Transportation Research Part A 181 (2024) 104003

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Assessing effects of pandemic-related policies on individual public transit travel patterns: A Bayesian online changepoint detection based framework

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ARTICLE INFO

Keywords:
Behavior change
Public transit
Smart card data
Bayesian online changepoint detection
Travel behavior
Policy making

ABSTRACT

During a pandemic or natural disaster, people may alter transit usage behavior due to perception of changes in the environment. To effectively respond to these crises, it is important for governments and public transit agencies to understand when these changes occurred and how they were affected by relevant policies and responsive strategies. In this study, we develop a methodological framework based on Bayesian online changepoint detection (BOCD) to identify the occurrence time, direction, and persistency of changes in individual-level transit usage. We demonstrate the effectiveness of this framework in informing government decision-making in the context of COVID-19. Using Jeju Island, South Korea as a case study, we apply the framework over a nearly two-year smart card dataset collected from the beginning of 2019 till nine months into the pandemic. By focusing on frequent transit users, we detect when these users significantly changed their transit usage frequency during the pandemic and identify several types of users who experienced different behavior change patterns. Besides demonstrating the great heterogeneity in individual-level behavior changes, we perform a regression analysis to further understand how these changes were affected by key government policies (e.g., Risk alert, Social distancing, Public transit policy, and Eased social distancing). Our results suggest that only certain sets of policies appear to have significant effects. In particular, introducing Risk alert would cause a 277% to 317% increase in the number of users who reduced transit usage frequency. Policies that eased social distancing, though, would cause a 134% to 155% increase in the number of users with travel frequency increase. The proposed BOCD framework enables a scalable solution to identifying and understanding changes of individual transit behavior. The methodology and findings are beneficial for developing targeted policies and interventions to facilitate daily travel and public transit operations during public health crises.

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https://doi.org/10.1016/j.tra.2024.104003

Available online 17 February 2024

1. Introduction

During crises such as pandemics or natural disasters, individuals may adjust their transit usage behavior as responses to the perceived changes in the environment (Ulfarsson et al., 2015; Liu et al., 2022; Ren et al., 2022). During a pandemic, for example, travelers may actively reduce transit usage to avoid exposure to the viruses in the confined spaces of buses and metros (Akim and Ayivodji, 2020; Chen et al., 2022; Kaplan et al., 2022; Shortall et al., 2022). In the course of a natural disaster, certain populations could become more reliant on public transit systems given the various damages that limit their access to road infrastructure and other means of transportation (e.g., automobile). (He et al., 2021). Therefore, it is crucial to understand these behavior changes and their driving factors. Such knowledge could benefit the operation of transit systems during the crises, and inform decision makings to improve resilience of the systems.

Existing studies have explored changes in people's transit usage behavior during crises such as floods and pandemics (Abad and Fillone, 2018; Jenelius and Cebecauer, 2020; Wielechowski et al., 2020). However, most of the studies approach this question through the means of collective behavior indicators, such as changes in the overall transit ridership (Jenelius and Cebecauer, 2020; Parker et al., 2021; Aydin et al., 2022; Wilbur et al., 2023). Although collective analysis could identify the general trends in travel behavior and provide a broad understanding of people's transit use pattern, it does not investigate how the change occurred at the individual level. A crisis may generate different impacts on travel behavior across individuals, and such impacts can be affected by socio-demographics, such as employment and income levels. Examining the disparity of individual behavior change is crucial for governments to develop personalized policies and interventions and alleviate social inequities. Individual-level analysis is capable of extracting occurrence time and persistency of behavior changes. An improved understanding of when an individual would change the transit use behavior and how long the change would persist during a crisis can provide valuable insights to inform governments' decision-making. For example, the occurrence time of the changes allows for identifying individual travel patterns, preferences and motivations. The change persistency is related to individuals' risk perception and travel attitudes. Thus, the individual-level analysis could provide a nuanced understanding of crisis impacts and guide effective policy responses.

Scholars have also examined driving factors behind changes in transit use behavior, with a utilization of survey data in the majority of studies (Heiskanen et al., 2022; Sogbe, 2021; Kamga and Eickemeyer, 2021). They have revealed some crucial factors, such as people's fear level and related policies during a crisis, providing valuable insights into the impact of a crisis on behavior changes (Kitchovitch and Liò, 2011; Lucchesi et al., 2022; Heiskanen et al., 2022; Kim et al., 2021; Mashrur et al., 2023). However, survey data often has limited spatio-temporal coverage. It is typically collected within a defined timeframe and geographic area, which may hinder studies of long-term and population-scale behavior changes. To mitigate the impact of the limitation, one approach is to investigate individual behavior changes over large-scale human mobility datasets. These datasets, such as smart card data, often document individuals' travel behavior over an extended period and larger geographic areas, thereby expanding our understanding of travel behavior change and its driving factors.

Given limited exploration of individual-level changes in transit usage behavior and their driving factors over large-scale datasets, we develop a methodological framework to analyze individual behavior changes from human mobility data. The framework is based on Bayesian online changepoint detection (BOCD), which is a statistical model to detect abrupt changes in time series data. It is capable of identifying occurrence time, persistency and direction (e.g., increase or decrease in transit use) of behavior changes for each traveler. Based on the underlying distribution of individual mobility data, BOCD can effectively detect the changepoints, which indicate the occurrence time of the change (Habibi, 2021). The period between changepoints is referred to as characteristic period, in which the individual use of public transit is relatively stable. Characteristic periods can be used to reflect the persistency of people's behavior change. The difference in travel behavior between consecutive periods demonstrates the direction of the change, which suggests the trends and patterns of individual travel behavior over time.

We apply the proposed framework to investigate the impact of the pandemic-related policies on the change in individual transit use behavior during COVID-19. The study area is Jeju Island, South Korea. The analysis focuses on an important group of transit users — frequent transit users who are highly reliant on public transit in their daily life (Vassallo et al., 2009; Esmailpour et al., 2022). Considering travel frequency as an important reflection of how users use public transit everyday, we use it as an indicator in BOCD to detect individual behavioral changepoints. Based on the changepoints, we identify the occurrence time, characteristic periods, and direction of changes (i.e., increase or decrease in travel frequency) for each user, and subsequently analyze the change patterns of them. Users are then classified into different categories based on their change patterns. For the users with multiple changepoints, we calculate the behavioral change persistency based on the characteristic periods between two adjacent changepoints. Combined with the announcement timing of the pandemic-related policies (i.e., Risk alert, Social distancing, Public transit policy, and Eased social distancing), we uncover the heterogeneous impact of policies on the changes in transit use among different individuals. This study undertakes a retrospective analysis to examine the profound effects of policies on individuals' transit use pattern in the context of COVID-19. The findings unveil invaluable applicability of this framework in informing governmental decision-making processes during a crisis. Notably, this approach enables the real-time change detection. This capability could support governments and authorities to respond swiftly and timely to align with the ever-evolving circumstances during a crisis.

2. Literature review

The outbreak of a crisis always brings a dampening impact on mobility and transportation (Batomen et al., 2023; Godfrey et al., 2019). Public transit is always one of the most affected sections (Müller et al., 2020; Lin et al., 2023; Pitale et al., 2023; Wilbur et al., 2023). By reporting results from a survey, Blendon et al. (2008) shown that 89% of participants indicated a limited usage of public transit during a pandemic influenza. According to a questionnaire survey, Sadique et al. (2007) found that 75% of participants demonstrated that they would avoid public transit during Severe Acute Respiratory Syndrome (SARS). Kim et al. (2017) uncovered that people's travel frequency on public transit declined significantly during Middle East Respiratory Syndrome (MERS). By analyzing a dataset provided by regional transport, Tiikkaja and Viri (2021) found that people reduced their transit use frequency and the number of passengers of public transit decreased by 70% during the COVID-19 pandemic. Marra et al. (2022) revealed that in terms of recurrent trips, people would reduce public transit use and switch to private vehicle. Transit use behavior of people is associated with the severity of crises. Fathi-Kazerooni et al. (2020) revealed a strong correlation between people's subway usage and pandemic severity. Shelat et al. (2022) found that users adapted their travel behavior on public transit to the dynamics of pandemic situation. The change in transit use behavior during a crisis varies with people's socio-demographic characteristics. Jones and Salathé (2009) demonstrated through an online survey that older individuals were more likely to avoid using public transit. Parker et al. (2021) uncovered a lower reduction in public transit usage of the people with lower income. By applying smart card data and socio-demographic data, Almlöf et al. (2021) showed that people with lower income and education level and from the areas with many non-employment were more likely to use public transit during COVID-19. Some scholars studied the reasons behind changes in travel behavior on public transit during a crisis. Aloi et al. (2020) demonstrated that people avoided using public transit during the COVID-19 pandemic due to crowdedness and risk of contagion. This is consistent with the finding of Shelat et al. (2022), which indicated that higher crowdedness, waiting time and infection rates would reduce the willingness of people to use public transit. Government policies and countermeasures implemented by public transit agencies are also determinants of individuals' transportation mode choice. Sogbe (2021) identified several essential factors influencing commuters' choice of public transit, including physical social distancing, vehicle cleanliness, travel safety, and wearing of face masks. Chen et al. (2022) observed diverse reactions among individuals towards the countermeasures introduced by the Dutch central government during COVID-19. Specifically, the older and highly educated individuals were found to be more susceptible to enforcement measures, such as social distancing and mask requirement, while young and single individuals displayed a greater openness towards non-compulsory measures, such as transit vehicle disinfection.

