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Analysis of the impact of non-compulsory measures on human mobility in Japan during the COVID-19 pandemic

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ABSTRACT

To curb the spread of the COVID-19 pandemic, countries around the world have imposed restrictions on their population. This study quantitatively assessed the impact of non-compulsory measures on human mobility in Japan during the COVID-19 pandemic, through the analysis of large-scale anonymized mobile-phone data. The non-negative matrix factorization (NMF) method was used to analyze mobile statistics data from the Tokyo area. The results confirmed the suitability of the NMF method for extracting behavior patterns from aggregated mobile statistics data. Data analysis results indicated that although non-pharmaceutical interventions (NPIs) measures adopted by the Japanese government are non-compulsory and rely largely on requests for voluntary self-restriction, they are effective in reducing population mobility and motivating people to practice social distancing. In addition, the current study compared the mobility change in three cities (i.e., Tokyo, Osaka, and Hiroshima), and discussed their similarity and difference in behavior pattern changes during the pandemic. It is expected that the analytical tool proposed in this study can be used to monitor mobility changes in real-time during the pandemic, as well as the long-term evolution of population mobility patterns in the post-pandemic phase.

1. Introduction

The outbreak of the respiratory Coronavirus disease 2019 (COVID-19) in December 2019 has triggered a worldwide health crisis, thereby posing a threat to the human society. To date, more than 168 million people have been infected by the virus, with more than 3.4 million deaths globally (WHO, 2021). To contain the transmission of COVID-19, countries around the world have responded through non-pharmaceutical interventions (NPIs), including various forms of lockdown, closure of non-essential businesses, shift to remote-working and distance education systems, canceling or postponing events, and travel restrictions (Galeazzi et al., 2020; Kang et al., 2020; Pepe et al., 2020; Shakibaei et al., 2021; Yabe et al., 2020). These intervention policies can be classified into two categories: enforceable behavioral restrictions that consider penalties using the legal system, and behavioral restrictions that do not use the legal system and are dependent on people’s sense of self-restraint (Parady et al., 2020). Japan belongs to the latter category. In contrast to the strict measures adopted in most countries, Japan has adopted fewer restrictive social-distancing policies following the COVID-19 pandemic. NPIs implemented by the Japanese government include non-mandatory closures and remote-working of non-essential business employees, closures of schools, stay-at-home requests, and inbound entry restrictions (Arimura et al., 2020; Yabe et al., 2020). Because the Japanese government cannot legally enforce lockdowns on citizens and residents, its strategies have relied largely on requests for voluntary self-restriction. However, the extent to which individuals have modified their travel behavior in response to such non-enforceable self-restriction requests is unclear. Accurately measuring the change in human mobility under these restrictions is essential to quantitatively assess the effectiveness of these measures on people’s mobility reduction in real time, as well as to monitor the long-term impact on human mobility patterns. These assessments can provide critical information for policymaking in the post-pandemic phase.

The study of population mobility in such an unprecedented situation would have been difficult in the past due to limitations on data availability. However, the emerging big data technology has offered a new tool to analyze and model human dynamics in relation to space and time. In particular, the large number of mobile-phone users worldwide makes mobile-phone data a representative proxy for population mobility patterns (Jeffrey et al., 2020). In comparison to traditional

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methods such as collecting census data and conducting a questionnaire survey, the use of mobile phone data is advantageous because of the following reasons: ability to obtain high-resolution population data in relation to time and space; accessibility of data without interview bias; availability of longitudinal data for a very large population (Wu et al., 2021). However, even if such data provide unique opportunities, there are also important methodological challenges that must be addressed. Because mobile spatial statistics are aggregate data of the population in a target grid cell, it remains a challenge to extract different mobility patterns from the aggregate data.

Therefore, the objective of this study is twofold. First, it aims to propose an appropriate method to extract different mobility patterns from aggregated mobile-phone data. Second, it attempts to examine the impact of non-compulsory NPI measures in Japan on individual mobility. The first objective corresponds to a class of latent variable analysis (LVA) problem that have been studied for decades (Cichocki & Amari, 2002; Sawada et al., 2019). In LVA problems, the underlying components are separated from the observed data without (or with limited) information of the sources and the mixing process. In our study, only the aggregate population in each grid cell is available, while we try to recover latent components (i.e., different mobility activities) for a better understanding of how human mobility patterns change during the COVID-19 pandemic. We use the non-negative matrix factorization (NMF) method to analyze mobile statistics data from the Tokyo area. The results confirmed the suitability of the NMF method for extracting behavior patterns from aggregated mobile statistics data. Specifically, six major behavioral patterns viz., working, commuting, social gathering, shopping, leisure and tourism, and in-house activities were successfully identified using the NMF method. Results from analysis of the research data using the NMF method indicate that even though the NPI measures adopted by the Japanese government are non-compulsory, they are effective in curbing population mobility and have significant impact on all behavioral patterns. Currently, more and more countries began to utilize large-scale mobile-device datasets to estimate the effectiveness of control measures during COVID-19 pandemic, including China, Germany, France, Italy, Spain, Sweden, the UK, and the US (Dahlgberg et al., 2020; Galeazzi et al., 2020; Heiler et al., 2020; Jia et al., 2020; Warren & Skillman, 2020). In particular, the European Commission asked European Mobile Network Operators to share fully anonymized and aggregated mobility data in order to support the fight against COVID-19 with data driven evidence (European Commission, 2020). The same approach proposed in this study can be easily adopted in other countries, for the purpose of global comparative studies of mobility patterns change during COVID-19 pandemic.

