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Changes in car and bus usage amid the COVID-19 pandemic: Relationship with land use and land price

Suji Kim [a], Sujin Lee [b], Eunjeong Ko [b], Kitae Jang [b], Jiho Yeo [c,*]

[a] Mechanical Engineering Research Institute, Korea Advanced Institute of Science and Technology, 291 Daehak-ro, Yuseong-gu, Daejeon 34141, South Korea
[b] The Cho Chun Shik Graduate School of Green Transportation, Korea Advanced Institute of Science and Technology, 193 Munji-ro, Yuseong-gu, Daejeon 34051, South Korea
[c] Department of Big Data Application, College of Social Economic & Interdisciplinary Studies, Hannam University, 70 Hannam-ro, Daedeok-gu, Daejeon 34430, South Korea

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ABSTRACT

This study aimed to explore the impacts of COVID-19 on car and bus usage and their relationships with land use and land price. Large-scale trip data of car and bus usage in Daejeon, South Korea, were tested. We made a trip-chain-level data set to analyze travel behavior based on activity-based travel volumes. Hexagonal cells were used to capture geographical explanatory variables, and a mixed-effect regression model was adopted to determine the impacts of COVID-19. The modeling outcomes demonstrated behavioral differences associated with using cars and buses amid the pandemic. People responded to the pandemic by reducing their trips more intensively during the daytime and weekends. Moreover, they avoided crowded or shared spaces by reducing bus trips and trips toward commercial areas. In terms of social equity, trips of people living in wealthier areas decreased more than those of people living in lower-priced areas, especially trips by buses. The findings contribute to the previous literature by adding a fundamental reference for the different impacts of pandemics on two universal transportation modes.

1. Introduction

The COVID-19 pandemic has brought severe health risks to many countries worldwide, with over 83 million confirmed cases and over 1.8 million deaths occurring for one year after its outbreak in December 2019 (World Health Organization, 2021). Many countries continue to struggle with the serious pandemic situation and are attempting to impede the spread of the virus by implementing various policies, such as social distancing, quarantines, flexible working, lockdowns, and travel bans. This unpredicted pandemic has led people to express growing worry and, as a result, has induced behavioral changes (Barber and Kim, 2021; Chernozhukov et al., 2021; Lüdecke and von dem Knesebeck, 2020).

In the transportation realm, behavioral changes have appeared in travel demand and the use of transportation modes (Beck and Hensher, 2020a, 2020b; International Energy Agency, 2020). A growing number of researchers have attempted to comprehend the impacts of COVID-19 on travel amid the pandemic. Some studies have conducted surveys about the travel-related behavioral changes induced by the pandemic (Beck and Hensher, 2020a, 2020b; Beck et al., 2020; Borkowski et al., 2021; Irawan et al., 2021; Li et al., 2020; Shakibaei et al., 2021; Shamshiripour et al., 2020). These studies have verified the presence of changes in travel demand and mode choice to avoid infection. They have reported that trip generation was reduced for diverse trip purposes and that people preferred more individual transportation modes to collective transportation modes. Other studies have focused on public transit using actual volume data as public transit, representing collective transportation modes, is more vulnerable than other modes to the spread of pandemics. The studies have analyzed the impacts of COVID-19 on public transit at the national level (Coelho et al., 2020), city level (Jenelius and Cebecauer, 2020; Liu et al., 2020), and station level (Brough et al., 2020; Chang et al., 2021), confirming a significant decline in ridership volume due to the COVID-19 pandemic. As a further approach, some researchers have tested the involvement of neighborhood attributes in the impacts of COVID-19 on public transit (Brough et al., 2020; Chang et al., 2021; Coelho et al., 2020; Liu et al., 2020). Studies analyzing other pandemics, such as SARS and MERS, have also

* Corresponding author.
E-mail addresses: suji3114@kaist.ac.kr (S. Kim), su-jin.lee@kaist.ac.kr (S. Lee), eunjeong.ko@kaist.ac.kr (E. Ko), kitae.jang@kaist.ac.kr (K. Jang), jihoyeo@hnu.kr (J. Yeo).

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considered changes in public transit ridership and verified pandemic impacts (Howland et al., 2020; Kim et al., 2017; Wang, 2014).

Private cars and public transit are primary modes of mobility in cities. However, studies using actual volume data have not yet covered changes in car usage amid the COVID-19 pandemic. The pandemic has affected car use patterns, which may differ from bus use patterns due to the opposing natures of the two modes. Because private cars and public transit have a complementary and substitutional relationship, a comparison of changes in their usage resulting from the COVID-19 pandemic is necessary. Previous studies based on survey data have shown differences in the use of private cars and public transit during the pandemic, and however, survey data occasionally involve sampling biases and record unreliable data (Giuliano and Hanson, 2017). Therefore, a comparative study using more accurate and actual data is required.

In this context, this study tested large-scale trip data to examine and compare patterns of changes in car and bus usage resulting from the COVID-19 pandemic in Daejeon Metropolitan City, South Korea. We appraised behavioral changes associated with the use of private cars and buses by time: weekdays, weekends, and times of day. The roles of land attributes—land use and land price—in the behavioral changes were also investigated under the conditions of the COVID-19 pandemic. Land price can be a proxy of the economic statuses of residents (Davidoff, 2006; Määttänen and Terviö, 2014; McQuinn and O'Reilly, 2008; Mirkatouli et al., 2018). In South Korea especially, the economic statuses of residents tend to correspond to the price of the properties where they live due to the specific urbanization and housing patterns in the country. Most households in South Korea live in apartments, generally referred to as condominiums. Wealthier households are more likely to live in the higher-priced apartments located in the dense, core regions of cities as they can afford expensive trading and renting prices. Several Korean studies have used property value as a proxy of local income level (Kang, 2019; Kim et al., 2019). Therefore, this approach enabled a look into the behavioral changes of people induced by their economic statuses amid the pandemic and addressing the social equity issue of the pandemic in the context of transportation.

The remainder of this study is organized as follows. Section 2 describes the temporal and geographical scope, and Section 3 elucidates the data processing procedures and the econometric model used in this study. The modeling outcomes are interpreted in Section 4, and Section 5 discusses the findings. Section 6 concludes this study by suggesting implications that can help transportation operations amid pandemic conditions.

2. Temporal and geographical scope

The initial period of the COVID-19 pandemic—the three months spanning February to April 2020—was tested as the temporal scope of this study. In South Korea, the first case of COVID-19 infection was discovered on January 20, 2020, in a foreigner who entered the country from Wuhan, China, according to the Korea Disease Control and Prevention Agency (KDCA). The first case of community transmission in Korea was later reported on February 16, 2020. The KDCA reported the beginning of high contagion around mid-February and the highest number of cases (1,062) on March 2, 2020. Because South Korea's prevention policies were not compulsory in the initial period, the effect of such policies on travel behavior did little to restrict the daily activities of people. South Korea's main policies instituted to impede the spread of the pandemic involved the promotion of social distancing and the wearing of face masks in public, while other countries, such as France, Germany, Spain, and the US, applied strong lockdown and mandatory stay-at-home policies. This initial period thus enabled us to observe the pure responses of people to the COVID-19 pandemic.

