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MOBILITY RESILIENCE OF COMMUTE TRIPS DURING THE COVID-19 PANDEMIC IN SEOUL, KOREA

X. Li[1], J. Ha[2], S. Lee[3,*]

[1]Dept. of Urban Planning and Engineering, Hanyang University, Seoul, Korea (lixuan@hanyang.ac.kr)
[2]Price School of Public Policy, University of Southern California, CA, U.S. (jaehyunh@usc.edu)
[3]Dept. of Urban Planning and Engineering, Hanyang University, Seoul, Korea (sugielee@hanyang.ac.kr)

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ABSTRACT:
Since early 2020, the number of COVID-19 cases has continued its rise and fall worldwide, greatly impacting sectors such as health outcomes, economics, housing, and transportation. To mitigate the spread of the pandemic, governments implemented various measures to reduce the mobility of the population, restricting international travel, hierarchical lockdowns, stay-at-home mandates, and work-from-home orders. In this aspect, early studies in the transportation field showed large changes in travel behaviour. However, we know less about the long-term impact of COVID-19 on people's travel behaviour. This paper explores the change in commute behaviour during the pandemic, focusing on the resilience index of transit users and its determining factors. The hist gradient boosting model was the most precise when compared with linear and other machine learning models (considering R^2, MSE, MAE). The results suggested the following: (1) commuters' trips decreased unevenly in Seoul. Through machine learning algorithms, social-economic factors, and accessibility, 50% of the heterogeneity can be explained. (2) Consumer and Service Industry and Foreigner Tourism were impacted negatively continually. Neighbourhoods with higher car ownership and a higher percentage of female residents show long term weak public transit resilience. (2) Short distance commuters (less than 20 minutes) and commuters visiting city centres, returned to public transport in the second year after avoiding it during the first year of the pandemic. Considering the uneven negative results of COVID-19, this research can be a reference for policy design and effective decision making.

1. INTRODUCTION

It has been more than two years since the first coronavirus disease 2019 (COVID-19) outbreak in December 2019. COVID-19 has been one of the crucial issues in the public domain. Viruses like SARS-CoV-2 are continuously evolving as changes in the genetic code (genetic mutations) occur, resulting in an increased proportion of cases or unique outbreak clusters (CDC, 2020). Countries including Korea and Germany are experiencing a large increase in confirmed cases as of 2022.

Human mobility plays an essential role in the fluctuating number of new positive cases. The spread of COVID-19 and human mobility has a complicated causality. Close contact generated from travel is regarded as an essential factor in the spread of the virus (Linka, Goriely & Kuhl 2021). On the other hand, it is known that the pandemic reduced the ridership worldwide because of policies including social distancing, curfews and travel restrictions. This means people went out or visited other places less frequently than before, even though these impacts are heterogeneous in different geo-sectors and social groups (Mack, Agrawal & Wang 2021; Nouvellet et al. 2021).

In terms of the mobility change during the pandemic, not only did the ridership decrease because of the pandemic, but also various features used to describe the mobility pattern vary from the pre-epidemic world, including the frequency, range, and centrality. Some research proved that average travel distance also plummeted in COVID-19, meaning long-distance travel was reduced more than shorter trips (De Haas, Faber, & Hamersma, 2020). Since city centres, with their high job and active population density, are the "most urban of urban locations", these dense locations may see the largest impact (Rosenthal, Strange & Urrego 2022).

* Corresponding author

Overall, life with masks and social distancing has already lasted for more than two years. Existing knowledge shows that planners and policy makers can take transformative steps toward creating more just and resilient cities through understanding COVID-19. We are still interested in the lasting influence of the pandemic. By examining the case of Seoul, we aim to find some hints about how the features of location, employment, and residence caused uneven public transit resilience during the pandemic.

To address the aims, we built the OD network based on the latest public transit data in the morning peak from 2020 to 2022. We found that the changing ridership of OD pairs is heterogeneous. This research interpreted the uneven mobility change considering the multidimensional data covering three types of characteristics (location and connection, employment, and housing) to describe the change in mobility. Based on the ridership in the past, we fit the linear model, which reveals some significant factors. Because of the complexity of the urban system, the linear model cannot make a sophisticated correlation between the driving factors. We will use the machine learning model to detect how the elements performed.

Our results indicate that for the citizens, the industries they work for, the distance to the job place, and the assets they have caused unequal levels of privilege to avoid higher transmission risks from crowded public transit to a certain degree.

2. LITERATURE REVIEW

2.1 Smart card and OD flow

Since the technology of data collection has matured, big fine-grained geolocated data, including traffic cards-, mobile phone cellular-, sharing bike usage- and social media data, have been widely used to detect human mobility patterns and infer potential demand (Roth, Kang, Batty & Barthélemy 2011; Louail et al.

