitors during his/her stay in Jeju reduced by 0.56 on average compared to it before COVID-19. The activity range decreased by 3.1 km from the pre-outbreak period to the 2nd wave (Fig. 5D). The decrease of these four indicators shows that visitors tended to be conservative in public transit use during the COVID-19 pandemic.

4.3. Spatial-temporal variation of change in public transit ridership

This part further analyzes the spatial-temporal variation of changes in the public transit ridership at the station level. 2,520 stations that can be traced by at least one trip during the study period (from January 1, 2019 to September 30, 2020) are identified for analysis. Fig. 6 shows the map of daily ridership and the hot spot analysis at station level during four periods in 2019 corresponding to the four pandemic stages in 2020, from which some spatial patterns in popularity are uncovered. According to Fig. 6A, it can be found that the stations with higher levels of

usage are concentrated along the coastline, where there are many attractions and hub stations. The most popular area in Jeju is located in the northern part of Jeju Island, which includes Jeju International Airport, the famous Shilla Duty-Free, Intercity Bus Terminal, etc. The east and south areas are also very popular mainly because many famous attractions are located in these areas. Fig. 6B is the hot spot analysis result of popularity. Similar to the results in Fig. 6A, the popular areas are located in the north and east of Jeju Island. The cold spots are mainly located around the north area and in the southeast of Jeju, where fewer attractions and hub stations can attract visitors.

Fig. 7 shows the results of the hot spot analysis on changes in ridership during different pandemic stages at station level. Compared to the less popular area, the ridership in the popular area declined notably when the pandemic situation was severe. During the 1st wave and 2nd wave, the ridership in the north and south areas, where the majority of stations had a higher level of usage in 2019, decreased significantly. The median changes of ridership in the north area were -62.8% and -39.2% during the 1st wave and 2nd wave, respectively. In the area around the north area and the southeast area, where the majority of stations had a lower level of usage in 2020, the decrease in ridership was less significant. The median changes of ridership in the southeast area were -33.1% and 3.8% during the 1st wave and 2nd wave, respectively. During the pre-outbreak and stable period, the ridership in the north areas and east areas declined less significantly, for example, during the pre-outbreak, the north area was identified as a hot spot, while during the stable period, the decrease of ridership in the north and east areas was not significant compared to other areas. Moreover, it can be found that the ridership in the southwest and northeast areas also declined notably during the pandemic period. In these areas, there are many famous attractions, e.g., Osulloc Tea Museum, Hello Kitty Island, The Venice Land, Manjanggul Cave, etc. These findings imply that when the pandemic situation was severe, visitors were more likely to avoid the popular areas, which might be overcrowded.