Daejeon Metropolitan City in South Korea was evaluated to investigate the impacts of COVID-19 on car and bus usage. The first confirmed case of COVID-19 in Daejeon appeared on February 21, 2020, during the first accelerated spreading period of the pandemic in South Korea. The city has a registered population of 1.5 million and an urbanization rate of 91.9% in 2020 (Korean Statistical Information Service, 2021) and includes the R&D (Research and Development) special zone for science and technology. The zone specializes in advanced integrated industrial technologies; the Korean government designated it in 2005, and the Korea Innopolice Foundation has been administering it. The zone comprises seven universities, twenty-six government-funded research institutes, over two thousand research centers of private enterprises, and over thirty thousand R&D workers.

Daejeon collects extensive data related to mobility due to its well-developed transportation infrastructure. The detection infrastructure for collecting vehicle information on roads has been densely constructed since the city was designated a pilot city for the Cooperative-Intelligent Transportation System (C-ITS). A total of 407 pieces of Road-Side Equipment (RSE) are installed throughout the city as of 2021. In addition, there are 2,890 bus stops located all around the city. Fig. 1(a) displays the locations of RSEs and bus stops, which cover most of the urbanized area.

To measure geographically varying variables, we divided the study site, Daejeon, into hexagonal cells with 500 m edges (See Fig. 1(b)). A hexagonal shape generates symmetrical neighborhoods, and this symmetricity reduces the bias of the edge effects that often occur in analyses using grid shape units (Birch et al., 2007). For the length of hexagonal cell edges, we assumed that people would take public transit or cars to go somewhere 500 m away from their current locations by adopting the general walking distance in South Korea; many Korean studies have defined 500 m as the walking distance in consideration of the walking access time of 10 min (Choi et al., 2012; Sohn and Shim, 2010; Sung and Oh, 2011; Woo, 2021).

3. Data and methodology

3.1. Data processing

For car and bus usage, we collected individual-level trip data—Dedicated Short-Range Communication (DSRC) record data obtained via RSEs and smart card data—and counted trip-chain-based travel volumes. Based on activity theory, trip-chain-based analysis helps to understand actual travel demand. Researchers have highlighted the importance of using trip-chain data to analyze travel behavior (Cheng et al., 2016; Feng et al., 2020).

Individual travelers can have multiple trip chains in one day, and each trip chain may be a sequence of multiple sub trips. Hence, we derived a trip-chain-level data set from the raw data containing many sub-trip records based on different algorithms for each car and bus. The trip-chain-level data set contains information on the date, traveler ID, departure time, departure location, arrival time, and arrival location of the trip chain. The data comprise 32,488,484 trip-chain records for bus usage and 99,024,947 trip-chain records for car usage during the temporal scope (February to April 2020).

After preprocessing, the dependent variables of car and bus usage were obtained by matching their departure and arrival locations (RSEs for cars and bus stops for buses) with the cells and subsequently aggregating the trip-chain-level data to the daily and hourly scales at the cell level. We extracted only valid cells where car and bus trips occurred during the temporal scope. In the econometric modeling, the dependent variables were defined as the sum of the departure and arrival volumes occurring in the individual cells throughout the day and during the morning (7–10 am), daytime (11 am–5 pm), and evening (5–8 pm) hours. The final sample size for the econometric modeling was 14,980 for car usage and 35,007 for bus usage. Fig. 2 depicts the data processing steps and the data structures.

3.2. Measure of explanatory variables

Seven geographical explanatory variables were measured at the cell level using data collected from various government portals (Environmental Geographic Information Service, Korea National Spatial Data

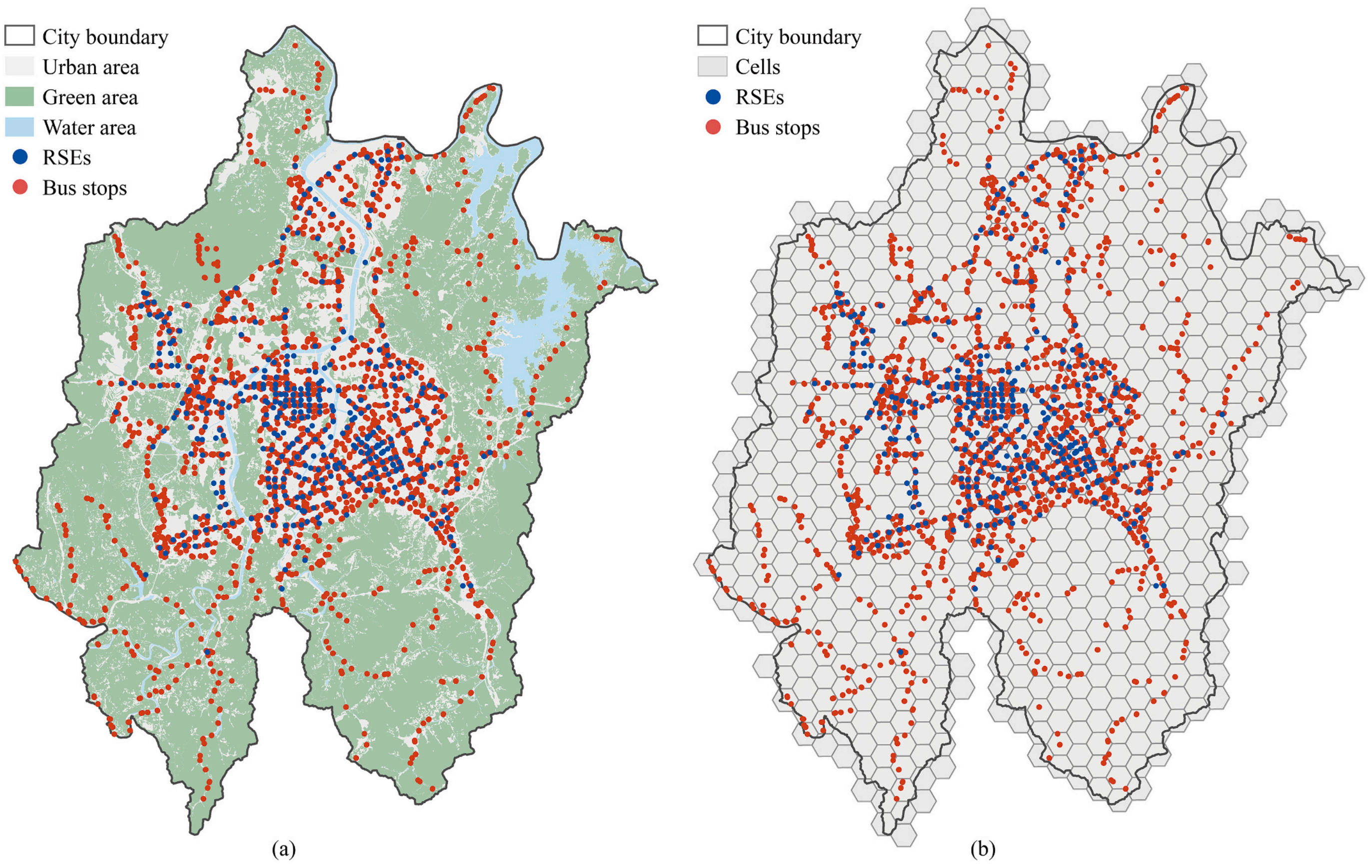


Fig. 1. Geographical distributions of RSEs, bus stops, and cells: (a) RSEs and bus stops; and (b) hexagonal cells.