While previous studies have made notable efforts to examine the behavior changes in people's transit use behavior and the influence of policies on these changes during a crisis, most of the studies investigate the changes from a collective perspective. There is limited research that delves into individual-level analysis, specifically improving the understanding of when and how long individuals would change their transit use pattern during a crisis. Moreover, most studies investigated the impact of policies on travel behavior by utilizing survey data. These studies provide valuable insights on users' behavior change during a crisis. However, survey data is often collected within a limited time span and geographic areas. The limited coverage may restrict our understanding of the long-term behavior change of various groups of population and the driving factors. To enhance the understanding, there is a need to develop effective and scalable approaches capable of identifying behavior changes from large-scale human mobility datasets which document more extensive information on travel behavior.

Changepoint detection is an effective technique for identifying abrupt changes within travel behavior data of individual (Aminikhanghahi and Cook, 2017). Depending on the timing of the detection, the changepoint detection approaches can be categorized into offline and online methods. The offline methods identify changepoints with a relatively high accuracy, but they lack ability to detect changes in a timely manner (Reeves et al., 2007). The online methods detect changepoints in near real time, which is a crucial capability for governments to capture dynamics of people's transit use behavior promptly and respond rapidly during a crisis (Zhao et al., 2018b; Downey, 2008). Therefore, this study adopts an online method to support dynamic decision-making of governments in their emergency management.

Some scholars conducted an online changepoint detection by measuring the dissimilarity between reference data and test data. Appel and Brandt (1983) introduced the classical Generalized Likelihood Ratio to qualify the dissimilarity in probability distributions between reference data and test data. As an improvement, Desobry et al. (2005) proposed a Kernel Change Detection algorithm, where the dissimilarity is measured according to an arc distance in feature space. However, several parameters need to be specified for a good performance in these dissimilarity-based methods. Instead of detecting changepoints based on dissimilarity, Adams and MacKay (2007) presented the BOCD approach, which outputs the probability of changepoints allowing us to identify a changepoint based on different certainty levels. BOCD detects the change with data that can be seen so far. Thus, the results of BOCD are robust. Zhao et al. (2018a) extended the BOCD method to detect the long-term individual travel pattern, which effectively detects the change at any given time for a behavior dimension. In this study, we propose a framework based on the BOCD approach developed by Zhao et al. (2018a) to analyze the transit use pattern of frequent transit users during a crisis from the individual perspective (Zhao et al., 2018a).

3. Methodology

3.1. Change detection of frequent transit users

Frequent transit users refer to those who rely heavily on public transit. They are a critical group for sustaining public transit ridership (Vassallo et al., 2009; Esmailpour et al., 2022). Understanding behavior changes of frequent transit users can assist transit agencies and governments in developing appropriate policies and strategies to respond to crises. Moreover, frequent transit users often include vulnerable groups, such as essential workers, the low-incomes, and transit-dependent populations like seniors and disables (Zuo, 2020). Understanding how their transit use behavior might change during a crisis is critical for implementing the targeted policies and strategies to maintain their normal life, and accordingly, alleviating social inequalities (Brown and Williams,

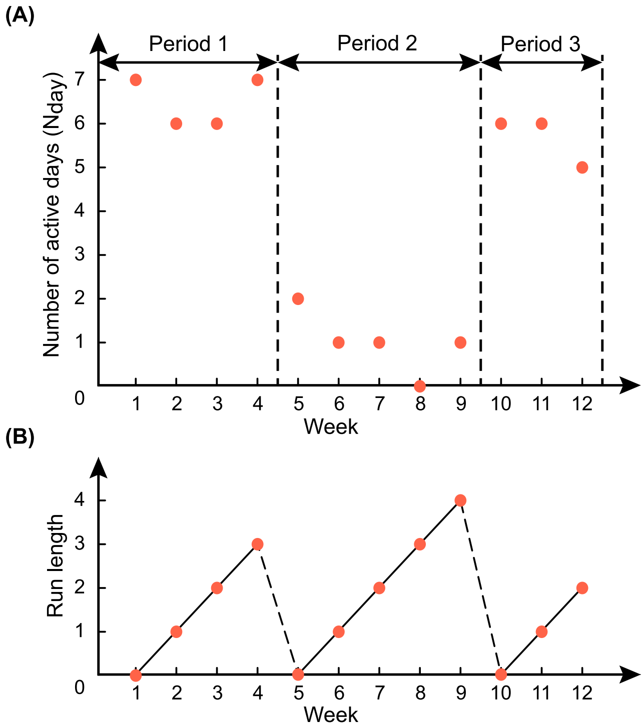

Fig. 1. Illustration of run length: (A) a time series of number of active days partitioned by two changepoints; (B) associated run length.

2023). In this study, frequent transit users are identified based on the number of active weeks, which refer to weeks where at least one travel record of the user can be traced in the public transit system during normal conditions (such as the period before a crisis). The users whose number of active weeks is not less than K are considered as frequent transit users, and K is determined based on datasets and research objectives. Considering that people's travel behavior change is mainly reflected in the travel frequency dimension, we detect frequent transit users' behavior change in terms of their transit use frequency. To capture the dynamics of transit use frequency, we define a time series of the number of active days (N_{day}). This metric represents the total count of days in which a user engages with public transit during a specific time unit. To account for the effect of the day-of-week, we set the time unit U as 7 days.

With the time series N_{day}, we aim to identify when an abrupt change occurs. Such a change is referred to as a changepoint, and can be detected using a changepoint detection algorithm. In this paper, we employ BOCD to detect the changepoints in the time series of N_{day} (Adams and MacKay, 2007; Zhao et al., 2018a). Let x_t denote an observation of N_{day} in week t. The value of x_t is basically determined by the daily decision of an individual regarding transit usage within the time unit U. The output for each day is a binary value. Specifically, the user chooses to use public transit on a given day is recorded as 1, while 0 otherwise. The frequency of "1" occurrences within U corresponds to x_t. This idea aligns with the concept of binomial distribution. Binomial distribution is often employed to model the number of successes in n independent experiments, where the output of each experiment is also binary. Hence, we assume that x_t follows a binomial distribution:

$$P(x_t = b|\theta, U) = \binom{U}{b} \theta^b (1-\theta)^{U-b}, \tag{1}$$

where b denotes the possible value of N_{day} within a time unit, and θ is the probability that a user chooses to use public transit in a day. $\boldsymbol{x}_{1:T}$ is a sequence of the observations from $t = 1$ to $t = T$. We assume that $\boldsymbol{x}_{1:T}$ can be divided into non-overlapping partitions, in which the data are i.i.d. samples obeying binomial distributions (Barry and Hartigan, 1992). The observation between any two partitions is identified as a changepoint (as shown in Fig. 1A).

BOCD works by modeling the duration since the last changepoint, which is called the "run length". The run length in week t is denoted as r_t, which can be expressed as follows:

$$r_t = \begin{cases} 0 & \text{if a changepoint occurs in week } t \\ r_{t-1}+1 & \text{otherwise.} \end{cases} \tag{2}$$

That is, r_t will increase by one or drop to zero. As shown in Fig. 1, the time series is divided by two changepoints occurring at $t = 5$ and $t = 10$. As such, r_t is added by one at each step when $t < 5$ and $5 < t < 10$, and drops to zero when $t = 5$ and $t = 10$.

Based on Bayesian inference, we assume that the predictive distribution of $\boldsymbol{x}$ can be computed with a given r_t, as shown in Eq. (3):

$$P(x_{t+1}|\boldsymbol{x}_{1:t}) = \sum_{r_t} P(x_{t+1}|r_t, \boldsymbol{x}_t^{(r)})P(r_t|\boldsymbol{x}_{1:t}), \tag{3}$$

in which, $\boldsymbol{x}^{(r)}$ represents the observations associated with r_t. $r_t = r$ means the last changepoint occurred r weeks ago. Thus, only the observations within last r weeks would be considered when predicting x_{t+1}. The posterior distribution, $P(r_t|\boldsymbol{x}_{1:t})$, is proportional to the joint distribution:

$$P(r_t|\boldsymbol{x}_{1:t}) = \frac{P(r_t, \boldsymbol{x}_{1:t})}{P(\boldsymbol{x}_{1:t})}. \tag{4}$$

We write the joint distribution recursively:

$$\begin{aligned} P(r_t, \boldsymbol{x}_{1:t}) &= \sum_{r_{t-1}} P(r_t, r_{t-1}, x_t, \boldsymbol{x}_{1:t-1}) \\ &= \sum_{r_{t-1}} P(r_t, x_t|r_{t-1}, \boldsymbol{x}_{1:t-1})P(r_{t-1}, \boldsymbol{x}_{1:t-1}) \\ &= \sum_{r_{t-1}} P(x_t|r_t, r_{t-1}, \boldsymbol{x}_{1:t-1})P(r_t|r_{t-1}, \boldsymbol{x}_{1:t-1})P(r_{t-1}, \boldsymbol{x}_{1:t-1}). \end{aligned} \tag{5}$$

With the modeling assumptions, we simplify the equation as:

$$P(x_t|r_t, r_{t-1}, \boldsymbol{x}_{1:t-1}) = P(x_t|r_t, \boldsymbol{x}^{(r)}). \tag{6}$$

Moreover, as shown in Eq. (2), the value of r_t is independent of everything else when given r_{t-1}. Thus,

$$P(r_t|r_{t-1}, \boldsymbol{x}_{1:t-1}) = P(r_t|r_{t-1}). \tag{7}$$

According to Eqs. (6) and (7), Eq. (5) can be written as:

$$P(r_t, \boldsymbol{x}_{1:t}) = \sum_{r_{t-1}} P(x_t|r_t, \boldsymbol{x}^{(r)})P(r_t|r_{t-1})P(r_{t-1}, \boldsymbol{x}_{1:t-1}). \tag{8}$$

In Eq. (8), $P(r_t|r_{t-1})$ is called as the changepoint prior. We assume that

$$P(r_t|r_{t-1}) = \begin{cases} H(r_{t-1}+1) & \text{if } r_t = 0 \\ 1 - H(r_{t-1}+1) & \text{if } r_t = r_{t-1}+1 \\ 0 & \text{otherwise,} \end{cases} \tag{9}$$

in which,

$$H(\tau) = \frac{f(\tau)}{S(\tau)}. \tag{10}$$

$S(\tau)$ is a survival function:

$$S(\tau) = P(T \geq \tau) = \sum_{\tau'=\tau}^{\infty} f(\tau'), \tag{11}$$

which is generally used to demonstrate the likelihood of an object of interest, such as a patient or device, surviving past a certain time. $f(\tau)$ is the probability density function. $H(\tau)$ is a hazard function, which refers to the rate that an event of interest, such as death or failure, is expected to occur at a specific time, given that the event has not happened before that time. As such, in this framework, the hazard function demonstrates the probability that a changepoint will occur at τ given that it has not occurred by run length τ. When $f(\tau)$ is a discrete exponential distribution with timescale λ, $H(\tau)$ is a constant, $1/\lambda$.