The stage-wise hot spot analysis reveals areas in Jeju where the

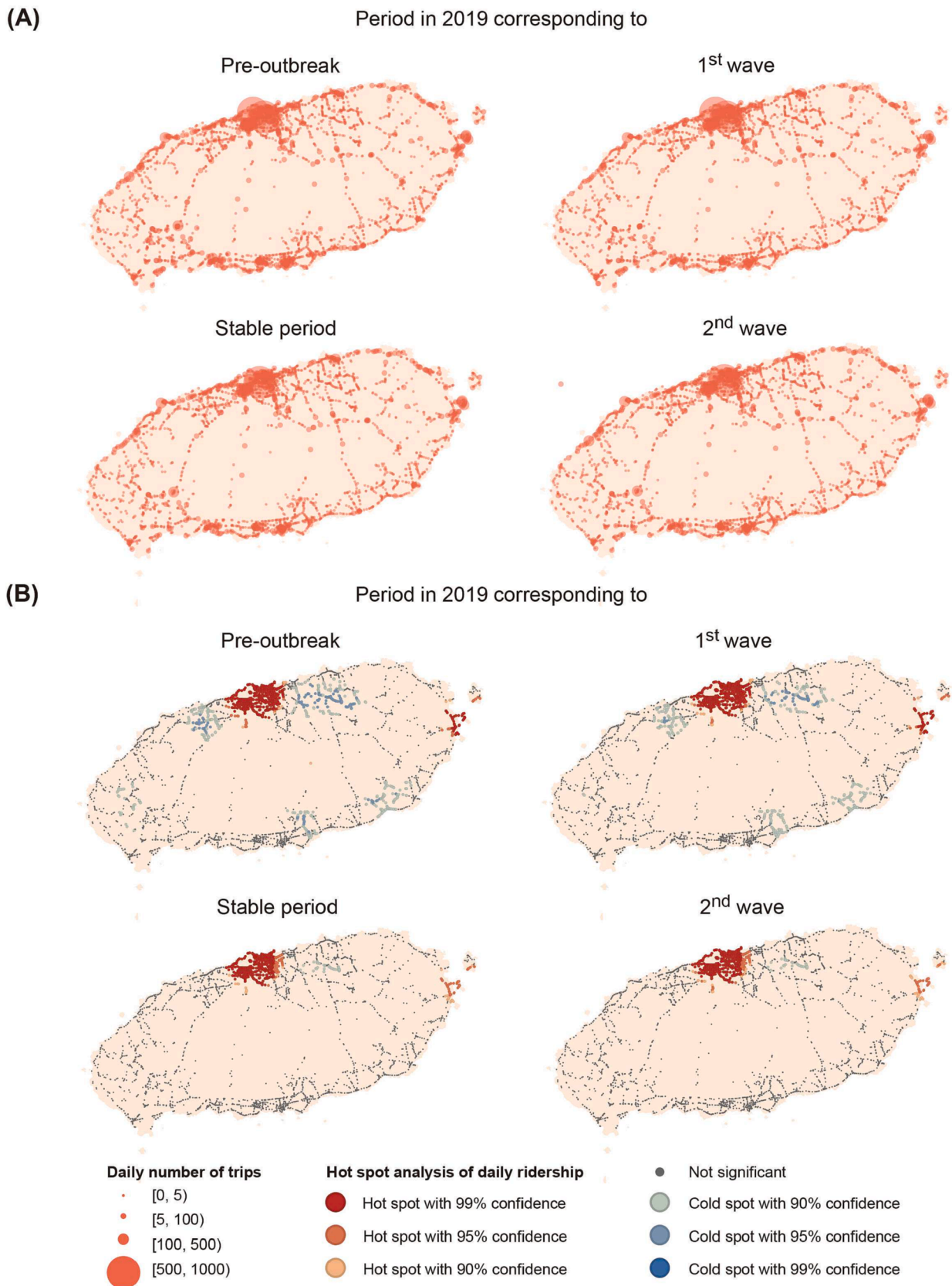


Fig. 6. (A) Daily ridership and (B) observed hot spots at station level during the four periods in 2019 (corresponding to the four pandemic stages).

