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Impact of pre-pandemic travel mobility patterns on the spatial diffusion of COVID-19 in South Korea

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ABSTRACT

Introduction: Physical mobility is critical for the spread of infectious diseases in humans. However, few studies have conducted empirical investigations on the impact of pre-pandemic travel mobility patterns on the diffusion of coronavirus disease 2019 (COVID-19). Therefore, this study examines its impact at the city-county level on the diffusion by the wave period during the two-year pandemic in South Korea.

Methods: This study first employs factor analysis by using the travel origin-destination data by travel mode at the county level as of 2019 to derive pre-pandemic travel mobility patterns. Next, the study identifies how they had affected the diffusion of COVID-19 over time by employing the negative binomial regression models on confirmed COVID-19 cases for each wave, including the entire pandemic period.

Results: The study derived five pre-pandemic mobility patterns: 1) rail-oriented mobility, 2) intra-county bus-oriented mobility, 3) road-oriented mobility, 4) high-speed rail-oriented mobility, and 5) inter-county bus-oriented mobility. Among them, the biggest risk to the diffusion of COVID-19 was the rail-oriented mobility before the pandemic if controlling such measures as accessibility, physical environment, and demographic and socioeconomic indicators. In addition, the order of the magnitudes for the impact of pre-pandemic travel mobility factors on its spatial diffusion had not changed during experiencing the three different wave periods during the two-year pandemic in South Korea.

Conclusions: The study concludes that the rail-oriented travel mobility pattern before the pandemic could pose the greatest threat factor to the spatial spread of COVID-19 at any scale and time. Policymakers should develop strategies to prevent the spatial spread of COVID-19 by reducing human mobility for daily living in areas with strong rail mobility patterns formed before the pandemic.

1. Introduction

Since the coronavirus disease 2019 (COVID-19) was first reported in Wuhan, China, in November 2019, it has rapidly spread, causing a sudden increase in the number of confirmed cases and deaths. The World Health Organization (WHO) has reported several potential factors affecting the spread of COVID-19 since declaring it as a pandemic on March 11, 2020. Human mobility is one of the most important causes of the spread of infectious diseases (Cheshmehzangi, 2022; Nouvellet et al., 2021). Therefore, most countries

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have implemented quarantine measures that limit human mobility to contain the spread of COVID-19 (Gargoum and Gargoum, 2021). Among them are factors closely related to local, regional, and international human mobility (Matthew and McDonald, 2006; Sung, 2020). Therefore, control measures that limit human mobility are important to suppress the spread of infectious diseases (Bajardi et al., 2011; Prakash et al., 2022; Summan and Nandi, 2022; Zaki et al., 2022).

Internal mobility for travel within a country, as well as for international travel, is important in controlling the spread of COVID-19. Analyzing the causes of COVID-19 transmission in 3132 counties in the U.S., Gaskin et al. (2021) reported that the number of confirmed COVID-19 cases and deaths is closely related to the proximity of airports. Hamidi et al. (2020) also demonstrated that inter-county travel mobility affected the spread of infectious diseases and mortality rates. Similarly, Murano et al. (2021) noted that restricting domestic human mobility may be more effective in controlling the spread of COVID-19 than controlling its spread between countries. For instance, several countries such as China and Italy have imposed lockdown measures to control the movement of urban residents, such as blocking major roads and closing public transport and airports, to effectively control human mobility (Choi, 2020). Additionally, many countries worldwide, such as China, Italy, and France, have attempted to contain the spread of COVID-19 by enforcing or recommending stay-at-home measures that restrict movement between cities and countries.

Travel mobility can be a derived demand to achieve a certain purpose of daily life and economic activities, where urban forms to accommodate them have formed over a long period of time (Cervero, 2002; Hymel, 2019; Mokhtarian and Salomon, 2001). Therefore, travel mobility patterns, which were aggregated in the spatial unit, may not have changed easily despite the occurrence of unprecedented temporary shocks, such as COVID-19. Thus, taking into consideration travel mobility patterns, the implementation of the various social distancing measures to reduce the spread of infectious diseases by suppressing travel mobility may be more effective. Furthermore, most of the various non-pharmaceutical intervention measures, such as social distancing, may have resulted in individual and socioeconomic costs, such as unemployment and negative effects of mental health and the quality of life (Fink et al., 2022; Koch and Park, 2022; Thunstrøm et al., 2020). Such measures may have been implemented during the recent COVID-19 pandemic without fully understanding their consequences (Musselwhite et al., 2022).

Most empirical studies have focused on either the change in or vulnerability to travel behavior during the COVID-19 pandemic. Some studies have investigated the association of travel mobility with COVID-19 have estimated how passenger travel behavior had changed during the COVID-19 pandemic (Klos-Adamkiewicz and Gutowski, 2022; Pawar et al., 2021; Zhang and Hayashi, 2022). Other studies had focused on which specific travel modes are more vulnerable to the spread of COVID-19 and deaths (Li, 2020; Shen et al., 2020). However, few studies have conducted empirical identification of the impact of pre-pandemic travel mobility patterns on the spatial diffusion of COVID-19 during the pandemic. In addition, previous studies have not focused on travel mobility patterns that may be more vulnerable to diffusion.

This study thus examines how the travel mobility pattern before the COVID-19 pandemic had influenced its spatial spread in South Korea over a two-year period from the beginning of the pandemic to the end of 2021. More specifically, the study does empirically identify which pre-pandemic travel mobility factor matters more to the diffusion of COVID-19 cases over time during the different waves of the pandemic. This study first extracts five potential factors of pre-pandemic travel mobility patterns by employing a principal factor analysis with data on modal split and the centrality measures of travel mobility by transport mode at the county level in 2019, before the first COVID-19 case was reported on January 20, 2020, in South Korea. Next, the study employs negative binomial regression models on the cumulative number of COVID-19 confirmed cases with the factors as explanatory variables as well as such control variables as accessibility, physical environment, demographical and socio-economic factors at the county level. Based on the results, the study discusses which pre-pandemic travel mobility pattern factors play a more important role in the spread of COVID-19.

2. Literature review

Human mobility is one of the most important causes of the spread of infectious diseases. Therefore, most countries have implemented quarantine measures that limit human mobility to contain the spread of COVID-19. Travel mobility has been changed by the COVID-19 pandemic as well as by non-pharmaceutical intervention measures to reduce it (Abouk and Heydari, 2021; Chen et al., 2022; Paiva et al., 2022). Individuals also tend to temporarily restrict travel for daily social and economic activities or use relatively low-risk modes of transportation to avoid contracting infectious diseases (Mehdizadeh et al., 2022; Tan and Ma, 2021; Yoo et al., 2021; Thombre and Agarwal, 2021). Such unexpected epidemics of infectious diseases and restrictions on human mobility in response to them could have led to changes in the travel mobility behavior, such as frequency, distance, mode choice, and destination of travel. Some studies (Abdullah et al., 2020, 2021; He et al., 2022; Jenelius and Cebeucuer, 2020; Politis et al., 2021; Subbarao and Kadali, 2022; Wielechowski et al., 2020; Wilbur et al., 2020) reported a decrease in the frequencies of travel or the usage of public transit modes. Its change resulted from the fact that people changed their daily travel modes from public transport such as subways, which are perceived as having a relatively high risk of transmission of COVID-19, to bicycles and private cars with lower risk (Baig et al., 2022; Muley et al., 2020; Orro et al., 2020; Ozbilen et al., 2021; Wang and Noland, 2021; Zafri et al., 2021). For example, Shamshiripour et al. (2020) demonstrated that people had changed their travel modes of public transit to personal transport modes such as walking and cycling during the COVID-19 period. Additionally, Tan and Ma (2021) found that during the COVID-19 pandemic in Chinese cities, 97.0% of commuters who did not choose rail transportation chose personal transportation, such as bicycles, cars, and walking. Harrington and Hadjicostinou (2022) found that the restrictions on non-essential work had rapidly reduced the use of public transit for commuting in the United Kingdom.