As for the initial condition of the recursive algorithm, we assume that a changepoint occurred before the first observation. As such,

$$P(r_0 = 0, \boldsymbol{x}_{1:t} = \emptyset) = 1. \tag{12}$$

With assumption that $\boldsymbol{x}_{1:t}$ obeys binomial distribution, which is a member of exponential family distribution, $P(x_t|r_t, \boldsymbol{x}^{(r)})$ can be estimated based on beta-binomial distribution. The probability density function of beta distribution is shown as follows:

$$P(\theta|\alpha, \beta) = \theta^{\alpha-1}(1-\theta)^{\beta-1}\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}, \tag{13}$$

where Γ is the Gamma function, and α and β are hyperparameters. According to Eqs. (1) and (13), we can get the beta-binomial distribution:

$$P(x_t|U, \alpha, \beta) = \frac{\Gamma(U+1)\Gamma(x_t+\alpha)\Gamma(U-x_t+\beta)\Gamma(\alpha+\beta)}{\Gamma(x_t+1)\Gamma(U-x_t+1)\Gamma(U+\alpha+\beta)\Gamma(\alpha)\Gamma(\beta)}. \tag{14}$$

As such, given r_t, the hyperparameters can be updated as:

$$\alpha_t^{(r)} = \alpha_{prior} + \sum_{t' \in r_t} (x_{t'}), \tag{15}$$

$$\beta_t^{(r)} = \beta_{prior} + \sum_{t' \in r_t} (U - x_{t'}). \tag{16}$$

It is worth noting that the changepoint detected by BOCD only detects the latest changepoint. We use $y_{u,-k} = 1$ to denote that the observation at time u is the kth latest changepoint. In other words, the BOCD algorithm can only detect $P(y_{u,-1} = 1|\boldsymbol{x}_{1:t})$. However, we want to find out the possibility that the observation at time u is a changepoint, denoted as $P(y_u = 1|\boldsymbol{x}_{1:t})$, not just a latest changepoint. According to marginal theorem, $P(y_u = 1|\boldsymbol{x}_{1:t})$ can be obtained as follows:

$$P(y_u = 1|\boldsymbol{x}_{1:t}) = \sum_k P(y_{u,-k} = 1|\boldsymbol{x}_{1:t}). \tag{17}$$

Moreover, based on the marginal theorem and chain rule in the probability theory, $P(y_{u,-k} = 1|\boldsymbol{x}_{1:t})$ can be calculated as follows:

$$\begin{aligned} P(y_{u,-k} = 1|\boldsymbol{x}_{1:t}) &= \sum_{v=u+1}^{t-k+1} P(y_{v,-(k-1)} = 1|\boldsymbol{x}_{1:t}) P(y_{u,-k} = 1|y_{v,-(k-1)} = 1, \boldsymbol{x}_{1:t}) \\ &= \sum_{v=u+1}^{t-k+1} P(y_{v,-(k-1)} = 1|\boldsymbol{x}_{1:t}) P(r_{v-1} = v - u - 1|\boldsymbol{x}_{1:v-1}). \end{aligned} \tag{18}$$

Thus, in a given week, the possibility that the observation is a changepoint can be estimated by BOCD and Eqs. (17) and (18) (Zhao et al., 2018a). The procedure of the changepoint detection algorithm is shown in Fig. 2.

3.2. Change pattern characterization and quantification of behavioral change persistency

A crisis might bring about diverse changes patterns of frequent transit users' travel behavior. During the COVID-19 pandemic, for example, some users reduced travel due to fear of contracting the virus, while others increased. Increase in travel frequency can be attributed to these users being essential workers, who were required to serve the public in-person, such as nurses, retail workers, etc. Some particularly sensitive users also modified the travel behavior constantly in response to dynamics of the pandemic situation.

To characterize the change patterns, we segment the time series of N_{day} into characteristic periods based on the derived changepoints. Each changepoint is linked to two periods (before vs. after). By analyzing the difference in the average N_{day} during the characteristic periods before and after the changepoint, we denote the changepoint as "UP" (U) or "Down" (D) point. Specifically, when the average N_{day} during the period after the changepoint is larger than it during the period before the changepoint, we denote the changepoint as U. Otherwise, the changepoint is denoted as D. Since we focus on users' travel behavior change during a crisis, we only take into account the changepoints during the crisis when characterize users' change pattern. Fig. 3 shows three examples of the change pattern characterization. The horizontal and vertical axes in the figure represent dates and hours of each day, respectively. The color coding describes a user's daily transit use. Light blue signifies no public transit use on the given day. Dark blue indicates the use of public transit on the day, while green denotes the specific hour of transit use. The vertical lines on the top of each sub-figures represent the changepoint detected by employing BOCD. Specifically, the orange lines denote the changepoints before the crisis period, while the red lines represent the changepoints during the crisis period. User 1 in Fig. 3 has a sequence of D-D for the average N_{day} decreasing from 5.29 to 1.89 and further down to 0. User 2 and User 3 have sequences of U-U and D-U-D, respectively, based on the differences in the average N_{day} between each two consecutive characteristic periods. As such, for each user, we get a string with U and D to reveal his/her adjustment of travel behavior on public transit during a crisis.

For users with multiple changepoints during the crisis period, we identify all pairs of adjacent changepoints. The durations between the adjacent changepoints can provide valuable insights into the persistency of users' behavior change. Considering that different combinations of adjacent changepoints reflect distinct processes of behavior change and travel decision-making, we classify them into four patterns, including U-U, U-D, D-U, and D-D. We then analyze the change persistency for each of these patterns individually.

4. Case study

4.1. Dataset

This study utilizes a large-scale smart card dataset from Jeju Island. Jeju Island, shown in Fig. 4, is the largest island in South Korea with more than 600,000 population. The public transit system in this island only contains bus, and there is no metro. The total number of bus stations is 2922. The smart card dataset captures 84 million transit trips of 2,585,507 users from January 7, 2019 to October 4, 2020. Each record documents the departure timestamp and station ID. Considering the public holiday, annual leave and summer and winter holidays, we set $K = 40$ to filter the frequent transit users, which results in a subset of 58,088 users with 30,609,438 records. That is, users who used public transit not less than 40 weeks in 2019 account for 2.25% of all users. These users contributed approximately 36% of the total records.

Input: a sequence of observations of N_{day} $\boldsymbol{x} = [x_1, x_2, \cdots, x_T]$
Initialize the hyperparameters α_{prior}, β_{prior} of beta-binomial distribution
$\alpha_1^{(0)} = \alpha_{prior}$
$\beta_1^{(0)} = \beta_{prior}$
$U = 7$
For t in $range(1, T+1)$:
  //**Step 1**: Evaluate predictive probability
  $P\left(x_t \middle| U, \alpha_t^{(r)}, \beta_t^{(r)}\right)$
  //**Step 2**: Compute growth probability
  $P(r_t = r_{t-1}+1, \boldsymbol{x}_{1:t}) = P(r_{t-1}, \boldsymbol{x}_{1:t-1})P\left(x_t \middle| U, \alpha_t^{(r)}, \beta_t^{(r)}\right)(1 - H(r_{t-1}))$
  //**Step 3**: Compute changepoint probability
  $P(r_t = 0, \boldsymbol{x}_{1:t}) = \sum_{r_{t-1}} P(r_{t-1}, \boldsymbol{x}_{1:t-1})P\left(x_t \middle| U, \alpha_t^{(r)}, \beta_t^{(r)}\right)H(r_{t-1})$
  //**Step 4**: Obtain distribution of run length
  $P(r_t | \boldsymbol{x}_{1:t}) = P(r_t, \boldsymbol{x}_{1:t}) / \sum_{r_t} P(r_t, \boldsymbol{x}_{1:t})$
  //**Step 5**: Update the parameters
  $\alpha_{t+1}^{(0)} = \alpha_{prior}$
  $\beta_{t+1}^{(0)} = \beta_{prior}$
  $\alpha_{t+1}^{(r+1)} = \alpha_{t+1}^{(r)} + x_t$
  $\beta_{t+1}^{(r+1)} = \beta_{t+1}^{(r)} + U - x_t$
End for
//Output the probability that t is the latest changepoint $P(y_{t,-1} = 1|\boldsymbol{x}_{1:T})$
For k in $range(2, T+1)$:
  for t in $range(1, T+2-k)$:
    for v in $range(t+1, T+1-(k-2))$:
      $P\left(y_{t,-k} = 1 \middle| \boldsymbol{x}_{1:T}\right) += (P(y_{v,-(k-1)} = 1|\boldsymbol{x}_{1:T})P(r_{v-1} = v - t - 1|\boldsymbol{x}_{1:v-1})$
//Output the probability that t is the k-th latest changepoint $P(y_{t,-k} = 1|\boldsymbol{x}_{1:T})$
For t in $range(1, T+1)$:
$P(y_t = 1|\boldsymbol{x}_{1:T}) = \sum_k P(y_{t,-k} = 1|\boldsymbol{x}_{1:T})$
Output: The probability that t is a changepoint $P(y_t = 1|\boldsymbol{x}_{1:T})$

Fig. 2. Procedure of changepoint detection.

