Changes in mobility amid the COVID-19 pandemic in Sapporo City, Japan: An investigation through the relationship between spatiotemporal population density and urban facilities

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Changes in mobility amid the COVID-19 pandemic in Sapporo City, Japan: An investigation through the relationship between spatiotemporal population density and urban facilities

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ABSTRACT

By the end of 2021, the Omicron variant of coronavirus disease 2019 had become the dominant cause of a worldwide pandemic crisis. This demands a deeper analysis to support policy makers in creating interventions that not only protect people from the pandemic but also remedy its negative effects on the economy. Thus, this study investigated people's mobility changes through the relationship between spatiotemporal population density and urban facilities. Results showed that places related to daily services, restaurants, commercial areas, and offices experienced decreased visits, with the highest decline belonging to commercial facilities. Visits to health care and production facilities were stable on weekdays but increased on holidays. Educational institutions' visits decreased on weekdays but increased on holidays. People's visits to residential housing and open spaces increased, with the rise in residential housing visits being more substantial. The results also confirmed that policy interventions (e.g., declaration of emergency and upgrade of restriction level) have a great impact on people's mobility in the short term. The findings would seem to indicate that visit patterns at service and restaurant places decreased least during the pandemic. The analysis outcomes suggest that policy makers should pay more attention to risk perception enhancement as a long-term measure. Furthermore, the study clarified the population density of each facility type in a time series. Improving model performance would be promising for tracking and predicting the spread of future pandemics.

Introduction

Coronavirus disease 2019 (COVID-19) is seen as the most severe pandemic in the 21st century. As of February 18, 2022, over four hundred million COVID-19 cases have been confirmed, including approximately-six million deaths (World Health Organization, 2022). In response to this new threat, certain measures have been implemented, including mobility restriction. As expected, early intervention reduced cases by 40 % (Chiba, 2021). However, these measures have also considerably distressed socioeconomic aspects in both the short and long terms. The relationship between risk effects and mobility patterns should be clarified to remedy the negative impacts of the pandemic and to enhance the policies' effectiveness.

In this context, researchers have been investigating the relationship between the COVID-19 pandemic and human mobility and build environment factors. Most studies agreed the pandemic has heavily constrained people from commuting through the implemented measures and the rise of risk perception. For instance, a survey in Australia showed that the average weekly number of household trips was reduced by approximately 50 % in the early stage of implementation (Beck and Hensher, 2020a). Similarly, Politis et al. (2021) reported that the average daily trips per person in Greece decreased by 50 % during the lockdown. Zhang et al. (2021) declared that the Metro Transit Railway travel volume in Hong Kong declined dramatically during the pandemic, especially on Sundays. Although these studies were conducted in different places and at various times, they are consistent with Google Community Mobility Reports (Google, 2022), which indicated a shrinkage of people's mobility during the COVID-19 pandemic.

Besides illustrating common trends of travel demand, various studies have shown the impact of the pandemic on the declines in trips related to work, school, and other purposes. For example, Yang et al. (2021) confirmed dramatic reductions in the visits to three place groups (retail and recreation venues, parks, and transit stations) in tourism cities. According to Simons et al. (2021), Ohio citizens reduced not only their

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work and shopping trips (by 11 %–19 %) but also their social visits and worship trips (by 49 %–61 %). During the transition of lockdown implementation, Pawar et al. (2021) stated that Indians decreased their work-related and nonwork-related trips during this period. Regarding outdoor activities and medical visits, Semple et al. (2021) found that the frequency of outdoor exercise trips dropped by up to 46.4 % in Scotland during the lockdown, whereas Kumagai (2021) reported a decline in physician visits in Japan because of the outbreak. Likewise, a substantial decrease in trip volume was found at amenities and grocery stores in the US (Sevtsuk et al., 2021; Wang et al., 2020). The above studies' findings would be valuable for identifying the relationship between the outbreak, restriction policies, and mobility changes.

Nevertheless, the connection between these two terms above is not a one-way relationship. Mobility and the build-up environment, in turn, also play a critical factor in driving epidemic transmission. Numerous studies declared human mobility, represented by population flows, the external and internal immigration, as the carrier that transmits the infection from place to place (J. Liu et al., 2021; López-Gay et al., 2022; Ramírez-Aldana et al., 2021). In more detail, the trip rate was identified as a substantial determinant of the number of newly infected cases in the USA and Italy (Badr et al., 2020; Cartenì et al., 2020). Also, studies pointed out that mobility reduction has significantly influenced the decrease in the incidence rate. On a global scale, Nouvellet et al. (2021) stated that the pandemic transmission considerably reduced when mobility declined initially in most analyzed countries. Likewise, a low incidence is associated with a reduction in mobility on the national, county, and city scales (Harris, 2022; Kephart et al., 2021; Tokey, 2021).

Besides the general mobility pattern, researchers have also paid attention to the mobility at locations and the built environment characteristics. For instance, Kan et al. (2021) and Kwok et al. (2021) found that the high risk is related to the high density of commercial land and high-rise buildings in Hongkong. Meanwhile, studies by Lee et al. (2021) and Tribby and Hartmann (2021) indicated green areas and parks negatively related to the low infected case in the U.S. and England. By contrast, Kato and Takizawa (2022) claimed that visits to parks were the determinant of the high risk. The authors also declared groceries and pharmacies were the sources of infection, but the transit station was not. Inconsistent with Kato and Takizawa (2022), Steiger et al. (2021) argued that the increase in mobility at groceries and pharmacies correlated to the low newly reported cases. Further, their study also reported mobility at retail and recreational areas or workplaces positively affected the rise of infection. The mentioned findings seem to strongly imply that the density at locations is a dominant factor influencing pandemic spreading.

From the literature review, we pinpoint that though mobility has been investigated on various scales, the variation of visits to facilities (building types), to our knowledge, has not been explored. Meanwhile, the examining scale significantly affects the analysis results, particularly in investigating the relationship between COVID-19 transmission and human factors and the built environment (Alidadi and Sharifi, 2022). Further, the population density alone would not fully explain the pandemic spreading, but the spatial distribution, socio-political situations, and mobility habits instead (Barak et al., 2021). Nonetheless, this density term was indistinct between urban and population, which might cause a misleading in interpreting the analysis's outcomes (Alidadi and Sharifi, 2022). Thus, analyzing this aspect of facilities would be worth understanding the mobility patterns from a micro view. Last but not least, since mobility has characteristics of space and time, investigating its variation should be a spatiotemporal analysis.

The spatiotemporal analysis is one element of the data mining field focusing on moving objects. The tasks in this topic may include object clustering, pattern detection, pattern predicting, and trajectory annotation (Körner et al., 2012; M. Nanni et al., 2008). Since the present study focuses on mapping the mobility pattern, we limit the background to the second task and its applied methods. In this sub-topic, the prominent assignments are spatiotemporal hotspot detection, frequent movement patterns detection, and pattern occurrences detection (Körner et al., 2012).

Regarding the first assignment, spatiotemporal hotspot detection, popular approaches are partitioning, hierarchical and density-based. For example, Cheng and Wicks (2014) and Li et al. (2018) detected spatiotemporal events using space–time scan statistics (STSS) and an adaptive method, respectively. STSS, introduced by Kulldorff et al. (2005), was also a favorable method in investigating COVID-19 cluster and its determinants by researchers (Andersen et al., 2021; Kan et al., 2021; M. Liu et al., 2021; Tyrovolas et al., 2021). For frequent movement pattern detection, the notably mentioned approaches should be trajectory-based and graph-based algorithms introduced by Hwang et al. (2005) and Lee et al. (2009), respectively. Besides, hierarchical trajectory clustering is also a promising method when it has the advantage of solving the hierarchical reference spots and sequence considerations (Zhang et al., 2018). Regarding the third task, practitioners may find useful solutions introduced by Taniar and Goh (2007) and Iwan and Safar (2010). Specifically, Taniar and Goh (2007) developed a framework to extract the list of sequences that mobile users commonly visit. Likewise, Iwan and Safar (2010) formulated two algorithms called location link and user link to discover patterns from indirect data sources.

The above approaches, except for STSS, seem unattractive to the researchers in investigating the mobility pattern. Instead, we found several works that recently relate to this topic, including a population flow-based spatial–temporal eigenvector filtering model by Chen et al. (2022), space–time kernel density estimation by Kato (2021), and a fuzzy clustering algorithm by Aljeri (2022). Notably, we have also noticed numerous studies applied the geographically weighted regression model (GWR) and its modifications in analyzing spatiotemporal characteristics of COVID-19 (Hassaan et al., 2021; Lak et al., 2021; Maiti et al., 2021; Raymundo et al., 2021; etc.) This fact implies that a simple regression model can solve the spatiotemporal problem, especially in the case of spatial panel data, as noted by An and Crook (2017).

Generally, the spatiotemporal analysis is not a simple task when it confronts the four challenges, including building the empirical objects, presenting and exploring the changes and moments, identifying and analyzing the evolution of relationships, and identifying the process underlying these changes (Mathian and Sanders, 2014). However, the common problem researchers encounter when implementing the analysis is building and collecting the data. A review of previous studies underscores the main issues that need to be solved, including the survey duration and observation size. For the first issue, since the outbreak began, researchers have been striving to explore the situation as quickly as possible. Thus, collected data in these works in only weeks or months. Given this short time, the results represent short-term changes, but long-term effects remain undisclosed or unpredictable. Moreover, because of the pandemic threat and policy implications, most research groups used indirect survey methods (e.g., web-based and telephone surveys) to collect data, which might have caused difficulties in validating the data and obtaining a large sample size.

Mobile phone data have supported researchers in overcoming this limitation. In recent decades, mobile phone data have become a useful tool for investigating travel behaviors because of their multidimensional information, namely, spatial, temporal, and demographic data (Servizi et al., 2021; Wang et al., 2018). Taking advantage of this aspect, researchers have been mining travel behavior data amid the COVID-19 pandemic with different mobile phone data sources. Several studies used Global Positioning System applications to examine the mobility patterns in Thailand, Switzerland, and the Netherlands (Haddawy et al., 2021; Marra et al., 2022; Molloy et al., 2021; Olde Kalter et al., 2021). Notably, the numbers of participants in these studies are relatively small, varying from 48 to 1515 people. Therefore, although tracking applications offer advantages such as high accuracy and proficiency in revealing trip routes, they are insufficient tools with regard to sample size. This disadvantage may have prevented these researchers from covering the mobility patterns of their populations on a larger scale.

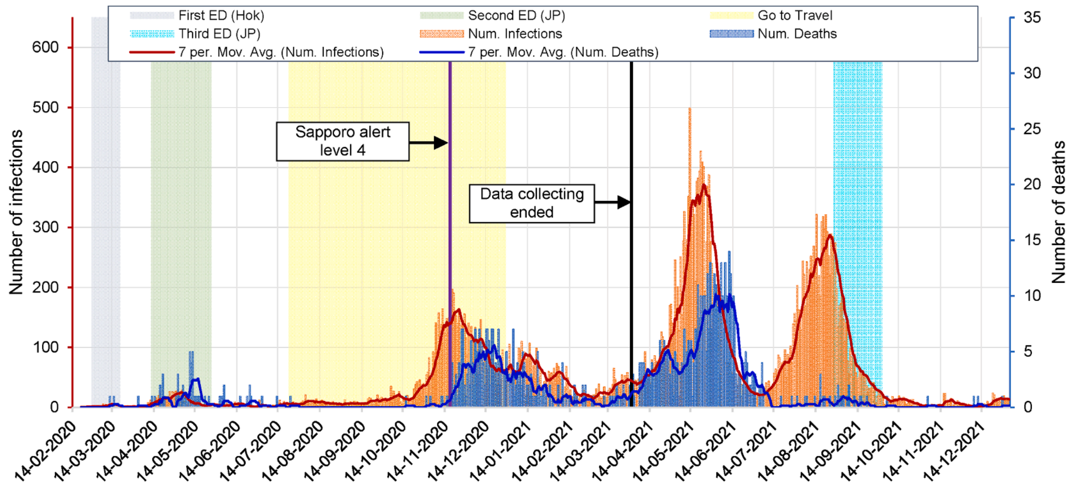


Fig. 1. COVID-19 pandemic progress in Sapporo City(Source: DATA-SMART City Sapporo https://ckan.pf-sapporo.jp/dataset/covid_19_patients).