Other studies had focused on which specific travel modes are more vulnerable to the spread of COVID-19 and deaths. Li (2020) and Shen et al. (2020) focused on major public transportation modes and the relationship between domestic mobility and the spread of COVID-19. Specifically, Li (2020) noted that the spread of COVID-19 is more closely related to airplanes, trains, or buses, where there
is a tendency to have a higher rate of contact among passengers than to the use of private transport such as cars. Shen et al. (2020) also reported that control measures on domestic public transportation are necessary to contain the spread of COVID-19 since public transportation is commonly used by a large majority of people. Moreover, Troko et al. (2011) reported that public transport, particularly buses, trams, trains, and subways contributed to the spread of other infectious diseases among users in Nottingham, UK. Zhu and Guo (2021) reported that the travel connectivity of high-speed rail and air had a positive impact on newly confirmed cases in Wuhan, China.

However, Gartland et al. (2022), reviewing the extensive literature on the transmission and control measures of COVID-19 on public transit up to May 2021, found mixed evidence on the association between them. They also argued that the routes and main factors of public transit in diffusing COVID-19 were still unclear during the early experiences of the pandemic. Some studies have found that such measures such as mask wearing, physical distancing, air conditioning, and filtering on public transit have a significant impact on reducing exposure to COVID-19 transmission (Kriegel et al., 2021; Matheis et al., 2022; Miller et al., 2022; Yang et al., 2022). Musselwhite et al. (2020) argues that restrictions on the operation of overcrowded public transit due to the higher possibility of individual transmission of COVID-19 needs to be well thought because the exposure in households can be higher.

Most travels are the induced demand to perform socio-economic activities (Cervero, 2002; Hymel, 2019). Travel patterns depends on urban forms and transport infrastructure, which have been formed over a long period of time. In this regard, the travel mobility pattern formed before the pandemic may still have detrimental impacts on the spatial diffusion of COVID-19, even if human mobility is constrained by social distancing measures to curb its diffusion. It can be even more true for many countries, including South Korea, which had not enforced strong domestic movement restrictions. While containing the spread of COVID-19, some countries such as Sweden and South Korea did not implement lockdown measures to sustain economic activity (Prakash et al., 2022; Zaki et al., 2022). Nevertheless, most studies have focused on changes in travel behavior during the pandemic.

Travel mobility patterns, which are also called travel connectivity, have also been investigated in relation to COVID-19 transmission. However, the previous studies empirically identifying the impacts of travel connectivity on COVID-19 transmission may also have some limitations, in that they have limited travel mobility patterns to specific modes of travel (Hamidi and Hamidi, 2021; Teller, 2021), or measured the degree of connectivity through social network analysis (Murano et al., 2021; Jo et al., 2021). In a study that conducted a simulation model of vulnerability to the spread of COVID-19 in Ohio, USA, Cuadros et al. (2020) employed degree centrality indicators for each travel mode calculated through social network analysis as another travel mobility and identified that the spread of infection was faster in areas with high connectivity than in areas with low connectivity.

In addition, the spatial transmission of COVID-19 is urban (Sharifi and Khavarian-Garmsir, 2020; Sung, 2016, 2020; Teller, 2021; Rader et al., 2020). Observing the proliferation of MERS in South Korea, Sung (2016) stated that overcrowding within facilities, outdoor spaces, and mass transit modes may play an important role in diffusing infectious diseases in urban physical environments. Urban characteristics that derive from both crowding and closeness between humans tend to influence the spatial spread of COVID-19. Teller (2021) emphasized that travel connectivity played a decisive role in disease spread, but also noted that density and other urban factors should be considered in the spread of infectious diseases. These studies have identified urban characteristics at the county level that influence confirmed COVID-19 cases (Hamidi et al., 2020; Cuadros et al., 2020; Ehlert, 2021; Jamshidi et al., 2020; Jo et al., 2021). Padmakumar and Patil (2022) investigated the impact of COVID-19 on travel mobility trends in the Indian metropolitan cities and found that such socio-economic factors, such as income, vehicle registration, and employment at the city level, had a significant impact on its change.

Specifically, the diffusion of COVID-19 can be affected by the demographic, socio-economic, and physical environments. Among them, better accessibility, such as roads (Arroyo et al., 2006), buses (Caicedo et al., 2021), railways (Wang and Noland, 2021; Tan and Ma, 2021), and airports (Gaskin et al., 2021; Wang et al., 2021) have a positive impact on the number of infectious diseases. Other studies have reported that the spread of infectious diseases, including COVID-19, is affected by population density (Ehlert, 2021; Huang and Li, 2022; Jo et al., 2021; López-Gay et al., 2022) and ethnically or socioeconomically vulnerable groups (Brough et al., 2021; Chang et al., 2021; Palm et al., 2021). The population density calculated by the former seems to be statistically insignificant (Hamidi et al., 2020; Teller, 2021) in influencing COVID-19 diffusion, whereas the latter tends to have a statistically significant positive effect on the same (Jo et al., 2021). Generally, the spread of COVID-19 is stronger in urban areas than in rural areas (Cuadros et al., 2020; Wang et al., 2021).

The restriction measures on travel mobility might have had either a temporally or spatially differentiated impact on the diffusion of COVID-19. Zhang and Hayashi (2022) found that the effectiveness of restricting travel mobility had both spatial and temporal variations in reducing COVID-19 transmission across the stages of the pandemic. The relationship between COVID-19 transmission and travel mobility can be bi-directional (Borkowski et al., 2021; Habib and Anik, 2021; Kartal et al., 2021). Hamidi and Hamidi (2021) found a bi-directional causal relationship between COVID-19 transmission and mobility in almost all the countries. Kartal et al. (2021) also found that the daily relationship between pandemics and mobility indicators has causality in the long term. These studies indicate that travel mobility patterns may have temporally differentiated impacts on the spread of COVID-19.

Compared with the previous studies, this study can contribute from three perspectives on the transmission and key factors of COVID-19 on travel mobility. First, the study empirically explores the impact of pre-pandemic travel mobility factors on the diffusion of COVID-19 in South Korea after controlling for demographic, socio-economic, and physical environment attributes at the municipal level. The South Korean government has not implemented strong movement restrictions such as lockdowns to reduce the spread of COVID-19. Although daily socioeconomic activities may have been temporarily reduced, the fundamental characteristics of pre-pandemic travel mobility may not have changed in this country. Second, the study extracted pre-pandemic travel mobility pattern factors by performing factor analysis on such indicators such as intra- and inter-county modal split and degree centrality by the transport mode through social network analysis. Third, the study empirically investigates whether the degree of the impact on the
transmission of COVID-19 has varied across the stages during the pandemic. By modeling the impact of each of the three different wave periods and the entire period, this study conducts a comparison of the modeling results among pre-pandemic travel mobility factors.