The nearly two-year smart card data records the travel behavior of frequent transit users in 91 weeks, which cover the period before and during COVID-19. Fig. 5 shows the timeline of COVID-19 in South Korea and Jeju. On January 3, 2020, National Infectious Disease Risk Alert Level (NIDRAL) was declared to “Level 1”. After the first case was reported in South Korea on January 20, the NIDRAL was raised to “Level 2” and rapidly raised to “Level 3” on January 27. A religious gathering in Daegu led to a significant increase in the daily number of confirmed cases from February 19 and rapidly increased to 909 cases during the following period. The government introduced some measures to control the spread of the virus. On February 23, NIDRAL was raised to the highest level — “Level 4”. Social distancing was introduced on February 29, followed by an enhanced social distancing announced on March 22. Public transit agency in Jeju Island also changed the bus schedule on some routes since April 11 and 12. By mid April, the daily confirmed cases were consistently below 50. In late-April and early May, the governments in South Korea gradually relaxed social distancing. In mid and late May, schools reopened at varied grade levels. However, another religious gathering in mid August rose the number of confirmed cases again. To flatten the curve, the governments introduced social distancing measure Level 2 across the country on August 23. Until the early October, the daily confirmed cases were below 100. The first case reported in Jeju was on

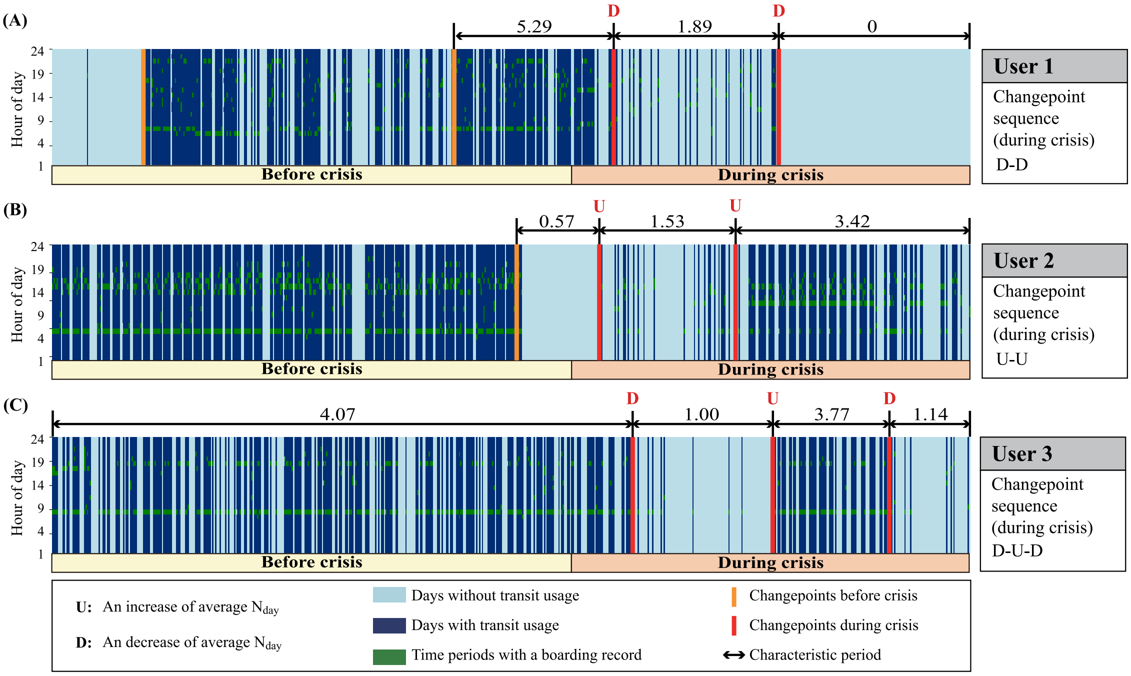

Fig. 3. Examples of change pattern characterization of users' transit use frequency. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

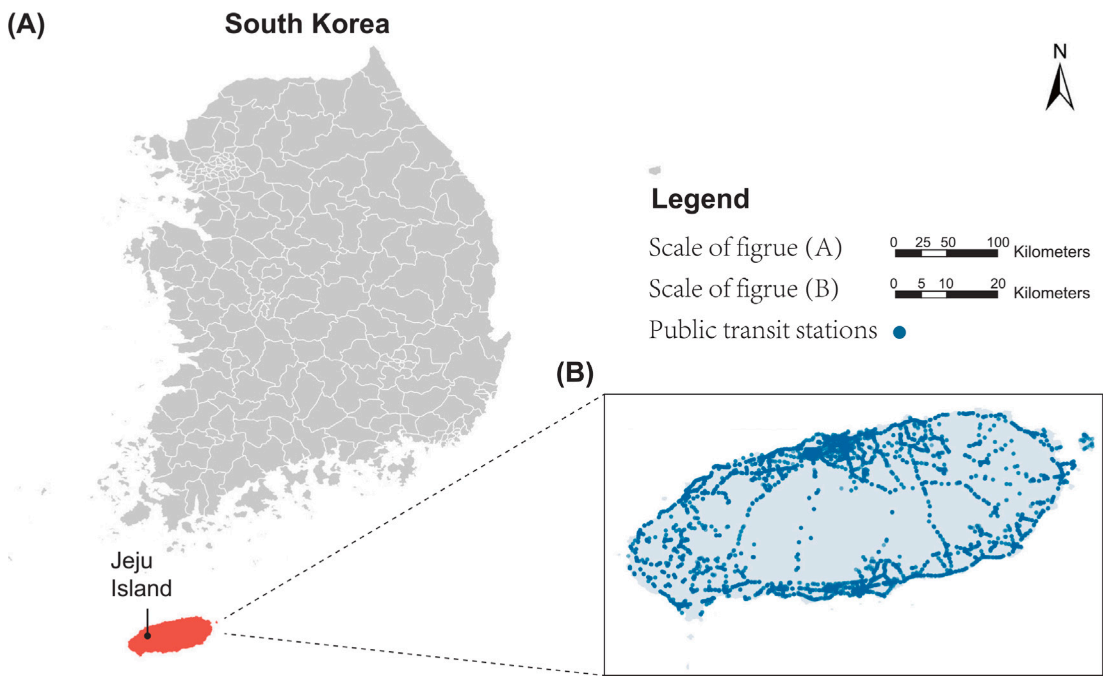

Fig. 4. The study area of Jeju, South Korea.

February 22. Without occurrence of a large-scale outbreak, the total number of cases was 59 between January 20 and October 4. To investigate the impact of pandemic-related policies on transit use behavior, the policies implemented from January 1 to October 4, 2020 are grouped into four categories, namely, Risk alert, Social distancing, Public transit policy, and Eased social distancing, as shown in Fig. 5.

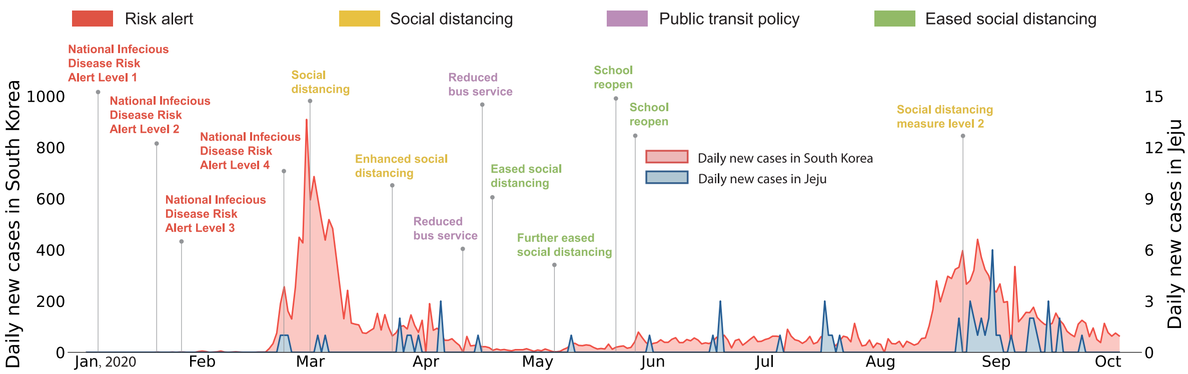

Fig. 5. Key government policies introduced during the study period in South Korea.

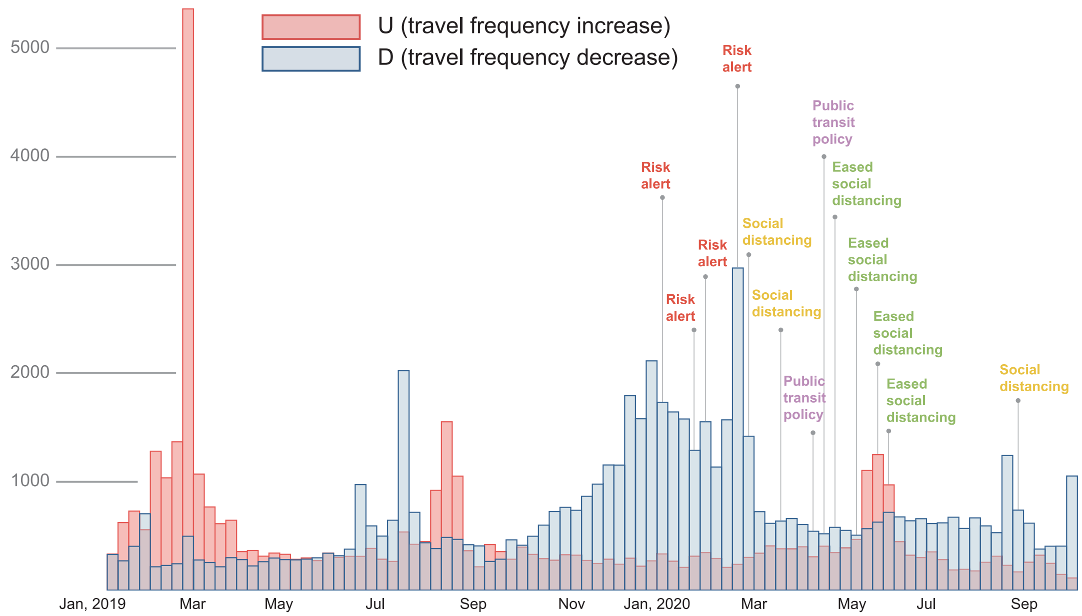

Fig. 6. Number of changepoints with travel frequency increase (U) and decrease (D) in each week before and during COVID-19.