Infrastructure Portal, Road Name Address). The primary land use types, residential use and commercial/office use, were included in the explanatory variables as a proportion of the corresponding lands within each cell. The land price variable was calculated as the average land price within the cells. Fig. 3 illustrates the distributions of land attributes over the hexagonal cells. To consider the level of public transit supply, we counted the number of bus routes that pass through individual cells. The length of arterial roads was also measured to control the increasing tendency of car traffic through well-constructed road infrastructure. We used the statistics of population and employment collected at the census block level to reflect differences in sociodemographic attributes and created their numbers in each cell using the ratio of the census block area covering each hexagonal cell.

In addition, we collected weather information of temperature and precipitation from the government data portal (Open MET Data Portal) to consider other environmental impacts on travel behavior (Liu et al., 2017; Ngo, 2019; Tao et al., 2018). The temperature variable was treated as a categorical variable and coded as three indicators to categorize the grade of temperature—cold, moderate, and hot. Another categorical variable was included to differentiate travel behavior between weekdays and weekends—the public holiday was coded as weekends. The Korean government has been updating the daily number of confirmed cases on its COVID-19 website since the day of the first case. We collected data on the day-by-day number of newly confirmed cases in South Korea from this website. The number was entered in the models as the three-day moving average of the newly confirmed cases to make up for non-recorded days. Details of the variables are elaborated in Table 1.

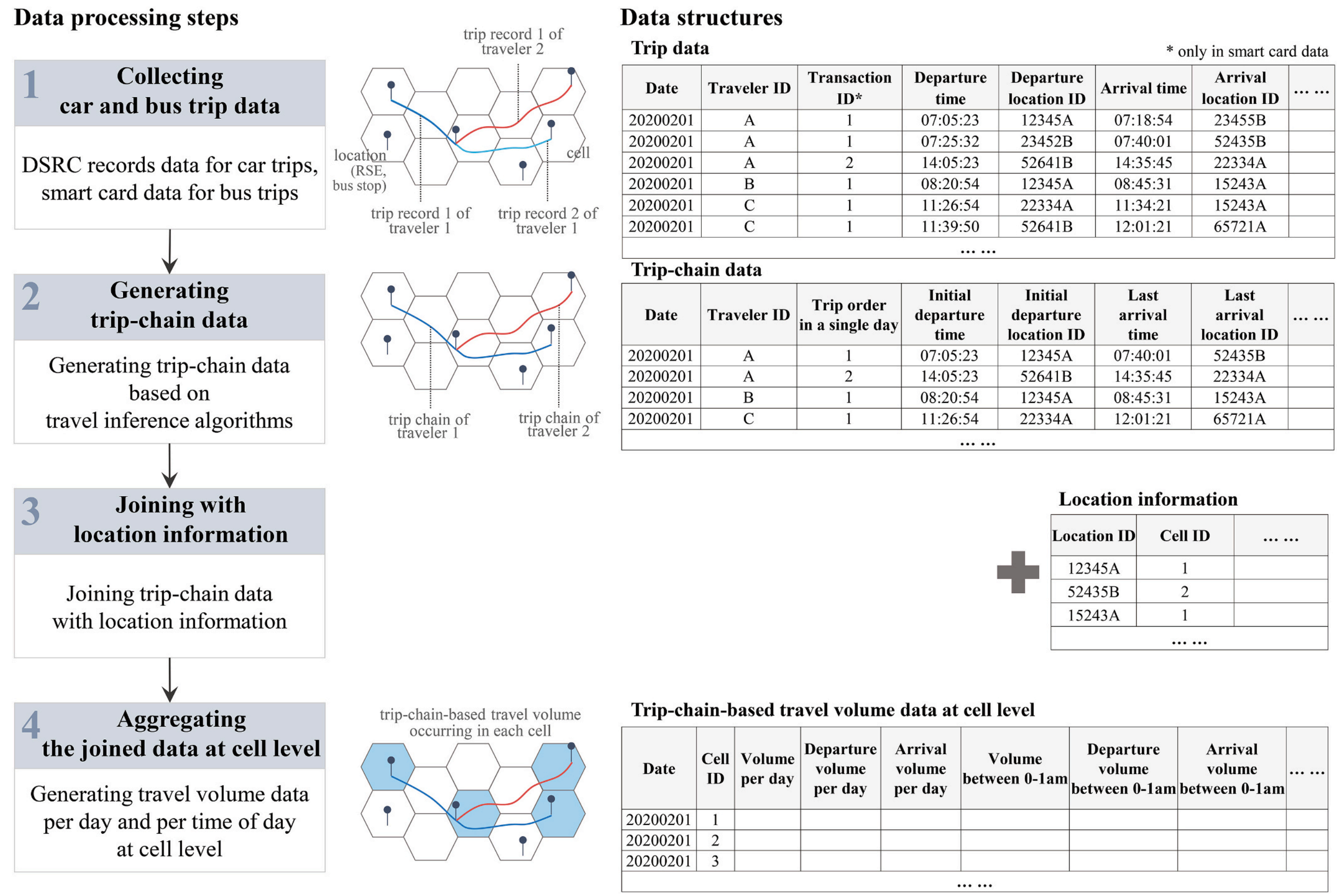
3.3. Econometric modeling

The data used in this study have repeated measures across the cells over time with a longitudinal data structure. An analysis using traditional linear regression for our data can bias the outcome because it may violate the independence assumption of the regression analysis. To handle the nature of longitudinal data, we adopted the mixed-effect regression model, which is a linear regression model with random effects, to consider heterogeneity across the cells in the generation of travel demand (Benfratello, 2014). The cells were entered in the modeling as a random component, and a specification of the model is written as follows:

$$y_{it} = \beta_0 + x_{it}\beta_1 + \mu_i + \varepsilon_{it}$$

where y_{it} is the dependent variable for individual cell i at time t, and x_{it} is a $1 \times k$ vector of explanatory variables captured for individual i at time t. β_0 denotes the overall intercept, and β_1 denotes a $1 \times k$ vector of coefficients. The error term is decomposed into μ_i and ε_{it}, where μ_i is an individual-dependent, time-invariant term and ε_{it} is a general error term for individual cell i at time t. These two error components are assumed to follow a normal distribution with means of zero and variances of σ^2. The inclusion of μ_i enabled consideration of unobserved heterogeneity at the cell level. The Breusch-Pagan test was conducted to validate the use of mixed-effect modeling for this analysis. This modeling was performed in R using the 'plm' package, which estimates a model based on generalized least squares (Croissant and Millo, 2008).