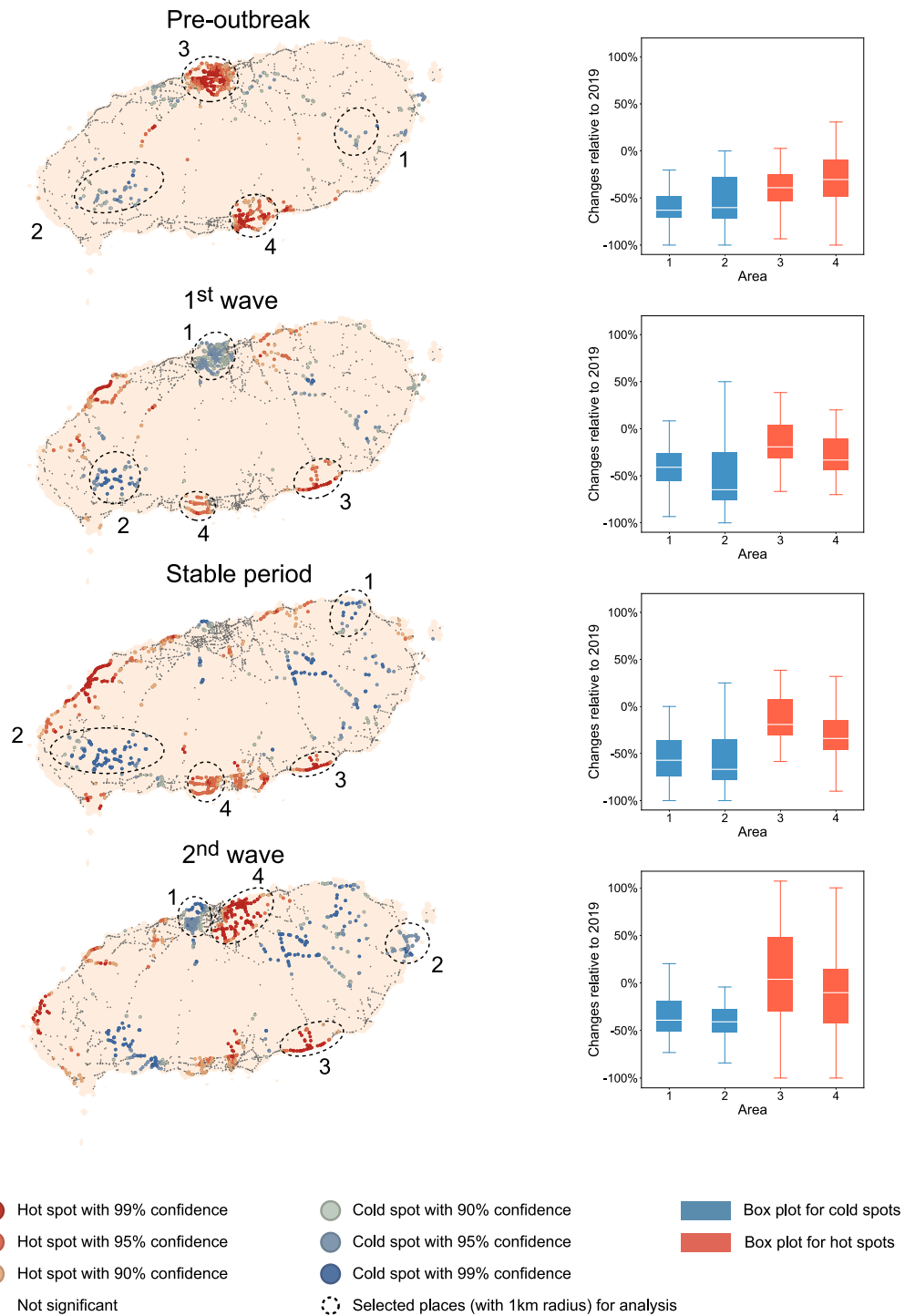


Fig. 7. Observed hot spots of changes in ridership at station level during the four pandemic stages relative to the corresponding periods in 2019.

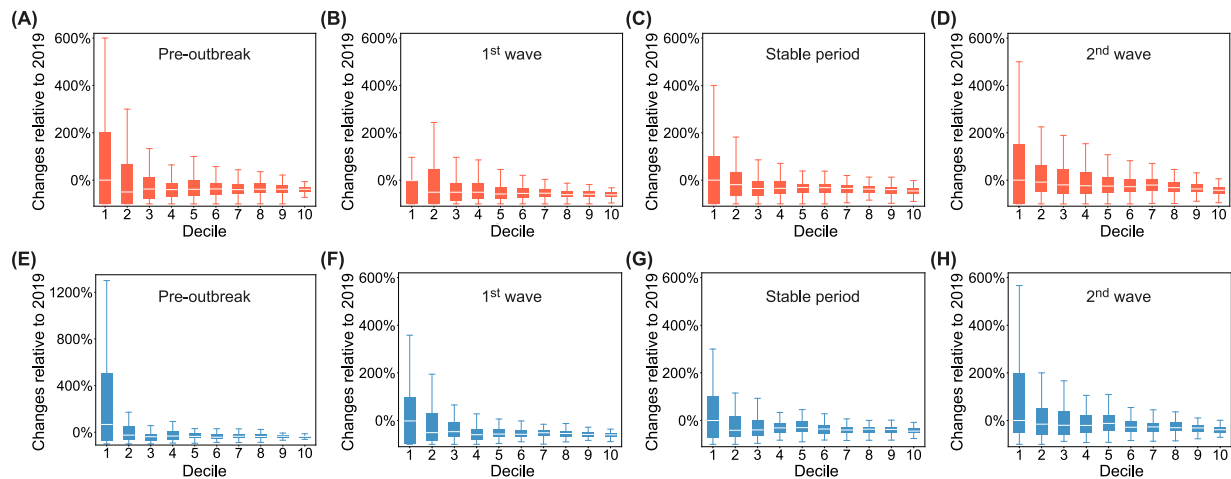


Fig. 8. Relationship between changes of ridership and level of usage in 2019 during the four pandemic stages at (A)–(D) station level and (E)–(H) grid level. The stations are sorted into ten deciles in ascending order based on the daily trips during the period in 2019 corresponding to the pandemic stage.

majority of stations experienced a notable ridership decay, compared to areas where the stations experienced a moderate decay or even an increase in transit usage. Another intriguing question is how the degree of changes relates to the usage level of the stations during the same period in 2019. To answer this question, for each stage, we sort the stations into ten deciles in ascending order based on their usage level in 2019. For each decile of stations, we plot out the distribution of the changes in ridership in 2020, as shown in Fig. 8A to Fig. 8D. During the 1st wave, we find a decrease in ridership for most of the stations. According to our statistics, the average and median value of the change are -57.3% and -32.8% , respectively. By comparing the distributions among the ten deciles, we find that stations with higher levels of usage in 2019 generally have a larger degree of ridership decay. For example, the median value for decile 1 to 5 are -1.8% , -50.9% , -50.9% , -50.9% , and -58.4% , while it for decile 6 to 10 are -55.9% , -55.1% , -61.3% , -59.5% , and -62.1% . According to the interquartile range of the box plot for each decile, it is uncovered that the within-decile variation of changes in ridership decreases as the level of usage of stations in 2019 increases. Moreover, for the deciles in which the stations have higher levels of usage in 2019, the ridership at the majority of the stations declined. While for the deciles in which the stations have lower usage levels in 2019, the percentage of stations with an increased ridership is higher. The findings also hold during the stable period and 2nd wave. We also plot out the distribution of the changes in ridership in 2020 at the grid level, as shown in Fig. 8E to Fig. 8H. The results are similar to those at station level.