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2015; Yang et al. 2016; Hasan, Zhan & Ukkusuri 2013; Puura, Silm & Masso 2022). The OD flows extracted from the smart card data were used to interpret travel patterns-, urban spatial structures-, job-housing balances-, and inequality in cities (Alsger, Tavassoli, Mesbah, Ferreira & Hickman 2018; Gao et al. 2018; Huang, Levinson, Wang, Zhou & Wang 2018; Kieu, Bhaskar & Chung 2014).

Although daily home-to-work trips make up only a portion of traffic, there are several sound reasons why these trips are important to focus on. Shopping and social trips are much less likely to be regular and consistent, while commute trips are likely to be repeated every day. Also, as Shurmur (2006) points out, the travels between work and home often serves to structure other trips made during the day. In addition, it is important to understand the mobility resilience in terms of the commuting behaviour because it reflects the unique significant impact of the pandemic: work from home (Barrero, Bloom & Davis 2021; de Haas, Faber & Hamersma 2020).

2.2 Global impact on mobility following the prevalence of COVID-19

The previous study concluded that COVID-19 impacts cities on multiple dimensions, including the volume and distance to the centrality. Some research shows mobility drops strongly associated with active populations, workers employed in sectors highly affected by lockdown, low-income nationhood, and number of hospitalisations per region, and moderately associated with the socio-economic level of the regions (Cartenì, Di Francesco & Martino 2020; Jay et al. 2020; Pullano, Valdano, Scarpa, Rubrichi & Colizza 2020). The COVID-19 pandemic significantly altered the mode of transport choices, shifting bus users towards private modes, both motorised and non-motorised (Scorrano & Danielis 2021). In terms of the city scale, the latest research indicated decentralisation (Rosenthal et al. 2022; Liu & Su 2021). Nevertheless, with the popularisation of the vaccine and the need to return to normal life, mobility has been recovering to some degree as the pandemic stretches on.

In terms of the pandemic's impact on mobility in the Seoul Metropolitan Area, there are some analyses that defined the COVID-19 wave and discussed how the socio-demographic factors caused the variance. The increased risk perception reduces public transit use (Kim, Lee, & Gim, 2021). The report from Seoul Transport Operation & Information Service (TOPIS) indicates that the use of public transportation decreased by 27% in 2021 and stabilized until the beginning of 2022 at 80% of the 2020 level. The human mobility change varied according to the travel distance, employee density and land use proportion in SMA (Seoul Metropolitan Area) (Eom, Jang & Ji 2022). Overall, existing knowledge from the previous studies revealed the closeness of social and mobility behaviour, which demonstrates the opportunity that the COVID-19 crisis entails for city planners and policymakers to take transformative actions to build a just and resilience city.

2.3 Machine learning methods for revealing nonlinearity and synergism

Progress in machine learning and interpretation methods makes it possible to capture better complex correlations between the built environment, social-economic factors and human activities (Nguyen, Coelho, Bastos & Krishnan 2021; Toch, Lerner, Ben-Zion & Ben-Gal 2019). Machine learning models can model interaction (synergistic) effects among independent variables; for example, in tree-based models, independent variables are hierarchically processed in a decision tree. Previous studies frequently use global methods such as permutation importance and partial dependence plot. Such methods summarise the contribution of input variables to overall predictions. By contrast, methods like SHAP provide local explanations for individual predictions (Lundberg & Lee 2017).

2.4 Research gap

It can be seen from the above review that compared to large Western cities; Seoul is understudied. Because of the different policies, there were never strict lockdowns at the city level in Korea. Thus, the change in mobility patterns shows variance when compared with Western- and Chinese metropolises. Existing mobility research on Seoul city was written in the early phase of the pandemic, which described the shock experienced from the epidemic, but did not touch on the recovery and long-term effects. We endeavour to fill the gap with a comprehensive mobility examination. We are curious about the special response under the unique work culture context, social distancing-, and curfew policy.

3. METHODOLOGY

3.1 Study area

Seoul, a big metropolis in East Asia that hosts nearly 10 million people, has 424 sub-administrative areas (referred to as "Dongs"), the average size of which is about 1.4 km^2. According to Seoul statistics, public transit is responsible for 65% of the average daily traffic of 32 million trips in the city – 40% corresponds to the metro system and 25% to the bus system (Urban Traffic Office 2022). To operate and manage the congestion level to control the physical distance between passengers and reduce the risk of an outbreak, some metro lines with high congestion levels had additional trains during rush hours.

3.2 Data source

3.2.1 Smart card data

The smart card data in this research was acquired from the smart card data platform. The data was generated by all the smart card users using the T-money cards or credit cards. The mobility data, which were aggregated by their corresponding smallest geographical units, administrative Dong, showed the number of passengers between and inside of each unit in 15-minute time intervals. In addition, they provided the average travel time from the departure point to the destination for each OD pair.

We will set the average travel time as the temporal distance between each OD pair to indicate accessibility. Because of the limited amount of data that we can request from the API, we chose one week in each year (2020, 2021, and 2022) to compare the changing patterns during the pandemic. The time range set in our research was marked by red bars in Figure 1.