Eight models were developed for each car and bus usage to examine differences in the impacts of COVID-19 among the i) times, ii) land use



Date	Traveler ID	Transaction ID*	Departure time	Departure location ID	Arrival time	Arrival location ID	… …
20200201	A	1	07:05:23	12345A	07:18:54	23455B	
20200201	A	1	07:25:32	23452B	07:40:01	52435B	
20200201	A	2	14:05:23	52641B	14:35:45	22334A	
20200201	B	1	08:20:54	12345A	08:45:31	15243A	
20200201	C	1	11:26:54	22334A	11:34:21	15243A	
20200201	C	1	11:39:50	52641B	12:01:21	65721A	
… …							

Date	Traveler ID	Trip order in a single day	Initial departure time	Initial departure location ID	Last arrival time	Last arrival location ID	… …
20200201	A	1	07:05:23	12345A	07:40:01	52435B	
20200201	A	2	14:05:23	52641B	14:35:45	22334A	
20200201	B	1	08:20:54	12345A	08:45:31	15243A	
20200201	C	1	11:26:54	22334A	12:01:21	65721A	
… …							

Location ID	Cell ID	… …
12345A	1	
52435B	2	
15243A	1	
… …		

Date	Cell ID	Volume per day	Departure volume per day	Arrival volume per day	Volume between 0-1am	Departure volume between 0-1am	Arrival volume between 0-1am	… …
20200201	1							
20200201	2							
20200201	3							
… …								

Fig. 2. Data processing steps and data structures.

types, and iii) land prices. The dependent variables of car and bus usage and the explanatory variables of population and employment were transformed into a logarithmic form in the modeling.

4. Results

4.1. Descriptive analysis: the spread of COVID-19 and decreases in car and bus usage

Car usage and bus usage were counted by date from the trip-chain-level data to verify the impact of COVID-19 arithmetically. The blue and red lines in Fig. 4 show the trip-chain-based daily car and bus travel volumes. The gray bars display the distribution of newly confirmed COVID-19 cases each day.

Car and bus usage rapidly decreased when the number of newly confirmed cases rose around the end of February; bus trips decreased by approximately 40%, and car trips decreased by approximately 12% compared to earlier weeks. This dramatic diminution in the travel volumes was seemingly due to the elevation of the pandemic crisis level in the country from 'warning' to 'serious' on February 23. At this point, the Korean government recommended the introduction of 'flexible working', such as working-from-home, flexi-time, and staggered hours, to all public offices and private enterprises. Given the decrease in travel volumes of almost 50%, the government recommendation seems to have affected people's travels even though the actual 'flexible working' actions might have differed among companies. At the end of April, when the pandemic condition was stabilized comparatively, the resilience level of car usage was higher than that of bus usage. This implies that people were unwilling to take public transit more than cars due to the perceived risk of infection.

4.2. Interpretation of modeling results

The econometric modeling outcomes are summarized in Tables 2–5. The results of the Breusch-Pagan test indicate that all mixed-effect regression models developed in this study outperform the general regression models because they consider the nature of the longitudinal data. The modeling results are interpreted by focusing on the coefficients of the 'number of confirmed cases' and its interaction terms.

4.2.1. Changes in car and bus usage by weekdays, weekends, and times of day

The modeling results of the COVID-19 impacts by the weekdays, weekends, and times of day are tabulated in Table 2 for car usage and in Table 3 for bus usage. The coefficients of the 'number of confirmed cases' denote that car and bus usage change by percentages as high as the corresponding coefficients multiplied by 100 for an increase of one hundred confirmed cases. The coefficients are negative in all models, meaning that the increased number of confirmed cases forced decreases in both car and bus usage. The absolute size of the coefficients is greater in the bus models than in the car models. Daily car usage declined by 2.0%, and daily bus usage declined by 6.7% when the number of confirmed cases increased by one hundred. This result implies that people reduced both their car and bus usage, but they were more reluctant to travel by collective mode during the pandemic due to the anxiety of being infected.

The negative coefficients of the 'number of confirmed cases'

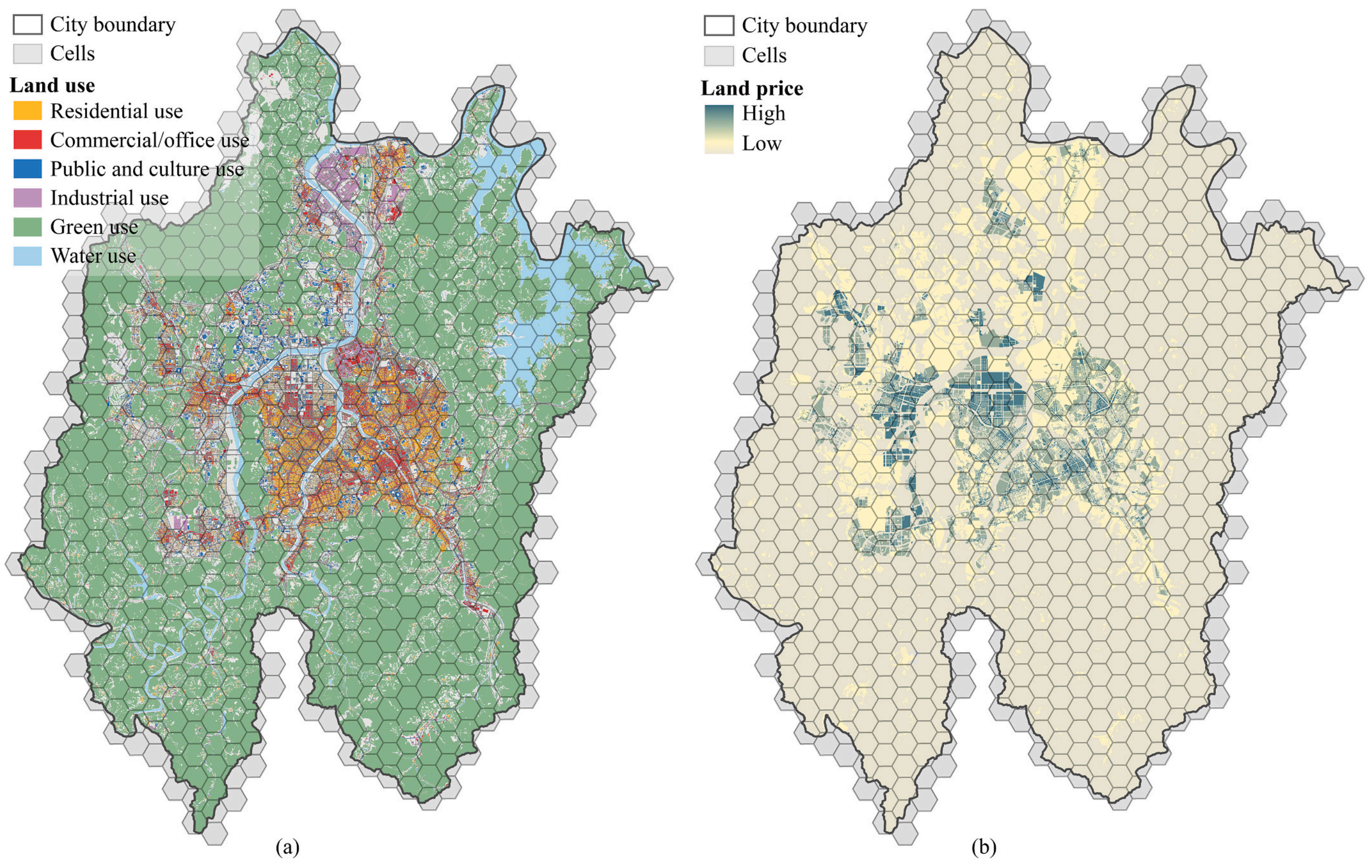


Fig. 3. Geographical distributions of land attributes: (a) land use; and (b) land price.