5. Discussion and conclusion

The outbreak of COVID-19 brought a great impact on travel, especially on public transit. Although some scholars have studied the impact of COVID-19 on public transit usage, how the public transit system is used by visitors during the pandemic period remains underexplored. With the general recovery of domestic and international travel, understanding the usage of public transit by urban visitors during COVID-19 can provide policy insights on how to restore tourism, public transit usage, and overall urban vibrancy.

In this study, we have investigated the impact of COVID-19 on the public transit use of urban visitors during multiple pandemic stages. The regression results suggest that the COVID-19 pandemic led to the reduction in public transit usage by visitors. The transit usage of visitors had a

notable association with pandemic severity during the 1st wave and 2nd wave outbreaks, while the association became insignificant during the stable period. The regression results indicate that both the national and local pandemic situations had a significant impact on visitors' transit usage. In particular, we find that the average daily new cases within the past n days at the national (ADC_{SK}^n) and local (ADC_{Jeju}^n) levels were significant, which indicates that COVID-19 had a lagged impact on public transit. By varying the value of n ($n \in \{7, 14\}$), we find that the combination of ADC_{SK}^{14} and ADC_{Jeju}^7 had the highest explanatory power. Each 1% increase in the local cases led to more reduction in transit ridership than the national cases. This implies that the local spread of COVID-19 had a greater impact on visitors' public transit use than the national pandemic. Compared to the 1st wave, the relative importance between national and local pandemic situations to visitors' public transit use changed during the 2nd wave. A few possible reasons may explain the associations between transit usage and key pandemic indicators (ADC_{SK}^{14} , ADC_{Jeju}^7). First, the results imply that the pandemic situation at the tourism destination (i.e., Jeju) and where the domestic visitors come from (i.e., other parts of South Korea) jointly affected people's willingness to visit Jeju, which subsequently affected the usage level of the public transit system. Second, for visitors who have arrived in Jeju, whether and how they used the public transit system could be directly impacted by the local spread of COVID-19. Therefore, the local pandemic situation may trigger a more immediate and stronger impact on transit usage compared to the national-level situation. Third, the impact of the national and local pandemic situations on visitors' willingness to visit Jeju and to use public transit could be different at different pandemic stages. A comprehensive investigation of these possible changes and driving forces is a potential direction for future work.

The dampening effect of COVID-19 on public transit usage observed in this study is consistent with some existing studies (Fathi-Kazerooni et al., 2020; Mashrur et al., 2022). However, these studies focused on quantifying the local impact of COVID-19 on public transit use and do not investigate the transit usage behavior from the perspective of visitors. Unlike other crises (e.g., floods, earthquakes), the spread of epidemic diseases is highly correlated with population movements. Considering the interconnectedness between cities, the transit usage behavior of people might be influenced by the pandemic situation within and outside the city. In terms of inbound visitors, who come from across the country, the willingness to travel to certain destinations and to use public transit in the destination might be affected by the pandemic situations both in the destination and where they come from. Thus, the

transit use of visitors could be jointly affected by the national and local pandemic situations. Our study confirms this point. In particular, although Jeju did not have a local outbreak and was far from the epicenter of the national outbreaks, public transit usage was significantly affected by the spread of the disease at the local and national levels. This suggests that both the national and local pandemic situations should be considered when forecasting transit ridership or developing response measures. Meanwhile, our results also reveal that local disease spread had a greater impact on visitors' travel behavior than external disease spread, implying that the management of local disease spread was important to the recovery of public transit and tourism activities.

By performing the time series decomposition analysis, we further investigate the long-term dynamics of four mobility indicators that describe transit usage behavior of individual visitors. These indicators capture the number of days with transit usage (N_{day}), the number of trips made per active day (N_{trip}), the total number of stations used ($N_{station}$), as well as the spatial range of transit use (R_g) during a visitor's stay in Jeju. By extracting the trend component of the indicators, we find that all the indicators continuously decreased from the 1st wave to the 2nd wave. The continuously decreased transit use by visitors reveals the persistent impact of the pandemic on all aspects of individual transit usage behavior. The analysis at the individual level is complement to the regression analysis. The results of the two analyses indicate the decay in visitors' willingness to travel to Jeju and propensity to use public transit in Jeju. The finding echoes with previous studies using survey data, which also reported that people tended to change their travel behavior — such as frequency of travel and mode of transportation — or even cancel their trips when perceiving higher health risks or uncertainty (Neuburger and Egger, 2021; Irawan et al., 2022). Our study focused on the change of public transit usage behavior by analyzing smart card data over a representative population. The decrease in individual transit usage suggests that visitors were concerned about using public transit during the COVID-19 pandemic. Thus, the governments should develop some strategies, such as providing adequate public transit and pandemic information, sanitizing public transit vehicles and facilities, to make visitors feel safe to use public transit during public health crises.