Another approach is to use location history data provided by Google (Google, 2022) because of its enormous number of users. Hakim et al. (2021) used these data to review mitigation policies in Australia, Japan, Hong Kong, and Singapore. Cot et al. (2021) and Wellenius et al. (2021) investigated the impact of the COVID-19 outbreak on mobility and the relationship between mobility reduction and the decreases of infection rates in Europe and the US. Nevertheless, Google data have some limitations. First, the report expresses the movement trends across locations by comparing the average visit between the reported and baseline days. The lack of hour-visit variation would hinder researchers in interpreting the mobility changes at a specific time. Second, the data collected visit at a large scale (province, prefecture) and illustrated by percentage, not an absolute number. Thus, the change levels at locations are likely incomparable. In addition, it would be difficult to reveal the relationship between visiting changes in reported places. We also believe that the extension of surveyed location types and the distinction between weekdays and holidays would help us understand the mobility changes more comprehensively.

Mobile phone network data can compensate for the limitations of the two abovementioned data types. Such data can be applied to model and predict the epidemic spread and to examine the mobility patterns during the pandemic. Regarding the former task, mobile phone network data were used to build COVID-19 spread models in Brazil and China (Jia et al., 2020; Peixoto et al., 2020). Regarding the latter topic, before the COVID-19 pandemic, Peak et al. (2018) used this type of data in mapping the mobility reduction caused by the Ebola epidemic in Sierra Leone. During the COVID-19 pandemic, various studies used mobile phone network data to investigate mobility changes in various countries and regions, such as France, China, Europe, and the US (Hu et al., 2021; Liu et al., 2021; Pullano et al., 2020; Santamaria et al., 2020).

In Japan, owing to the spread of the pandemic, NTT Docomo Insight Marketing Inc. released mobile phone data called mobile spatial statistics (MSS) to support researchers and policy makers in finding effective measures. The data were then used in numerous studies to examine Japanese mobility. Watanabe and Yabu (2021a, 2021b) used MSS to examine the self-restraint level during the pandemic at the national and prefecture scales. As stated by the authors, the declaration of emergency and the rise of infection cases influenced the increase in the number of Japanese individuals staying home. Furthermore, the extent of staying home was found to have a positive relationship with age. Mizuno et al. (2021) used data covering the first half of 2020 to visualize the stay-home rate in Japan's prefectures. The results showed that the peak stay-home rate exceeded 60 % in Tokyo during the state-of-emergency period. Moreover, Hara and Yamaguchi (2021) used data from the same period to examine travel patterns and found the same trend of decline in people's travel volume and number of trips made.

On a small scale, Arimura et al. (2020) investigated the change in the population density of Sapporo City and found that its crowded areas experienced a 90 % decrease in population density during the second wave of the pandemic. Nakanishi et al. (2021) used MSS to analyze the relationship between the infection trend and the population variation in selected restaurant and bar areas in Tokyo. The authors concluded that the population in these areas increased when the number of cases decreased, thus possibly increasing the number of cases afterward. The above studies used data collected within 2020. Despite the relatively long data period, an extension of the survey duration would have been meaningful as the later wave of a pandemic usually has a stronger surge than the precedent.

To fill the abovementioned gaps, the present study investigates the changes in mobility before and during the COVID-19 pandemic by revealing the relationship between the spatiotemporal population density and urban facilities. Specifically, we propose the use of MSS data from Sapporo City, Japan, to address the following research questions:

(1) During the COVID-19 pandemic, which urban facilities were associated with the spatiotemporal population density?
(2) Which facility had a larger influence on the spatiotemporal population density compared with other facilities?
(3) To what extent did these facilities' influence change during a day, from weekdays to weekends/holidays, and across different times?

Our results contribute to the knowledge in this field in two ways. First, they help in the thorough understanding of the interaction between the pandemic spread and urban mobility. Second, they clarify the spatiotemporal relationship between urban facilities and population density. Overall, this study will support policy makers in evaluating and adjusting policy's intervention to enhance effectiveness in the short and long terms.

This paper has four remaining sections. Section 2 presents the dataset and the proposed method. It briefly explains the progress of the pandemic spread in the study area and the data characteristics. Section 3 shows the primary results of the analysis of the three research questions. In Section 4, we discuss the results and related policy implications. Finally, Section 5 states the study's limitations, future research intentions, and conclusions.

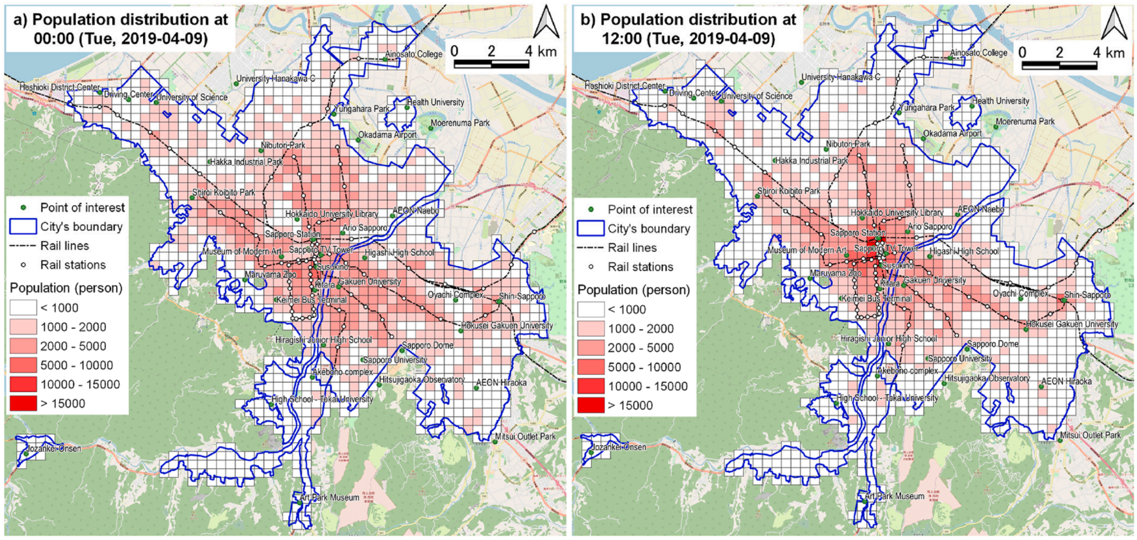


Fig. 2. Distribution of the city's population at specific times.

Table 1
Explanatory variables.

No	Variable	Type of facility	Applicable buildings (Zenrin classification)
1	X01. Hou	Residential housing	Private housing, condominiums, general stores, combined housing, houses with restaurants, houses with offices or workplaces, and flats in mixed commercial or office buildings
2	X02.Ser	Daily services	Shops or stores selling daily needs, such as food, beverage, and clothes, and beauty salon services
3	X03.Res	Restaurants and entertainment	Facilities serving food, beverage, and entertainment activities, such as restaurants and karaoke bars
4	X04. Com	Commercial buildings	Facilities used for commercial purposes, such as shopping malls, mass retailers, and exhibition centers
5	X05.Off	Office buildings	Facilities used for official purposes, such as administration and company offices
6	X06.Hea	Health care facilities	Hospitals, clinics, medical centers, sports clubs, and social welfare facilities
7	X07.Edu	Education institutions	Schools, colleges, universities, and research institutes
8	X08.Pro	Production facilities	Factories, plants, and warehouses
9	X09. OpS	Open spaces	Roads, walking and cycling routes, small parks, green areas, and the like (excluding large water and forest areas)

Data and methodology

Data collection

Summary of COVID-19 pandemic and preventive measures in Sapporo City

The first COVID-19 case in Japan was recorded on January 16, 2020, whereas Hokkaido reported its first case on February 6, 2020. However, Hokkaido was the first prefecture to announce a state of emergency in Japan, which began on February 28, 2020, and was lifted on March 19, 2020 (Fig. 1). In the second wave of the pandemic, the prefecture proactively enacted an emergency declaration (ED) on April 14, 2020, before the national ED (from April 16, 2020 to May 31, 2020). During these EDs, activity restrictions were imposed, including school closures (from elementary to high school), shortening of serving hours of restaurants, and event cancelations. People were advised to refrain from going out, businesses were requested to switch to teleworking, and all activities had to be conducted while avoiding the "triple C" (crowding, close contact, and closed spaces). Under these restrictions, the population density in crowded areas in the city decreased by up to 90 % (Arimura et al., 2020).

After the second wave of the pandemic, the Japanese government launched the Go To Travel campaign to address the heavy economic damage caused by the lockdowns. The campaign was planned to run from July 22, 2020 to December 31, 2020, but was stopped on December 28, 2020, because of the adverse progress of the pandemic. The government of Hokkaido intensified its measures to level 2 on October 28, 2020, and further increased them to level 3 on November 7, 2020, in light of the sharp increase in the number of infections. For Sapporo City, the measures were upgraded to level 4 because of the urgent situation of the medical system. Although this period was not under a state of emergency, the restrictions resembled those that were implemented during the ED. These actions strongly affected citizen travel behavior.

MSS data

In the present study, we used the MSS data provided by NTT Docomo Insight Marketing Inc. The data's structure was the same as that used by Arimura et al. (2020) but had a longer survey time. The collected MSS covered the period of January 1, 2019 to March 31, 2021 (821 days) (Fig. 1). As an extension of the survey, the data encompassed the population spatial distribution under various conditions, namely, before the pandemic (February 14, 2020), the two EDs in Hokkaido, the Go To Travel campaign, and long holiday events.

Unlike census data, MSS data have richer information that assists practitioners in mining mobility patterns. Fig. 2 illustrates the city population distribution at 0000 (midnight) and 1200 (noon) on Tuesday, April 9, 2019, in a 500 m square mesh. According to the graph, the city central business district (CBD) had the highest population density at midday, but the situation changed at midnight. The population spread to the residential areas, and a high density appeared mainly in areas of night activities (Susukino District). This reveals the resident flow between the residences and other facilities at the studied times. Thus, this relationship should be examined to create policies controlling the pandemic spread.

Explanatory variables

As mentioned in the previous section, we propose the use of all building types to estimate the population in a specific area. The building characteristics were obtained from a site survey conducted by Zenrin Co., Ltd. Table 1 shows the categories of the explanatory variables,

Table 2
Summary of the dataset.

No	Variable	Value (1.000 m²)						Percentage (*)
		Min	Median	Mean	Max	SD	Total	
1	X01.Hou	0.00	80.73	87.36	377.55	62.39	111,738.50	69.76 %
2	X02.Ser	0.00	1.34	3.20	99.63	6.14	4,088.43	2.55 %
3	X03.Res	0.00	0.08	0.88	81.59	3.11	1,130.21	0.71 %
4	X04.Com	0.00	3.54	14.89	1,306.79	58.30	19,039.88	11.89 %
5	X05.Off	0.00	1.71	3.01	128.08	5.67	3,854.73	2.41 %
6	X06.Hea	0.00	0.62	3.49	109.72	8.59	4,468.30	2.79 %
7	X07.Edu	0.00	0.14	4.83	131.68	9.98	6,172.51	3.85 %
8	X08.Pro	0.00	3.01	7.57	123.09	13.36	9,680.95	6.04 %
9	X09.Ops	0.00	57.00	52.03	144.35	22.84	66,551.55	–

SD: Standard deviation; (*): applied to building floor area only.