4.2. Changepoints: Temporal evolution and interpersonal variations

Based on the empirical data, we provide additional validation for our assumption that N_{day} of each user follows a binomial distribution, as shown in Appendix A. Then, the changepoints of each frequent transit user are detected according to the proposed framework, with $\alpha_{prior} = 0.5$, $\beta_{prior} = 1$, and $\lambda = 30$ (Zhao et al., 2018a). For detailed sensitivity analysis of the parameters, please refer to Appendix B. Fig. 6 demonstrates the distribution of the number of Up points and Down points in each week from January 1, 2019 to October 4, 2020. With users' travel pattern in 2019 as a reference, the distinct travel patterns during COVID-19 suggested that some pandemic-related factors affected the transit use behavior. Compared to 2019, there were more users reduced their transit use frequency in each week during the pandemic. In early 2020, when the NIDRAL was rapidly raised from "Level 1" to "Level 4", a considerable number of users decreased the travel frequency. Despite the implementation of Social distancing and Public transit policy during the following period, the number of users who reduced travel frequency did not increase further. When implementing Eased social distancing, a number of users increased travel frequency.

According to the changepoint sequence of each user, we identify the frequent transit users exhibiting different change patterns during the pandemic. As shown in Fig. 7, users are classified into "No changepoint" (47%), "Always increase" (32%), "Always decrease" (4%), and "Mixed patterns" (17%). "No changepoint", which is the largest category, denotes the users with no significant change in transit use frequency during the pandemic. "Always increase" indicates that the users increased public transit usage during the pandemic. In "Always increase", 97% of the users increased their travel frequency once during COVID-19. Similarly, "Always decrease" denotes that the users decreased transit use frequency during the pandemic. Among the users in this category,

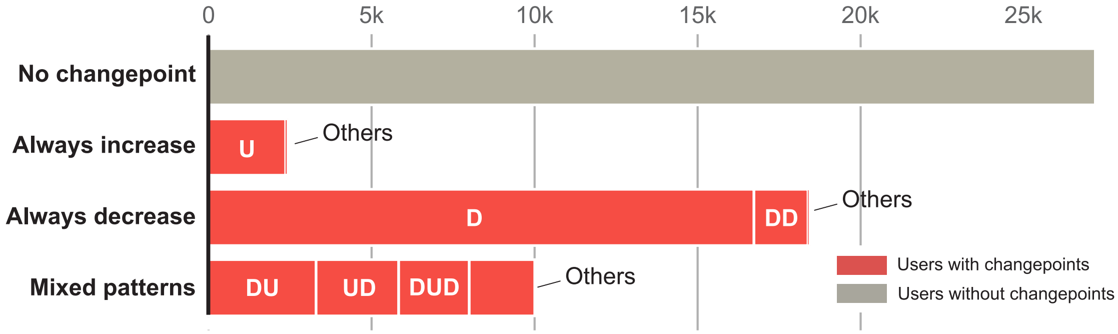

Fig. 7. Distribution of frequent transit users with different behavior change patterns.

91% experienced a single decrease during COVID-19, while 9% experienced two decreases. “Mixed patterns” depicts that the users demonstrated fluctuations in their transit use frequency during the pandemic, with both increases and decreases observed. The most common change sequences in “Mixed pattern” are D-U (33%), U-D (25%), and D-U-D (22%).

The various categories of users highlight the heterogeneity of the policies impact on users’ transit use behavior. Although users were subjected to similar external influences, such as the dynamics of the pandemic severity and the implementation of the policies, their adjustment to the transit use behavior was different. The varying responses to the pandemic and the policies might be due to the endogeneity of the users. By combining with users’ socio-demographic information, the endogenous factors affecting the users’ transit use behavior could be uncovered, which is crucial for developing targeted policies and alleviating social inequality (Lin et al., 2022).

4.3. Occurrence and persistency of behavior changes

Fig. 7 reveals that a significant number of frequent transit users experienced multiple changes during the pandemic period. As such, we identify the adjacent changepoints of these users and analyze the duration of characteristic periods between each pair of adjacent changepoints. Fig. 8 shows the duration and key occurrence time of adjacent changepoints for different patterns, namely D-U, D-D, U-D, and U-U. The dot symbols in the arc diagrams represent time, where each dot corresponds to one week. The first and second rows of dots represent the initial and subsequent occurrences of adjacent changepoints. The dot size indicates the percentage of the changepoints compared to the total number of adjacent pairs in the pattern. The color of the dots signifies the policies implemented during that specific week. The arcs connect the initial and subsequent points of the adjacent pairs at their left and right ends. The thickness of the arcs represents the percentage of adjacent changepoints occurring in the two corresponding weeks relative to the total number of adjacent changepoints in the pattern.

According to Fig. 8, we find that the pandemic situation and policies introduced by the government led to a significant change in travel frequency of frequent transit users. As for the pattern — decreasing first followed by an increase (D-U), most of the users reduced the travel frequency when Risk alert was implemented. The decreased transit usage persisted until the government announced Eased social distancing, when many users returned to the public transit system. Different from the D-U pattern, the key occurrence time and behavior change persistency of the consecutive decreasing pattern (D-D) exhibited an association with Risk alert, Social distancing, and the outbreak of the pandemic. Some users reduced travel frequency on public transit in accordance with the implementation of Risk alert during the early stage of the pandemic in South Korea. A number of users decreased the transit use at the start of the two outbreaks in South Korea or the time of the related policies issued, i.e., Risk alert and Social distancing. The pattern — rising first followed by a decrease (U-D) — predominantly emerged when Eased social distancing was introduced and the 2nd outbreak began. There was no apparent key occurrence time and persistency of travel frequency change observed for the pattern of consecutive increase (U-U).

As shown in Fig. 9, the average change persistency in the pattern D-U was 11.96 weeks and the variance was 53.31. Most changes in this pattern lasted for no more than 21 weeks, which was the time interval between the introduction of Risk alert (on January 3, 2020) and Eased social distancing (in early May, 2020). The average change persistency and variance of the D-D pattern were 12.92 weeks and 79.54, respectively. The majority of changes in this pattern lasted for less than 10 weeks, and the variance was much higher than that in the D-U pattern, indicating a wider spread and diversity among the changes in D-D pattern. The average persistency of behavior change for the U-D pattern was 10.89 weeks with variance of 48.37. Changes in this pattern mostly lasted for no more than 15 weeks, which was approximately the time interval between the announcement of Eased social distancing (in early May) and the 2nd outbreak, and the introduction of Social distancing on 23 August. For the U-U pattern, the average change persistency was 10.84 weeks and the variance was 50.73, with 12% of changes in this pattern lasted for 2 weeks.

From the collective perspective, we find that the change in users’ transit use frequency lasted for an average of two to three months, regardless of the change pattern and the timing of the policy announcement. However, delving deeper into an individual-level analysis of transit use can allow researchers to better understand the case-to-case implications and effects of these policy changes. The above-mentioned may partly explain why it is important to analyze the change in individual-level transit use behavior.

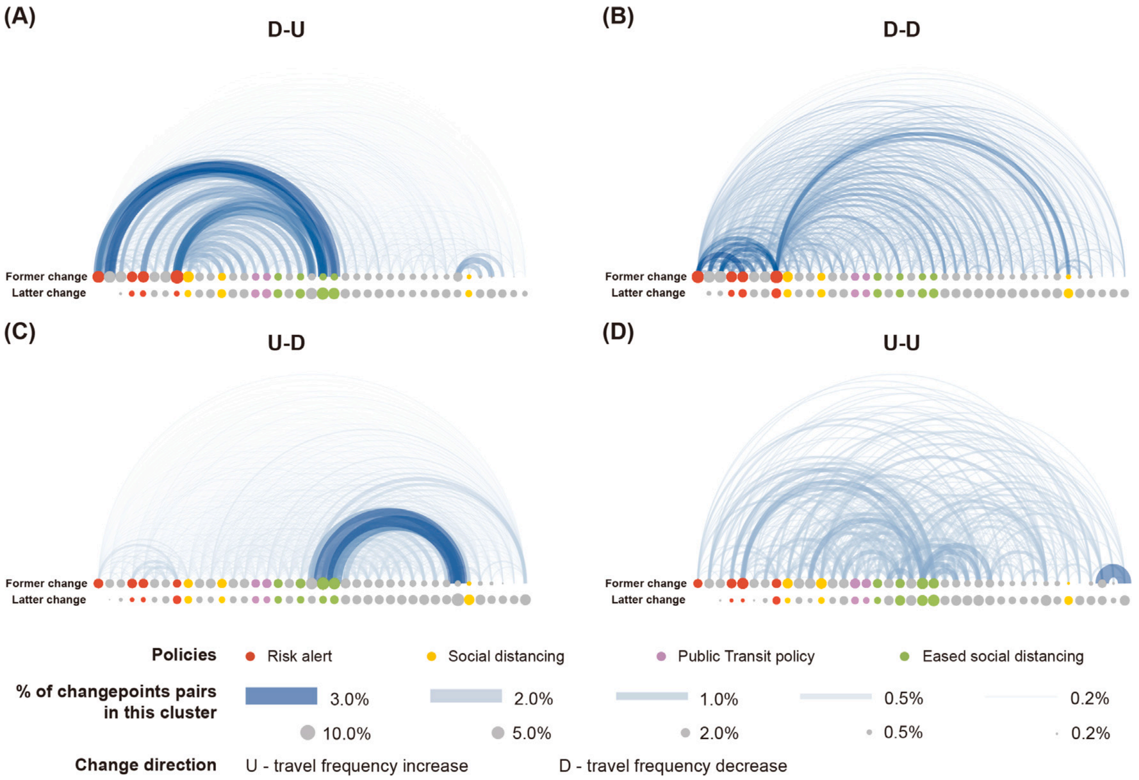

Fig. 8. Occurrence time of adjacent changepoints for users with different behavior change patterns: (A) D-U; (B) D-D; (C) U-D; (D) U-U.