According to the spatial analysis, the ridership decreased in most of the areas during the four pandemic stages compared to the ridership during the corresponding periods in 2019. The changes in ridership are heterogeneous across the space. The decline in ridership was more notable in the areas where the majority of the stations with a higher level of usage in 2019. During the 1st wave and 2nd wave, the ridership in the north and east areas, which were identified as hot spots based on the usage level of stations there, dropped significantly. The ridership in the area around the north area and the southeast area, which was identified as cold spots based on the usage level of stations there, declined moderately compared to other areas. Then, by exploring the relationship between the changes in ridership and popularity, we find that the stations or grids with higher popularity generally have a larger and uniform degree of ridership decay. Our findings are in general agreement with existing studies, suggesting that people tended to avoid popular places and preferred less popular places during the pandemic (Park et al., 2021; Östh et al., 2023). As such, for the areas which were less popular before COVID-19, the public transit service might become insufficient during the pandemic due to the transition of visitors from the popular areas. Visitors were likely to choose other modes — such as private cars, walking, or cycling — to travel to these areas. This potential modal shift behavior might further lead to a reduction

in public transit usage by visitors.

At the time of writing, most countries have reopened the borders and lifted the travel restrictions, while the impact of COVID-19 on visitors' transit use preferences and patterns was likely to persist in the near future (Dong et al., 2020; Kathirvel, 2020). Thus, this study has important implications for many cities, especially for those tourist cities that rely on public transit, such as Hong Kong and Singapore. This study is also helpful for transit and tourism management in future pandemics. The results in this study suggest that controlling the local outbreak is vital to recovering public transit and protecting the local tourism economy. Meanwhile, governments should develop effective strategies to regain visitors' confidence in public transit. Considering the change in visitors' preferences for visiting places during the pandemic, it is expected that the public transit service may become insufficient in the areas which were less popular before the pandemic. Providing alternative transportation means (e.g., bike sharing) and facilities (e.g., pedestrian walkways) in those places may improve the travel experience of visitors and enhance the resilience of the local tourism economy.

We want to discuss a few limitations of the research. First, this study uses 14 days as the threshold to identify users who were active in the transit system for no more than 2 weeks. Although this practice allows us to capture a majority of one-time visitors who traveled to Jeju during the study period, we were not able to further identify repeat visitors who visited the island multiple times. Understanding how individual transit usage behavior may change across two or multiple consecutive visits to the city during the pandemic is a meaningful question worth investigating. Answering the question could provide additional insights into the variation of personal mobility behavior and its linkage with possible changes in risk perception and travel attitude. The identification of repeat visitors from the transit system, though, would require innovative methodologies (e.g., machine learning) combined with ground truth observations. This represents a possible future work of this study. Second, in the spatial analysis of this study, the changes in ridership during key pandemic stages were calculated using the ridership in 2019 as baselines. This means the baseline values in 2019 would consist of ridership contributed by both domestic inbound visitors as well as international visitors. Although we were not able to remove the impact of foreign visitors, it is necessary to mention that the number of foreign visitors only accounts for about 10% of all visitors to Jeju⁵. Therefore, the year-over-year difference in ridership would still capture meaningful patterns in spatial preference mainly from the perspective of domestic visitors. Nevertheless, we believe this study provides some initial and important insights into how urban visitors used the transit system during the early stage of COVID-19. The analytical framework can be applied or extended in other cities to inform public transit usage and operation during public health crises.

CRedit authorship contribution statement

Yuqian Lin: Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Yang Xu:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Zhan Zhao:** Methodology, Writing – original draft, Writing – review & editing. **Sangwon Park:** Data curation, Writing – original draft, Writing – review & editing. **Shiliang Su:** Conceptualization, Writing – original draft, Writing – review & editing. **Mengyao Ren:** Conceptualization, Writing – review & editing.

⁵ Official statistics from the Jeju Tourism Organization: <https://ijto.or.kr/korean/>

Appendix A. Variance inflation factors of the pandemic severity indicators.

Table A.1.

Table A.1

VIF of COVID-19 factors in different pandemic stages.