The remainder of this paper is organized as follows. Section 2 provides a brief review of relevant studies. Section 3 describes the research area and data used in this study. The methodology and results of the data analysis are discussed in Sections 4 and S, respectively. Finally, the conclusions are summarized along with a discussion of important future research issues in the last section.

2. Literature review

Human mobility has been widely studied for over a decade under multiple disciplines, such as geography, transportation, urban planning, physics, computer sciences, and public health (Rang et al., 2020). Recently, with the spread of COVID-19 around the globe, a growing number of published reports have expressed great concern over the influence of pandemics and corresponding measures on mobility issues (Gao et al., 2020; Lee et al., 2020; Pepe et al., 2020). Most of the studies have focused on mobility changes within a certain country and showed that the pandemic has had a significant influence on mobility style changes, including the overall reduction of mobility, drop in shared mobility, and increased dependency on private mobility (Cui et al., 2020; Engle et al., 2020; Heiler et al., 2020; Meena, 2020; Przybylowski et al., 2021). For example, Beria and Lunkar (2021) analyzed the mobility dynamics during the first wave of COVID-19 outbreak and lockdown in Italy. Their research revealed the spatial distribution of people in different regions of the country. Wielchowski et al. (2020) analyzed the change of mobility in public transport during COVID-19 pandemic in Poland. Their study indicated that government restrictions lead to a greater decrease in mobility rather than a local epidemic status. Some studies argued that the restrictive measures adopted during the pandemic would cause mobility reduction and result in substantial and long-lasting structural changes in the mobility network (Schlosser et al., 2020). Some studies have attempted to determine whether the characteristics of the underlying population play a role in determining the mobility change during the COVID-19 pandemic. For example, Engle et al. (2020) estimated how individual mobility is affected by local disease prevalence and restrictive orders to stay-at-home in the US, and their research results revealed that the behavior of counties with relatively a higher elderly population is more altered than that of counties with a predominantly younger population. Ruiz-Euler et al. (2020) argued that income levels influence differences in labor market flexibility. Their research found a strong evidence that, within most cities in the US, the decline in human mobility during lockdown occurred at different rates among high-income and low-income groups. This phenomenon was named the mobility gap. Similarly, the research conducted by Atchison et al. (2020) suggested that the ability to adopt and comply with certain NPIs is lower in the most economically disadvantaged in society. Meanwhile, Dahlberg et al. (2020) found similar mobility reductions following the COVID-19 pandemic in areas with different socioeconomic and demographic characteristics in Sweden.

Meanwhile, some studies have attempted to compare changes in mobility patterns in response to COVID-19 in different counties. Galeazzi et al. (2020) analyzed the effect of the pandemic on the mobility patterns in France, Italy, and the UK; they revealed that the impact differs among countries according to their initial mobility structure. Fraiberger et al. (2020) studied the impact of NPIs during the COVID-19 pandemic on the human mobility in Colombia, Mexico, and Indonesia. Their research uncovered large and persistent differences in mobility reduction between wealth groups. Specifically, individuals in the top decile of wealth reduced their mobility up to twice as much as those in the bottom decile. Some studies (Chan et al., 2020) focused on the impact of people’s risk attitudes and their research indicated that risk-taking attitudes are a critical factor in predicting reductions in human mobility and social confinement around the globe. Other researchers have focused on aggregate patterns, exploring differences in state and national COVID-19 policies, and their effects on mobility change. For example, the study conducted by Gargoum and Gargoum (2021) established links between mobility trends, COVID-19 infections, and COVID-19 mortality rates across different countries where different policies were adopted. Vannoni et al. (2020) conducted a cross-city time series analysis of 41 cities in 22 countries to investigate the impact of different non-pharmaceutical countermeasures on mobility change. Their findings demonstrated that several policy restrictions, particularly the closures of public transport, workplaces, and schools, had a substantial impact on the reduction in population mobility. Although extensive research has been conducted to investigate the mobility change during COVID-19 in Europe, the US, and China, the impact of the non-compulsory measures on mobility change in Japan has been understudied (Shaw et al., 2020).