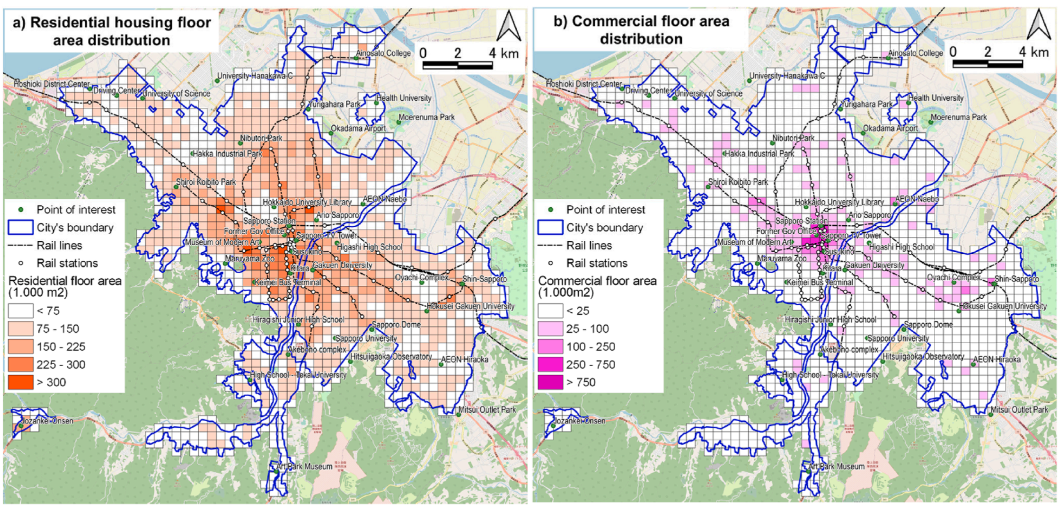


Fig. 3. Residential housing and commercial floor area distribution.

which were derived from the original dataset, which is shown in the Appendix (Table A). In addition to the eight building types, open spaces were deemed a dependent variable. We argued that such facilities are associated with intensive movement time (i.e., rush hour) and outdoor activities, especially on weekends and holidays. Thus, the addition of open spaces was necessary and might help the population is being predicted better.

After extracting the floor area of each building, we summarized the explanatory variables (Table 2). As indicated by the data, residential housing accounted for the largest proportion of the total floor area, followed by commercial buildings; they accounted for 69.76 % and 11.89 %, respectively. Restaurants accounted for the smallest proportion of the total floor area (0.71 %). The floor areas of the other facilities occupied 3.41 %–6.04 % of the total. Regarding open spaces, the average area in each grid was approximately 52,000 m^2, which was equal to about 20.81 % of the cell's area.

Fig. 3 illustrates the distribution of the two highest-value variables: residential housing and commercial buildings. As shown in Fig. 3a, the common grid's residential housing floor area was 75,000–150,000 m^2. High residential housing densities were found around Sapporo Station, in the CBD, and along the subway lines. Unlike residential housing, the commercial facilities were mainly concentrated in the CBD and close to the subway stations. We supposed that these areas would have large population variations between the day and night because of the difference in their facility functions.

Analysis methodology

To examine the relationship between population density and building facilities, we applied a multilinear regression (MLR) model as a predictive model. Although MLR is not an outstanding method, it is easy to implement and interpret, as discussed in a later section. Equation (1) expresses the form of the applied MLR model.

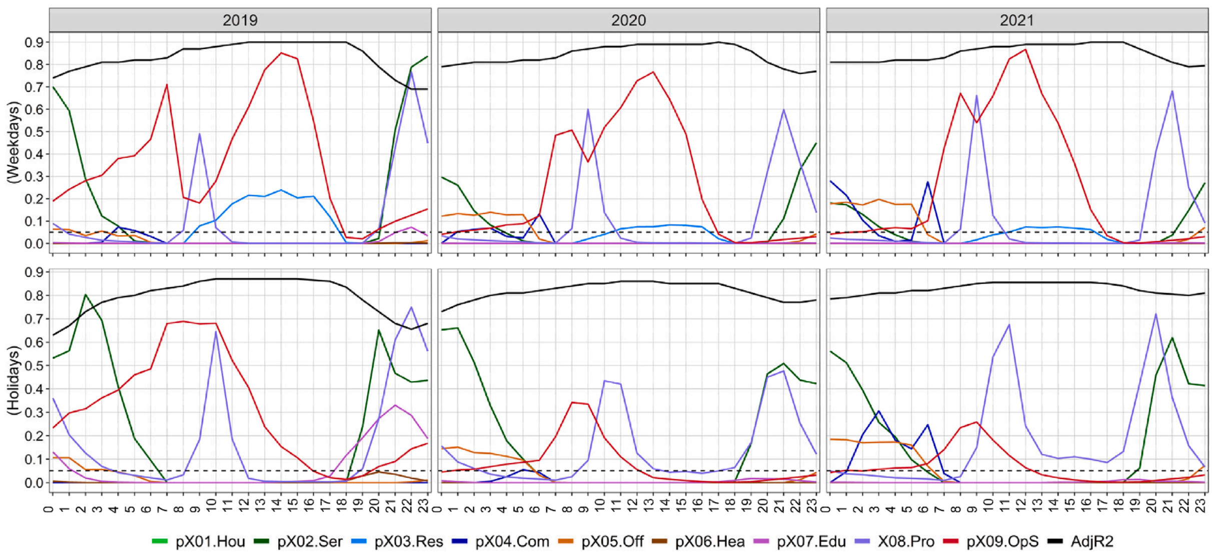
As travel patterns change between normal days and holidays, we created two models to identify this difference. The first model was run on the weekdays dataset, whereas the holidays dataset was used for the second model. The term "holidays" refers to weekends, national holidays, and special holidays (e.g., Golden Week and Obon). When a national holiday falls on a Sunday, the next Monday becomes a holiday. Moreover, a day that falls between two national holidays also becomes a holiday. The two datasets were defined after checking the calendars of three years (2019–2021).

$$y_{t,m} = \beta_{1,t}x_{1,m} + \beta_{2,t}x_{2,m} + \cdots + \beta_{i,t}x_{i,m} + \cdots + \beta_{9,t}x_{9,m} + C_t, \quad (1)$$

where

$y_{t,m}$: population in grid m at time t (person),
$x_{i,m}$: floor area of facility i in grid m (1,000 m^2),
$\beta_{i,t}$: regression coefficient of facility i at time t,
C_t: constant term (person),
t: time of day (from 0000 to 2300),
m: grid's code, and
i: type of facility (from 1 to 9; Tables 1 and 2).

One of this study's objectives is to reveal the degree of association between the predictors and population density. We used standardized coefficients as the variables' influence indicators. The value of a standardized coefficient (or beta weight) is illustrated in Equation (2). This formulation is one of the six standardized approaches introduced by Menard (2004, 2011). The author stated that the given method yields a



(Note: The dashed line indicates the 0.05 significance level.)

Fig. 4. Adjusted R-squared and median p-values for each hour.

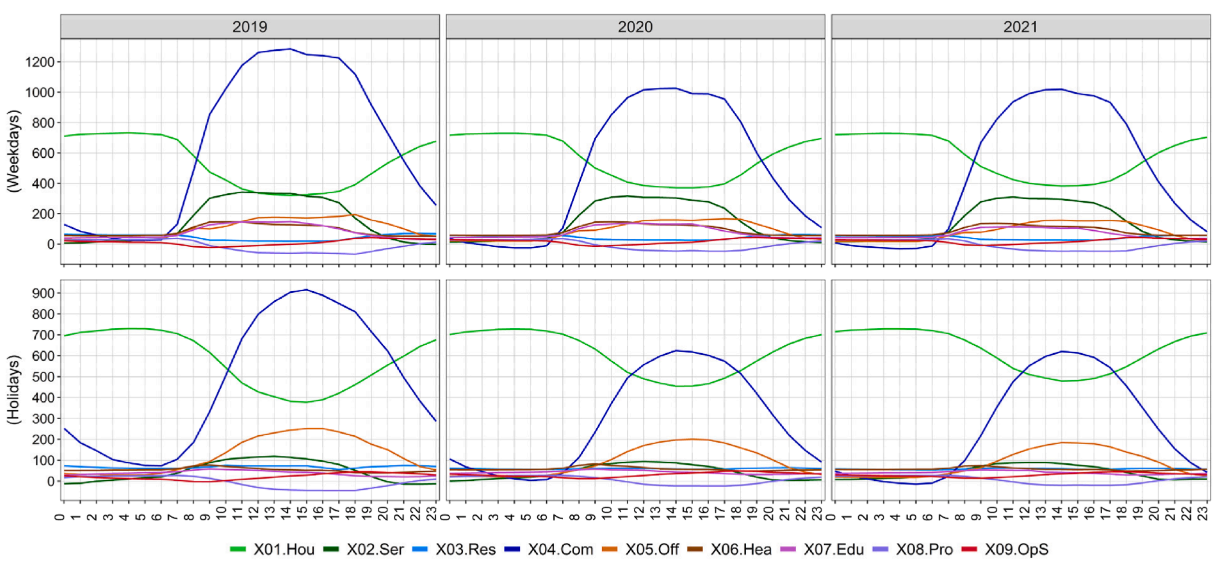


Fig. 5. Variation of median standardized coefficients in a day.

partially standardized coefficient, and it would not change the predictors' ranking order. In accordance with Nathans et al. (2012), a standardized coefficient is interpreted as follows: an increase of one standard deviation in a facility's area (x_i), with the other variables unchanged, will increase or decrease the population in a given grid by β_i^* standard deviation units.

$$\beta_i^* = \beta_i SD_i, \tag{2}$$

where β_i, β_i^*, and SD_i are the estimated, standardized coefficient, and standard deviation, respectively, of the explanatory variable *i*.

With the use of beta weights, the analysis outcomes offer two advantages. First, they show the influence level of a facility on population density compared with other facilities. That is, the beta weights account for the population visits to facilities at specific times, thereby addressing the first two research questions. Second, the variation of the beta weights represents the change in population visits over time, thus answering the third research question.

Results

Association between urban facilities and population density variation

The main outputs of the models are summarized in the Appendix (Tables B and C for weekdays and holidays, respectively). We also visualized the p-values of the variables and the models' adjusted R-squared values (Fig. 4). As the results demonstrated, the models performed well when the adjusted R-squared values reached 0.9. This means that they could explain up to 90 % of the population variation in a mesh. Although model performance was excellent in the daytime (from 0800 to 1900), the R-squared values declined gradually from 1900 to midnight.

Model performance was slightly better in the daytime in 2019 compared with that in 2020 and 2021. By contrast, at night, model performance was the best in 2021, with an adjusted R-squared value of approximately 0.8–0.84; these values were 0.69–0.83 in 2019 and

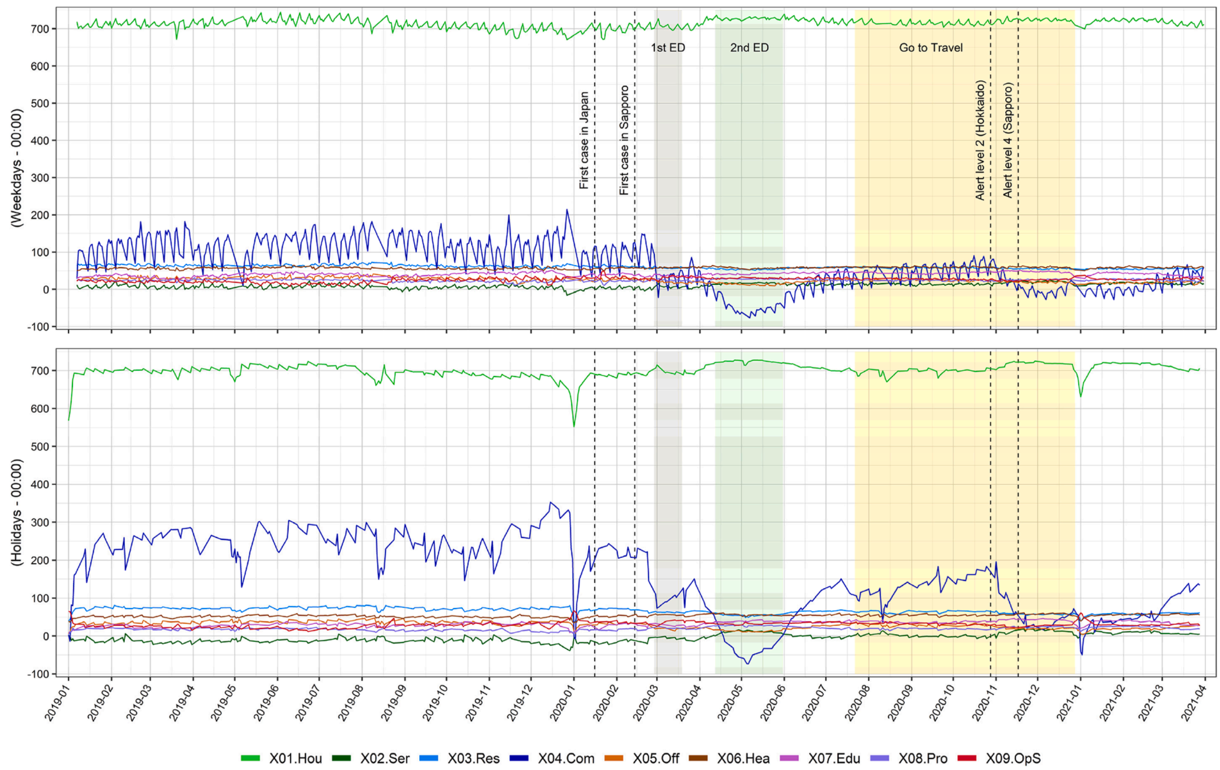


Fig. 6. Standardized coefficients at 0000.