	DNC_{SK}	DNC_{Jeju}	ADC_{SK}^7	ADC_{Jeju}^7	ADC_{SK}^{14}	ADC_{Jeju}^{14}
1 st wave	18.17	1.24	20.65	2.49		
Stable period	27.90	1.10	28.05	1.46		
2 nd wave	37.92	1.64	47.86	3.60		
1 st wave	13.21	1.25			15.95	3.35
Stable period	24.67	1.10			26.84	2.36
2 nd wave	41.48	1.56			64.78	6.63
1 st wave	13.08	1.25		2.24	13.51	
Stable period	24.58	1.10		1.45	24.41	
2 nd wave	30.63	1.63		3.95	40.68	

Appendix B. Sensitivity analysis of the visitors identification

B.1. Regression and decomposition results of visitors with time span ≤ 7 days

Tables B.2 and B.3.
(See Fig. B.1).

Table B.2

The regression results of daily number of visitors (N_V).

Model setting	Period	R^2	P	Factors						
				Intercept	DNC_{SK}	DNC_{Jeju}	ADC_{SK}^7	ADC_{Jeju}^7	ADC_{SK}^{14}	ADC_{Jeju}^{14}
1-1	1 st wave	0.57	0.000	1870.58	-93.04	-309.77	-224.76***	-1756.06***		
	Stable period	0.05	0.539	435.93	192.07	49.44	-328.04	65.90		
	2 nd wave	0.59	0.000	3159.01	136.26	-193.58	-565.64	-1812.26***		
1-2	1 st wave	0.36	0.000	1637.17	-140.12*	-278.57			-137.60*	-1739.21**
	Stable period	0.04	0.648	378.04	157.38	50.34			-267.49	-137.62
	2 nd wave	0.57	0.000	5739.98	69.80	-192.28			-1096.32**	-872.52
1-3	1 st wave	0.55	0.000	1975.88	-146.46**	-354.26			-2025.61***	-181.45***
	Stable period	0.04	0.666	412.10	155.66	51.66			48.42	-281.51
	2 nd wave	0.62	0.000	4593.25	94.90	-134.43			-1322.64**	-859.51**

Note: * significant at 0.05 level, ** significant at 0.01 level, and *** significant at 0.001 level.

Table B.3

The regression results of daily number of trips (N_T).

Model setting	Period	R^2	P	Factors						
				Intercept	DNC_{SK}	DNC_{Jeju}	ADC_{SK}^7	ADC_{Jeju}^7	ADC_{SK}^{14}	ADC_{Jeju}^{14}
2-1	1 st wave	0.51	0.000	4415.97	-208.70	-706.12	-545.04**	-3986.60***		
	Stable period	0.06	0.114	1509.10	685.25*	150.40	-1163.93*	1094.35		
	2 nd wave	0.54	0.000	6293.92	260.32	-356.17	-1130.85	-3434.60***		
2-2	1 st wave	0.33	0.001	3881.23	-318.97*	-640.36			-348.58*	-3794.85*
	Stable period	0.04	0.611	691.12	412.87	75.35			-612.83	-254.74
	2 nd wave	0.53	0.000	11329.40	127.87	-339.49			-2159.47*	-1660.52
2-3	1 st wave	0.50	0.000	4681.06	-337.25*	-815.87			-4639.49***	-443.01**
	Stable period	0.04	0.624	764.43	408.19	77.27			154.53	-642.07
	2 nd wave	0.57	0.000	9332.51	181.59	-226.08			-2407.92*	-1761.38*

Note: * significant at 0.05 level, ** significant at 0.01 level, and *** significant at 0.001 level.