3.2.2 Census data and POI data

In light of the literature review and local data availability, we endeavour to examine the relationship between patterns of human mobility change and socio-demographic factors. Socio-demographic data includes the employee density by industry, household information and car ownership. All of them were aggregated into the same geo unit level with the public transit data. The dataset is an open dataset which can be downloaded from Seoul Open Data Plaza.

To fill some important components related to morning peak trips which are not included in the census, we used POI data to indicate

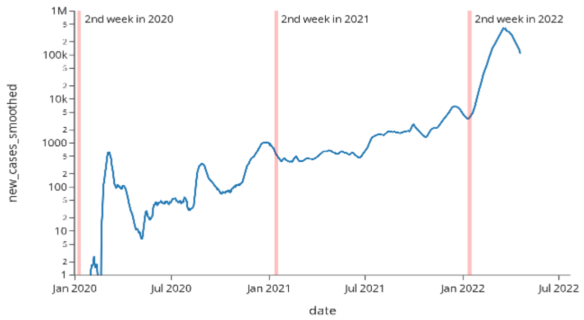


Figure 1. Daily new positive COVID-19 cases and study timee range

the transit facilities and the important destination for morning peak trips. We derived it from the POI Application Programming Interface (API) offered by one of the most popular map service companies, Kakao Map (like Google Maps) in Korea. The data are based on updated information in 2019.

3.3 OD network and Resilience index

To analyse the resilience of each specific OD flow, we built a directed network by OD matrix. The node is the set of geo units (Dong), and the edge is the trips between the origin and the destination, which is weighted by the average daily ridership. We assume that the passengers flow in the morning peak is commute flow. Thus, the origins of the network are the residence places, and the destinations are workplaces. To evaluate the dynamic change pattern of the public transit usage, we built the resilience index to indicate the degree of the impact of COVID-19 on the public transit.

Resilience is a classic economic and ecology concept. Regional economic resilience is the ability of a regional or local economy to resist, recover, and restructure in the face of the market, competitive, and environmental shocks to its development and growth path (Martin and Sunley, 2015). Similarly, population mobility can be resilient to external shocks, with reference to Giannakis and Bruggeman (2020). To indicate the significance of OD pairs with higher ridership, the Resilience Index was weighted by the natural logarithm of average daily ridership for each OD pair (Schläpfer et al., 2021).

In addition, in the later phase of Covid, the government stopped announcing the specific outbreak locations of COVID-19 viruses. Thus, we can assume that people living in the whole of Seoul city faced similar fears of COVID-19, which can be a controlled variable of the resilience index.

This study derived the following formula for a local mobility resilience index:

$$RES_{it} = \frac{(T_t^L - T_0^L)/T_0^L - (T_t^C - T_0^C)/T_0^C}{|(T_t^C - T_0^C)/T_0^C|} \times ln(T_0^L) \quad (1)$$

Where:

T^L = the average daily passengers travelling between OD pair i

T^C = the total average daily passengers travelling in Seoul city

t = the subsequent year (we used 2021 and 2022)

The resilience index was weighted by the intensity of ridership *($ln(T_0^L)$).*

A positive local mobility index indicates that the OD Pair is more resilient than the urban average or recovered faster than the average; that is, it was more resilient than the urban average.

3.4 Independent Variable

Based on theories about job-house relationship and commute behaviour (Blumenberg & Siddiq 2022), we assume that the Resilience index is a function of three types of characteristics—location, employment, and housing. The models take the following basic form:

$$RES = f(E, H, L)$$

Where:

E denotes a vector of employment characteristics (percentage of employees in different industries in the tract, density of other potential destinations like university)

H denotes a vector of housing characteristics (percentage of female residents and foreigners, car ownership level and total Residence Density)

L denotes a vector of locational characteristics (travel time to a destination, difference between the eigenvector centrality of the destination and the origin for an OD pair, the density of public transit facilities including the buses and subways).

In general, the average income or house price of the place of residence is considered as the economic level of the commuter, but these two factors have strong multicollinearity (positive correlation) with the existing variables of employment-occupancy ratio and car ownership, so we had to remove the redundant variables to ensure the stability of the model. All the examining indicators of these models are listed in **Appendix Table 1.**

3.5 Machine learning regression model and its interpretation based on cooperative game theory

To search for the best model which can predict the resilience index more accurately according to our variables, we tested the Linear Regression, Random Forest, XGBoost, Gradient Boosting and Hist Gradient Boosting Regressor by basic parameters setting. Because of the complexity of our data, machine learning model algorithms fit better than the linear model according to R^2, which proved that the potential driving factors have non-linear relationships with the local resilience index.

In terms of machine learning algorithms, the gradient boosting decision tree strategically assembles several weak decision trees into a strong model. The Overall objective is to minimise the expected value of loss function. Loss function measures the deviation between the predicted value and ground truth value. The most frequently used loss function is the mean squared error (MSE), which measures the average squared differences between predicted and ground truth values. Specifically, the gradient boosting process sequentially incorporates new trees to correct the error produced by the previous trees.