3. Materials and methods

3.1. Study area and COVID-19 measure

This study examines the impact of pre-pandemic travel mobility pattern factors, which are characterized by intra- and inter-county splits of travel modes and travel centrality by mode, on confirmed COVID-19 cases at the county level in South Korea. This study adopted the city-county-district unit of South Korea, which corresponds to the county level in the United States. It is the autonomous administrative jurisdiction unit, planning and policy subject area, and public health administrative authority unit in South Korea. This study used this municipal-level unit, since the decisions and responsibilities for land use, transport, and public health that it is subject to were made in terms of it being a spatial measurement unit. Furthermore, South Korea comprises 228 cities, counties, and districts. When examining the effect of public transportation such as buses, railroads, subways, and high-speed rails on the confirmation of COVID-19, islands such as Ulleungdo and Jejudo were excluded from the analysis because these major transportation modes were not in operation in these areas. Finally, 221 cities, counties, and districts were subjected to a spatial analysis in this study. Cities, counties, and districts will be expressed as counties in the rest of the manuscript.

Most previous studies have measured the number of confirmed cases as the spatial transmission of COVID-19. Therefore, this study employed the cumulative number of confirmed COVID-19 cases during an approximately two-year period from January 20, 2020, to December 24, 2021. Fig. 1 shows the daily trend of newly confirmed COVID-19 cases in South Korea and their cumulative distribution. By December 24, 2021, South Korea had experienced four waves during the COVID-19 pandemic. The first pandemic period was a large-scale cluster infection that was centered in Daegu City. The rapid spread of COVID-19 during this period in South Korea was attributed to one case from a super-spreading event that led to more than 3900 secondary cases; this case originated from church services in the city (Shim et al., 2020). The second wave period was the nationwide spread of COVID-19 due to several large-scale illegal assemblies in Seoul and the summer vacation in August 2020. These periods can be used to track and manage contacts if they are diagnosed with COVID-19. This study analyzed the first two wave periods by setting them as one period.

Conversely, this can be said to be the stage of community transmission which could not be managed, such as tracing and isolating contacts during the third and fourth wave periods. In the third wave period from mid-November 2020 to January 2021, unlike the previous two periods, there were no special large-scale cluster infections, and the direct cause was unknown since cluster infections occurred in unspecified groups (Yoo et al., 2021). In the fourth wave, from July 7, 2021 to December 24, 2021 it had reached the stage of community transmission where the person who caused the infection was unknown. The fourth wave was sustained by the time of writing of this paper. Travel mobility may have a different impact on the diffusion of COVID-19 cases by a different wave over time during the two-year pandemic. Thus, the analysis period of this study allowed us to empirically identify how travel mobility during the COVID-19 pandemic has had different impacts on the number of cases over time.

Fig. 2 shows the spatial distribution of the cumulative number of COVID-19 cases by the major wave period and over the entire period of the analysis. Fig. 2(b) shows the spatial distribution during the 1st and 2nd wave periods, indicating that community transmission occurred due to cluster infection in the areas centering on the Daegu metropolitan city. Fig. 2(c) indicates that the widespread spatial spread of COVID-19 confirmed cases was concentrated in the Seoul metropolitan area during the third wave period. Fig. 2(d) shows that such a pattern during the 3rd wave period is stronger and more widespread, and the range expanded to the surrounding areas of the Busan metropolitan city. As a result, Fig. 2(a) shows that the number of confirmed cases has mainly occurred in the surrounding areas centered on metropolitan cities and their surrounding counties since the third wave period.

Fig. 1. Daily trend on newly confirmed COVID-19 cases and their cumulative pattern over wave periods.
3.2. Data description and processing

Table 1 presents the summary statistics of the variables employed in the study and their processing and sources. The dependent variables in Table 1 present the cumulative number of COVID-19 confirmed cases by wave period and during the entire period of this analysis. None of the Korean authorities provide data on the cumulative number of confirmed cases at the county level in South Korea. We thus collected data for each wave period by visiting the websites from provincial governments. During the entire period, the average number of cumulative COVID-19 cases was 2445.25, with a standard deviation of 3083.621. The maximum number of confirmed cases was 13,143 for the entire period. The average cumulative number of confirmed cases was 93.76, 223.095, and 1713.814 for the first-, third-, and fourth-wave periods, respectively.

We measure herein the indicators of estimated travel mobility in 2019 under the assumption that no COVID-19 has occurred, to identify their impact on the confirmation of infectious diseases. The pre-pandemic travel mobility attributes were extracted from the origin–destination (O-D) data for each transport mode at the county level at that till the end of December 2019 from the Korea Transport Database. The OD data consists of six major transport modes: private car, bus, rail and subway, high-speed rail, and aviation.

Fig. 2. Spatial distribution of the number of confirmed COVID-19 patients by wave periods.
Table 1
Data description and summary statistics.

| Description on Variables (No. Observations = 221, Spatial Analysis Unit = City, County or District) | Summary statistics | Data Source |
|--------------------------------------------------------------------------------------------------|--------------------|-------------|
|                                                                                                  | Mean               | Std. Dev.   | Min | Max |
| Dependent Variables                                                                              |                    |             |     |     |
| Model A Cumulative confirmed COVID-19 cases during the entire period (January 20, 2020 to December 24, 2021) | 2445.25            | 3083.62     | 19  | 13143 |
| Model B Cumulative confirmed COVID-19 cases during the 1st & 2nd wave period (January 20, 2020 to September 17, 2020) | 93.76              | 198.56      | 0   | 1671  |
| Model C Cumulative confirmed COVID-19 cases during the 3rd wave period (November 28, 2020, to January 28, 2021) | 223.095            | 281.561     | 0   | 1454  |
| Model D Cumulative confirmed COVID-19 cases during the 4th wave period (July 14, 2021, to December 24, 2021) | 1713.814           | 2240.449    | 10  | 9039  |
| Pre-pandemic travel mobility attributes                                                           |                    |             |     |     |
| Car modal split by entire county (= total trips of passenger car/total trips)                     | 0.741              | 0.163       | 0.314 | 0.961 |
| Bus modal split by entire county (= total trips of bus transit/total trips)                      | 0.178              | 0.078       | 0.038 | 0.482 |
| Rail modal split by entire county (= total trips of rail and subway transit/total trips)        | 0.078              | 0.111       | 0    | 0.493 |
| HSR modal split by entire county (= total trips of high-speed rail transit/total trips)        | 0.19               | 0.21        | 0    | 0.93 |
| Intra-county car modal split (= total intra-county trips of passenger car/total intra-county trips) | 0.766              | 0.157       | 0.281 | 0.965 |
| Intra-county bus modal split (= total intra-county trips of bus transit/total intra-county trips) | 0.208              | 0.13        | 0.035 | 0.647 |
| Intra-county rail modal split (= total intra-county trips of rail and subway transit/total intra-county trips) | 0.027              | 0.048       | 0    | 0.38 |
| Inter-county car modal split (= total inter-county trips of passenger car/total intra-county trips) | 0.711              | 0.16        | 0.317 | 0.962 |
| Inter-county bus modal split (= total inter-county trips of bus transit/total intra-county trips) | 0.171              | 0.071       | 0.036 | 0.409 |
| Inter-county rail modal split (= total inter-county trips of rail and subway transit/total intra-county trips) | 0.111              | 0.139       | 0    | 0.551 |
| Degree centrality by car                                                                        | 234,723            | 193,082     | 20,860 | 1,140,656 |
| Degree centrality by bus                                                                         | 73,427             | 68,484      | 1522  | 298,935 |
| Degree centrality by rail                                                                        | 47,347             | 92,809      | 0     | 610,993 |
| Degree centrality by HSR                                                                          | 940                | 1425        | 0     | 9483  |
| Control variables                                                                                 |                    |             |     |     |
| Accessibility attributes                                                                         |                    |             |     |     |
| Road length density (= road length [m]/administrative area [km²])                                 | 11,585             | 11,640      | 1212  | 69,491 |
| No. railway stations per area (= No. subway stations/county area [km²])                          | 1.38               | 0.98        | 3    | 4    |
| log-transformed distance from the nearest highway interchange [m]                               | 0.65               | 0.75        | 0    | 5    |
| log-transformed distance from the nearest airport [m]                                             | 3.15               | 0.95        | 1    | 5    |
| Demographic-Socio-Economic attributes                                                             |                    |             |     |     |
| Population density (= no. pop./administrative area [km²])                                        | 5097               | 6398        | 349   | 51,157 |
| Ratio of population over 65 (= no. people over 65 years of age/total population)                 | 21.87              | 8.37        | 8.2   | 41.5  |
| Ratio of foreign population (= no. registered foreigners/total population)                      | 0.02               | 0.02        | 0    | 0.1  |
| Park area per county area (= park area [m²]/administrative area [km²])                          | 19,043             | 18,546      | 369   | 132,335 |
| Park area per county area (= park area [m²]/administrative area [km²])                          | 19,043             | 18,546      | 369   | 132,335 |
| GRDP per person (= growth regional domestic product [one million Korean won]/total population)  | 34                 | 31          | 8     | 386   |
| Urban area (=1, rural area = 0)                                                                   | 0.66               | 0.48        | 0    | 1    |
| Daegu city (=1, others = 0)                                                                       | 0.04               | 0.19        | 0    | 1    |