To monitor, analyze and evaluate the impact of COVID-19 and the corresponding policies on mobility patterns, large-scale mobile phone data have been identified as an effective data source (Oliveir et al., 2020). Previous studies on human mobility analysis have shown that such large-scale mobility data collected from mobile devices may be used to assist in the modeling of epidemic spread (Bengtsson et al., 2015; Finger et al., 2016). During the current COVID-19 crisis, researchers have also discussed how mobile-device data could help them monitor epidemic-spreading dynamics, inform public health policy, optimize
policymaking, and quantify the effectiveness of policy interventions (Bonato et al., 2020; Dahlberg et al., 2020; Kraemer et al., 2020; Lai et al., 2020; Schlosser et al., 2020; Wellensius et al., 2020). For example, the European Commission asked European Mobile Network Operators to share fully anonymized and aggregated mobility data to improve the quality of modeling and forecasting for the pandemic at EU level (European Commission, 2020). These data have supported policy-makers and practitioners with evidence and data-driven knowledge to understand and predict the spread of the disease, the effectiveness of the containment measures, their socio-economic impacts while feeding scenarios at European Union scale and in a comparable way across countries (Iacus et al., 2021; Vespe et al., 2021). Because most mobile-device data are aggregate data of population in a target grid cell, information that can provide more detailed mobility patterns is not available. As a result, current studies that utilized mobile-device data only focused on the aggregated mobility patterns (e.g., mobility intensity, mobility characteristics) in a specific area (Angell and Potoglou, 2020), but few studies have investigated changes in specific activity patterns. However, understanding the extent of changes in specific activity patterns is essential to evaluate the pandemic’s influence on different sectors including commerce, transportation, employment, and environment, and so on (Liu et al., 2021).

Some studies have conducted questionnaire surveys to investigate respondents’ activity patterns before and during COVID-19. For example, based on a panel web-survey conducted in Japan’s Kanto Region, Parady et al. (2020) analyzed behavioral changes of residents’ non-work-related activities and observed significant decrease in leisure and eating out activities, and moderate decrease in grocery shopping activity. The study conducted by Angell and Potoglou (2022) employed a cross-sectional survey to investigate the immediate and anticipated long-term impacts of the COVID-19 pandemic on work-related travel behaviors in the UK. The research indicated the potential for low-frequency work travel but increased car dependency following the pandemic. Using survey data collected in Italy, Braut et al. (2022) analyzed the lockdown’s impact on the household mobility in food purchasing. The results show that the lockdown moved the preferences of people from public and shared means to foot and private vehicles for food purchasing activity. Based on a longitudinal panel survey conducted in Istanbul, Turkey, Shalikaei et al. (2021) analyzed the changes in commute, social/recreational/leisure (SRL), and shopping activities during the early stages of the epidemic and revealed the heterogeneity of the changes among different socio-demographic groups. These studies mainly use questionnaire survey to get information about people’s activity pattern during the pandemic. These methods rely on the accurate recall of activity by the participants and hence are a relatively crude measure with wide margins of error. Meanwhile, the results might be biased because the limited number of samples usually cannot reveal overall activity patterns of all population. Furthermore, it might be expensive and time-consuming to conduct longitudinal analysis based on the questionnaire survey. To overcome these limitations, some studies have used big data to explore the change of activity pattern during COVID-19. For example, based on one-year longitudinal mobile phone positioning data for more than 31 million users in Beijing, Liu et al. (2021) investigated changes in dwelling and working activities during COVID-19 pandemic. The results show that working intensity decreased about 60% citywide, while dwelling intensity decreased about 40% in some work and education areas during COVID-19 outbreak. Zhang et al. (2021) analyzed the changes in the travel behavior of various population groups in Hong Kong during COVID-19 by using smartcard data obtained from the Mass Transit Railway Corporation (MTRC) system. Their analysis showed that the daily trips of commute, shopping, and leisure activities decreased by 42%, 42%, and 81%, respectively. However, these studies focused on the specific types of activities. The analysis of changes in all the major behavior patterns in people’s daily life remains limited.