Among all the models we tested, the best model, Hist Gradient Boosting Regressor, is inspired by gradient boosting over decision trees, which is based on an advanced base learner,

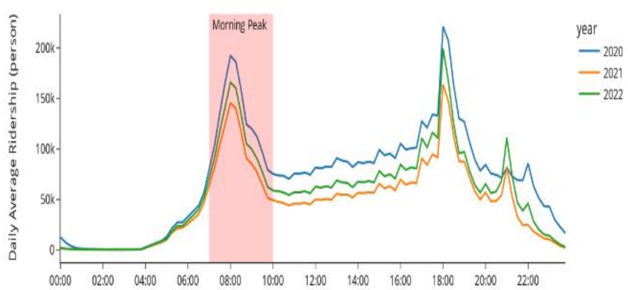
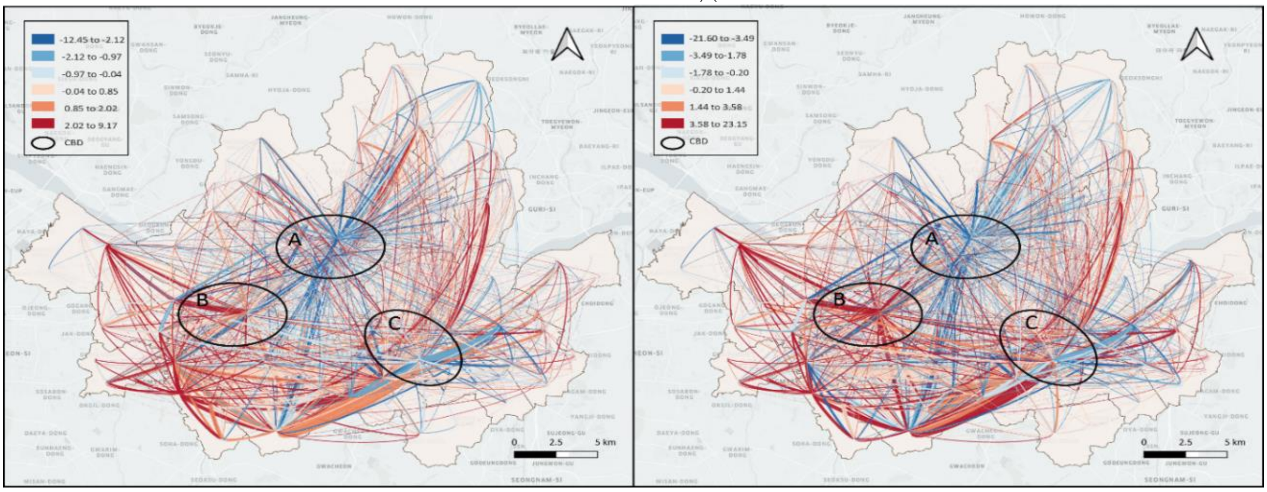


Figure 2. Temporal Fluctuating of ridership

(a) Resilience Index of 2020-2021 (b) Resilience Index calculated of 2020-2022



CBD-A: Jung-gu; CBD-B: Yeongdeungpo-gu; CBD-C: Gangnam-gu

Figure 3. Resilience Index of OD flow

piecewise linear tree, with linear functions as predictions in leaves (Guryanov 2019). It shows better quality with a decrease in inference time and higher accuracy on our dataset. SHAP values (SHapley Additive exPlanations) is a method based on cooperative game theory and used to increase the transparency and interpretability of machine learning models (Lundberg and Lee, 2017), which was used to interpret the contribution of the factors to the resilience index in our research.

4. ANALYSIS RESULTS

4.1 Description analysis

To mine the effect from COVID-19 on the commute behaviour, we observed the ridership curve in a day. With Cross-corroboration of the previous literature in Seoul (Ha, Lee & Ko 2020), we define the morning peak as 7:00 -10:00 in this research. Figure 2 shows the temporally fluctuating ridership on weekdays. As with most cities in the world, the fluctuation demonstrated the apparent commute peak in the morning (7:00 -10:00) and the evening (17:00-19:00) respectfully. In addition, the general changing pattern in 2020, 2021 and 2022 fits with the statistics shown by coarse-grained traffic flow data: The ridership in 2022 was higher than in 2021, which indicated the recovery pattern. The ridership in 2021 decreased by almost 30% compared with 2020; in 2022, it recovered to around 80% of the pre-pandemic level seen in 2020 (Urban Traffic Office 2022). It is worth mentioning that the last peak in the evening occurred earlier than pre-pandemic (blue line) because of the curfew policy (changed from 22:00 to 21:00).