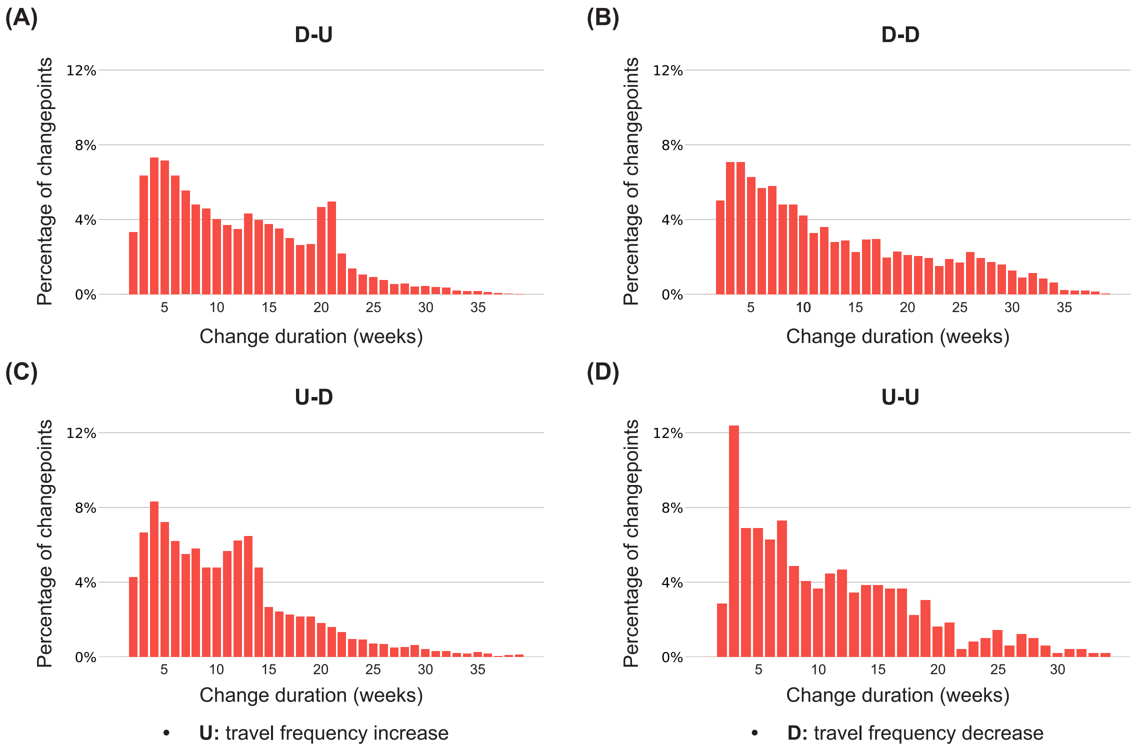

Fig. 9. Distribution of characteristic period duration between adjacent changepoints with different patterns: (A) D-U; (B) D-D; (C) U-D; (D) U-U.

Table 1
The regression results of policy impacts on the number of changepoints.

Change direction	Time lag (day)	R^2	P	Factors					
				Intercept	RA	SD	PTP	ESD	$Case_J$
Up (travel frequency increase)	7	0.34	0.014	−0.09	−0.46	0.03	−0.27	1.36***	−0.05
	14	0.56	0.000	−0.26	−0.37	0.25	−0.35	1.55***	−0.05
	21	0.53	0.000	−0.16	−0.47	0.38	−0.49	1.42***	−0.09
	28	0.52	0.000	−0.36	−0.30	0.44	0.05	1.34***	−0.07
Down (travel frequency decrease)	7	0.48	0.000	1.33	2.92***	0.41	−0.23	−0.25	−0.16
	14	0.53	0.000	1.03	2.77***	0.21	0.07	−0.21	−0.09
	21	0.67	0.000	0.64	3.17***	−0.16	0.34	−0.06	0.01
	28	0.64	0.000	0.84	2.92***	−0.67	0.58	−0.43	0.02

Note: * significant at 0.1 level, ** significant at 0.05 level, and *** significant at 0.01 level.

Based on the average persistency of users' behavior change, the policymakers and public transit agencies can better predict users' transit use and travel demand, which is crucial for effective public transit planning and emergency management. By leveraging insights derived from the individual persistency, policymakers can enhance their understanding of the impact and duration of specific policies on users' behavior changes. This knowledge empowers governments to effectively assess and optimize polices, thereby improving the overall effectiveness and efficiency of public transit system.

4.4. Policy impacts on the observed changes

The aforementioned findings suggest the potential influence of policy announcement on the change in the travel frequency of frequent transit users. In this section, we aim to quantify this influence by conducting regression analyses. The independent variable $z_{i,j}$ is binary for the policies of Risk alert, Social distancing, Public transit policy, and Eased social distancing. More specifically, if a policy i is announced at week j, then we set the binary variable $z_{i,j} = 1$; additionally, we also take the hysteretic nature of the policy announcement into consideration. For example, if the time lag is 7 days, then both $z_{i,j}$, $z_{i,j+1}$ are set by one. We will conduct the sensitivity analysis to determine the optimal time lag. To control for the impact of the local pandemic on users' behavior change, the daily new cases in Jeju is included as an independent variable considering with the same time lag in each regression model. Regression analyses were conducted separately for the number of Up points and Down points as dependent variables to investigate the impact of policy announcement on the separate aspects of users' transit use behavior. To eliminate the impact of seasonality on the behavior change, the number of Up points and Down points were processed using the year-over-year method.

Table 1 illustrates the association between the change in travel frequency of frequent transit users and the pandemic-related policies, in which RA, SD, PTP, and ESD denote Risk alert, Social distancing, Public transit policy, and Eased social distancing, respectively. $Case_J$, which is used to control the impact of the local spread on the users' travel behavior, represents the weekly new cases in Jeju. According to the regression results, we find that Eased social distancing would significantly promote more users to increase the transit usage. The implementation of Eased social distancing resulted in a 134% to 155% increase in the number of users who increased transit use frequency relative to the same period in 2019. Risk alert had a significant impact in encouraging more users to reduce the travel frequency on public transit. Compared to the corresponding period in 2019, the implementation of Risk alert could lead to the number of users who reduced transit use frequency increasing by 277% to 317%. Other polices, i.e., Social distancing and Public transit policy, did not exhibit a significant association with the change in users' travel frequency.

Fig. 10 summaries the key findings of the regression analyses, which show that different polices had various effects on users' transit use frequency during COVID-19. Specifically, Risk alert and Eased social distancing had a significant impact on users' change in travel frequency, while other policies and local spread had an insignificant effect. A few reasons might explain the results. Jeju Island did not experience a large-scale outbreak during COVID-19, which might partially explain why the local cases had an insignificant impact on users' behavior change. Thus, the policies and national outbreak could be important signals for the users in Jeju to evaluate the severity of the pandemic before travel decision. Combining timely policy interventions with national outbreak could assist users in evaluating infectious risk and adapting their transit usage behavior accordingly. If the implementation of policies lagged behind the outbreak of the pandemic, the users would adjust their travel behavior based on the national pandemic situation. Risk alert policies were introduced both before and shortly after the outbreak of the pandemic, while Social distancing and Public transit policy were not implemented until some time after the outbreak of the pandemic. As such, many users adjusted their travel behavior when the pandemic rapidly spread and Risk alert were introduced. The implementation of Social distancing and Public transit policy did not result in a substantial number of users changing their travel behavior. In addition, the introduction of the Public transit policy was to reschedule some routes, most of which were tourist routes. This might be another explanation for the insignificant impact of Public transit policy on changes in users' transit use frequency. Unlike the sudden onset of an outbreak, flatten the curve could be a gradual process. During the period when the national pandemic returning to the stability, the users might not make an abrupt change based on the pandemic situation. The policies, i.e., Eased social distancing, were signals for the users to perceive a reduced risk, leading some users to significantly increase the use of public transit.