0.76–0.83 in 2020. The results also indicated that the model performance on weekdays was better than that on holidays. Specifically, the adjusted R-squared values on weekdays and holidays were 0.69–0.9 and 0.69–0.87, respectively.

In addition to showing the adjusted R-squared values, Fig. 4 depicts the significance levels of the variables by hour each year. We used the median to represent the relevant values.

As shown in Fig. 4, X01.Hou and X06.Hea were significant at all times of the survey. X03.Res was significant on holidays but insignificant in the daytime on weekdays (from 0900 to 1700 in 2019 and from 1100 to 1600 in 2020 and 2021). By contrast, X07.Edu was significant on weekdays and most of the time on holidays. Notably, in 2019, X07.Edu was insignificant from 1800 to 0100 only on holidays.

X04.Com, commercial buildings, was significant almost the entire day. On weekdays, it was insignificant at some hours (from 0000 to 0600). On holidays in 2021, X04.Com was only insignificant from 0200 to 0600.

The results also showed similar significance patterns for X02.Ser and X05.Off. They were significant most of the time, but X05.Off had a longer period of significance. Specifically, on weekdays, the period of significance of X02.Ser increased gradually from 16 h in 2019 to 18 h in 2021. However, this period was 13 h on holidays in all three years. Furthermore, the period of significance of X05.Off decreased from 21 to 17 h on weekdays and from 20 to 16 h on holidays.

X08.Pro had notably different significance levels between holidays and weekdays. On weekdays, X08.Pro was significant from midnight to 1900, except for 3 h (from 0800 to 1000). Its period of significance on holidays was reduced year by year. Specifically, in 2019, it was significant for 12 h (from 0500 to 1900). In 2021, the period of significance declined to 10 h (from 0600 to 1600). In 2021, X08.Pro was significant for only 9 h (from 0000 to 0800).

As for the last variable, the significance of X09.OpS increased year by year, and it was stronger on holidays than on weekdays. On weekdays, the period of significance increased from 2 h in 2019 (at 1800 and 1900) to 8 h in 2020 and 9 h in 2021 (from 1700 to midnight). Similarly, on holidays, X09.OpS was significant for 4 h in 2019 (from 1600 to 1900). In 2020 and 2021, the hours of significance were extended to approximately 12 h (from 1300 to approximately 0100).

Variation of facilities' influence during a day

This section explains the variation of the variables' impact levels per hour per day. The influence level is represented via the median beta weight values shown in Fig. 5. The following paragraphs mention only the significant beta weights expressed in the previous section. Detailed information is available in Tables B and C in the Appendix.

Overall, X01.Hou and X04.Com were the primary determinants of population density. X01.Hou was the strongest predictor at night; its beta weight values reached approximately 730 from 2200 to 0700. These values declined from 0800 and dropped to the lowest point at 1500. Notably, although the nighttime values remained unchanged during the survey period, the daytime values were higher on holidays than on weekdays and increased year by year. For example, in 2019, the lowest weighted values of X01.Hou were approximately 319 and 377 on weekdays and holidays, respectively. In 2021, these values were approximately 381 and 478 (increased by 19 % and 27 %), respectively.

X04.Com was the strongest explanatory variable in the daytime. Its beta weight value increased significantly from 0700 and peaked at 1400. On weekdays in 2019, 2020, and 2021, these peak values were 1284, 1025, and 1020, respectively. The same trend was identified on holidays but with lower values. Specifically, in 2019, 2020, and 2021, the highest beta weight values were approximately 915, 624, and 620 (decreased by 29 % to 60 %), respectively. These nighttime findings indicate that this variable had a very weak influence, especially in 2020 and 2021.

Following X01.Hou and X04.Com were X02.Ser and X05.Off. X02.Ser highly affected the population density in the daytime (from 0800 to 1700), but its influence level, which was three times higher on weekdays than on holidays, decreased during the pandemic. The peak value declined by 10 % (from 342 to 310) on weekdays and by 25 % (from 118 to 89) on holidays. Likewise, the influence level of X05.Off was reduced

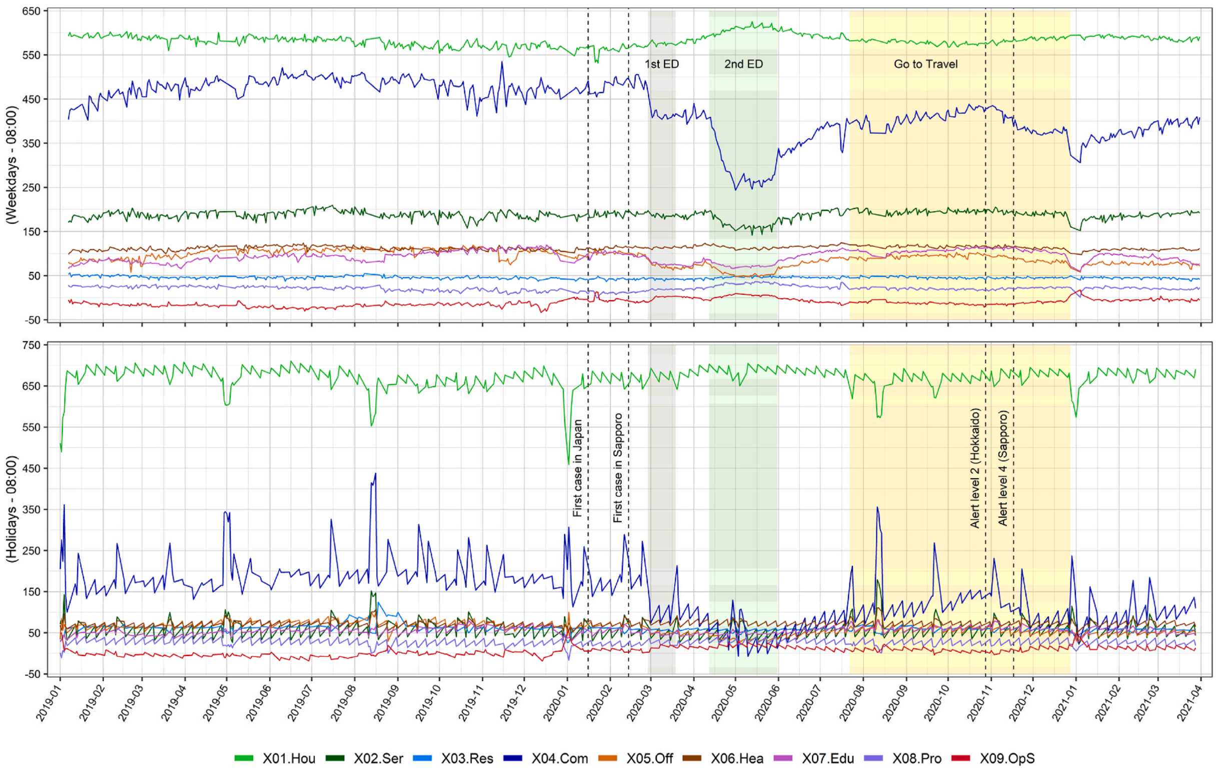


Fig. 7. Standardized coefficients at 0800.

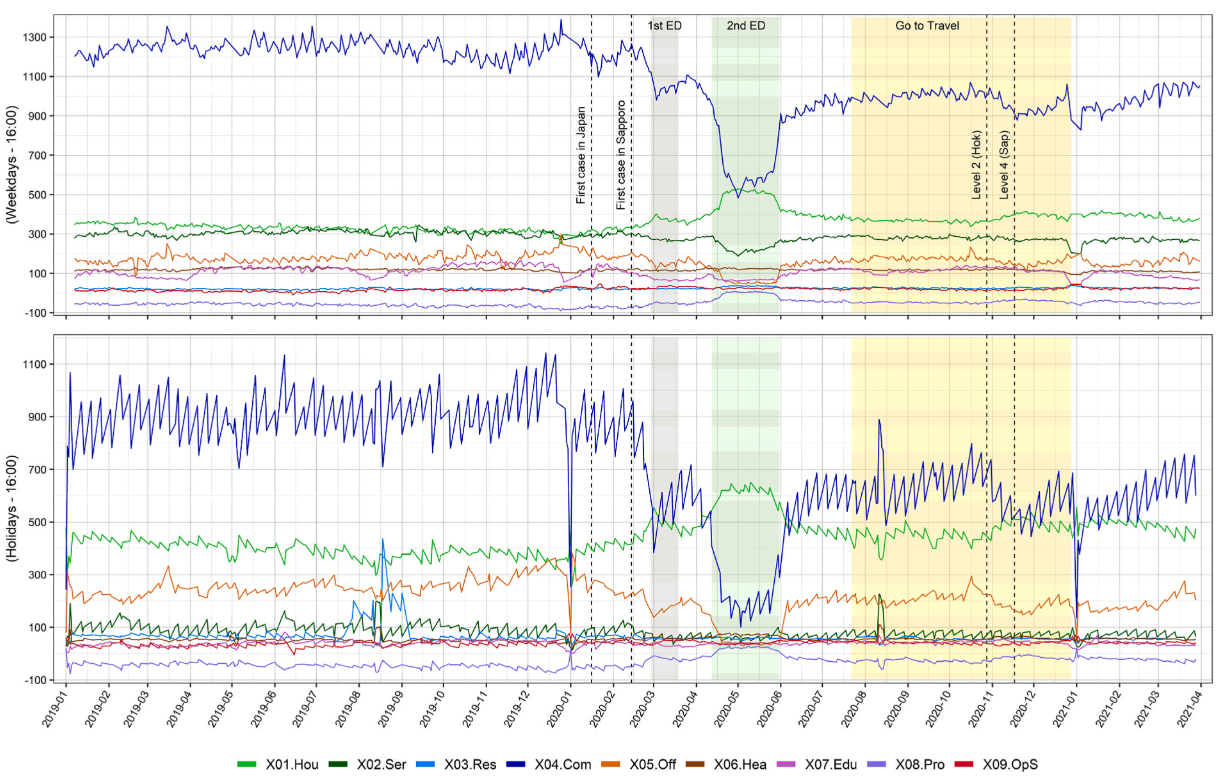


Fig. 8. Standardized coefficients at 1600.

year by year, and its beta weight values were higher on weekdays than on holidays. Between 2021 and 2019, its beta weights decreased by 35 % (from 250 to 185) on holidays and by 25 % (from 195 to 155) on weekdays.