Based on the understanding of the general trend, we extracted the trips generated from the morning peak (7:00 -10:00) to evaluate the resilience of each OD pair. The spatial distribution of resilience for each OD pair is demonstrated in Figure 3. Map (a) is the resilience index compared to ridership between 2020 and 2021; Map (b) is the resilience index compared to ridership between 2020 and 2022. Red means the positive resilience value. OD pairs with red colour had less reduction than the city average level. Blue means the negative resilience value. OD pairs coloured with blue had less reduction than the city average level. In addition, stroke width is weighted by the intensity of ridership in the previous year (2020). In terms of the spatial distribution, OD pairs with a negative resilience index were concentrated around one of the city centres (Jung-gu). In general, the positive resilience in the first phase (2020-2021) indicates the ability of resistance, and the positive resilience in the whole phase (2020-2022) means the ability to recover from the damage. The cold (blue) middle region (Jung-gu) is observed in both phases, which indicated Jung-gu experienced slight decentralisation. According to this, we assumed that the special industries in Jung-gu (CBD-A) might cause this difference when compared with the other two job centres, Yeongdeungpo-gu (CBD-B) and Gangnam (CBD-C). In terms of the recovery phase (2020-2021), one of the city centres, Yongdeongpu-gu, shows stronger resilience. Since we are interested in the commuting behaviour, the data during the morning peak hour (from 7:00-10:00) were extracted to make the mobility resilience index as mentioned in 3.3. According to the law of large numbers (LLN), when we regard each trip as the random event of testing the job-house relationship, it tends to come closer to the expected value as more trials are performed (Hsu & Robbins 1947). The change of OD pairs with a small number of passengers is not statistically and economically significant. Therefore, we only included the OD pair (5105 OD Pairs), which had more than 50 people at the average level before the pandemic and accounts for 71% of passengers in Seoul city.

4.2 Machine learning modelling and evaluation

By testing the data on the linear model, XGBoost, Random Forest, and Gradient Boosting Regressor with basic parameters, the Gradient Boosting Regressor shows the best accuracy of the regression (see in **Appendix Table 2.**). We chose a gradient boosting model and optimised the hyper-parameters through the grid research method. The Hyper-parameters are shown in the **Appendix Table 3.**, with the driving factors on 4.3 as inputs and the composite resilience indexes from 2020-2021 and 2020-2022 as output. The model performances are presented in Table 1.

Dependent variables	Train data			Test data		
	R^2	MSE	MAE	R^2	MSE	MAE
2020-2021_RES	0.571	2.313	1.188	0.533	2.555	1.255
2020-2022_RES	0.488	9.022	2.324	0.472	9.264	2.387

Table 1. Model performances.

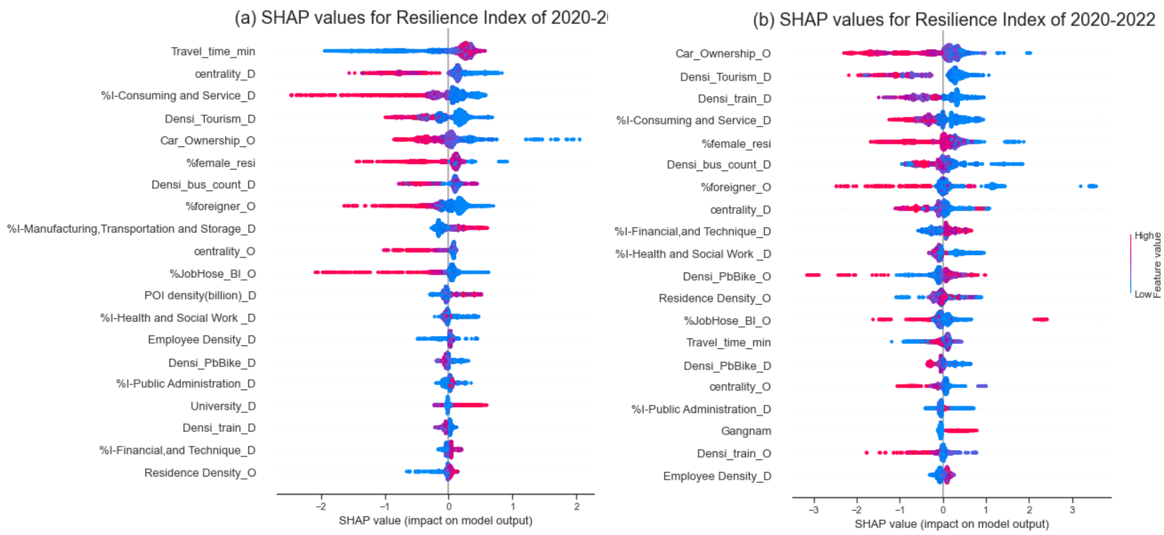


Figure 4. Relative importance of independent variables and local explanations.

4.3 Relative importance and SHAP value of determining factors

The machine learning algorithm is able to identify the irrelevant variables and others affecting the results.