Several previous studies on spatial statistics have proposed methods to extract the major behavior patterns from aggregated population data (Secchi et al., 2015; Urata et al., 2018; Zanini et al., 2016). Zanini et al. (2016) suggested that the application is a blind source separation problem where the aggregated population data must be decomposed into a mixture of mobility features. One of the widely used methods for blind source separation is the independent component analysis (ICA) approach (Hyvarinen et al., 2001). However, classical ICA method has been criticized for its limited ability to incorporate spatial dependence, which is an important feature of mobility behavior. To address this issue, Zanini et al. (2016) proposed a spatial-colored ICA (scICA) method to incorporate spatial dependence within the spatial sources. Recently, Urata et al. (2018) confirmed that the scICA method can clearly identify the main spatio-temporal patterns by applying it to analyze the effect of a natural disaster on the population movement. Another drawback of the ICA approach is that it does not impose non-negative constraints on the source components; therefore, it is difficult to provide an obvious interpretation of the obtained components in some cases. To solve this problem, some researchers propose to employ the NMF approach, because NMF has the advantage of factorizing the data into basis components with non-negative entries (Lee & Seung, 1999). For example, Wu et al. (2021) employed NMF to analyze population movement in the wake of a natural disaster. Because the study area of their research was characterized by low population density, the corresponding signals of interest were sparse in a given representation domain. Consequently, NMF failed to demonstrate good performance with regard to decomposing the aggregated data into basis components. This study attempt to examine the capability of the NMF method to extract behavior patterns from aggregated mobile statistics data in a region characterized by high population density.

3. Study area and data

Even though the first case of COVID-19 in Japan was confirmed on January 24, 2020, the development of new cases was rather slow between January and February, until the growth began to accelerate in the last week of March 2020. In an attempt to curb the pandemic, the Japanese government declared a state of emergency on April 7 in seven prefectures, including the Tokyo area, which was later expanded nationwide on April 16. The declaration, effective through May 25, enabled prefectural governors to take stronger preventive steps, ranging from instructing citizens to stay at home to restricting the operation of schools and other facilities, although there have been no legal penalties for noncompliance. The major non-pharmaceutical measures taken by the government are summarized in Fig. 1. Because these measures are not mandatory or legally enforceable under the Japanese law, they revolve around self-restriction, and their success largely depends on compliance by the population. Such differences in policies and COVID-19 spread dynamics make the situation in Japan an interesting case study for international comparative analysis.

In this research, we use mobile spatial statistics, which are statistics of the actual population that are generated continuously from mobile terminal network operational data of NTT DOCOMO, Inc. (one of the major mobile phone operators in Japan). The ensure service availability, the company periodically monitored mobile phones that are operational within each base station area. After aggregating the total number of mobile phones in each area, the overall population was estimated by considering the NTT DOCOMO, Inc.’s adoption rate in the target area. For the privacy consideration, the estimated population data was subjected to the de-identification, aggregation, and confidential processing (Terao et al., 2006). After that, the data are provided as demographic information purely representing the number of people in groups of different individual characteristics (i.e., gender, age, residential area). Therefore, individual users cannot be identified from the obtained the mobile spatial statistics. The use of mobile spatial statistics facilitates the calculation of the hourly population distribution (based on gender, age, and residential area) with a minimum of 500 m mesh. In addition, the
data can be collected in real time.

In this study, we used mobile spatial statistics in the central area of the Tokyo Metropolitan Region (Fig. 2), which includes 1490 grid cells (each grid cell with an area of $500 \times 500 \text{ m}$). Data were collected from January 1 to May 31, 2020.

4. Methodology

In the field of signal processing, different methods have been developed to extract original signals from observed signals. The broad topic of separating mixed sources is referred to as latent variable analysis (LVA), a commonly used approach to restore a set of unknown latent variables from a set of observed signals that are mixtures of these latent
variables, with unknown mixture of parameters. Lately, NMF (Lee & Seung, 1999) has been applied successfully in several fields for facial recognition and text mining applications, and it was applied to analyze the observed population in this study.

The purpose of the NMF method is to decompose the obtained data into a limited number of basis components, which can approximate the original data as accurately as possible. Given a set of observations of variables that is represented by matrix $X$ (here, $X$ is an $n \times p$ non-negative matrix), the objective of NMF is to recover the $r$ source (here, $r$ is an integer larger than 0) signals by approximating the matrix $X$ with the following factorization:

$$X \approx WH$$  \hspace{1cm} (1)

Eq. (1) states that each column of the matrix $X$ can be approximated by a linear combination of the columns of $W$ (i.e., the basis components) that is non-negative, and the coefficients are given by the corresponding column of $H$ (i.e., the mixture coefficients). The existing studies have proposed different methods of latent variable decomposition. Most of these methods do not make non-negative constraints for basis components, it will lead to subtractive combinations of basis components. In the cases of population movement, it might be difficult to provide the obvious interpretation of data from the obtained components. Because it allows only additive combinations of basis components, the basis components can be directly interpreted as population with different behavior activities in each observed sample.