X06.Hea and X07.Edu had similar patterns of beta weight variations, but X06.Hea was stronger than X07.Edu. On weekdays, their high-influence hours extended from 0800 to 1700. The peak values of X06. Hea varied from approximately 146 in 2019 and 136 in 2021 (decreased

Table 3
Summary of median standardized coefficients at specific times.

Period	Time	X01.Hou	X02.Ser	X03.Res	X04.Com	X05.Off	X06.Hea	X07.Edu	X08.Pro	X09.OpS
Weekdays										
BP (baseline)	00:00	709.5***	5.45	63.75***	124.46***	29.81	56.83***	39.24***	23.32	22.29
	08:00	580***	188.4***	46.13***	481.8***	104.19***	111.82***	94.58***	21.36*	−16.46
	16:00	329.7***	305.3***	19.13	1236***	176.66***	120.5***	121.32***	−60.4***	11.92
1st ED	00:00	704.8*** (-1%)	6.33	57.2*** (-10 %)	39.18** (-69 %)	19.2	58.01*** (2 %)	34.95*** (-11 %)	24.7** (6 %)	33.44** (50 %)
	08:00	575.4*** (-1%)	185.1*** (-2%)	42.57*** (-8%)	412.3*** (-14 %)	69.63*** (–33 %)	114*** (2 %)	76.13*** (-20 %)	18.57	2.85
	16:00	376.7*** (14 %)	269.9*** (-12 %)	21.69	1034.1*** (-16 %)	141.1*** (-20 %)	114.6*** (-5%)	66.93*** (-45 %)	−49.67*** (18 %)	33.6* (182 %)
2nd ED	00:00	727.2*** (2 %)	16.31	54.04*** (-15 %)	−51.27*** (-141 %)	13.46	57.27*** (1 %)	41.93*** (7 %)	28.4*** (22 %)	30.07*** (35 %)
	08:00	610.2*** (5 %)	162.7*** (-14 %)	46.86*** (2 %)	270.1*** (-44 %)	51.92*** (-50 %)	113.6*** (2 %)	71.21*** (-25 %)	32.26*** (51 %)	5.04
	16:00	512.6*** (55 %)	221.2*** (-28 %)	35.03*** (83 %)	587.1*** (-53 %)	52.91*** (-70 %)	124.4*** (3 %)	67.15*** (-45 %)	4.63	23.38
IP	00:00	718.9*** (1 %)	14.56	57.39*** (-10 %)	23.66* (-81 %)	20.58	59.23*** (4 %)	43.62*** (11 %)	25.18** (8 %)	27.88** (25 %)
	08:00	585.4*** (1 %)	190.3*** (1 %)	45.37*** (-2%)	392.5*** (-19 %)	83.07*** (-20 %)	114.48*** (2 %)	100.33*** (6 %)	21.16	−8.97
	16:00	381.9*** (16 %)	276.2*** (-10 %)	24.92	982.3*** (-21 %)	161.3*** (-9%)	115.9*** (-4%)	108.17*** (-11 %)	−45.79*** (24 %)	20.8
Holidays										
BP (baseline)	00:00	693.7***	−13.17	72.44***	243.5***	35.9	50.72***	27.56	16.78	27.43
	08:00	670.2***	63.75***	62.28***	183.5***	71.25***	71.89***	52***	21.78*	−1.84
	16:00	393***	95.06***	64.38***	883.4***	251.71***	51.22***	38.11**	−45.73***	35.96*
1st ED	00:00	696.3*** (0 %)	−4.06	62.72*** (-13 %)	95.94*** (-61 %)	19.01	56.44*** (11 %)	29.11** (6 %)	21.85	38.64** (41 %)
	08:00	678.1*** (1 %)	46.79*** (-27 %)	58.01*** (-7%)	96.02*** (-48 %)	50.1*** (-30 %)	73.01*** (2 %)	47.17*** (-9%)	28.28** (30 %)	14.39
	16:00	510.5*** (30 %)	61.06*** (-36 %)	57.59*** (-11 %)	521.8*** (-41 %)	163.7*** (-35 %)	60.03*** (17 %)	29.81*** (–22 %)	−15.68	47.2*** (31 %)
2nd ED	00:00	724.6*** (4 %)	12.69	54.84*** (-24 %)	−44.44*** (-118 %)	12.07	56.12*** (11 %)	38.45*** (40 %)	26.88*** (60 %)	32.56*** (19 %)
	08:00	682.2*** (2 %)	56.88*** (-11 %)	54.94*** (-12 %)	38.64** (-79 %)	32.21*** (-55 %)	77.21*** (7 %)	48.85*** (-6%)	25.27*** (16 %)	21.93
	16:00	620.7*** (58 %)	59.62*** (-37 %)	57.11*** (-11 %)	173.5*** (-80 %)	37.67*** (-85 %)	71.25*** (39 %)	38.87*** (2 %)	21.93** (148 %)	37.16*** (3 %)
IP	00:00	703.2*** (1 %)	4.05	60.74*** (-16 %)	94.16*** (-61 %)	22.66	55.59*** (10 %)	37.43*** (36 %)	20.33	32.73** (19 %)
	08:00	672.9*** (0 %)	60.99*** (-4%)	58.54*** (-6%)	106.15*** (-42 %)	53.21*** (-25 %)	75.85*** (6 %)	56*** (8 %)	22.38** (3 %)	10.71
	16:00	472.8*** (20 %)	73.98*** (–22 %)	55.95*** (-13 %)	600.3*** (–32 %)	194.87*** (–23 %)	55.29*** (8 %)	39.96*** (5 %)	–22.03* (52 %)	42.42*** (18 %)

BP: Before the pandemic; ED: emergency declaration; IP: during the pandemic;
***, **, *: Significant at all hours, at approximately 70 %, and at approximately 50 % of a day, respectively;
(): change in percentage compared with the BP period.

Table A
Facility statistics by Zenrin classification.

No	Category	Class	Variable	Interpretation	Total floor area (1.000 m^2)
1	**Housing**	1001	X01. Hou	Detached houses	51,669.19
2		1002	X01. Hou	Mansions	44,826.08
3		1003	X01. Hou	Apartments	4,864.64
4		1004	X01. Hou	Social housing (Danchi)	3,669.13
5		1005	X01. Hou	Dormitory, company houses	802.65
6		1006	X01. Hou	Mixed resident and office use	507.46
7		1008	X01. Hou	Mixed resident, store, and/or office use	2,071.61
8	**Business**	2001	X03.Res	Serving food and/or drink (food shop, restaurant, bar)	465.86
9		2002	X02.Ser	Selling food, beverages, grocery	253.12
10		2003	X02.Ser	Selling clothes, accessories	126.04
11		2004	X02.Ser	Selling daily products (tobacco, cosmetics, offices goods, etc.)	866.27
12		2005	X02.Ser	Rental services (Cars, CD, …)	194.40
13		2006	X02.Ser	Ceremony services (Wedding, funeral, cemetery, …)	111.75
14		2007	X02.Ser	Beauty services (barber, hair, salon, …)	263.65
15		2008	X02.Ser	Automotive related services	357.49
16		2009	X02.Ser	Animal services	27.19
17		2010	X04. Com	Mass retailers, shopping malls	880.92
18		2011	X05.Off	Financial, insurance offices	160.57
19		2012	X05.Off	Real estate offices	275.36
20		2013	X05.Off	Energy services (gas, fuel stations)	266.17
21		2014	X05.Off	Professional offices (law, public offices, government offices, …)	51.26
22		2015	X06. Hea	Sport facilities (fitness, sport clubs, …)	307.38
23		2016	X03.Res	Entertainment and dining relations, recreations, amusement parks	529.29
24		2017	X01. Hou	Hotel, ryokan	2,199.21
25		2018	X06. Hea	Hospitals and clinics, medial facilities	4,030.47
26		2019	X02.Ser	Museums, library, police, fire department	1,039.45
27		2020	X07. Edu	Education institutions (kindergarten, schools, universities, colleges)	5,933.86
28		2021	X05.Off	Home delivery, moving, post offices	233.15
29		2022	X05.Off	Transportation facilities	214.81
30		2023	X05.Off	Comprehensive construction, building renovation, water supply, architecture design offices	205.81
31		2024	X05.Off	Car dealer, motorcycle sale	208.21
32		2025	X05.Off	Business cooperative	6.54
33		2026	X02.Ser	Religion institutions	619.59
34		2027	X08.Pro	Other than 2001–2026 (stores, warehouses)	9,867.57
35	**Commercial**	3001	X04. Com	Buildings with mixed commercial offices and residential flats	2,428.45
36		3002	X04. Com	Buildings with a high proportion of commercial rooms	3,242.60
37		3003	X04. Com	Buildings with mixed offices and residential flats	1,974.34
38		3004	X04. Com	Buildings with a high proportion of offices	11,219.92
39		9999	X05.Pro	Buildings that other than the above (warehouse, factories, …)	3,310.50
	Total				**160,281.98**

by 7 %). Those of X07.Edu were approximately 145 and 113 in 2019 and 2021 (decreased by 28 %), respectively. On holidays, the influences of X06.Hea (approximately 50 %) and X07.Edu (65 %) were lower than those on weekdays. Off official hours, X06.Hea's effect was stable on weekdays over the three years but increased by 10 % in 2020 and the first quarter of 2021. Likewise, X07.Edu became significant during the pandemic, with its beta weight value ranging from approximately 30 to 45.

The influence level of X03.Res on population density was stable. However, its beta weights still decreased during the pandemic. On weekdays, its peak beta weight value decreased by 13 % (from 70 to 62), whereas the decrease on holidays was 21 % (from 75 to 62).

X08.Pro and X09.OpS were weak explanatory variables. Except for X08.Pro on weekdays in 2019, their beta weights were under 50. Remarkably, X08.Pro had a negative association with population density in some hours. On weekdays, in the afternoon, its beta weights were approximately −60 in 2019 and −47 in 2020 and 2021. On holidays, these values increased to approximately −44 and −23 in 2019 and 2020, respectively. This indicates a decrease in the influence level of X08.Pro. In addition, the correlation of X09.OpS with population density was higher on holidays than on weekdays; the period of influence was longer, and the beta weights increased from approximately 43 to 48.

Variation of facilities' influence in the periods of time

In this section, we interpret the changes in the beta weights at specific times. Specifically, we compare the variables' effect between the time before the pandemic (BP), before the detection of the first case in Sapporo City, the first and second EDs (1st ED and 2nd ED, respectively), and the time of the pandemic (IP). Note that IP excluded the 1st ED and 2nd ED periods. Based on the results expressed in Section 3.2, we summarized the mobility variations in a day into three patterns regarding time-frames: nighttime, daytime, and rush hours. The first pattern, from about 2100 to 0700, suggested the immobility of residents (refer to Fig. 5). Likewise, in the daytime, from 1000 to 1800, mobility expressed daily activities. And the final pattern, 0700 to 1000 and 1800 to 2100, described the significant movement at the start and end of office hours. Thus, we chose one hour in each time-frames to represent these three patterns. The results are shown in Figs. 6–8 and Table 3,

Table B
Beta weights and adjusted R-squared values for weekdays.