Figure 4 visualises the relative importance of determining factors and how the variable values of each OD Pair contribute to resilience. The top 20 important variables are sorted in descending order by their global importance, while the left section (a) depicts important variables for Resilience Index of 2020-2021; the right section (b) depicts important variables for Resilience Index of 2020-2022. SHAP vale plot is an aggregation of scatters. Each scatter displays the local reaction between the independent variables (determine factors) and dependent variables (resilience index). The color of the scatters displays the feature value (dependent variable). Red means the scatter represents an analysis unit that has a high value. In our case, a red scatter means the OD pair has a high value of resilience index. In contrast, blue means low feature value. The position of the scatter on the horizontal axis represents the value of the independent variable corresponding to this one unit of analysis. Therefore, we can conclude how the independent variable affects the feature value from SHAP value plot.

Basically, we consider variables with red scatters on the right-hand side as those that contribute positively to the resilience index (higher independent value corresponds to higher resilience value), and conversely, variables with blue on the right-hand side as negative variables (higher independent value corresponds to lower resilience value). As "positive" factors, OD pairs with high travel time, high percentage of employees in Manufacturing, Transportation and Storage sectors, and arriving destination with high POI density are related to a higher Resilience Index of 2020-2021; other factors are mostly "negative".

Comparing these two subplots, we can understand which are the short-term and which are the long-term factors of the resilience index. According to the feature importance, we take the factors that have high importance in the two graphs for long-term effectors; on the other hand, the variables that are only significant in the 2020-2021 phase are short-term factors.

The effect caused by the later ones on the resilience indicator didn't continue if we look at the change comparing 2022 with 2020. For instance, the top negative factor on graph (a) of Figure 4, Travel_time_min, falls to 14^{th}, which means the effect from the temporal distance is only important in the first period of the pandemic. %I-Manufacturing, Transportation and Storage is another short-term factor.

In contrast, the Car ownership kept affecting the resilience index in 2021 and 2022, which is a potentially remarkable factor. Similarly, the %I-Consumer and Service_D and Densi_Tourism_D are sustained negative factors. Both are related to the economic recession caused by the necessary social policy and restrictions on international travel. In addition, the centrality of the destination during the pandemic is also a negative factor in public transit resilience.

4.4 Non-linear relationship

Previous studies use partial dependence plots to reveal the global impacts of a certain independent variable on the dependent variable after controlling for other independent variables. It is important to know whether the value of an independent variable has a constant effect or whether the effect varies depending on different combinations with values of other independent variables. However, traditional methods (like OLS or geographic weighted regression) cannot depict such variability of effect across all data samples. This study uses local dependence plots to reveal both global and local patterns of influences of potential determining variables. As Figure 5 presents, each local dependence plot corresponds to an independent variable, showing how the variable changes the resilience of each OD pair.

The position on the x-axis represents the variable value, and the position on the y-axis represents the local effect. Plots for travel time and metro frequency both reveal upward trends. In 2020-2021, the routes that take more than 30 minutes revealed the strong positive effects on resilience, which means these passengers relied on public transit more than people who don't need to travel long distances. This result corresponds with the classic demand elastic theory; elasticity is consistently higher for short-distance trips than long-distance trips because they have more choices than public transit. When the percentage of