Formally, the objective of NMF is to solve the following problem:

$$\arg\min_{W,H} \sum_{i,t} d(X_{it}||WH_{it})$$  \hspace{1cm} (2)

Here, $X_{it}$ is the value at row $i$ and column $t$ of the original matrix $X$, $[WH]_{it}$ is the same element of the reconstructed matrix, and $d(X_{it})$ is a cost function. In the previous studies, several methods have been proposed to solve this problem, using different cost functions (Cichocki et al., 2011; Gillis & Plemmons, 2011; Hopke, 2016). Most of the existing studies constructed the cost function using the square of the Euclidean distance $\|X-WH\|^2$ or the divergence $D(X||WH)$ (Lee & Seung, 2001), which is a classical technique employed to solve several LVA problems.

$$\|X-WH\|^2 = \sum_{it} (X_{it} - (WH)_{it})^2$$  \hspace{1cm} (3)

and

$$D(X||WH) = \sum_{it} X_{it}\log \frac{X_{it}}{(WH)_{it}} - X_{it} + (WH)_{it}$$  \hspace{1cm} (4)

In this study, we used mobile statistical data from 1490 grid cells. Let matrix $X = (x_1(t), \ldots, x_{1490}(t))$ denote the observed population (Here, $x_i(t)$ is a column vector representing the observed population in the given grid cell $i$ along time period $t$. As we have hourly data of 1490 grid cells for 152 days, $X$ is a matrix with 3648 rows and 1490 columns), and the objective is to decompose the information contained in $X$ into several latent variables. Here, the model was estimated using the NMF method.

$$X = WH$$  \hspace{1cm} (5)

where columns of $W$ are the independent latent components, which represent the temporal patterns of the mobility behaviors, and $H$ is a matrix of weight parameters that represent the spatial weights.

To better understand the result, the regression model was used to analyze the source components $W_i$.

$$W_i = \sum_{a=1}^{52} \beta_a x_{ia} + \sum_{d=1}^{6} \beta_d x_{id} + \sum_{c=1}^{23} \beta_c x_{ic} + \epsilon_i$$  \hspace{1cm} (6)

Here, the dependent variable is the source component, $W_i$, which is derived from non-negative matrix factorization. The explanatory variables are dummy variables $x_{iw}$, $x_{id}$, and $x_{ic}$ that represent the week, day in a week, and time in a day, respectively (Table 1).

5. Estimation results and discussion

5.1. Latent behavior pattern derived from NMF

In this study, six latent components are derived from NMF analysis (the number of latent components is determined by increasing the number until some obtained components are not interpretable and do not represent any behavior pattern). The model estimation results are presented in Figs. 3–8. Based on these results, we attempted to interpret the latent component $W_i$.

Fig. 3(1) shows the estimation result for $W_1$, which represents the temporal pattern of the first latent component. It can be observed that the value of $W_1$ changes periodically; it exhibits relatively higher values on weekdays and lower values on weekends and holidays. With regard to the estimation result of the regression analysis in Fig. 3(2), the estimated parameter of time in a day has a positive value during daytime and reaches a peak value around 12 pm. The estimated parameters of the day in a week show negative values for Saturday and Sunday. Fig. 3(3) shows the estimation result of $H_1$, which represents the spatial weight of the first component. It can be observed that the area near Tokyo station, Shinbashi, Shinjuku, and Shinagawa have relatively higher values of $H_1$ than those of other areas. These results indicate that the first latent component may describe the working behavior.

Fig. 4(1) shows the estimation result for $W_2$, which represents the temporal pattern of the second latent component. Similar to the first component, it shows relatively higher values on weekdays, lower values on weekends and holidays, and two peak hours within a certain day. In terms of the estimation result of the regression analysis shown in Fig. 4(2), the estimated parameter of time in a day has a positive value during daytime, reaches the morning peak value at approximately 8 am, and reaches the afternoon peak value at approximately 6 pm. The estimated parameters of the day in a week show negative values for Saturday and Sunday. Fig. 4(3) shows the estimation result of $H_2$, which represents the spatial weight of the second component, and it can be observed from the results that $H_2$ exhibits a relatively high value in the transportation hub areas (e.g., Ikebukuro station, Shinjuku station, Tokyo station, Akihabara station). These results indicate that the second latent component may describe the commuting behavior.

Fig. 5(1) shows the estimation result for $W_3$, which represents the temporal pattern of the third latent component. The results show that $W_3$ has a relatively higher value on weekdays, especially on Fridays.

**Table 1**

| Dependent variable | Source component $W_i$ that is derived from NMF |
|--------------------|----------------------------------------------|
| Explanatory variables | Dummy variables for week [''] |
|                     | Dummy variables for day in a week (Sunday, Monday, Tuesday, Thursday, Friday, Saturday) [''] |
|                     | Dummy variables for time in a day (0:00, 1:00, 2:00, 3:00, 4:00, 5:00, 6:00, 7:00, 8:00, 9:00, 10:00, 11:00, 12:00, 13:00, 14:00, 15:00, 16:00, 17:00, 18:00, 19:00, 20:00, 21:00, 22:00, 23:00) [''] |

a There are 23 weeks from January 1 to May 31. Here, the week starting from January 19 is chosen to be the baseline week, and 22 dummy variables are used to represent each week.