Year	Time	X01.Hou	X02.Ser	X03.Res	X04.Com	X05.Off	X06.Hea	X07.Edu	X08.Pro	X09.OpS	AdjR2
2019	0:00	710.97*	5.65	63.93*	128.84*	30.27	56.83*	39.24*	23.70	21.26	0.74
	1:00	722.34*	7.45	62.01*	83.42*	27.92	55.83*	40.62*	26.55*	17.50	0.77
	2:00	725.94*	13.42	60.63*	58.91*	29.14*	55.71*	42.32*	26.69*	15.24	0.79
	3:00	728.85*	18.65	59.05*	36.79*	25.74	56.05*	43.61*	28.13*	14.07	0.81
	4:00	731.91*	20.92	59.74*	23.36	27.80*	55.62*	44.17*	29.02*	11.68	0.81
	5:00	727.31*	29.42*	59.40*	23.56	27.30*	57.47*	45.54*	29.75*	11.17	0.82
	6:00	720.57*	34.18*	59.76*	26.64*	36.20*	57.45*	46.10*	33.00*	9.35	0.82
	7:00	687.92*	68.11*	58.99*	130.82*	68.91*	69.91*	56.62*	37.44*	−0.79	0.83
	8:00	581.52*	188.42*	46.34*	481.96*	105.03*	111.79*	93.82*	22.22	−17.11	0.87
	9:00	474.13*	301.50*	24.93	853.21*	99.59*	144.17*	126.71*	−10.29	−22.76	0.87
	10:00	421.46*	324.89*	24.47	1022.28*	116.30*	146.10*	137.66*	−28.22	−19.63	0.88
	11:00	362.69*	342.28*	21.69	1176.00*	148.50*	145.12*	145.06*	−44.83*	−14.06	0.89
	12:00	335.99*	337.63*	19.91	1260.64*	173.68*	134.83*	144.40*	−56.60*	−9.92	0.90
	13:00	324.87*	334.09*	20.07	1275.12*	176.09*	129.23*	143.59*	−58.84*	−4.93	0.90
	14:00	319.44*	332.74*	19.04	1284.41*	174.59*	127.46*	147.68*	−60.54*	−1.02	0.90
	15:00	324.86*	315.45*	19.84	1247.71*	171.58*	123.07*	136.17*	−57.92*	3.19	0.90
	16:00	332.10*	306.34*	19.11	1240.49*	175.52*	120.77*	121.32*	−59.59*	11.26	0.90
	17:00	347.06*	271.85*	23.21	1224.36*	181.82*	105.51*	99.64*	−62.73*	22.15	0.90
	18:00	390.84*	170.68*	40.36*	1118.87*	194.03*	75.21*	74.13*	−66.59*	37.29*	0.90
	19:00	463.24*	90.55*	54.92*	915.09*	158.02*	61.24*	55.59*	−48.74*	41.63*	0.86
	20:00	532.24*	40.15*	63.15*	730.66*	133.87*	53.25*	43.40*	−30.74	37.60	0.79
	21:00	590.75*	12.57	69.45*	548.40*	99.89*	51.05*	34.23*	−14.41	36.09	0.73
	22:00	643.02*	1.46	70.11*	382.58*	62.13*	51.64*	30.48	2.08	33.85	0.69
	23:00	676.28*	−1.55	67.91*	255.65*	49.97*	51.49*	33.16*	12.31	29.15	0.69
2020	0:00	716.22*	13.24	57.84*	35.99*	21.25	58.78*	42.91*	25.12*	29.2*	0.79
	1:00	724.53*	13.97	56.83*	9.43	20.44	57.56*	44.08*	26.71*	26.62	0.80
	2:00	726.66*	17.18	55.60*	−3.68	20.28	57.28*	45.04*	27.03*	25.17	0.81
	3:00	728.92*	20.15	54.88*	−17.47	19.25	57.61*	45.26*	27.78*	24.03	0.81
	4:00	729.18*	23.28*	55.34*	−25.22*	19.73	57.17*	46.52*	28.58*	22.64	0.81
	5:00	725.87*	28.98*	55.18*	−25.32*	19.40	58.21*	46.95*	29.45*	21.97	0.82
	6:00	716.01*	36.38*	56.20*	−10.76	29.53*	59.82*	47.94*	32.63*	19.80	0.82
	7:00	677.67*	76.87*	55.87*	106.38*	60.29*	74.95*	60.34*	35.12*	8.87	0.83
	8:00	582.52*	189.98*	44.98*	402.53*	87.10*	115.17*	101.31*	20.75	−8.65	0.86
	9:00	500.26*	283.68*	31.01*	694.59*	91.64*	143.66*	126.22*	−5.42	−14.34	0.87
	10:00	452.46*	308.16*	28.83*	850.86*	109.44*	146.13*	131.68*	−21.36	−10.74	0.88
	11:00	407.10*	316.53*	26.76	963.86*	133.77*	143.40*	137.11*	−34.10*	−6.35	0.88
	12:00	385.09*	306.19*	25.81	1015.15*	154.19*	132.75*	136.37*	−41.52*	−1.48	0.89
	13:00	375.78*	306.61*	25.56	1023.87*	158.35*	128.20*	130.47*	−44.74*	4.07	0.89
	14:00	370.92*	303.76*	25.06	1025.92*	158.69*	126.19*	130.60*	−46.61*	8.49	0.89
	15:00	370.27*	288.31*	24.21	990.06*	155.79*	122.05*	132.24*	−43.91*	11.74	0.89
	16:00	375.65*	278.18*	24.66	988.60*	161.77*	118.35*	109.09*	−46.45*	21.25	0.89
	17:00	396.40*	234.79*	30.09*	954.28*	166.72*	102.10*	85.09*	−47.05*	31.87*	0.90
	18:00	454.49*	147.00*	43.04*	804.49*	163.73*	75.43*	67.47*	−43.20*	41.40*	0.89
	19:00	530.47*	77.28*	53.37*	599.33*	131.91*	63.46*	51.84*	−27.55*	42.87*	0.86
	20:00	593.04*	39.76*	59.26*	431.79*	99.67*	58.87*	43.35*	−10.84	39.20*	0.81
	21:00	639.53*	22.82	62.49*	292.05*	64.03*	57.48*	40.80*	2.31	37.72*	0.78
	22:00	674.44*	13.95	61.90*	185.34*	40.37*	57.06*	39.05*	12.28	35.84*	0.76
	23:00	695.62*	9.99	60.44*	107.96*	31.14*	56.61*	40.68*	19.45	33.56*	0.77
2021	0:00	720.19*	15.80	55.58*	7.22	17.94	58.67*	41.43*	25.44*	27.30*	0.81
	1:00	724.22*	15.92	55.20*	−10.00	17.46	57.12*	40.97*	26.07*	25.91*	0.81
	2:00	726.60*	17.92	54.75*	−18.80	17.73	57.15*	41.68*	26.24*	25.43	0.81
	3:00	728.70*	20.58	53.94*	−25.74*	16.62	57.29*	42.44*	27.25*	24.07	0.81
	4:00	727.48*	23.82*	54.38*	−31.78*	17.36	57.02*	43.29*	27.87*	23.25	0.82
	5:00	724.12*	29.18*	53.92*	−29.40*	17.05	58.14*	43.81*	29.24*	23.37	0.82
	6:00	714.97*	36.99*	54.84*	−12.81	26.18*	60.00*	45.45*	31.75*	20.81	0.82
	7:00	678.34*	78.55*	54.98*	98.30*	55.68*	73.68*	57.59*	34.42*	10.02	0.83
	8:00	589.85*	186.53*	44.60*	380.00*	76.39*	108.99*	90.20*	20.76	−5.35	0.86
	9:00	510.58*	277.69*	30.57*	667.91*	77.02*	134.50*	109.66*	−5.83	−9.38	0.87
	10:00	464.92*	301.70*	28.24*	822.63*	95.48*	136.73*	111.41*	−21.21	−6.94	0.88
	11:00	423.83*	309.27*	27.56	936.69*	121.59*	133.16*	113.59*	−33.41*	−2.79	0.88
	12:00	399.36*	299.44*	25.77	990.94*	142.54*	123.07*	112.99*	−41.92*	2.66	0.89
	13:00	388.91*	298.51*	25.54	1015.49*	155.00*	118.57*	108.32*	−45.41*	7.31	0.89
	14:00	381.88*	294.88*	25.26	1019.09*	156.99*	115.80*	103.73*	−47.23*	10.52	0.89
	15:00	384.42*	282.97*	25.03	990.71*	151.99*	113.01*	104.65*	−46.07*	15.63	0.89
	16:00	392.93*	270.52*	25.02	975.72*	152.33*	110.06*	88.58*	−47.00*	23.53	0.90
	17:00	415.59*	229.68*	30.12*	932.97*	155.07*	97.00*	70.13*	−47.36*	32.64*	0.90
	18:00	468.81*	150.62*	40.56*	791.34*	148.40*	72.79*	55.43*	−45.46*	42.11*	0.90
	19:00	538.90*	83.17*	50.48*	587.45*	122.42*	62.24*	43.59*	−27.58*	42.54*	0.87
	20:00	601.82*	43.56*	55.70*	409.16*	93.07*	58.41*	38.65*	−9.92	37.30*	0.84
	21:00	649.03*	26.69*	57.85*	267.98*	57.26*	57.78*	36.46*	3.69	36.12*	0.81
	22:00	683.35*	18.57	58.38*	157.72*	33.44*	57.46*	36.39*	13.95	33.77*	0.79
	23:00	703.47*	13.97	56.97*	80.91*	24.48	57.50*	37.75*	20.42	30.43*	0.80

* – significant variables.

Table C
Beta weights and adjusted R-squared values for holidays.