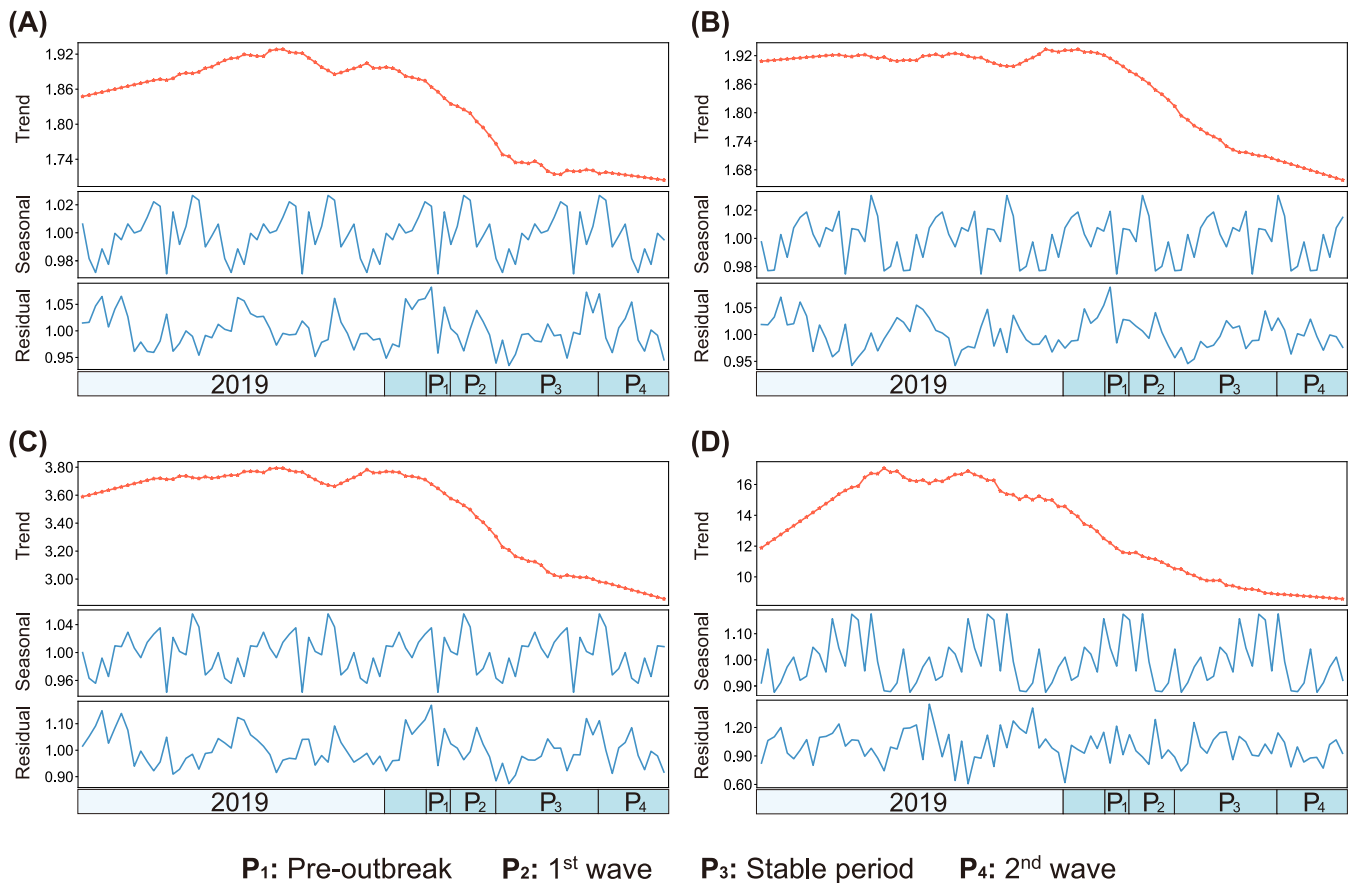


Fig. B.1. Time series decomposition result of (A) number of active days, (B) total number of trips per active day, (C) total number of stations used, and (D) radius of gyration of transit usage of individual visitors during their stay in Jeju.

B.2. Regression and decomposition results of visitors with time span ≤ 5 days

See [Table B.4](#).
 See [Table B.5](#).
[Fig. B.2](#).

Table B.4
 The regression results of daily number of visitors (N_V).

Model setting	Period	R^2	P	Factors						
				Intercept	DNC_{SK}	DNC_{Jeju}	ADC_{SK}^7	ADC_{Jeju}^7	ADC_{SK}^{14}	ADC_{Jeju}^{14}
1-1	1 st wave	0.57	0.000	1941.41	-86.75	-305.44	-218.84***	-1679.29***		
	Stable period	0.06	0.111	726.58	269.97*	96.35	-495.96**	364.59		
	2 nd wave	0.58	0.000	3009.45	132.89	-173.30	-554.19	-1616.00***		
1-2	1 st wave	0.37	0.000	1576.23	-132.95*	-276.17			-134.10*	-1677.14**
	Stable period	0.04	0.653	345.01	150.57	43.04			-250.02	-133.31
	2 nd wave	0.57	0.000	5421.24	74.75	-163.91			-1057.31**	-710.44
1-3	1 st wave	0.55	0.000	1899.67	-138.84**	-348.63		-1941.79***	-176.45***	
	Stable period	0.04	0.671	377.11	149.04	44.36			41.21	-263.31
	2 nd wave	0.61	0.000	4359.22	91.08	-119.09		-1152.50*	-828.11**	

Note: * significant at 0.05 level, ** significant at 0.01 level, and *** significant at 0.001 level.

Table B.5
The regression results of daily number of trips (N_T).