Table 1
Descriptions and summary statistics of variables.

Variable	Description	Unit	Mean	Max	Std. Dev.
Dependent variables					
Car usage					
Daily usage	Daily car travel volume	volume	6610.477	42125.000	4843.141
Hourly usage in the morning	Hourly average car travel volume between 7 and 10 am	volume	438.006	3061.000	342.378
Hourly usage in the daytime	Hourly average car travel volume between 11 am and 5 pm	volume	365.419	2568.000	280.267
Hourly usage in the evening	Hourly average car travel volume between 5 and 8 pm	volume	493.293	3040.000	358.843
Bus usage					
Daily usage	Daily bus travel volume	volume	928.057	31615.000	1993.112
Hourly usage in the morning	Hourly average bus travel volume between 7 and 10 am	volume	62.873	1445.000	119.629
Hourly usage in the daytime	Hourly average bus travel volume between 11 am and 5 pm	volume	53.047	1967.000	118.218
Hourly usage in the evening	Hourly average bus travel volume between 5 and 8 pm	volume	71.660	2852.000	163.673
Explanatory variables					
Number of confirmed cases	Three-day moving average of the day-by-day number of newly confirmed COVID-19 cases	hundred cases	1.188	8.250	1.803
Weekend	Weekends = 1, weekdays = 0	indicator	0.309	1.000	0.462
Land attributes					
Residential use	Ratio of residential areas in each cell	ratio	0.048	0.379	0.073
Commercial/office use	Ratio of commercial and office areas in each cell	ratio	0.037	0.407	0.055
Land price	Mean of land prices in each cell	million KRW	0.431	4.446	0.506
Transportation infrastructure					
Length of arterial roads	Length of arterial roads in each cell	km	2.683	10.027	2.006
Number of bus routes	Number of bus routes stopping in each cell	number	6.441	36.000	6.522
Sociodemographic attributes					
Population	Number of residents in each cell	person	3675.560	23273.000	5239.364
Employment	Number of employments in each cell	person	1208.391	24091.000	2331.516
Weather conditions					
Temperature: cold	Daily temperature less than 5 °C = 1, others = 0	indicator	0.221	1.000	0.415
Temperature: moderate	Daily temperature between 5 and 15 °C = 1, others = 0	indicator	0.745	1.000	0.436
Temperature: hot	Daily temperature more than 15 °C = 1, others = 0	indicator	0.034	1.000	0.180
Precipitation	Daily precipitation	mm	1.466	55.300	6.303

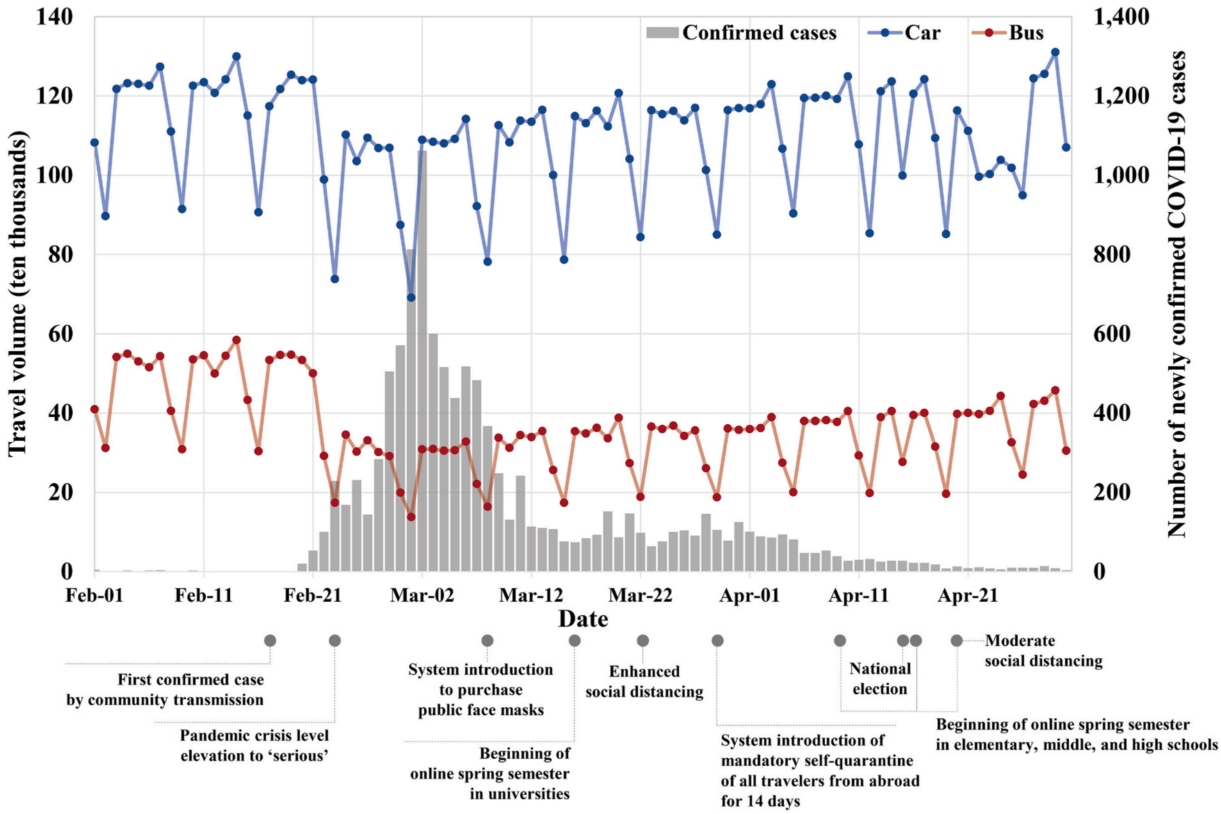


Fig. 4. Daily number of confirmed COVID-19 cases and changes in car and bus travel volumes during the study period.

Table 2
Changes in car usage by weekdays, weekends, and times of day.