Year	Time	X01.Hou	X02.Ser	X03.Res	X04.Com	X05.Off	X06.Hea	X07.Edu	X08.Pro	X09.OpS	AdjR2
2019	0:00	695.39*	−12.94	72.82*	251.97*	36.61	50.74*	27.64	16.82	25.96	0.63
	1:00	711.44*	−10.27	69.28*	183.59*	31.89	51.12*	31.04	21.46	21.00	0.67
	2:00	718.78*	−0.96	65.66*	145.57*	32.72	51.09*	34.00*	22.55	17.01	0.73
	3:00	726.52*	4.93	63.21*	103.38*	29.25	52.51*	36.68*	24.44	14.52	0.77
	4:00	729.95*	10.16	62.10*	87.19*	28.87*	52.77*	37.99*	24.84*	11.72	0.79
	5:00	729.26*	16.53	60.75*	74.71*	29.91*	53.48*	40.02*	25.70*	10.17	0.80
	6:00	721.84*	19.88	60.43*	73.05*	37.59*	53.90*	41.78*	25.92*	9.33	0.82
	7:00	705.52*	38.13*	60.54*	104.74*	54.93*	59.29*	44.94*	27.69*	4.13	0.83
	8:00	671.94*	65.65*	62.82*	184.88*	71.93*	72.48*	52.52*	22.80*	−2.60	0.84
	9:00	615.62*	88.33*	68.69*	331.68*	93.49*	77.17*	58.66*	13.37	−3.43	0.86
	10:00	542.92*	103.79*	75.32*	505.36*	136.01*	70.47*	55.24*	−0.30	2.37	0.87
	11:00	469.46*	110.95*	73.06*	681.74*	185.93*	65.38*	53.74*	−16.46	8.85	0.87
	12:00	426.95*	115.31*	71.98*	798.12*	215.73*	59.66*	51.50*	−30.98*	13.30	0.87
	13:00	403.69*	118.56*	71.95*	859.05*	230.98*	55.39*	46.83*	−39.22*	19.16	0.87
	14:00	381.82*	113.45*	72.43*	903.73*	244.05*	53.82*	43.40*	−42.45*	24.73	0.87
	15:00	377.05*	105.80*	72.84*	915.49*	251.20*	51.39*	42.06*	−44.28*	28.39	0.87
	16:00	389.29*	95.44*	64.39*	888.74*	251.30*	51.19*	38.13*	−44.79*	35.11*	0.87
	17:00	420.65*	79.13*	55.75*	849.57*	235.15*	48.59*	31.76*	−45.29*	40.04*	0.86
	18:00	461.06*	51.69*	62.12*	810.37*	213.97*	40.94*	25.73	−44.94*	44.69*	0.84
	19:00	507.56*	21.60	69.00*	714.94*	176.55*	38.95*	22.18	−33.70	44.43*	0.78
	20:00	554.76*	−3.62	71.41*	622.94*	150.11*	39.23*	21.57	−21.93	40.44	0.73
	21:00	597.97*	−14.67	74.96*	495.15*	108.05*	42.09*	20.22	−8.83	38.22	0.68
	22:00	644.08*	−14.89	73.56*	383.13*	69.96*	45.33*	21.51	3.00	34.70	0.66
	23:00	676.03*	−13.23	70.06*	286.56*	53.34*	47.52*	25.16	9.91	29.30	0.68
2020	0:00	701.51*	0.34	62.19*	105.88*	23.87	54.87*	36.80*	20.05	33.66*	0.73
	1:00	713.65*	2.53	60.28*	67.98*	22.66	54.09*	37.87*	22.60	30.61	0.76
	2:00	720.43*	7.80	58.62*	46.10*	22.14	53.93*	39.01*	23.44	28.18	0.78
	3:00	725.77*	12.07	56.98*	24.33*	20.70	54.48*	40.88*	24.67*	25.61	0.80
	4:00	727.00*	15.47	56.91*	11.11*	20.60	54.64*	41.77*	25.78*	23.64	0.81
	5:00	725.85*	18.98	56.16*	3.53	21.38	55.20*	42.89*	26.07*	22.89	0.81
	6:00	717.80*	24.53*	56.14*	7.32*	27.39*	56.61*	44.32*	26.65*	21.50	0.82
	7:00	702.83*	40.38*	56.87*	38.6*	40.03*	62.16*	48.06*	27.20*	16.41	0.83
	8:00	672.41*	58.86*	58.63*	113.12*	54.39*	75.34*	54.33*	23.26*	11.58	0.84
	9:00	631.91*	77.06*	60.30*	234.56*	72.49*	82.25*	57.55*	16.17	11.96	0.85
	10:00	574.52*	83.81*	62.17*	371.59*	103.38*	74.14*	54.20*	7.46	16.71	0.85
	11:00	520.39*	90.60*	60.93*	493.85*	141.40*	70.81*	53.03*	−3.85	21.58	0.86
	12:00	489.49*	93.70*	60.37*	556.68*	170.38*	64.70*	51.92*	−15.21	26.73	0.86
	13:00	468.76*	91.48*	59.40*	597.69*	187.21*	59.20*	46.63*	−20.70	32.47*	0.86
	14:00	453.51*	86.80*	57.73*	624.28*	197.25*	56.67*	43.41*	−22.87*	36.03*	0.85
	15:00	454.48*	78.18*	56.65*	617.55*	200.28*	55.90*	41.70*	−22.40*	38.86*	0.85
	16:00	465.31*	70.26*	56.56*	601.70*	197.60*	55.73*	39.86*	−23.36*	42.47*	0.85
	17:00	492.66*	57.22*	57.11*	573.72*	182.65*	52.87*	36.04*	−23.40*	47.25*	0.85
	18:00	528.64*	37.39*	60.16*	514.26*	159.01*	47.79*	32.65*	−19.72	48.20*	0.83
	19:00	574.69*	19.03	62.23*	418.69*	134.81*	47.84*	31.54*	−12.21	46.80*	0.81
	20:00	618.35*	5.43	63.79*	314.42*	100.84*	49.67*	32.23*	−0.46	41.84*	0.79
	21:00	655.91*	3.72	64.40*	219.31*	64.48*	52.09*	32.97*	8.34	39.69*	0.77
	22:00	683.31*	4.91	62.65*	146.70*	43.01*	52.89*	34.74*	14.25	36.43*	0.77
	23:00	701.04*	6.28	59.66*	91.12*	31.78*	53.56*	36.59*	19.21	33.76*	0.78
2021	0:00	715.16*	7.50	58.37*	47.03*	19.00	56.04*	37.17*	23.52*	29.89*	0.79
	1:00	722.38*	8.19	57.05*	24.89*	18.27	55.37*	37.34*	24.53*	28.11	0.79
	2:00	724.81*	10.49	56.31*	10.46	18.36	55.39*	38.36*	24.65*	26.73*	0.80
	3:00	727.75*	13.23	55.75*	−2.75	17.90	55.08*	39.57*	25.41*	25.30	0.81
	4:00	728.09*	15.24	54.67*	−10.30	17.68	56.17*	39.85*	25.98*	24.43	0.81
	5:00	726.78*	19.27	54.55*	−14.68	17.98	56.57*	40.52*	25.7*	24.02	0.82
	6:00	720.00*	23.08*	54.16*	−9.25	22.86	57.18*	41.66*	26.10*	22.19	0.82
	7:00	706.14*	35.66*	55.21*	23.36*	35.59*	61.69*	45.61*	27.48*	18.25	0.83
	8:00	674.97*	56.87*	57.51*	98.03*	49.10*	71.99*	50.45*	22.81*	14.48	0.84
	9:00	636.30*	71.86*	60.32*	217.23*	63.65*	73.95*	53.26*	14.60	13.60	0.85
	10:00	589.27*	84.00*	62.94*	354.50*	95.11*	69.11*	52.43*	6.42	17.12	0.86
	11:00	539.23*	86.76*	62.36*	475.54*	127.61*	62.87*	51.69*	−4.11	20.95	0.86
	12:00	509.72*	89.03*	61.11*	551.72*	153.79*	59.30*	51.45*	−13.72	25.70	0.86
	13:00	493.49*	88.55*	61.09*	596.43*	171.54*	56.20*	43.00*	−18.59	31.23*	0.86
	14:00	478.78*	83.52*	58.99*	619.84*	184.56*	56.14*	41.41*	−20.18	34.91*	0.86
	15:00	480.51*	75.56*	56.73*	613.33*	182.39*	54.92*	39.12*	−18.96	37.80*	0.86
	16:00	491.00*	69.09*	56.15*	591.70*	178.79*	55.93*	37.20*	−20.37	42.01*	0.86
	17:00	512.79*	57.32*	56.80*	543.41*	164.08*	53.72*	33.72*	−20.07	44.42*	0.85
	18:00	547.27*	41.24*	59.00*	455.81*	139.13*	48.05*	29.04*	−17.60	44.81*	0.84
	19:00	589.71*	24.41	60.72*	351.88*	118.34*	48.58*	29.32*	−8.97	42.99*	0.82
	20:00	632.23*	9.24	60.23*	247.05*	90.43*	50.29*	31.38*	2.09	38.03*	0.81
	21:00	667.50*	6.66	60.40*	153.95*	55.47*	53.26*	33.48*	11.11	35.84*	0.81
	22:00	693.90*	9.34	57.98*	87.27*	34.45*	54.22*	34.68*	16.65	33.16*	0.80
	23:00	709.29*	10.12	57.10*	41.81*	25.19	56.58*	36.94*	21.03	30.43*	0.81

* – significant variables.

where 0000, 0800, and 1600 denote the changes at midnight, in the early morning, and during office hours, respectively.

As shown by the results, the influences of the facilities appeared to change in January 2020, even before the first detected case in Japan. However, these changes were small and mainly concerned commercial facilities. Significant changes occurred in the 1st ED period and became more obvious in the 2nd ED period. In the two ED periods, we found dramatic decreases in the beta weights of X04.Com, X05.Off, and X02. Ser, whereas the influence of X01.Hou increased significantly. After the 2nd ED period, these facilities tended to recover to their approximate impact levels from the 1st ED period. During the Go To Travel campaign, the changes were similar to those in the ED periods, when the prefecture upgraded the level of its measures. However, the amplitudes were lower. Among the three timestamps, significant changes were found at 1600; at 0000 and 0800, considerable changes were found for X04.Com. These changes are discussed in the paragraphs below.

At 1600 in the 2nd ED period, the effect of X01.Hou increased by 55 % on weekdays and by 58 % on holidays. Specifically, its beta weights rose from approximately 330 to 513 and from 393 to 621 on weekdays and holidays, respectively. By contrast, the beta weights of X04.Com declined from 1236 to 587 (53 %) and from 883 to 173 (80 %) on weekdays and holidays, respectively. The decrease in the percentage of X04.Com was high at 0000 but lower than that at 1600. In the IP period, the influence of X01.Hou increased by 16 % on weekdays and by 20 % on holidays. On the contrary, the effect of X04.Com decreased by 21 % on weekdays and 32 % on holidays.

At 1600, the beta weights of X02.Ser decreased by approximately 28 % (from 305 to 221) on weekdays and by 37 % (from 95 to 60) on holidays in the 2nd ED period. The decreases in the 1st ED and IP periods were 12 % and 10 % on weekdays and 36 % and 22 % on holidays, respectively. Moreover, in the 2nd ED period, the effect of X05.Off dropped by nearly 70 % (from 177 to 53) on weekdays and by 85 % (from 252 to 38) on holidays. Likewise, these decreases in the IP period were 9 % and 23 % on weekdays and holidays, respectively.

The results indicated a slight increase in the influence of X06.Hea on holidays. For instance, at 1600, the beta weights of X06.Hea rose by 18 %, 39 %, and 8 % in the 1st ED, 2nd ED, and IP periods, respectively. Contrary to the effect of X06.Hea, that of X07.Edu decreased significantly on weekdays but increased on holidays. Specifically, at 1600 on weekdays, the beta weights reduced by 45 % in the two ED periods. At 0000 on holidays, they increased by 40 % and 36 % in the 2nd ED and IP periods, respectively.

The effect of X03.Res decreased over the studied periods, except at 1600 in the 2nd ED period. For example, at 0000 in the 2nd ED period, the beta weights lost approximately 10 units (15 %) on weekdays and 18 units (24 %) on holidays. This figure reached seven units (10 %) on weekdays in the 1st ED and IP periods. At 0800 and 1600, the decrease of the beta weights was 10 % in the three periods on holidays.

The influence of X08.Pro changed differently between the 2nd ED and other periods. For example, at 1600 on weekdays, the beta weights rose by 18 % and 24 % in the 1st ED and IP periods, respectively. In the 2nd ED period, the beta weights increased by 22 % (0000) and 51 % (0800). On holidays, the effect of X08.Pro appeared mainly in the 2nd ED period, with increases of 60 % and 148 % at 0000 and 1600, respectively.

Regarding the last variable, X09.OpS, the results showed that its effect rose mainly at 0000 and 1600 on both weekdays and holidays during the pandemic. For instance, on weekdays, the beta weights increased by 50 %, 35 %, and 25 % in the 1st ED, 2nd ED, and IP periods, respectively, at 0000. These figures were reduced to approximately 33 % to 39 % on holidays. At 1600 on holidays, the beta weight values rose by 31 % and 18 % in the 1st ED and IP periods, respectively.

Discussions

Spatiotemporal population density determinants

Regarding the first and second research questions, the results indicated that all facilities were associated with spatiotemporal population density. In particular, housing and commercial buildings were major determinants. These findings are consistent with our hypothesis that population flowed between residential and commercial areas in a day. At nighttime, people were more likely to be staying home, which made housing the strongest variable in the evening. At daytime, people would leave the home to perform various activities, thus decreasing the density in residential areas but increasing the densities at other locations (e.g., workplaces, schools, and shopping malls). A similar situation was reported by Mizuno et al. (2021), who indicated that the ratio of the daytime population to the nighttime population in Tokyo was approximately 0.8. According to the authors, commercial and office areas have higher populations in the daytime than in the nighttime. Supporting this statement, Arimura et al. (2020) stated that the population in Sapporo's CBD at night is lower by 75 % compared with that during daytime.

X02.Ser, X04.Com, X05.Off, X06.Hea, and X07.Edu had strong influences at daytime (the office hours in Japan are from 0900 to 1700). Nevertheless, the effects of X04.Com and X05.Off remained highly significant until 2000, even on holidays. This might suggest the extra working hours in the Japanese working style. Recent studies report that approximately 30 % of services workers and 80 % of manufacturing workers work over the standard working hours per week (Ishimaru and Fujino, 2021; Okazaki et al., 2019).

Regarding the X02.Ser and X03.Res facilities, the results appeared to reflect the common habits of the Japanese. Specifically, they are more likely to do daily goods shopping trips during daytime and on weekdays. They also prefer to visit restaurants and leisure places at night and on holidays than on weekdays.

Aside from workplaces, X06.Hea and X07.Edu facilities were associated with people's visits at both nighttime and daytime. As for X06. Hea, the high impact at daytime implies outpatient visits, whereas the nighttime impact might reflect inpatient stays. Likewise, the relationship between X07.Edu and people's visits at nighttime and on holidays would likely represent boarding school students, especially those in higher educational institutions, such as universities, colleges, and vocational schools.