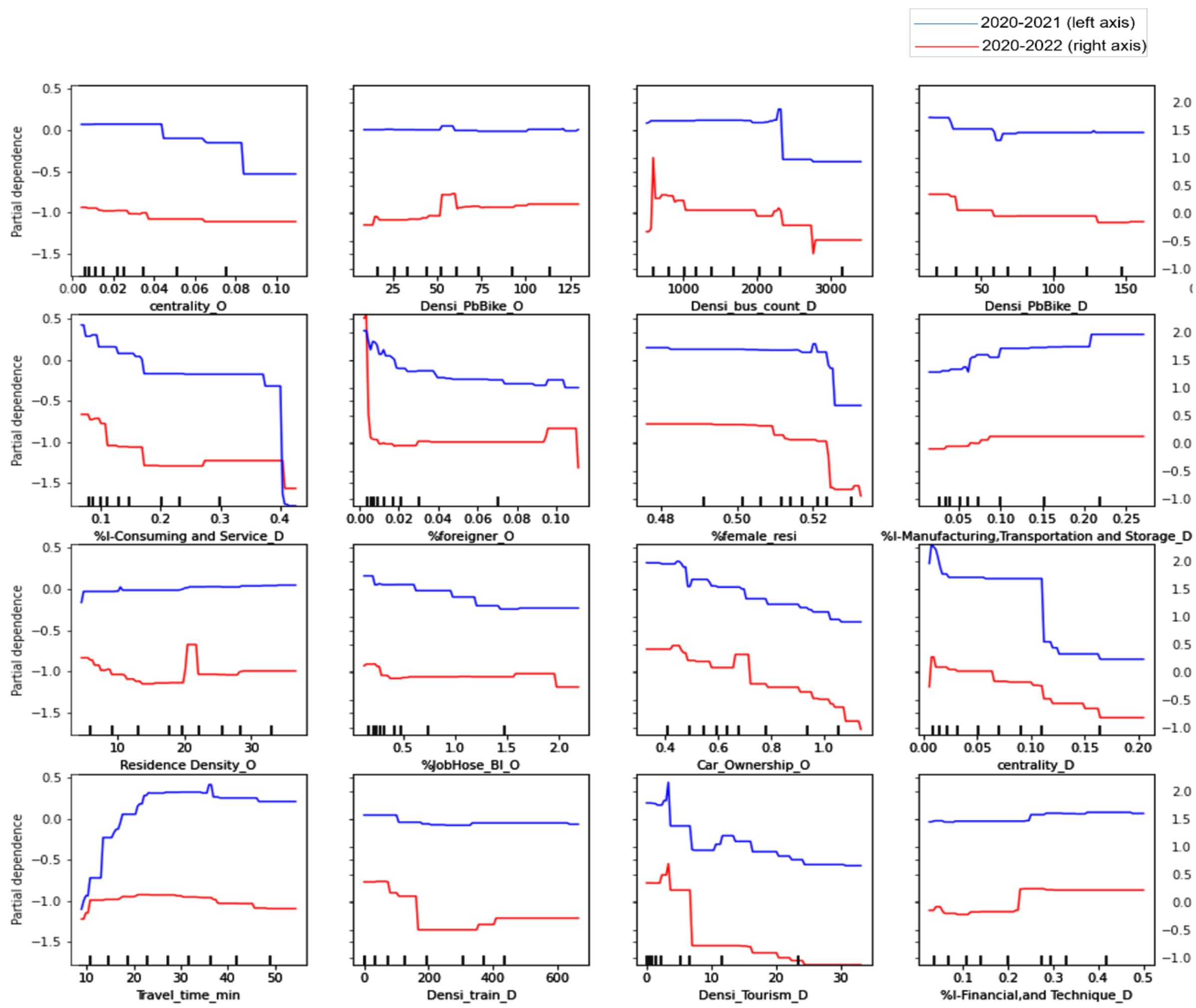


Figure 5. Non-linear effects of determine variables on mobility resilience.

employees working in Manufacturing, Transportation and Storage is over 0.1, the number of commuters arriving at these areas is more fixed to the previous level.

When the percentage of employees working in the Consumer and Service industry is over 0.15, the number of commuters arriving at these areas decreases more significantly than in others, especially when the percentage is higher than 0.4. In terms of the Consumer and Service industry, the hospitality industry and the general food service were hit hard because of the detrimental effect on international tourism from COVID-19 and social distancing policies. The negative signal in the morning peak might indicate the unemployment in these consumer-led areas. Car ownership is a long-term negative factor which lasted for two years, which shows the negative effect when the average car ownership per family is more prominent than 0.5. Even though there is an outlier shown at 0.7, the general trend is still meaningful. We infer that the COVID-19 pandemic significantly altered the transport mode choices for families who have private cars. In addition, destinations with higher centrality (greater than 0.1) experienced a stronger negative impact.

5. CONCLUSIONS

5.1 Discussion

COVID-19 is still tied to citizens' daily lives. Even though some experts have started to use the term “the post-pandemic” to depict new life patterns, the fluctuating number of new positive cases of COVID-19 patients reminds us we are still in the pandemic phase. The resilience index proposed in this paper can help avoid the instability of the results brought on by the variation caused by OD Pairs with small ridership, while ensuring the significance of OD Pairs with large ridership by logarithmic weighting.

Through the resilience index, this research revealed those who keep riding transit during the pandemic, because it implies that they have no other options and that they are having high vulnerabilities. Based on the previous report, the massive transit system in Seoul lost 20 % transit riders due to the pandemic, who even didn’t come back even in the recovery phase. This study deciphered whether they are coming back, whether they have switched their mode or change their lifestyle. According to these results, we can be more targeted in proposing policies to incentivise the use of public transport, using other low carbon modes of transport as an alternative.

The following is detailed discussion of the results:
In terms of the dense city centres, Jung-gu was damaged more than other areas in terms of the resilience index. In our machine learning model, the dummy variable of Jung-gu is not significant, which means the negative factors of this area have been explained by other factors which are significant on the global scale. In addition, the higher centrality of the destination is a significant negative factor. This founding is similar to the results in other countries mentioned in the literature review. It is worth

mentioning that car ownership is a potential long-term factor in the public transit use caused by COVID-19. The government stimulate the usage of low-carbon substitute person-based transit modes rather than indulge in energy-consumer automobiles during the pandemic when passengers are crowd-averse.

Some social-economic factors were related to the unevenly changed mobility pattern, varying by the industries citizens work for and their economic status. In general, the travellers who travel longer distances are more 'captive' than other travellers. Their travel is less flexible since there are less viable substitutes to public transit compared with shorter trips. In particular, the long-distance commuters were usually found in the low- and middle-income subgroups. It is not consistent with some assumptions that long-distance travel shrank more than the short distance travel, at least not in Seoul city in terms of the public transit. The correlation analysis echoes the latest evidence showing (Cartenì et al. 2020; Jay et al. 2020) that the flexibility also varies according to their jobs and the industries they belong to. In the future, when the government implements a social distancing policy, it must consider these subgroups.