Model setting	Period	R^2	P	Factors						
				Intercept	DNC_{SK}	DNC_{Jeju}	ADC_{SK}^7	ADC_{Jeju}^7	ADC_{SK}^{14}	ADC_{Jeju}^{14}
2-1	1 st wave	0.50	0.000	4225.50	-194.56	-709.35	-528.77***	-3749.91***		
	Stable period	0.06	0.107	1417.27	661.69*	72.50	-1107.04*	1017.21		
	2 nd wave	0.52	0.000	6058.92	248.49	-305.05	-1122.75	-2975.10***		
2-2	1 st wave	0.32	0.001	3725.50	-303.73*	-650.29			-336.67*	-3633.83*
	Stable period	0.04	0.616	609.19	394.21	41.71			-567.54	-245.23
	2 nd wave	0.53	0.000	10685.99	130.95	-270.97			-2078.25**	-1312.59
2-3	1 st wave	0.49	0.000	4482.17	-320.57*	-816.78			-4409.30***	-427.28**
	Stable period	0.05	0.629	678.07	389.95	43.65			130.02	-595.15
	2 nd wave	0.56	0.000	8865.23	164.95	-185.78			-2050.94*	-1692.52**

Note: * significant at 0.05 level, ** significant at 0.01 level, and *** significant at 0.001 level.

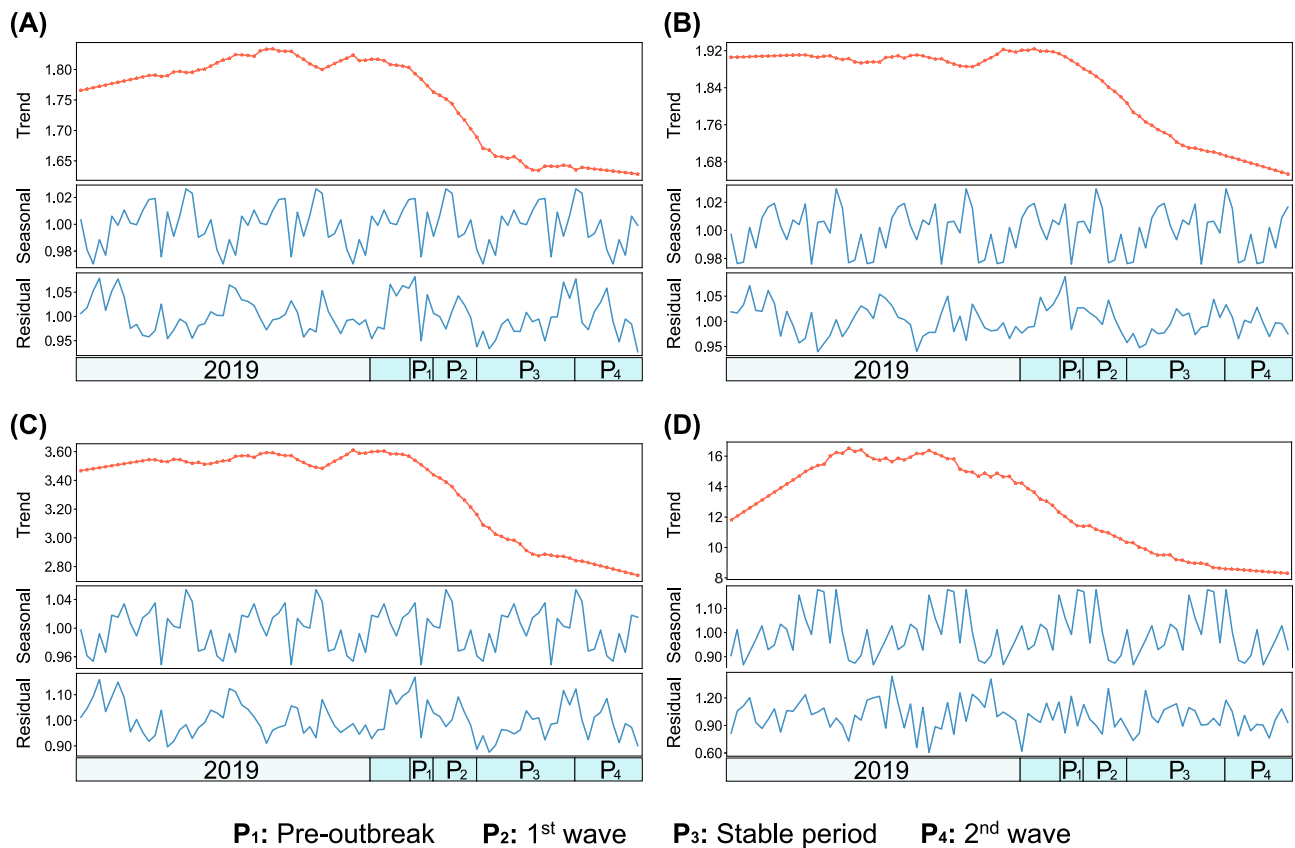


Fig. B.2. Time series decomposition result of (A) number of active days, (B) total number of trips per active day, (C) total number of stations used, and (D) radius of gyration of transit usage of individual visitors during their stay in Jeju.

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