Variable	All day						Morning			Daytime			Evening		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
Fixed effect															
Intercept	6.781	0.321	***	6.775	0.321	***	4.320	0.319	***	3.823	0.327	***	4.189	0.313	***
Number of confirmed cases	−0.020	0.001	***	−0.013	0.001	***	−0.007	0.001	***	−0.018	0.001	***	−0.006	0.001	***
Weekend	−0.265	0.003	***	−0.233	0.004	***	−0.818	0.006	***	0.126	0.004	***	−0.401	0.005	***
Length of arterial roads	0.065	0.029	*	0.065	0.029	*	0.054	0.028	*	0.069	0.029	*	0.065	0.028	*
Population	0.066	0.044		0.066	0.044		0.038	0.044		0.061	0.045		0.065	0.043	
Employment	0.147	0.058	*	0.147	0.058	*	0.167	0.058	**	0.142	0.060	*	0.152	0.057	**
Temperature: cold	0.008	0.003	*	−0.002	0.004		−0.008	0.005		0.009	0.004	*	−0.012	0.005	**
Temperature: hot	0.077	0.008	***	0.072	0.008	***	0.074	0.012	***	0.035	0.009	***	0.068	0.011	***
Precipitation	−0.002	0.000	***	−0.003	0.000	***	−0.002	0.000	***	−0.002	0.000	***	−0.003	0.000	***
Number of confirmed cases * Weekend				−0.027	0.002	***	−0.040	0.003	***	−0.019	0.002	***	−0.032	0.002	***
Random effect	Variance	Std. Dev.		Variance	Std. Dev.		Variance	Std. Dev.		Variance	Std. Dev.		Variance	Std. Dev.	
Cells	0.367	0.606		0.367	0.606		0.362	0.602		0.382	0.618		0.550	0.741	
Number of groups		167			167			167			167			167	
Number of observations		14,980			14,980			14,980			14,980			14,980	
R-squared		0.350			0.360			0.701			0.125			0.447	
Adj. R-squared		0.350			0.360			0.701			0.124			0.447	
Breusch-Pagan test		0.000 (chisq = 565,152)			0.000 (chisq = 565,153)			0.000 (chisq = 466,629)			0.000 (chisq = 556,904)			0.000 (chisq = 499,317)	

Notes: references for categorical variables (temperature: moderate, weekend: weekdays), statistical significance notation (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

obtained in all models for different times indicate that both car and bus trips decreased at all times of day during the pandemic. However, the magnitudes of these coefficients vary with the time of day. It is worth noting that, compared to the morning and evening, both car and bus usage significantly diminished during the daytime when non-mandatory trips such as leisure or shopping trips typically occur. The reductions in car and bus usage during the morning and evening hours are inferred to result from the governmental recommendation of 'flexible working'. However, their lower reductions may be due to people who needed to continue commuting during the pandemic.

The interaction term between the 'weekend' and 'number of confirmed cases' variables has negative coefficients in the models for

Table 3
Changes in bus usage by weekdays, weekends, and times of day.

Variable	All day						Morning			Daytime			Evening		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
Fixed effect															
Intercept	−0.281	0.130	*	−0.288	0.130	**	−1.395	0.104	***	−1.657	0.102	***	−1.930	0.108	***
Number of confirmed cases	−0.067	0.001	***	−0.059	0.001	***	−0.038	0.001	***	−0.056	0.001	***	−0.042	0.001	***
Weekend	−0.487	0.004	***	−0.451	0.005	***	−0.671	0.005	***	−0.194	0.004	***	−0.446	0.005	***
Number of bus routes	0.069	0.009	***	0.069	0.009	***	0.060	0.007	***	0.074	0.007	***	0.064	0.007	***
Population	0.604	0.042	***	0.604	0.042	***	0.482	0.033	***	0.546	0.032	***	0.487	0.034	***
Employment	0.191	0.040	***	0.191	0.040	***	0.144	0.032	***	0.040	0.031		0.205	0.033	***
Temperature: cold	0.035	0.005	***	0.024	0.005	***	0.037	0.005	***	0.057	0.004	***	0.058	0.004	***
Temperature: hot	0.117	0.011	***	0.112	0.011	***	0.069	0.011	***	0.064	0.008	***	0.079	0.010	***
Precipitation	−0.007	0.000	***	−0.007	0.000	***	−0.003	0.000	***	−0.006	0.000	***	−0.004	0.000	***
Number of confirmed cases * Weekend				−0.031	0.003	***	−0.022	0.002	***	−0.021	0.002	***	−0.018	0.002	***
Random effect	**Variance**	**Std. Dev.**		**Variance**	**Std. Dev.**		**Variance**	**Std. Dev.**		**Variance**	**Std. Dev.**		**Variance**	**Std. Dev.**	
Cells	0.801	0.895		0.801	0.895		0.514	0.717		0.490	0.700		0.550	0.741	
Number of groups		398			398			398			398			398	
Number of observations		35,007			35,007			35,007			35,007			35,007	
R-squared		0.353			0.356			0.473			0.271			0.353	
Adj. R-squared		0.353			0.356			0.472			0.271			0.352	
Breusch-Pagan test		0.000 (chisq = 1,039,441)			0.000 (chisq = 1,040,787)			0.000 (chisq = 954,354)			0.000 (chisq = 1,125,613)			0.000 (chisq = 1,033,129)	

Notes: reference for categorical variables (temperature: moderate, weekend: weekdays), statistical significance notation (***p < 0.01, **p < 0.05, *p < 0.1).

daily car and bus usage, indicating that travel volumes decreased more on weekends than on weekdays, unrelated to the type of transportation mode, as the number of confirmed cases increased. Compared to weekdays, the negative impacts of the pandemic increased by 2.7% for car usage and 3.1% for bus usage on weekends. The interaction term also has negative coefficients at all times of day (morning, daytime, and evening). However, the size of coefficients for car usage differs among the times of day, while its size for bus usage is similar at all times and ranges between −1.8 and –2.2%. The negative pandemic impacts on car usage increased by 4.0% in the morning and 3.2% in the evening on weekends—its impact increased only by 1.9% in the daytime. Interestingly, car trips increased more in the daytime on weekends than in the daytime on weekdays under normal conditions, but this increasing tendency gradually lessened as the number of confirmed cases increased.

The modeling outcomes indicate that people responded to the pandemic by reducing their trips for inessential purposes during the daytime or weekends while maintaining trips that directly affected their livelihood, such as commuting.

4.2.2. *Changes in car and bus usage by land use*

Table 4 shows changes in car and bus usage by land use types under

Table 4
Changes in car and bus usage by land use.

Variable	Car						Bus					
	Residential			Commercial/office			Residential			Commercial/office		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
Fixed effect												
Intercept	7.110	0.376	***	7.108	0.376	***	0.116	0.139		0.116	0.139	
Number of confirmed cases	−0.019	0.001	***	−0.017	0.001	***	−0.065	0.001	***	−0.066	0.001	***
Weekend	−0.265	0.003	***	−0.265	0.003	***	−0.487	0.004	***	−0.487	0.004	***
Residential use	−1.234	0.682	*	−1.253	0.682	*	1.726	0.892	*	1.682	0.892	*
Commercial/office use	3.108	1.054	***	3.165	1.054	***	6.511	1.264	***	6.554	1.264	***
Length of arterial roads	0.056	0.029	*	0.056	0.029	*						
Number of bus routes							0.043	0.009	***	0.043	0.009	***
Population	0.103	0.047	**	0.103	0.047	**	0.551	0.043	***	0.551	0.043	***
Employment	0.049	0.067		0.049	0.067		0.149	0.040	***	0.149	0.040	***
Temperature: cold	0.008	0.003	**	0.008	0.003	**	0.035	0.005	***	0.035	0.005	***
Temperature: hot	0.077	0.008	***	0.077	0.008	***	0.117	0.011	***	0.117	0.011	***
Precipitation	−0.002	0.000	***	−0.002	0.000	***	−0.007	0.000	***	−0.007	0.000	***
Number of confirmed cases * Residential use	−0.016	0.009	*				−0.037	0.015	**			
Number of confirmed cases * Commercial/office use				−0.048	0.012	***				−0.036	0.020	*
Random effect	**Variance**	**Std. Dev.**		**Variance**	**Std. Dev.**		**Variance**	**Std. Dev.**		**Variance**	**Std. Dev.**	
Cells	0.351	0.592		0.351	0.592		0.722	0.849		0.722	0.850	
Number of groups		167			167			398			398	
Number of observations		14,980			14,980			35,007			35,007	
R-squared		0.351			0.352			0.356			0.356	
Adj. R-squared		0.351			0.351			0.356			0.356	
Breusch-Pagan test		0.000 (chisq = 560,375)			0.000 (chisq = 560,458)			0.000 (chisq = 996,834)			0.000 (chisq = 996,805)	

Notes: reference for categorical variables (temperature: moderate, weekend: weekdays), statistical significance notation (***p < 0.01, **p < 0.05, *p < 0.1).