Note 1: CDC = Center for Disease Control, KTDB = Korea Transport DataBase, KOSIS = Korea Statistical Information System.
Note 2: The number of COVID-19 confirmed cases by county was collected by visiting each province’s webpage.
It may be limited in that the data for non-motorized modes such as walking and bicycles, which have relatively shorter travel distances than motorized ones, are not provided. Nevertheless, it can be useful in identifying the patterns of travel mobility before the pandemic, using indicators such as the degree of connectivity and modal split according to inner- and inter-county.

The study measured various indicators, such as the modal split of each travel mode, both intra- and inter-counties, and the centrality of connection by travel mode through social network analysis. Among the travel mobility indicators, each modal split was classified into three levels: entire county, intra-county, and inter-county. The reason for this classification into inner- and inter-county travel mobility behavior between the two might have been different in influencing the spread of COVID-19. Travel modes were defined as passenger cars, buses, railways and subways, and high-speed railways (HSRs). Table 1 shows that the modal split by county level is, on average, 74.1% for passenger cars, 17.8% for buses, 7.8% for railways and subways, and 0.19% for HSRs. The average number (0.741) of passenger cars at the county level was relatively high in South Korea. This was because the O-D data according to the mode of transport used in the study excluded non-motorized modes of travel, such as walking and bicycles. Comparing the modal splits between intra- and inter-county, passenger cars and buses have higher intra-county share rates of 5.5% and 3.7%, respectively, and railways and subways have an 8.4% higher inter-county modal split. In general, railways and subways tend to be the preferred modes of transportation for medium-to-long-distance travel rather than short-distance travel. By comparing the values of degree centrality by travel mode in Table 1, we found that the connection centrality of passenger cars was the highest, followed by buses, railways, and subways, and HSRs.

The control variables adopted in the study can be divided into three categories: 1) accessibility; 2) demographic and socioeconomic; and 3) other physical attributes. First, the study employs such accessibility indicators as road length per county area (average $= 1.38 \text{ m/km}^2$), log-transformed distance (m) from the nearest highway interchange (IC) (average $= 1.38$), number of railways and subway stations per county area (average $= 0.65$ no. stations/km$^2$) and log-transformed distance (m) from the nearest airport (average $= 3.15$). Accessibility to the airport and highway IC was measured in the form of a logarithm function, which is a distance decaying function that assumes that the effect decreases to a greater extent as the distance increases. The second controlling indicator was demography and socioeconomic attributes. This study employs the population per county area, that is, population density (average $= 5097$ persons/km$^2$), ratio of the population occupied by those aged 65 and over (average $= 0.2187$), park area per 1000 residents (average $= 19.043$ m$^2$/1000 persons), and per capita growth regional domestic product (GRDP) (average $= 34.06$ million Korean won/person). The study also measured the ratio of the registered foreign population over the entire population as one of the control variables. Most of the counties with a high proportion of foreigners are low-income areas, since most of the foreigners tend to work in low-wage jobs. However, the study also used as a proxy variable, that counties where people from countries with different cultural norms live differed from others in complying with COVID-19 quarantine guidelines and prevention measures, which may have affected its spatial spread. On average, the ratio of registered foreigners to the entire population was 0.02. The final control indicators describe other attributes: whether the county is a city or rural area, by how much the size of the administrative area in the county is different, and whether it is in Daegu metropolitan city. Daegu was the epicenter of the spread of COVID-19 during the first wave period. Table 1 shows that, out of 221 counties, 66% are city-level areas. In addition, since the area of administrative districts for each county is different, the larger the area, the higher is the likelihood of COVID-19 confirmation. The average administrative area of the county was 78 km$^2$. Whether or not the county is within Daegu metropolitan city was employed to control the characteristics of the first pandemic period for COVID-19 due to the geographical spread to neighboring areas caused by group infection. There are eight autonomous districts in Daegu metropolitan city, accounting for 4% of the total.

### 3.3. Methodology

This study empirically identified the effects of pre-pandemic travel mobility pattern indicators on the cumulative number of confirmed COVID-19 cases at the county level. As the dependent variable, the study employed the cumulative number of COVID-19 confirmed cases during the entire analysis period (January 01, 2020, to December 24, 2021) and by the three respective wave periods. This study employed a Poisson model, negative binomial regression model, or zero-inflated negative binomial regression model for a count variable rather than a continuous variable as the dependent variable (Gelman and Hill, 2006). Therefore, this study assumed that the cumulative number of confirmed cases by county was the incident that occurred by chance. Since the Poisson model assumes that the mean of the number of occurrences is the same as its variance, its application is limited in case of occurrence of an overdispersion (Jeong and Choi, 2014). Table 1 shows that the number of COVID-19 confirmed cases during the entire period and during the third pandemic period has both forms of overdispersion with a larger variance than the average. The mean and variance are 2445.25 and 9, 518,718 ($=3083.621^2$) for the entire period, 93.76 and 39426 for the first two-wave period, 281.561 and 79277 for the third wave period, and 2240.449 and 5019612 for the fourth wave period, respectively.