b Wednesday is chosen to be the baseline day.

c 2:00 is chosen to be the baseline time.
Fig. 5 (2) shows the estimation result of the regression analysis, which suggests that the estimated parameter of time in a day has a negative value during morning hours, turns positive in the afternoon, and reaches a peak value around 8 pm. The estimated parameters of day in a week exhibit a positive value for Friday, slightly positive value for Thursday, and negative values for other days. Fig. 5 (3) shows the estimation result of $H_3$, which represents the spatial weight of the third component and exhibits relatively higher values in areas with a high density of restaurants, nightclubs and bars (please refer to Fig. 13 in the Appendix). These results indicate that the third latent component may describe the social gathering behavior.

Fig. 6 (1) shows the estimation result for $W_4$, which represents the temporal pattern of the fourth latent component. In contrast to the first component, it shows a relatively higher value on weekends and a lower
value on weekdays. In terms of the estimation result of the regression analysis shown in Fig. 6(2), the estimated parameter of time in a day increases from 9 am and reaches a peak value at 3 pm. The estimated parameters of day in a week show relatively higher values on weekends and lower values on weekdays. Fig. 6(3) shows the estimation result of $H_4$, which represents the spatial weight of the fourth component. It can be observed from the results that $H_4$ has relatively high values in areas with a high density of shopping facilities (e.g., Shinjuku, Ikebukuro, Shibuya, Ginza area). These results indicate that the fourth latent component may describe the shopping behavior.

Fig. 7(1) shows the estimation result for $W_5$, which represents the temporal pattern of the fifth latent component. It shows an obvious trend that it has a relatively higher value on holidays (e.g., the New Year holiday) and weekends. In terms of the estimation result of the regression analysis shown in Fig. 7(2), the estimated parameter of time in a day shows a positive value from 9 am to 9 pm, and the peak hour appears around 2 pm. The estimated parameters of day in a week show relatively high values on weekends and low values on weekdays. Fig. 7(3) shows
the estimation result of $H_5$, which represents the spatial weight of the fifth component. It can be observed from the results that $H_5$ has relatively high values in areas with popular tourist attractions (e.g., Tokyo station, Tokyo Dome, Ginza, and Asakusa area). These results indicate that the fifth latent component may describe the leisure and tourism behavior.

Fig. 8(1) shows the estimation result for $W_5$, which represents the temporal pattern of the sixth latent component. As indicated by Fig. 8 (2), the estimated parameter of time in a day shows a negative value during the daytime. The estimated parameters of day in a week show relatively higher values on weekends and lower values on weekdays. In particular, it shows a negative value for Thursday and Friday. Fig. 8(3) shows the estimation result of $H_6$, which represents the spatial weight of the sixth component. The results suggest that residential areas have
relatively high values of $H_6$. These results indicate that the sixth latent component may describe the in-house activities.

From the estimation results of $W_1$–$W_6$, we can observe the changes in each mobility activity with relation to time and the restriction measures on these activities. The working and commuting activities exhibit a moderate decrease (16.1% decrease for working activity and 18.9% decrease for commuting activity) after the government issued a remote-working request on February 26. Both activities decreased significantly (47.8% decrease in working activity and 49.1% decrease in commuting activity) after the declaration of state of emergency on April 7. It is worth noting that a mild drop in working and commuting activities was observed at the end of March, suggesting that individuals started to change their mobility behavior even before the official declaration of the state of emergency, probably due to the increasing number of confirmed cases.
cases of COVID-19. The trend of social gathering activity is similar to that of working activity. We also observe a two-stage decrease in social gathering activity: a mild drop (13.7% decrease) after the government's remote working request, and a sharp decrease (84.1% decrease) after the declaration of state of emergency. Compared with working activity, the social gathering activities decreased to a much greater extent because they are associated with a higher risk of infection. Shopping activity decreased gradually from the end of March and showed a sudden drop (75.2% decrease) after the state of emergency declaration. The weekend peak for shopping activity subsequently disappeared. This could be partially attributed to the closure of most department stores and shopping complexes during the emergency period. The specific shops and shopping-complex floors selling groceries and items of daily use are exceptions to the above-mentioned closure. Leisure and tourism activities decreased much earlier than other activities. These activities decreased significantly (57.8% decrease) from the beginning of March,
and almost disappeared (90.8% decrease) after the state of emergency declaration. On the one hand major leisure and recreational sites were closed during the state of emergency declaration, on the other hand people are restraining from unnecessary travel during the COVID-19 pandemic. In-house activity displayed contrasting trends compared with those of other activities. It exhibited a slight increase after the government’s remote-working request and a more pronounced increase after the state of emergency declaration. Such results indicate that even though the NPI measures adopted by the Japanese government are non-compulsory and rely largely on requests for voluntary self-restriction, they have been effective in reducing population mobility and compelling people to practice social distancing, such as working from home, avoiding crowded places, and avoiding unnecessary travel. The analysis results (as summarized in Table 2) suggest that the state of emergency declaration has had the most obvious impact on leisure and tourism activities, followed by social gathering and shopping activities.
However, its impact on working and commuting activities has been relatively moderate.