The positive influence of X08.Pro at nighttime might implies the activities in some areas related to logistics or industries that operate mainly at night. For example, among the country's 11 industrial zones, the Oyachi Logistics hub occupies the largest area, which is on the east side of the city. The negative influence of X08.Pro at daytime suggests that these areas are less likely to attract people's visits. Nonetheless, these facilities were found to play a role in explaining the population density.

As expected, X09.OpS was not associated with population density during office hours and on weekdays, but its influence was significant during the afternoon rush hour and on holidays. The results also implied a change in these facilities' influence over time, which is discussed in the next section.

Eventually, the models' performance improved and stabilized in the IP period. We suggest that the change in travel patterns was the major factor that caused this issue. During the spread of the pandemic, inter-prefecture and intercity trips were reduced by 50 % because of the policy implications stated by Hara and Yamaguchi (2021). This change caused the city population to become purer, which might have affected the models' accuracy. Moreover, the models may have assumed that users turn off their mobile phones at night. This may have led to an under-counting of the MSS data, thus compromising the model's performance during the nighttime. Nonetheless, the applied model may be sufficient for predicting population densities in facilities in a time series. This outcome would be worthwhile to establish the measures against pandemic spreading, as claimed by Hay et al. (2005).

Changes in mobility during the COVID-19 pandemic

Regarding the third research question, the results showed variations in the facilities' influences, indicating significant changes in people's mobility since the beginning of the spread of the pandemic. Specifically, the growth of X01.Hou's beta weights represented an increase in the stay-home rate, whereas the decreases of X04.Com and X05.Off expressed the decline of workplace visits. These trends support our hypothesis regarding the two major facilities in the city. Furthermore, they are consistent with the findings of other studies. For example, Mizuno et al. (2021) claimed that the stay-home rates in Hokkaido and Tokyo increased by 40 % and 60 %, respectively, during the ED periods. According to Watanabe and Yabu (2021b), the stay-home rate in Tokyo peaked at 55 % at the same time. The difference between these cases is as follows. For Tokyo, Watanabe and Yabu used weekday data only, whereas Mizuno et al. included holidays in their analysis. Hence, these two studies' outputs nearly fit our results. Regarding the preventive measures set, the Japanese government called for a change of the work model to teleworking. This might have been a strong influence that decreased the workplace visits. Moreover, the beta weight variation in our study is similar to the visit pattern at the places in the study of Marra et al. (2022). In their study, the authors claimed that the decrease in workplace visit represented the impact of working from home and the closure of temporary working places. The same situation has been found in various countries, such as Australia, Brazil, Greece, and Argentina, where there have been common increases of teleworking, teleconferencing, or the number of working-from-home days (Balbontin et al., 2021; Bracarense and Oliveira, 2021; Jain et al., 2022).

Compared with that of commercial facilities, the decline of office visits was softer in the IP period. This gap might represent the difference in flexibility between the public and private sectors. The office term in our study included many public services that need to be maintained to serve the residences' needs. Thus, the encouragement of shifting to teleworking might not affect the public sector. Nevertheless, this situation is predicted to change soon, especially in the private sector. As stated in a recent report of the Japan Productivity Center (JPC), although the telework intention of staff increased, the telework implication decreased, mainly at medium and large companies in Japan (JPC, 2022). The explanation for the worker's intention is that they might have adapted to the new working style because their working environments have improved. Moreover, fear of health problems would likely motivate people to work from home. To our knowledge, although the Japanese working style is directly met, the reason for reducing the telework implication is still unknown. Thus, it is necessary to investigate the pressures and difficulties that the companies are confronting.

For health care facilities, our results expressed a slight decrease in population density in the daytime but a medium increase at nighttime. For this phenomenon, we would assume two trends that existed simultaneously during the pandemic. The first trend was the decline in outpatient visits because of the activity restrictions and the fear of epidemic infection, which are reported in the studies of Chatterji and Li (2021), Kumagai (2021), and Tsai and Yang (2021). The second trend might be from an increase in inpatient number related to COVID-19, which caused a high ratio of occupied beds. These inverse changes seemed likely to lead to the balance of the health care facility's population. Furthermore, on holidays, various medical facilities close, which may cause differences in visit numbers between weekdays and holidays at these places.

Behind the patient visit trend, a new health care model was developed and advanced during the pandemic: virtual or telehealth visits (Baum et al., 2021; Pendrith et al., 2022; Qian et al., 2021). This new model was designed to be a substitute for in-person visits. Although this measure seems suitable for the outbreak period, its application would likely remain limited. The cost-effectiveness, accessibility, and quality of this new model should be assessed to promote its advantages and to control its disadvantages.

Our analysis highlighted that visit frequency at daily service and restaurant facilities declined to a certain extent during the pandemic. This situation is in line with the findings of Kawasaki et al. (2022) and Yabe et al. (2021). Besides reporting declines in visiting volumes, these studies revealed changes in shopping styles (from direct shopping to e-shopping) and restaurants' enhanced takeout and home delivery services. As the results showed, the decrease in service facility visits was high in the 2nd ED period only. This may suggests that some services are essential for living and need to remain, as declared by Parady et al. (2020). Furthermore, even though e-shopping has advantages such as convenience and avoidance of close contact, it still may not prevail over direct shopping. People might engage in e-shopping for enjoyment purposes only (Irawan et al., 2021). Thus, in addition to promoting online shopping, businesses should implement measures such as extending store opening hours to flatten the daytime density.

Facilities related to dining and entertainment were significant during the pandemic, even in the ED periods. This would seem to be highly related to policy enforcement and compliance. Interventions in Japan appear to be voluntary lockdowns, and they are not as strict or as legally binding as interventions or curfews in other countries (Watanabe and Yabu, 2021b). During the EDs, the Japanese government called for the service sector's cooperation by asking them to reduce their business hours. Under this agreement, restaurants would receive subsidy, which might not compensate the financial loss. Restaurants are claimed as poor ventilation places, and shortening their hours has a better effect than teleworking interventions (Chiba, 2021). Thus, these businesses should give more attention to policy compliance. Supplemental policies should support these businesses not only during the outbreak but also after the pandemic to recover.

Regarding educational facilities, the decline in their visits matches the implemented policies. Schools also employed online learning to avoid interruption of the school year. This would explain the soft decrease in schools' visits after the restrictions were lifted. However, online learning reportedly hindered students from achieving direct communication, thereby causing difficulties in digesting lessons because of lack of skills or access to facilities (e.g., Internet connection and computer). Consequently, students might encounter health problems and downgraded achievements (Aurini and Davies, 2021). As school attendance is one factor that causes COVID-19 incidence, policies should balance the two abovementioned issues. Also, the change from insignificant to significant school visits at nighttime on holidays seems abnormal. We suggest a further investigation into these facilities, risk perception and countermeasures at different education levels, for instance, would help to understand this variation.

There was an interesting result showing that open spaces were likely to become more attractive on holidays during the pandemic. This suggests that the demand for outdoor activities remained high and even increased during the outbreak. This is consistent with the study of Yang et al. (2021), who reported that visit frequencies to parks in Osaka and Tokyo were stable in the early stages of the pandemic spread compared with those to foreign metropolitans. Moreover, as risk awareness increased, people became likely to change their behavior in choosing their exercise types and venues. For example, Seoul citizens changed their leisure preferences from crowded areas to disinfected, natural, socially distanced places (Bayrsaikhan et al., 2021). Likewise, Swedish became more likely to switch their activities from indoor to outdoor endeavors, such as walking, hiking, and trips to forests, parks, and beaches (Bohman et al., 2021).

The results further indicated that the city's mobility is less likely to recover to its pre-pandemic level. This pattern is contrary to that of the US (Kim and Kwan, 2021) but consistent with those in several other nations, such as Australia, Sweden, and Bangladesh (Beck and Hensher, 2020b; Bohman et al., 2021; Bracarense and Oliveira, 2021). We suggest that the failure to fully recover is associated with impact sources, policy implications, and risk awareness. Specifically, restrictive measures would seem to be the principal cause of mobility decline in the ED periods. By contrast, in the IP period, the pandemic threat was more likely to play a crucial role in decreasing mobility. For instance, before an infection was detected in Hokkaido, people in Sapporo City had reduced their mobility (Figs. 6–8). Then, in the IP period, the heightened risk awareness would motivated people to refrain from engaging in close contact or going to high-risk places. Hence, policy implications might have a great impact in the short run, but changes in awareness seem to influence mobility for a long time.

Although the EDs seemed to have obvious efficiencies in controlling the pandemic (e.g., slowing down of transmission, alleviation of medical system burden, and reduction of fatalities), they might negatively affect certain socioeconomic aspects. The EDs could cause an economic downturn and stagnancy, income reduction, increase in the unemployment rate, and physical and mental health problems, among others. Thus, a possible conclusion would be that an ED should not be applied frequently or for a long time. Furthermore, risk awareness and perception appeared to exhibit long-term effectiveness in flattening the infection curve. However, despite rising quickly right after a disaster occurs, risk awareness and perception are likely to decrease gradually over time. Therefore, we believe that programs that enhance public awareness are necessary.

Limitations, future works, and conclusions

The limitations of the present study are as follows. First, the data used here lacked important variables, such as demographic and socioeconomic factors. Because travel behaviors have an intrinsic relationship with personal characteristics, the addition of this missing information will help in further elucidating the effects of the pandemic on different groups of people, especially the vulnerable ones (e.g., disabled and elderly). Thus, in the future, we will examine the effect of the pandemic on the mobility of different groups, such as the elderly, students, and women. Second, although the proposed method is easy to interpret, it is sensitive to outliers and multicollinearity. The bypassing of model accuracy validation might also be a weakness. In addition to our proposed solutions, these issues can be solved with more advanced techniques, such as the machine learning or complex models introduced by Kubíček et al. (2019) and Bachir et al. (2018).

The present study investigated mobility changes during the COVID-19 pandemic using MSS data covering three years (from 2019 to 2021) in the city of Sapporo, Japan. Results showed that Sapporo's citizens were more likely to stay home and less likely to visit their workplaces. Specifically, places related to daily services, restaurants, commercial ventures, and offices exhibited decreased visits, with the highest decline identified for commercial facilities. Visits to health care and production facilities were stable on weekdays but increased on holidays. Educational institutions' visits decreased on weekdays but increased on holidays. Visits to residential housing and open spaces increased, with the rise in residential housing visit being more substantial. Eventually, the results would seem to indicate that visit patterns at service and restaurant places were significant during the pandemic, even in states of emergency.

Solving the spatiotemporal problem is problematic due to the complex and high dimension data. However, the application of the MLR model in the present study ascertains two things. First, though the spatiotemporal task is complicated, the applied method is not necessary to be advanced. The determinants are the data structure and the study's objectives. Second, even if the data do not contain a high dimension, we are able to capture the mobility pattern with the supplement data, such as the facilities information. We suppose this outcome would serve as a good alternative for researchers in spatiotemporal data mining.

From the analysis outcomes, two suggestions for policy making are presented. First, measures for target facilities should be based on their functions and the habits of people in using these facilities. This would help not only in remedying the negative effects of the pandemic but also in increasing compliance. Second, public awareness should be enhanced and integrated into policies as it appears to produce longer-term effectiveness compared with intensive measures (e.g., lockdowns and EDs). Overall, this study might serve as a primary step in estimating dynamic population densities by facility type. Our results can be improved to achieve a high resolution of population distribution that supports policy makers not only in identifying risk clusters but also in establishing suitable interventions on time.

CRediT authorship contribution statement

Tran Vinh Ha: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Takumi Asada:** Conceptualization, Investigation, Methodology, Software, Supervision, Validation, Writing – review & editing. **Mikiharu Arimura:** Project administration, Supervision, Conceptualization, Data curation, Funding acquisition, Methodology, Resources, Validation, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

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Appendix

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