Even though we had some significant correlation between the industry and economic factors, mobility is a more complicated index to describe a society than other social indicators like GDP, which is constant from the macroscopic and the microscopic perspective. The less the ridership is reduced at the city level, the more prosperous and resilient the city is. However, at the individual level, the more minor reduction in ridership indicated these travellers have less chance to reduce their trips and shift to working online, in contrast with employees with high skills and salaries, who have more opportunities to shift to working online. The mechanism between the complicated giant system, city, and the fluctuating urban ridership has multiple interpretations, which are incompatible: flexibility and vulnerability. Both might intensify the recession of mobility during the pandemic. Considering the city and the ridership's complicated interaction and correlation, we will enrich our dataset (by using more fine-grained data) and develop the regression model with an advanced machine learning algorithm.

Because of the limited available data and measurement, our research has some disadvantages. For instance, the acclivity of the public transit facilities is always highly related to the economic vitality of a tract. Therefore, it is hard to control these factors to determine the number of trains is the direct cause rather than other undetected explanations. We can only infer the correlation instead of the causal up to now.

Korea is one of the countries that minimised the impact of the pandemic on daily life, as it was one of their policy principles (Arora, Rajput, & Changotra, 2021). These results enable us to understand the similarity and variance between the mega Asia cities and Western metropolitan regions under different social distancing policies during the pandemic. The present research findings on COVID-19 can be used as a reference for an epidemic response by society and effective policy design. Furthermore, in recent years, people have moved their activities online because of the well-developed internet infrastructure services, referred to as the massive substitution of Information and Communications Technology (ICT) for physical movement (Couclelis, 2020). The advanced techniques, especially the ubiquitous techniques, IoT and online services, enabled mobility in the real world to be replaced by mobility in the virtual world, which was accelerated by COVID-19. In our further studies, we will endeavour to comprehend how the real world shifts online and how the so-called 'virtual cities' interact with the real cities.

5.2 Conclusions

This research examined the qualitative mobility change through the mobility resilience index. We found the consequences of the COVID-19 crisis were felt differently across places (even within the same city) and the variation by distance.
There are 3 ways we can explain the uneven resilience in transit ridership according to this study:

1) Mode shifting
Trips less than 20 min decreased more significantly than longer trips in the first year, which differs from other results based on a larger scale (national or international). The elasticity theory of public transport can explain this: there are more substitutes available to replace the public transit in the megacity (like walking or cycling), short-distance trips have higher elasticity to shift to other modes. Furthermore, most short-distance travellers shifting their modes in 2021 went back to the public transit in 2022.In addition, owing to the long-term significantly negative variable, 'Car Ownership', we infer that the private car is another potential substitution for the public transit system during the pandemic in Seoul city. Compared with the short-distance travellers, people who shifted to private cars did not return to the public transit in the recovery phase.

2) Economic regression
The Service and Consumer Industry and Foreigner Tourism are the two which suffered the most severe long-term impact, which is also proven by Consumer Reports issued by the government.
Even though only morning peak travels were included in this research, the dramatic decline related to tourism and consumer industries were not only relevant to service providers (commuters) but also to consumers. We assume that workers in these industries lost their jobs or worked less frequently because of a decline in consumers. Factors related to economic regression in these specific sectors are still significantly negative. Therefore, the Service and Consumer Industry and Foreigner Tourism are not getting back on track like other sectors.

3) Work from home or work in exposure
In addition, the ability to work from home depends more on the characteristics of the residence place than on the characteristics of workplace. This is because the characteristics of the place of residence are a better indicator of the economic conditions of the commuter than the characteristics of the place of work. In the context of promoting work from home nationwide (in 2021), there is one industry that is an exception where people have less chance to stay at home, which shows abnormal 'positive' effect on the resilience: employees in the Manufacturing, Transportation and Storage Industry. Further, considering the concept of the local resilience, we have evidence that people working in other sectors (except the Service and Consumer Industry, Foreigner Tourism and Manufacturing, Transportation and Storage Industry) have similar opportunities to work from home to avoid higher transmission risks from crowded public transit and workplaces.

In conclusion, the industries they work for, the assets they have, and the flexibility of the commute trips caused unequal levels of privilege to choose their mode of commute. To inform policy makers at the national and state levels, understanding the explanatory forces and related confounding factors with spatial patterns is of paramount importance. This study can be a reference for future spatial mobility research during a pandemic, policy design and informing decision making in the case of uneven social equity, to take transformative steps towards creating just resilient, and sustainable cities.

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APPENDIX

Due to lack of space, we attach the appendix in this link. You can find detailed tables and graphs of this paper here: https://drive.google.com/file/d/1bWtSSes6ODyf-vA19Liy9mNZrToLVLIm/view?usp=sharing