Conversely, there were few counties with zero confirmed cases for the entire analysis period and the three respective periods. Therefore, it is more appropriate to use a negative binomial regression model than a zero-inflated negative binomial regression model since there are not many zero values in the number of confirmed cases by county. In addition, the influence of outliers on the data is avoided accordingly. Finally, this study employed a robust negative binomial regression model to examine the impact of travel mobility on the cumulative number of confirmed COVID-19 cases by county. This negative binomial regression model has also been used in previous studies that identified the relationship between either the number of confirmed cases or deaths from COVID-19 at the level of either county (Gaskin et al., 2021; Jo et al., 2021) or country (Oztug and Askin, 2020).

Fourteen travel mobility indicators before the pandemic were measured in this study. The study selected a modal split according to the entire and inner- and inter-county and degree centrality according to the transport mode. The travel modes used in this study were limited to the surface transport modes, such as passenger cars, buses, railways, subways, and high-speed rails. This was because the
intra- and inter-mobility travel mobility patterns within and between counties are mostly performed by the travel modes. The study also used the indicator, degree centrality, for each mode to measure the centrality of travel connectivity according to the county. Furthermore, this study included the modal split and degree centrality of air transport in the initial factor analysis to extract the pre-pandemic travel patterns. However, from the results, it was difficult to categorize them as any factor due to the low value of the Kaiser–Meyer–Olkin statistics to estimate the validation of the variables in the factor analysis; therefore, they were excluded from the final analysis. Air transport can be a form of travel mobility that influenced the diffusion of COVID-19 significantly. Therefore, this study included the accessibility of airports in the model, rather than travel mobility patterns. As aforementioned, the correlations between these travel mobility indicators in 2019 were either negatively or positively high. Therefore, a factor analysis, which extracted compressed low-dimensional factors from diverse high-dimensional variables, was performed to solve this complex interdependence problem prior to the application of the regression model. Factor analysis is a method for grouping similar variables while considering their correlations. Additionally, this study applied the varimax method to remove the correlation of the extracted factors.

4. Results

4.1. Factor analysis of pre-pandemic travel mobility patterns

The study employed a factor analysis to compress high-dimensional complex indicators of pre-pandemic travel mobility into low-dimensional simple factors without significant loss of information. Table 2 presents the results of compressing the 14 travel mobility pattern indicators before the pandemic into five factors. Prior to the interpretation of the results, the study employs two statistical criteria to verify the validity of this factor analysis: KMO (Kaiser–Meyer–Olkin) and communality. KMO is a statistic that indicates the proportion of variance in the travel mobility indicators caused by underlying factors. Generally, an indicator can be classified as acceptable if the value of KMO is equal to or greater than 0.5 (Kaiser, 1974). An indicator with a higher communality, ranging between 0 and 1, is considered to be a useful measure for predicting its value in factor analysis. The indicator is considered a principal component if the communality is equal to or greater than 0.4 (Lee and Lee, 2012). Table 2 shows that the overall averages of KMO and communality are 0.6184 and 0.946, respectively, satisfying these criteria. To determine the number of factors, the scree test was applied, and a total of five factors from 14 travel mobility indicators were extracted accordingly. Table 2 shows that these five factors have little loss of information since they account for 97.81% of the

| Variable                      | Factor 1       | Factor 2       | Factor 3       | Factor 4       | Factor 5       | KMO   | Communality |
|-------------------------------|----------------|----------------|----------------|----------------|----------------|-------|-------------|
| Total modal split             | Car modal split by entire county -0.693 | -0.655         | 0.601          | 0.993          | 0.6184         | 0.946 |
|                               | Bus modal split by entire county 0.841 | 0.446          | 0.474          | 0.965          |                |       |
|                               | Rail modal split by entire county 0.911 | 0.568          | 0.986          | 0.911          |                |       |
|                               | HSR modal split by entire county 0.911 | 0.412          | 0.9            |                |                |       |
| Inner-county modal split      | Car modal split within the county -0.561 | -0.786         | 0.633          | 0.984          | 0.6184         | 0.946 |
|                               | Bus modal split within the county 0.907 |                | 0.585          | 0.987          |                |       |
|                               | Rail modal split within the county 0.905 |                | 0.547          | 0.869          |                |       |
| Inter-county modal split      | Car modal split without the county -0.753 | -0.447         | -0.413         | 0.68           | 0.971          |       |
|                               | Bus modal split without the county 0.96  |                | 0.274          | 0.991          |                |       |
|                               | Rail modal split without the county 0.883 |                | 0.674          | 0.958          |                |       |
| Degree centrality by SNA      | Degree centrality by car 0.906  |                | 0.716          | 0.902          |                |       |
|                               | Degree centrality by bus 0.482  | 0.748          | 0.853          | 0.97           |                |       |
|                               | Degree centrality by rail 0.851  | 0.889          | 0.877          |                |                |       |
|                               | Degree centrality by HSR 0.544  | 0.705          | 0.788          | 0.892          |                |       |
| Naming Factor                 | Rail-oriented mobility Overall = 0.6184 | Overall = 0.946 |
|                               | Intra-county bus-oriented mobility Overall = 0.6184 | Overall = 0.946 |
|                               | Road-oriented mobility Overall = 0.6184 | Overall = 0.946 |
|                               | HSR-oriented mobility Overall = 0.6184 | Overall = 0.946 |
|                               | Inter-county bus-oriented mobility Overall = 0.6184 | Overall = 0.946 |

Note: blanks represent abs(loading) < 0.4; SNA represents social network analysis.
variance of all indicators. Additionally, these five factors have independent relationships, as the correlation between these factors is close to zero.

By comparing the factor loadings of the indicators of pre-pandemic travel mobility for each of the extracted factors, the five factors obtained from this study were as follows: 1) rail-oriented mobility, 2) intra-county bus-oriented mobility, 3) road-oriented mobility, 4) HSR-oriented mobility, and 5) inter-county bus-oriented mobility (Table 2). Factor loading indicates the relationship between each variable and the factors. If the value is 0.3 or higher, the relationship can be considered significant; the higher the value, the closer the relationship.

The first factor, ‘rail-oriented mobility’, has the characteristics of a low share of transportation for passenger cars and both high degree centrality and greater modal split of travel for railways and subways. Factor 2, ‘intra-county bus-oriented mobility’, has the characteristics that the travel modal split of passenger cars is low, the bus modal split within the county is high, and the degree centrality of buses is somewhat high. This study named Factor 3 as ‘road-oriented mobility’. This factor was characterized by the degree centralities of both passenger cars and buses as the highest among travel mobility indicators compared to other factors, and the degree centrality of high-speed rail is rather high. Factor 4, ‘high-speed rail-oriented mobility’, has the highest factor loading compared to other factors with modal split and degree centrality for HSR. Lastly, the fifth factor is named as ‘inter-county bus-oriented mobility’. This factor is closely related to the modal split of inter-county buses; however, the modal split of inter-county passenger cars is relatively low.

4.2. impacts on confirmed COVID-19 cases

Table 3 summarizes the results of the eight negative binomial regression models both with and without control variables for the entire period and a respective wave period that identified the impacts of the five factors, which compressed travel mobility indicators from the factor analysis, on the number of COVID-19 confirmed cases. Model A was for the entire period, Model B was for the first two-wave period, Model C was for the third wave period, and Model D was for the fourth wave period. Among these, Models A-1, B-1, C-1, and D-1 included only pre-pandemic travel mobility factors, while Models A-2, B-2, C-2, and D-2 included control factors. Prior to interpreting these results, model statistics were used to determine the validity of the models.