5.2. Comparison with Google’s COVID-19 community mobility reports

In order to provide insights into the mobility change in response to policies aimed at combating COVID-19, Google has been publishing Community Mobility Reports, which provides data about population movement trends over time across different categories of places including retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential (Google, 2021). Fig. 9 presents the comparison of different behavior patterns derived in our study with that of Google’s COVID-19 Community Mobility Reports in Tokyo. The result confirmed that working, commuting, shopping, and inhouse activities have high correlation with workplace, transit stations, retail, and residential, respectively. It is reasonable that leisure and tourism activities do not show high correlation with park, as most of these activities are carried out at tourism attractions that is not limited to parks. The social gathering is not included into the comparison analysis, because there is no corresponding category in Google’s COVID-19 Community Mobility Reports.

Although Google’s Community Mobility Reports provide important information of population movement trends across different categories of places, the analysis results from the current study still show several advantages. One of the important issues to contain the spread of COVID-19 is to control the spatial and temporal distribution of population, in order to avoid crowdedness of population at the same place during same time. By comparing with daily Google data, the current analysis provided information of hourly change of different behavior patterns, which enable us to monitor the population movement with a higher resolution in time. Meanwhile, this study also enables us to understand the spatial distribution of different activities with a high resolution (500 m × 500 m), which is not available in Google’s Community Mobility Reports.

### Table 2
Change of different activities after the state of emergency declaration.

| No. | The Latent components | Change after the state of emergency declaration |
|-----|-----------------------|-----------------------------------------------|
| 1   | Working activity      | -47.8%                                        |
| 2   | Commuting activity    | -49.1%                                        |
| 3   | Social gathering activity | -84.1%                                    |
| 4   | Shopping activity     | -75.2%                                        |
| 5   | Leisure and tourism activities | -90.8%                                |
| 6   | In-house activity     | +21.6%                                        |

The data in Google’s COVID-19 Community Mobility Reports show how visitors to (or time spent in) categorized places change compared to the baseline value, which is the median value from the 5-week period Jan 3–Feb 6, 2020. Therefore, we transform our data using the same method.

**In Google’s COVID-19 Community Mobility Reports, the Residential category shows the change in duration instead of total population. In our data, the Inhouse activities present the accumulated hourly population over a certain day.**

![Fig. 9. Comparison with Google’s COVID-19 Community Mobility Reports.](image-url)
5.3. Impact of the stringency of anti-COVID-19 restrictions on mobility

This section attempts to investigate the impact of the stringency of anti-COVID-19 restrictions on population mobility. The Oxford Covid-19 Government Response Tracker (OxCGRT) collects systematic information on policy measures that governments have taken to tackle COVID-19 (Hale et al., 2021). It develops a COVID-19 Stringency Index, which is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled from 0 to 100 (100 = strictest). Here, correlation analysis is conducted between six behavior patterns and COVID-19 Stringency Index in Japan (Fig. 10). The results suggest that working, commuting, social gathering, shopping, leisure and tourism activities have negative correlation with COVID-19 Stringency Index, while inhouse activities have positive correlation with it. Furthermore, the results indicate that leisure and tourism activities are mostly impacted by the composite measure, followed by commuting and working activities. In terms of social gathering and shopping activities, the correlation coefficients show relatively low value. It suggests that although these activities have significantly decreased after the state of emergency declaration, other measures might not have obvious impact on them.

5.4. Mobility change in different cities

In order to compare mobility changes in different cities, the data of Osaka and Hiroshima are also analyzed in the current study. From the data analysis results, one can notice that the changes of six behavior patterns in Osaka city (Fig. 11) are similar with that of Tokyo city. However, some differences are identified in mobility change in Hiroshima city (Fig. 12). Firstly, the decrease of working activities after the state of emergency declaration in Hiroshima was not as significant as Tokyo and Osaka. Nevertheless, the sharp decrease of commuting activities was observed in Hiroshima as well. Since the car ownership in Hiroshima was higher than that in Tokyo and Osaka (note: the car ownership in Tokyo, Osaka, and Hiroshima is 0.42/household, 0.63/household, and 1.1/household, respectively [Japan Automobile Manufacturers Association, 2020]), it gives people more flexibility to use private car to commute during pandemic. The results indicate that although a large percentage of people were still working in Hiroshima, they shift from public mode to private car during the pandemic. In terms

Fig. 10. Impact of the stringency of anti-COVID-19 restrictions on different activities.