In addition, the results exhibit that Eased social distancing and Risk alert produce the highest explanatory power for the change in travel frequency of frequent transit users when the time lag is 14 and 21, respectively. For many frequent transit users, such

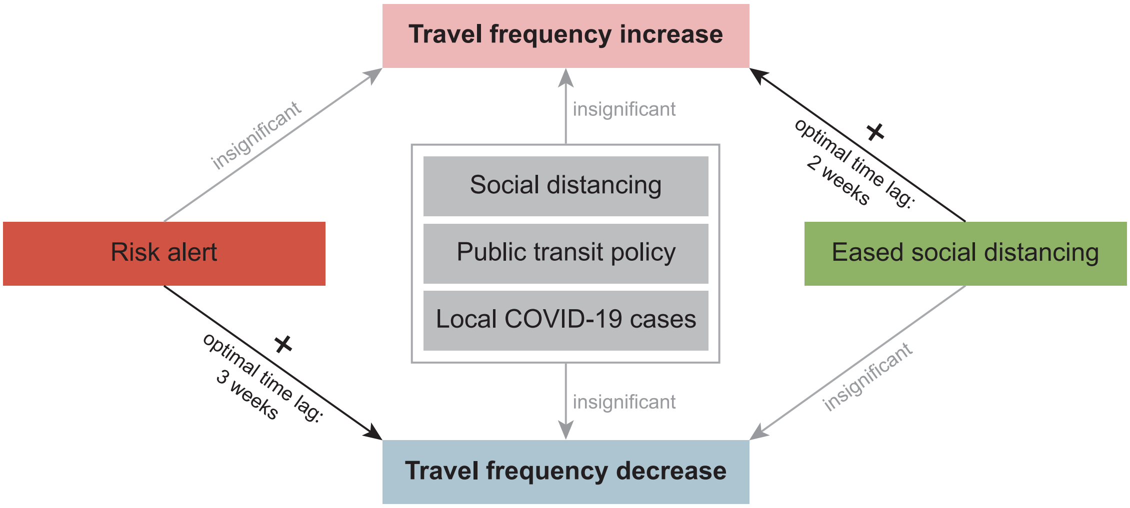

Fig. 10. Pathways of the policy impacts on changes of individual transit usage.

as seniors and the disables, public transit could be an essential transportation mode in their daily life. Reducing the use of public transit for them could have a significant impact on their daily lives, as well as increased the cost of living. After perceiving the risk signaled by the policies, they might spend more time weighting the trade-offs between personal safety and maintaining their normal routine, or finding alternative transportation modes to continue daily activities. When official safety signals were released, those who had been struggling to find solutions for the affected lives might quickly return to the public transit system. Moreover, the implementation of Risk alert conveyed some infectious risk signals to people without imposing restrictions or requirements on people's travel behavior. Eased social distancing contained the policies of school reopening, which was a stronger signal that stimulates travel demand from people, such as teachers, students, and parents. As a result, compared to Risk alert, some users changed the travel behavior in a relatively short time after the announcement of Eased social distancing.

5. Discussion and conclusion

This paper develops a framework based on Bayesian online changepoint detection (BOCD) to investigate changes in individual-level transit usage behavior during a crisis. The framework is capable of identifying the occurrence time, direction (i.e., increase vs. decrease) of the behavior changes, as well as how long these changes tended to persist during a crisis. With the integration of additional information (e.g., the dynamics of the crisis and the policies), the potential causes and duration of the causes' effects can be uncovered, which is critical for emergency management and public transit operation to ensure people's safety and basic travel demand during a crisis.

The proposed framework was employed to examine the impact of pandemic-related policies on individual transit use behavior during COVID-19 using Jeju Island, South Korea as a case study. In this study, we focused on frequent transit users which represent an important group of transit users that relied heavily on public transit when there was no pandemic. Through the changepoint analysis, we were able to uncover several types of users — for example, those who had no change point (47%), and those who actively reduced (32%) or even increased (4%) their transit usage frequency during the pandemic period. A notable fraction of users had mixed patterns (17%), meaning that each of these users had multiple significant changes, among which some referred to travel frequency increase, while others being travel frequency decrease.

Given a transit user, any two consecutive changepoints allow us to observe how long the behavior change tended to persist. Thus, for the users with multiple changepoints, we analyzed their persistency of changes in transit use frequency. The two consecutive changes indicate the processes of behavior change and travel decision-making. To gain insight into various effects of the pandemic-related policies on the changes and decision-making processes, we analyzed the key occurrence time and persistency of several change patterns in travel frequency — consecutive decrease (D-D) and increase (U-U), decrease followed by increase (D-U), and increase followed by decrease (U-D). The results shown that a large number of significant behavior changes occurred within a short timeframe of the policy announcement, which subsequently affected the individual change persistency.

We conducted regression analyses to further quantify the impact of the policies on users' behavior changes during COVID-19. The results shown that certain policies, such as Risk alert and Eased social distancing, had a significant impact on behavior changes during the pandemic, while the impact of other policies and the local COVID-19 cases was insignificant. The implementation of Eased social distancing resulted in a 134% to 155% increase in the number of users' who increased the transit use frequency during COVID-19 relative to the same period in 2019. The introduction of Risk alert significantly affected users' behaviors to decrease the transit use frequency. It resulted in a 277% to 317% increase in the number of users who decreased travel frequency during COVID-19 compared to the same period in 2019. Moreover, according to the R^2 in the regression models with different time lag, we found that Risk alert might have a relatively shorter lag time to affect users' transit use frequency compared to Eased social distancing.

Several policy implications can be drawn based on the findings. Firstly, users with different patterns of behavior changes exhibit diverse responses of individuals to the pandemic and the related policies, which may be attributed to socio-demographics. Governments should pay attention to heterogeneity of individuals when develop policies. Personalized and targeted polices and countermeasures are needed to alleviate social inequity. Furthermore, the change persistency analysis reveals that individuals tend to maintain their altered transit use behavior for a period of two to three months before making the next change. This duration can serve as a useful indicator for governments to predict the impact of policies and forecast the demand for public transit. From the individual perspective, we observe various impacts and implications of these policies. Therefore, it is crucial for governments to conduct specific policy analyses and combine the results from the collective perspective to enhance policy evaluation and improve transit management. Finally, the regression analysis highlights the significant and lagged impacts of policies on individuals' transit use behavior. During a crisis, people's perception and policy constraints would reduce their transit use. Conversely, in the recovery phase of the crisis, which is often gradual and slow, governments' policies act as a strong safety signal to encourage users return to public transit system. Therefore, governments should employ effective policies to control the crisis and facilitate the recovery of public transit.

Based on the empirical study in the context of COVID-19, we have found that our framework is practical and applicable for informing policy-making. By detecting the changepoints in transit usage behavior for each user, the framework is capable of explaining the important time points of the change in people's transit use, and subsequently, could help us identity the key factors that influence people's change in transit use behavior during a crisis. Policymakers and public transit agencies can use this information to develop targeted policies that minimize negative impacts on public transit system, ensuring the safety and basic travel needs of people. Moreover, with the changepoint sequence of each user, we can identify several categories of users based on their change patterns. The endogenous factors affecting users' transit use behavior change could be further uncovered by analyzing the change pattern of different categories of users combined with their socio-demographics. Based on the endogenous factors, public transit agencies could develop some personalized service for different users. Finally, the knowledge of the behavioral persistency is an essential information for predicting people's future transit use behavior and travel demand to optimize public transit planning and transportation system management during and after a crisis.

To our best knowledge, this study is the first attempt to analyze individual-level transit usage behavior change during a crisis by employing BOCD. The current research can be extended from several aspects. Firstly, people's transit use behavior change can be quantified from multiple perspectives, such as travel frequency, spatial and temporal diversity. In this study, we focus on the change in travel frequency. The future works can uncover the transit use behavior change in multiple dimensions to help us gain a more comprehensive understanding of users' behavior change (Kusakabe and Asakura, 2014; Zhao et al., 2018a). For example, the understanding of the change in spatial and temporal diversity is useful to infer which types of travel (e.g., commute and leisure travel) are most affected. Secondly, by leveraging additional data, this framework enables analyzing the changes in transit use behavior from different perspectives. For instance, by integrating demographic data, we can examine how transit use change pattern vary across different segments of the population. This allows governments to gain insights into how transit use changes among distinct groups of people and develop targeted policies to enhance social equity. By incorporating travel data from diverse transportation modes, we can delve into how individuals change the travel pattern during a crisis, facilitating a deeper understanding of the factors driving transit use change, such as a transition towards private vehicles. Furthermore, this study provides a retrospective view of the impact of key government policies on people's transit use behavior during COVID-19. However, BOCD is capable of detecting people's travel behavior change in real-time, which can help governments dynamically adjust policies. The framework can support government in policy decision-making and emergency management in future crises.

CRediT authorship contribution statement

Yuqian Lin: Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Yang Xu:** Conceptualization, Investigation, Writing – original draft, Writing – review & editing. **Zhan Zhao:** Methodology, Writing – original draft, Writing – review & editing. **Wei Tu:** Conceptualization, Writing – original draft, Writing – review & editing. **Sangwon Park:** Data curation, Writing – original draft, Writing – review & editing. **Qingquan Li:** Conceptualization, Writing – original draft, Writing – review & editing.

Acknowledgments

The authors would like to thank the anonymous reviewers for their valuable comments on earlier versions of the manuscript. This research was jointly supported by the National Natural Science Foundation of China under Grant 42171454 and Hong Kong Polytechnic University Research Grant (4-ZZNC).