First, the validity of the negative binomial regression models over the Poisson models was confirmed by using the alpha statistics presented in Table 3. The Poisson model assumed an alpha value of 0. However, all four negative binomial regression models demonstrated that the alpha was not significantly zero. The validity of the negative binomial regression model for the ordinary least squares (OLS) linear regression model was verified using Akaike’s Information Criteria (AIC) and Bayesian Information Criteria (BIC). Table 3 shows that the AIC and BIC statistics for all four negative binomial regression models have smaller values than those of the OLS models. These results illustrate that the negative binomial regression model is more suitable than both the Poisson and OLS regression models. However, serious multicollinearity between independent variables can cause bias in the analysis results. This diagnosis was confirmed by the variation inflation factor (VIF) presented in Table 3. In general, if VIF is > 5, serious multicollinearity should be suspected. The VIF of each independent variable in this study was <5. Therefore, we conclude that there was no significant multicollinearity.

Table 3 also presents the results of the negative binomial regression models. The regression coefficients of the five factors for travel mobility used in these models were factor scores. Since factor scores are standardized values, it is possible to compare the magnitudes of the regression coefficients between the factors in the models, such as the standardized coefficient of a linear regression model. In other words, it is possible for us to compare the difference in influence, that is, the importance, among the factors of pre-pandemic travel mobility in confirmed COVID-19 cases. In the models without control variables, three factors, except for Factor 4 (HSR-oriented mobility) and Factor 5 (inter-county bus-oriented mobility), had statistically significant positive effects on spatial diffusion of COVID-19 cases. In addition, when we compare the magnitudes of the values between these regression coefficients, we find that the most important factor is Factor 3 (road-oriented mobility indicator), followed by Factor 2 (intra-county bus-oriented mobility), and Factor 1 (rail-oriented mobility). This suggests that road-oriented mobility is more important in the spatial diffusion of COVID-19 than either intra-county or rail-oriented mobility. Factor 5 has significant positive impacts during the entire period as well as in the fourth wave period, while it has a negative impact on the first two-wave period.

The results of these models, including only pre-pandemic travel mobility pattern factors without control variables, suggest that the connectivity of the inter-county road network is more important than the modal split for travel during the diffusion of COVID-19. In other words, counties highly connected by a network of passenger cars and buses on roads are more vulnerable to the spread of COVID-19. Conversely, Table 3 shows that the degree of vulnerability for the travel mobility of the intra- and inter-county rail and subway (Factor 1) or the intra-county bus (Factor 2) was not significantly different between those without the control variables (Model A-1, B-1, C-1, and D-1) and those with them (A-2, B-2, C-2, D-2). This finding implies that the primary use of public transportation for travel is almost equally vulnerable to the spread of COVID-19.

The models including both pre-pandemic travel mobility factors and control variables present the results of analyses of the effects of travel mobility factors on the diffusion of COVID-19 after controlling for attributes such as accessibility and demographic socio-economic factors. These results seem to be somewhat different from those of the models that include travel mobility factors without control variables. In the models that included both the five factors and control variables, the regression coefficient of Factor 4 was not statistically significant. This indicates that travel mobility based on the high-speed rail does not play a significant role when other variables are controlled. In contrast, both Factor 2 and Factor 3 still had a statistically significant positive effect in the models that included control variables, however, the magnitude of the influence was greatly reduced. In contrast to the differences in the results of these factors, Factor 1, which represents rail-oriented travel mobility, has a statistically significant positive effect on the spread of
COVID-19, and there is no significant difference in the regression coefficient among the regression models compared with the models without control variables.

Notably, the results of the control variables are the demographic, socioeconomic, and physical environment attributes in the study. The results for the entire period (Model A) demonstrate that the number of confirmed COVID-19 cases increased as the road length density decreased. The farther away from the highway IC, the fewer railway stations per area; the closer to the nearest airport, the higher the ratio of people aged 65 and over; and the higher the proportion of foreigners, the lower the park area per area; and the lower the GRDP per capita, the more urbanized and larger the administrative area. Among the control variables that were statistically significant in the entire period (Model A), some variables, such as highway access, GRDP per person, urban area, and administrative area, were also statistically significant in all of the periods (Models B, C, and D). In contrast, the other control variables showed no significant impact on the diffusion of confirmed COVID-19 cases for a specific period. The control variables, such as road length density and population density, were statistically significant only in the 4th wave period (Model D) and highway accessibility only in the 3rd wave period (Model C). The other control variables, such as railway station density, elderly ratio, foreigner ratio, and park area density, were statistically significant in the 3rd and 4th wave periods (Models C and D). These results demonstrated the dynamic change over time and suggested that the characteristics of the population, socioeconomic status, and physical environment may have no fixed impacts on the spatial diffusion of COVID-19.

Another important control variable in this study was the temporally varying effect of Daegu City. In early February 2020, the rate of infection chains from church activities in the city reached 55% of that of the entire country (Shim et al., 2020). The results for the 1st and 2nd wave period (Model A) indicated that the dummy variable for Daegu City had a statistically significant positive effect on the behavior of citizens in responding to and adapting to COVID-19. Such results may be caused by a change in the behavior of citizens against COVID-19, especially in the city. People who lived at the initial epicenter of the transmission were more sensitive to COVID-19 than those in other cities and countries in the subsequent period. Conversely, the result for the 4th wave period (Model D) showed that there were no statistically significant differences between Daegu City and the other counties and cities. These dynamic changes indicated that the collective behavior of citizens in responding to and adapting to COVID-19 may have been more closely related to the spread of COVID-19.

Table 3
Summary on the results of negative binomial regression models.

|                  | Model A: Entire Period | Model B: 1st & 2nd Wave Period |
|------------------|------------------------|-------------------------------|
|                  | Model A-1 | Model A-2 | Coef. | Z  | Coef. | Z  | Coef. | Coef. |
| Pre-pandemic     |           |           |       |    |       |    |       |      |
| travel mobility  | Factor 1 (Rail/Subway) | 0.661    | 9.92  | 0.660 | 8.76 | 0.845 | 4.64 | 0.662 | 3.91 |
|                  | Factor 2 (Intra-county bus) | 0.767    | 11.07 | 0.224 | 4.51 | 0.645 | 5.72 | 0.266 | 3.23 |
|                  | Factor 3 (Road) | 0.793    | 11.20 | 0.275 | 5.85 | 0.816 | 5.31 | 0.546 | 3.06 |
|                  | Factor 4 (HSR) | 0.067    | 1.42  | 0.039 | 1.14 | 0.313 | 2.26 | 0.003 | 0.96 |
| Factors          | Factor 5 (Inter-county bus) | 0.106    | 1.69  | -0.066 | -1.71 | -0.267 | -2.35 | -0.341 | *** |
| Control variables| Road length density | -1.00E-6 | 3.52  | 4.72E-6 |

log-transformed distance from the nearest highway interchange
No. railway stations per area
log-transformed distance from the nearest airport
Population density (= no. pop./county area)
Ratio of population over 65
Ratio of foreign population
Park area per county area
GRDP per person
Urban area (= 1, rural area = 0)
County area
Daegu city (= 1, others = 0)
Constant
Alpha
Model Statistics
Wald chi-squared
Pseudo R-squared
AIC
BIC
OLS Model Statistics
R-squared
AIC
BIC

Note: p-value <0.001 ***, <0.01 **, <0.05 *, and <0.1 +.
5. Discussion

The pre-pandemic travel mobility pattern is still an important key factor in the diffusion of COVID-19, even though both pandemic shock and non-parametric intervention measures in response to it might have changed the current mobility pattern. Many studies have focused on either the change (Baig et al., 2022; Zafri et al., 2021) or vulnerability (Shen et al., 2020; Zhu and Guo, 2021) of travel behavior during the COVID-19 pandemic. Restrictions on travel mobility may have been effective in containing its transmission (Mahmoudi and Xiong, 2022). However, for a long time before the pandemic, travel mobility patterns developed both urban forms and transport networks (Cervero, 2002; Hymel, 2019; Mokhtarian and Salomon, 2001). This study found that most of the pre-pandemic travel mobility patterns may be fundamental factors in the spatial diffusion of COVID-19.