*The data for six behavior patterns are 7-day moving average value.
of shopping, and leisure and tourism activities, it recovered more quickly in Hiroshima by comparing with Tokyo and Osaka. This is because that the state of emergency declaration was relieved earlier (May 14) in Hiroshima. Meanwhile, we also observe some similarities in Tokyo, Osaka, and Hiroshima. In these three cities, social gathering, shopping, and leisure and tourism activities decreased to a much greater extent by comparing with working activity. In addition, leisure and tourism activities decreased much earlier than other activities, which indicates that people are restraining from unnecessary travel at the initial stage of the pandemic, even before the restriction measures were carried out by government. Such results are consistent with research findings from other countries, which suggested that COVID-19 pandemic and the related restriction measures have greater and more persistent impact on social, recreational, leisure, and amusement activities than working and commuting activities (Shakibaei et al., 2021; Zhang et al., 2021).

6. Conclusion

To contain the transmission of COVID-19, countries around the world have implemented different types of NPIs. A major challenge in this situation is to quantitatively assess the impact of these NPIs on people’s mobility patterns in real time. Since each country has its own approach and policy for handling the crisis, the pandemic has affected people living in various countries in different ways. This study provides a quantitative assessment of the impact of such measures on population mobility patterns in Japan through the analysis of large-scale anonymized mobile-phone data. The contributions of this study are summarized as follows.

First, this study confirmed the suitability of the NMF method for extracting behavior patterns from aggregated mobile statistics data. The method performs satisfactorily in terms of decomposing the aggregated data into basis components with non-negative entries. Specifically, six
major behavioral patterns (i.e., working, commuting, social gathering, shopping, leisure and tourism, and in-house activities) were identified separately using NMF. Understanding the extent of changes in these behavioral patterns can provide useful implication to evaluate the pandemic’s influence on different sectors including commerce, transport, employment, and environment, and so on. As more and more countries begun to utilize large-scale mobile-device datasets to support the fight against COVID-19, the NMF method can be easily adopted to evaluate the impact of COVID-19 and the related policies on people’s mobility patterns in other countries as well.

Second, this study indicates that real-time monitoring of mobility changes following NPIs is feasible through the analysis of large-scale mobility data collected from mobile phones, and it could be used to guide intervention policy during a pandemic. During the COVID-19 pandemic, mobility restriction has proved to be an effective mitigation strategy in many countries. To apply these measures more efficiently in the future, it is important to understand their effects in detail. The analytical approach proposed in this study will be useful to (1) quantitatively determine how compulsorily imposed measures and recommendations translate into reduced mobility at specific scales and times; (2) help governments to evaluate the effectiveness of different intervention measures in real time; and (3) assist the government’s decision-making during the COVID-19 pandemic, as well as for future pandemics and any other unprecedented scenarios.

Third, this study offers an analytical tool to monitor the long-term evolution of population mobility patterns in the post-pandemic phase.

![Fig. 12. Change of six behavior patterns in Hiroshima.](image-url)
through analysis of longitudinal data provided by mobile spatial statistics. The COVID-19 pandemic has caused upheaval around the world. The preventive measures issued by the governments, such as social distancing, coupled with public fear of the contagion have caused people around the world to change their daily routines. Long-established routines, such as commuting to the workplace and in-store shopping, are being replaced by telecommuting and online shopping to avoid crowds and physical interactions. Consequently, rapid and drastic changes have become apparent in people’s mobility patterns. Because many economic, social, and civic functions are largely dependent on population mobility, it is critical to investigate the effect of changes in people’s mobility styles and habitual travel behaviors, as well as the extent of these changes, during the COVID-19 pandemic, and to explore whether these changes will persist afterward. The analysis will provide useful information of the temporal changes in mobility patterns as well as the spatial distribution of different travel behaviors.

There are some limitations in the current research, which could be extended in several ways in a future study. As argued by previous studies, the characteristics of the underlying population play a role in determining the mobility change in the wake of COVID-19 (Engle et al., 2020). Because mobile spatial statistics include breakdown data in terms of gender, age, and residential area, further analysis can be performed using these data to understand the behavior of people with different characteristics. Such analysis will enable government to implement effective restrictions to adjust to region-specific socio-economic features. Furthermore, we also see the potential for extension of this research beyond the COVID-19 pandemic. As mentioned above, the long-term effects of pandemics remain unknown; Therefore, a longitudinal analysis could be conducted to clarify the long-term effects of pandemics on population mobility.

CRediT authorship contribution statement

Liling Wu: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft. Tetsuo Shimizu: Project administration, Resources, Supervision, 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.

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Appendix A

Fig. 13. Distribution of restaurants and bars in the target area. *The number of restaurants and bars in each mesh are derived by using Overpass turbo in OpenStreetMap.

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