Table 5
Changes in car and bus usage by land price.

Variable	Car			Bus		
	Coef.	Std. Err.		Coef.	Std. Err.	
Fixed effect						
Intercept	7.556	0.423	***	0.278	0.148	*
Number of confirmed cases	−0.007	0.002	***	−0.056	0.002	***
Weekend	−0.264	0.006	***	−0.400	0.007	***
Residential use	−0.618	0.732		2.386	0.904	***
Commercial/office use	2.680	1.059	**	4.912	1.333	***
Land price	0.260	0.118	**	0.513	0.136	***
Length of arterial roads	0.047	0.029				
Number of bus routes				0.041	0.009	***
Population	0.081	0.047	*	0.511	0.044	***
Employment	−0.015	0.072		0.131	0.040	***
Temperature: cold	−0.002	0.004		0.024	0.005	***
Temperature: hot	0.072	0.008	***	0.112	0.011	***
Precipitation	−0.003	0.000	***	−0.007	0.000	***
Land price * Weekend	0.039	0.007	***	−0.120	0.010	***
Number of confirmed cases * Weekend	−0.023	0.003	***	−0.024	0.003	***
Number of confirmed cases * Land price	−0.007	0.002	***	−0.007	0.003	**
Number of confirmed cases * Land price * Weekend	−0.005	0.003	*	−0.016	0.005	**
Random effect	**Variance**	**Std. Dev.**		**Variance**	**Std. Dev.**	
Cells	0.343		0.585	0.704		0.839
Number of groups			167			398
Number of observations			14,980			35,007
R-squared			0.364			0.365
Adj. R-squared			0.364			0.365
Breusch-Pagan test			0.000 (chisq = 559,610)			0.000 (chisq = 990,914)

Notes: reference for categorical variables (temperature: moderate, weekend: weekdays), statistical significance notation (***p < 0.01, **p < 0.05, *p < 0.1).

the pandemic. We tested the changes for primary land use types: residential use and commercial/office use, which are the most common land use types in urban regions.

The positive coefficients of the 'commercial/office use' variable show that, under normal conditions, both car and bus usage increase more in areas with higher commercial/office use densities. On the other hand, the coefficients of the 'residential use' variable are negative in the model for car usage and positive in the model for bus usage, indicating fewer car trips and more bus trips in denser residential areas.

To understand the role of land use in the impacts of COVID-19, we focused on the interaction terms between the 'number of confirmed cases' and the variables of land use. All coefficients of the interaction terms are negative, showing greater reductions in car and bus trips around residential and commercial/office areas under the pandemic. The different size of coefficients indicates the different impacts of COVID-19 by land use types and transportation modes. Car usage fell even more in neighborhoods with higher densities of commercial facilities and offices than in neighborhoods with higher residential densities amid the pandemic. The negative impacts of COVID-19 on car usage increased as much as 4.8% per unit increase in the 'commercial/office use' variable and only 1.6% for the same unit increase in the 'residential use' variable. Unlike car usage, the negative impacts of COVID-19 on bus usage similarly grew for both land use types, with an increase of 3.7% for 'residential use' and 3.6% for 'commercial/office use'. One rationale behind the large decrease in travel volumes observed in neighborhoods with offices under the pandemic conditions may be the diffusion of 'flexible working' by the government recommendation for infection prevention.

An interesting finding is the difference between the usage behavior of cars and buses. To avoid being infected with the COVID-19 virus, people reduced their bus trips regardless of land use types. People also reduced their car trips, but they reduced more car trips toward commercial/office areas where, as well as commuting trips, many non-mandatory trips for maintenance and discretionary activities, such as meeting friends, shopping, going to the gym, and eating out, typically occur. This finding implies that people avoided crowded or shared spaces due to the fear of being infected.

4.2.3. Changes in car and bus usage by land price

The involvement of land price in the COVID-19 impacts was evaluated in the models including the interaction terms among the variables of 'number of confirmed cases', 'land price', and 'weekend'. The inclusion of the 'land price' variable allows an investigation of how the usage behavior of cars and buses differs due to economic status since the local land price is positively connected to the economic statuses of residents, as mentioned in the introduction (Davidoff, 2006; Määttänen and Terviö, 2014; McQuinn and O'Reilly, 2008; Mirkatouli et al., 2018).

The modeling outcomes are summarized in Table 5. The 'land price' variable has positive coefficients for both car and bus usage, showing a growing trend of car and bus usage with land price increases under normal conditions. These estimates indicate that people living in higher-priced areas tend to use cars and public transit more than people living in lower-priced areas. That is, this intimates that people with wealthier statuses are more active than others.

The interaction term between the 'number of confirmed cases' and 'land price' has negative coefficients in the models for both car and bus usage. This shows that people living in neighborhoods with higher land prices diminished their car and bus trips more as the number of confirmed COVID-19 cases increased. The negative impacts of COVID-19 on both car and bus usage grew as much as 0.7% per unit increase of the 'land price' variable. Meanwhile, the estimated coefficients of the interaction term between the 'land price' and 'weekend' show that, under normal conditions, people living in wealthier neighborhoods drive their private cars more and take buses less on weekends versus on weekdays. This result is believed to be close to reality, given that wealthier people have more affordability of purchasing and maintaining cars. The interaction terms among the 'number of confirmed cases', 'land price', and 'weekend' have negative coefficients in all models for car and bus usage. This result means that the growing tendency of car usage by land price increase gradually weakened, and the diminishing tendency of bus usage by land price increase became reinforced as the number of confirmed cases rose. Notably, the coefficient size for the corresponding interaction term differs in the car and bus models. The negative impact of COVID-19 on bus usage rose by 1.6% per unit increase in the 'land price' variable, but its impact on car usage was an increase of only 0.5%. People living in higher-priced areas had a tendency to reduce their trips more than people living in lower-priced areas; moreover, the former group reduced bus trips much more than car trips on weekends.

The results of the land price models show the social disparities in travel for the daily lives between people with different economic statuses under normal and pandemic conditions. The findings indicate uneven travel options between groups with different economic statuses, which manifested itself more apparently under the pandemic. People with wealthier economic statuses were more likely to reduce their trips or take their private cars instead of buses during the pandemic.