Most pre-pandemic travel mobility patterns have had temporally consistent and positive impacts on the diffusion of COVID-19 during the pandemic. In addition, in terms of the magnitudes of the regression coefficients, it is noteworthy that there are no distinguished ordering differences in the results among all the models in the effects of travel mobility as well as control variables on the spread of COVID-19. Previous studies have reported differences in human mobility depending on the timing and magnitude of the spread of infectious diseases (Yoo et al., 2021; Choi, 2020; Zhang and Hayashi, 2022). This indicated that the association between COVID-19 transmission and travel mobility may have been bi-directional (Borkowski et al., 2021; Habib and Anik, 2021; Kartal et al., 2021). In general, people tend to refrain from physical movement at the initial stage of the spread of an infectious disease because of the fear associated with contracting it. However, as the spread of an infectious disease continues over time, it is inevitable that individuals may resume daily life and activities before the outbreak due to fatigue from the restraint of physical movement. However, based on our findings, travel mobility patterns developed both urban forms and transport networks for a long time before the pandemic and may have had uni-directional, and not bi-directional, causal relationship with the transmission of COVID-19.

Travel mobility patterns of the rail and subway modes before the pandemic may have posed the greatest threat to the spatial spread of COVID-19 at any scale and time. This study found that travel mobility patterns by rail and subway before the pandemic could be the biggest threat to the spatial spread of COVID-19, regardless of its scale and time, if we control for other factors, such as accessibility and physical, demographic, and socioeconomic properties. Policymakers should develop strategies to prevent the spatial spread of COVID-19 by reducing human mobility for daily life in areas with the pattern of strong rail and subway transit mobility formed before the pandemic.
pandemic. In this regard, the authorities may not only shut down the operation of public transit but also consider either reducing its operation frequency or restricting its ridership to control the diffusion of COVID-19. However, public transit tends to be mainly used by low-income populations who cannot afford a private car (Palm et al., 2021). In addition, the link between COVID-19 transmission and public transportation has been found to be mixed (Gartland et al., 2022). While using public transportation, measures such as the wearing of masks, physical distancing, air conditioning, and filtering on public transit may contain the spread of COVID-19 effectively (Kriegel, 2022; Miller et al., 2022; Muathesis, 2022; Yang et al., 2022). Quarantine measures, such as suspension of operations or restrictions to prevent the spread of infectious diseases, may cause unexpectedly high socioeconomic costs, such as increases in mental health conditions and the deepening of socioeconomic inequality (Fink et al., 2022; Koch and Park, 2022; Thunström et al., 2020).

Restriction measures on rail and subway transit mobility need to be the last option to control the diffusion of infectious disease during the pandemic. Although the operating cost of public transportation is also incurred, policymakers should make efforts to prevent the aggravation of socioeconomic inequality caused by the COVID-19 pandemic.

During the COVID-19 pandemic, pre-pandemic travel mobility patterns could be closely associated with urban characteristics such as demographic, socioeconomic, and physical environment attributes. This study found that the magnitude of the impact of road-oriented travel mobility patterns on the diffusion of COVID-19 greatly decreased when they were included in the models. Urban socio-economic and physical environments may be key factors in promoting the spread of infectious diseases by providing the environment for their spread, such as crowding and closeness (Hamidi et al., 2020; Cuadros et al., 2020; Ehlert, 2021; Jamshidi et al., 2020; Jo et al., 2021; Padmakumar and Patil, 2022). They may also have a very close relationship with the transportation network for diffusing COVID-19 (Teller, 2021). This study also demonstrated that road-oriented pre-pandemic travel mobility patterns were associated positively with the spread of COVID-19. This suggested that the effective control of closed and overcrowded physical environments may further reduce the potential transmission by travel mobility and vice versa. In this regard, developing containment and adaptation strategies that take into account travel mobility patterns and urban forms may be effective in intervening in the transmission of infectious diseases.

Despite its empirical identification of the effect of pre-pandemic travel mobility patterns on the spatial spread of COVID-19, this study had some limitations. The first limitation was that the OD data used in the study did not provide information on non-motorized travel modes, such as walking and bicycling. The non-motorized transportation modes may be sustainable alternative transportation modes that may maintain human mobility in daily life, while reducing the risk of infection during the COVID-19 pandemic. Therefore, travel mobility patterns before the pandemic should be considered in future studies, as they may also have significant impacts on the spatial spread of infectious diseases. The second limitation was that the study did not include and analyze the mobility indicators of air transport with surface travel modes. Instead, the study measured the physical accessibility of airports and found a close positive correlation with the spatial spread of COVID-19. This supported the findings of previous studies (Choi, 2020; Gaskin et al., 2021; Li, 2020; Zhu and Guo, 2021). However, the modal split and degree centrality of air transport may be more closely related to international travel mobility than to domestic mobility. Third, the study did not control the effectiveness of non-pharmaceutical interventions such as the wearing of a mask, working from home, limiting business operations, and limiting public transportation operations. These measures, implemented with varying strengths due to the extent of the spread of COVID-19, might have had a significant impact on the diffusion of COVID-19 by changing travel mobility patterns during the pandemic. Although the study identified differences in the effects according to the wave period, it was still a limitation in that the effect could not be controlled because the data used for the analysis were not time series. In this regard, future studies should be conducted on how the various non-pharmaceutical interventions have affected the pre- and during-pandemic patterns of travel mobility.

6. Conclusions

Physical mobility is one of the most important determinants of the spread of infectious diseases. However, pre-pandemic travel mobility patterns that developed both urban forms and transport networks for a long time before the pandemic, may also be key fundamental factors in the spatial diffusion of infectious diseases. The results of this study empirically identified the temporally consistent impacts of pre-pandemic travel mobility at the county level on the spread of COVID-19. Pre-pandemic travel mobility patterns may have had an uni-directional, and not a bi-directional, causal relationship with the transmission of COVID-19. Developing containment and adaptation strategies to take into account pre-pandemic travel mobility patterns may be effective in intervening in the transmission of infectious diseases. Travel mobility patterns by public transit, especially rail and subway, may be the greatest threat to the transmission of infectious diseases. However, its suspension or restriction must be the last option to control the diffusion of infectious diseases during the pandemic.

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Conflicts of interest

The authors have declared that there are no competing interests.

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Data availability

Data will be made available on request.

References

Abdullah, M., Ali, N., Hussain, S.A., et al., 2021. Measuring changes in travel behavior pattern due to COVID-19 in a developing country: a case study of Pakistan. Transport Pol. 108, 21–33.
Abdullah, M., Dias, C., Muley, D., et al., 2020. Exploring the impacts of COVID-19 on travel behavior and mode preferences. Transp. Res. Interdiscip. Perspect. 8, 100255.
Abouk, R., Heydari, B., 2021. The immediate effect of COVID-19 policies on social-distancing behavior in the United States. Publ. Health Rep. 136 (2), 245–252. https://doi.org/10.1177/0033354920976575.
Arroyo, M.A., Sateren, W.B., Serwadda, D., et al., 2006. Higher HIV-1 incidence and genetic complexity along main roads in Rakai District, Uganda. J. Acquir. Immune Defic. Syndr. 43 (4), 440–445.
Baig, F., Kirytopoulos, K., Lee, J., Tsamilis, E., Mao, R., Ntzeremes, P., 2022. Changes in people’s mobility behavior in Greece after the COVID-19 outbreak. Sustainability 14, 3567. https://doi.org/10.3390/su14063567.
Bajardi, P., Poletto, C., Ramasco, J.J., et al., 2011. Human mobility networks, travel restrictions, and the global spread of 2009 H1N1 pandemic. PLoS One 6 (1).
Bajardi, P., Poletto, C., Ramasco, J.J., et al., 2011. Human mobility networks, travel restrictions, and the global spread of 2009 H1N1 pandemic. PLoS One 6 (1), e16591.
Borkowski, P., Jądżewska-Gutta, M., Szmelter-Jarosz, A., 2021. Lockdowned: everyday mobility changes in response to COVID-19. J. Transport Geogr. 90 https://doi.org/10.1016/j.jtrangeo.2020.102906.
Brough, R., Freedman, M., Phillips, D.C., 2021. Understanding socioeconomic disparities in travel behavior during the COVID-19 pandemic. J. Reg. Sci. 61 (4), 753–774.
Caicedo, J.D., Walker, J.L., González, M.C., 2021. Influence of socioeconomic factors on transit demand during the COVID-19 pandemic: a case study of Bogota’s BRT system. Frontiers in Built Environment 7, 63.
Cervero, R., 2002. Induced travel demand: research design, empirical evidence, and normative policies. J. Plann. Lit. 17 (1), 1–20.
Chang, S., Pierson, E., Koh, P.W., et al., 2021. Mobility network models of COVID-19 explain inequities and inform reopening. Nature 589 (7840), 82–87.
Chen, C., Feng, T., Gu, X., Yao, B., 2022. Investigating the effectiveness of COVID-19 pandemic countermeasures on the use of public transport: a case study of The Netherlands. Transport Pol. 117, 98–107. https://doi.org/10.1016/j.trapol.2022.01.005.
Cheshmezangi, A., 2022. Vulnerability of the UK’s BAME communities during COVID-19: the review of public health and socio-economic inequalities. J. Hum. Behav. Soc. Environ. 32 (2), 172–188.
Choi, S., 2020. Characteristics and distribution of teleworkable jobs based on physical working conditions. J. Econ. Geograph. Soc. Korea 23 (3), 276–291.
Choi, S.H., 2020. Preventive measures during outbreak of coronavirus disease 2019. Kor. J. Med. Kor. Assoc. Intern. Med. 95 (3), 134–140.
Cudros, D.F., Xiao, Y., Mukandavire, Z., et al., 2020. Spatiotemporal transmission dynamics of the COVID-19 pandemic and its impact on critical healthcare capacity. Health Place 64, 102404.
Ehlert, A., 2021. The socio-economic determinants of COVID-19: a spatial analysis of German county level data. Soc. Econ. Plann. Sci. 78, 10183.
Fink, G., Tediosi, F., Felder, S., 2022. Burden of Covid-19 restrictions: national, regional and global estimates. eClin. Med. 45, 101305 https://doi.org/10.1016/j.eclinm.2022.101305.
Gargoum, S.A., Gargoum, A.S., 2021. Limiting mobility during COVID-19, when and to what level? An international comparative study using change point analysis. J. Transp. Health 1, 100255.
Gartland, N., Fishwick, D., Coleman, A., Davies, K., Hartwig, A., Johnson, S., van Tongeren, M., 2022. Transmission and control of SARS-CoV-2 on ground public transport: a rapid review of the literature up to May 2021. J. Transport Health 26, 101356. https://doi.org/10.1016/j.jth.2022.101356.
Gaskin, D.J., Zare, H., Delarmente, B.A., 2021. Geographic disparities in COVID-19 infections and deaths: the role of transportation. Transport Pol. 102, 35–46.
Gelman, A., Hill, J., 2006. Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge University Press.
Hamidi, S., Hamidi, I., 2021. Subway ridership, crowding, or population density: determinants of COVID-19 infection rates in New York City. Am. J. Prev. Med. 60 (5), 614–620.
Thombre, A., Agarwal, A., 2021. A paradigm shift in urban mobility: policy insights from travel before and after COVID-19 to seize the opportunity. Transport Pol. 110, 335–353.

Thunström, L., Newbold, S.C., Finnoff, D., Ashworth, M., Shogren, J.F., 2020. The benefits and costs of using social distancing to flatten the curve for COVID-19. J. Benefit-Cost Anal. 11 (2), 179–195. https://doi.org/10.1017/bca.2020.12.

Troko, J., Myles, P., Gibson, J., et al., 2011. Is public transport a risk factor for acute respiratory infection? BMC Infect. Dis. 11 (1), 16.

Wang, H., Noland, R.B., 2021. Bikeshare and subway ridership changes during the COVID-19 pandemic in New York City. Transport Pol. 106, 262–270.

Wang, Y., Liu, Y., Struthers, J., et al., 2021. Spatiotemporal characteristics of the COVID-19 epidemic in the United States. Clin. Infect. Dis. 72 (4), 643–651.

Wielechowski, M., Czech, K., Grzeda, Ł., 2020. Decline in mobility: public transport in Poland in the time of the COVID-19 pandemic. Economies 8 (4), 78.

Wilbur, M., Ayman, A., Ouyang, A., et al., 2020. Impact of COVID-19 on public transit accessibility and ridership arXiv Preprint arXiv. 2008.02413.

Yang, Y., Wang, Y., Tian, L., Su, C., Chen, Z., Huang, Y., 2022. Effects of purifiers on the airborne transmission of droplets inside a bus. Phys. Fluids 34 (1), 017108.

Yoo, M.S., Kim, Y.J., Bake, S., et al., 2021. The concept of reproduction number and changes according to government response policies. Kor. Dis. Contr. Prev. Agency 14 (6), 282–289.

Zafri, N.M., Khan, A., Jamal, S., et al., 2021. Impacts of the COVID-19 pandemic on active travel mode choice in Bangladesh: a study from the perspective of sustainability and new normal situation. Sustainability 13 (12), 6975.

Zaki, B., Nicoli, F., Wayenberg, E., Verschueren, B., 2022. In: Trust We Trust : the Impact of Trust in Government on Excess Mortality during the COVID-19 Pandemic. PUBLIC POLICY AND ADMINISTRATION. https://doi.org/10.1177/09520767211058003.

Zhang, J., Hayashi, Y., 2022. Research frontier of COVID-19 and passenger transport: a focus on policymaking. Transport Pol. 119, 78–88. https://doi.org/10.1016/j.trapol.2022.02.014.