5. Discussion

The spread of COVID-19 pandemic induced a significant decrease in travel volumes in the city as the pandemic made people use cars and buses less. The decreasing rate was much higher for bus usage than for car usage, and moreover, the resilience level when the pandemic condition was relatively stabilized was lower for bus usage than for car usage. This phenomenon indicates people's reluctance to take buses in which they must share spaces with strangers. Given that the Korean government implemented noncoercive measures to impede the spread of COVID-19, the significant fall in travel volumes is believed to be a result of the combination of the voluntary participation of companies in working from home and the travel abandonment due to the people's perceived risk of being infected with the COVID-19 virus. The different COVID-19 impacts over time indirectly confirm the existence of the fear of infection. Car and bus usage remarkably diminished during the daytime when non-mandatory trips mainly occur. Moreover, the spread of COVID-19 led to a greater diminution in travel volumes on weekends than on weekdays. These findings imply that people responded to the pandemic by traveling less for inessential activities for livelihood.

People reduced their car trips to commercial/office areas more than they made car trips to residential areas. In contrast, they reduced bus trips toward both commercial/office areas and residential areas by similar amounts. One of the reasons for a significant decrease in travel volumes around commercial/office areas may be due to people working from home, according to the recommendation of the Korean government. However, the similar decreases in bus trips regardless of land use types are additional evidence that people felt threatened by strangers in crowded or shared spaces due to the pandemic. The metropolitan cities in South Korea, including Daejeon (the study site in this study), have been built at a very high-density level and have mixed-use structures and many tower blocks. Numerous metropolitan citizens in Korea live and spend lots of time in dense, crowded neighborhoods, and therefore, they may have felt more threatened by staying in shared spaces such as buses and commercial/office areas during the pandemic.

Furthermore, people living in wealthier areas reduced their bus trips more under the pandemic, especially on weekends. Car trips were also reduced in wealthier areas, but its reduction rate was less than that of bus trips. Namely, people with lower economic statuses decreased their trips less, bus trips in particular, than others during the pandemic. This finding shows the social disparities in the availabilities of transportation mode change and travel abandonment between people with different economic statuses under pandemic conditions. A simple reason for such uneven decreases in car and bus trips by economic status may be the lower abilities of people with lower economic statuses to buy or maintain private cars. Thus, these people are less likely to shift their transportation mode from public transit to private cars. One rationale for the more significant decrease in wealthier areas amid the pandemic may be the governmental recommendation of 'flexible working'. As mentioned above, R&D workers at many public institutions and private research centers live in Daejeon, and their economic statuses are relatively higher than those of other people. With the governmental recommendation of 'flexible working', most public institution employees, as well as some private research center employees, began working from home when the pandemic became severe.

On the one hand, the finding connects to the idea that people living in wealthier areas traveled less so than other people to protect themselves from the COVID-19 virus. A possible example is related to accessibility to home-delivery services—South Korea has a great delivery service system, and its market has rapidly grown under the COVID-19 pandemic. Wealthier people are more likely to have greater access to online shopping or home-delivery services via e-commerce (Figliozzi and Unnikrishnan, 2021; Sanchez-Diaz et al., 2021). From the geographical perspective, higher-priced areas have more diverse options for home-delivery services from retail stores such as cafes, restaurants, and grocery stores than other areas by virtue of denser, better neighborhoods with various living facilities. Economically, the costly home-delivery charges can be a barrier that makes people with lower economic statuses unable to enjoy the benefits of the services. For these reasons, travel demands may have disproportionately decreased by economic statuses during the pandemic, and thereby, the risk of viral exposure may have been greater in people with lower economic statuses when the pandemics worsened (Baena-Díez et al., 2020; Demenech et al., 2020).

6. Conclusion

This study appraised the impacts of COVID-19 on car and bus usage and their relationship with land use and land price using large-scale trip data in Daejeon Metropolitan City, South Korea. We made a trip-chain-level data set from the individual-level trip data to analyze travel behavior using activity-based travel volumes. We defined the hexagonal cells with 500 m edges as an areal unit for analysis and, at the cell level, captured the geographical explanatory variables in the categories of land attributes, transportation attributes, and sociodemographic attributes. Daily weather conditions were also included in the explanatory variable group to control natural environmental impacts. We applied the mixed-effect regression modeling to determine the COVID-19 impacts by considering the nature of longitudinal data. The modeling outcomes demonstrated decreases in car and bus usage and people's behavioral differences in using them during the pandemic. The key findings are summarized as follows: i) people traveled less due to the pandemic and avoided taking collective modes of transportation (public transit) in particular; ii) all travel volumes using cars and buses diminished more in the daytime and on weekends than other times; iii) reduction of car trips was greater in areas in which commercial facilities and offices are intensively located, while reduction amount of bus trips was similar in all areas; and iv) people living in wealthier neighborhoods reduced their trips more, especially trips by taking buses, than others.

The finding from the social equity aspect, in which people with lower economic statuses are more likely to use public transit under pandemics, is meaningful in that it suggests to policymakers a reason to contemplate sustainable policies for public transit. Although shutting down public transit services may be the safest way to halt the pandemic spread, the government should endeavor to provide reliable and safe public transit services, given that public transit is an important transportation mode to ensure people's mobility and livelihood amid pandemics. One of the reasonable policies is to reinforce pandemic prevention measures for public transit. Measures such as shortening the dispatch interval and limiting the number of passengers on board can help people maintain safe distances. Such measures can be effective on routes passing through commercial or office areas during peak hours. Secondly, we can consider introducing a flexible public transit system, such as demand-responsive transit with no fixed times or routes, as an alternative to the general transit system. The operation of a flexible transit system may shrink operating deficits caused by reduced demands during pandemics and ensure much safer environments by providing passenger-customized services. We can try to design a prototype of a demand-responsive transit system by utilizing mobility data during the COVID-19 pandemic, such as the data used in this study. This will be one of our next research topics.

This study is worthy as it represents the first attempt to compare changes and differences in using private cars and public transit during the COVID-19 pandemic using micro-level mobility data. We provide statistical evidence to improve the understanding of the different usage behaviors of cars and buses by time, land use, and land price amid the pandemic. The findings in this study extend the result reported in the previous literature that covered public transit only by adding a fundamental reference of the pandemic impacts on two universal transportation modes in people's daily lives.

Despite the outstanding findings revealed in this study, the challenge of discovering the impacts of COVID-19 on travel behavior still remains. With the mobility data used in this study, we can investigate changes in travel patterns by tracking individual travelers. For example, it would be possible to analyze how travelers have changed their trip frequencies, trip distances, and trip intervals during the pandemic at different time scales. Such an analysis including geographical factors—such as land use and land price—can provide additional information on the impacts of COVID-19. Further studies will give a chance to suggest specific and differentiated transportation strategies for different regions.

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CRediT authorship contribution statement

Suji Kim: Conceptualization, Formal analysis, Visualization, Writing – original draft. **Sujin Lee**: Conceptualization, Data curation. **Eunjeong Ko**: Conceptualization, Data curation. **Kitae Jang**: Conceptualization, Funding acquisition. **Jiho Yeo**: Writing – review & editing, Supervision.

Declaration of Competing Interest

None.

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