Appendix A. Examples of distribution of N_{day} during a characteristic period

The BOCD algorithm detects changepoints by identifying changes in the parameters of the observations' distribution. When an abrupt change in the parameters is detected at a specific observation, it is referred to as a changepoint. Between changepoints, the

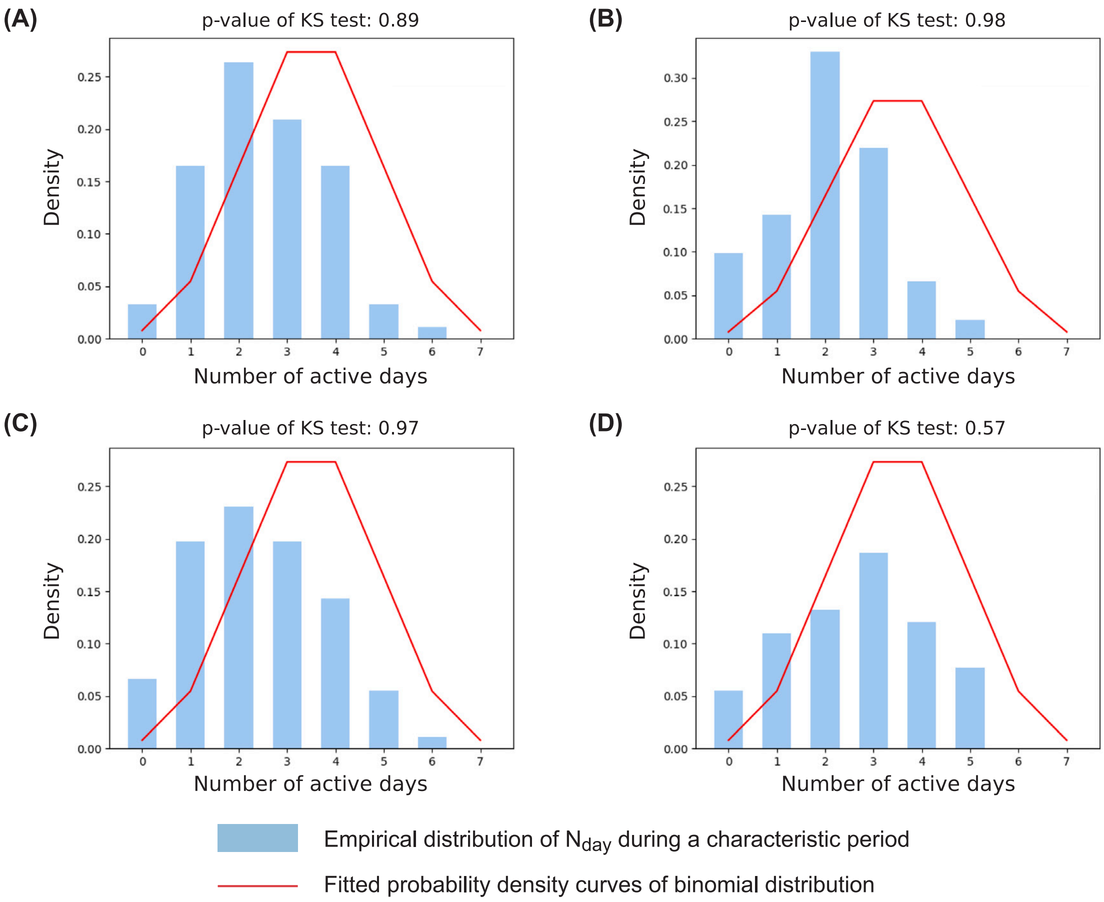

Fig. A.1. Examples of distribution of N_{day} and fitted probability density curves of binomial distribution.

distribution of observations is relatively stable. As such, we focus on fitting the observations of N_{day} between the changepoints – within the characteristic period – when validating our assumption that N_{day} follows binomial distribution. However, if the number of observations within a characteristic period is small, it may result in insufficient statistical power. Fewer observations make it difficult to estimate parameters accurately. Additionally, the fitting process may suffer from overfitting, where it overly relies on the limited observations and overlooks broader data trends. Therefore, we only perform fitting on the characteristic periods that span at least 30 weeks, ensuring that we have a sufficient number of observations (30 or more) for accurate estimation. Upon applying the selection criteria, we obtain available data from 41,730 users. Given the maximum value of N_{day} is 7, we determine one of the parameters n for the binomial distribution as 7. Using maximum likelihood estimation, we estimate the value of another parameter p. Finally, through Kolmogorov–Smirnov Test, the $Nday$ of 26,040 (about 62%) users are found to follow a binomial distribution (see Fig. A.1).

Appendix B. Sensitivity analysis of BOCD parameters

In this study, BOCD detects changes in individuals' transit use frequency based on beta-binomial distribution, which relies on two essential parameters — α and β. Through conducting sensitivity analyses on these parameters, we discovered that our results remain robust by variations in these parameters.

B.1. $\alpha = 1, \beta = 0.5$

See Fig. B.2 and Table B.1.

B.2. $\alpha = 1, \beta = 1$

See Fig. B.3 and Table B.2.

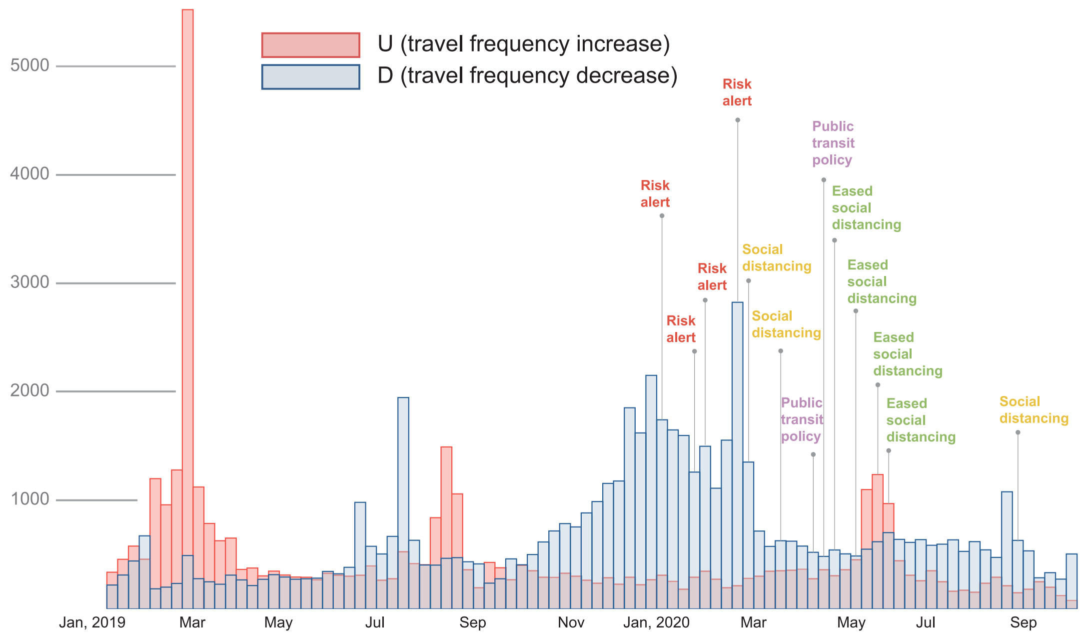

Fig. B.2. Number of changepoints with travel frequency increase (U) and decrease (D) in each week before and during COVID-19.

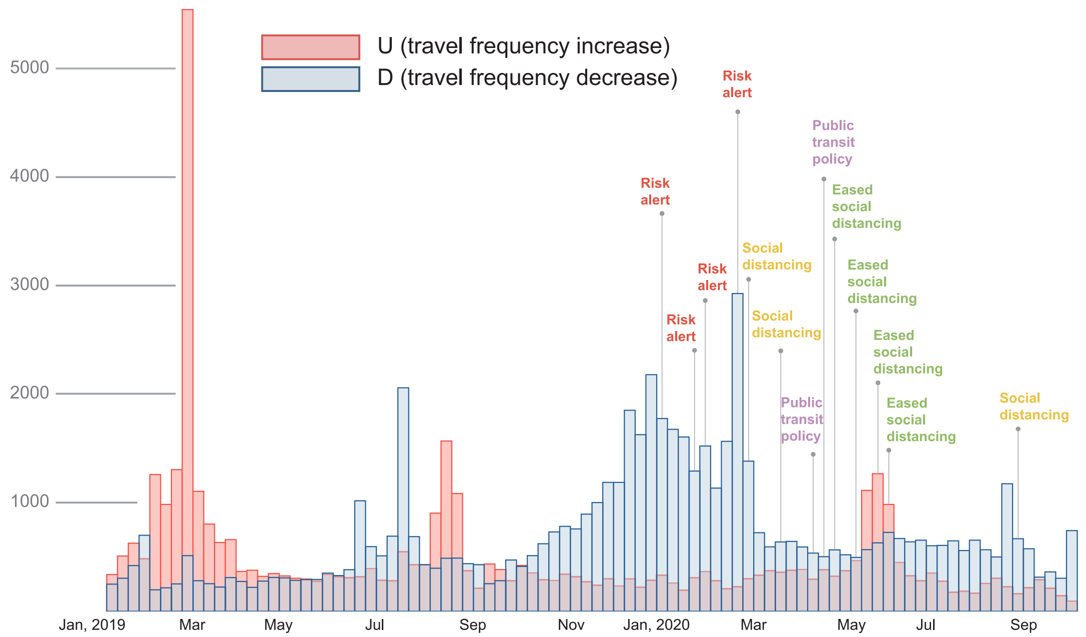

Fig. B.3. Number of changepoints with travel frequency increase (U) and decrease (D) in each week before and during COVID-19.

Table B.1
The regression results of policy impacts on the number of changepoints.

Change direction	Time lag (day)	R^2	P	Factors					
				Intercept	RA	SD	PTP	ESD	$Case_J$
Up (travel frequency increase)	7	0.37	0.008	−0.05	−0.45	−0.02	−0.40	1.37***	−0.09
	14	0.57	0.000	−0.25	−0.33	0.16	−0.46	1.56***	−0.06
	21	0.54	0.000	−0.15	−0.46	0.33	−0.59	1.41***	−0.11
	28	0.52	0.000	−0.39	−0.25	0.37	0.01	1.37***	−0.07
Down (travel frequency decrease)	7	0.50	0.000	1.36	3.34***	0.18	−0.43	−0.29	−0.19
	14	0.55	0.000	1.09	3.08***	0.13	−0.12	−0.25	−0.15
	21	0.66	0.000	0.62	3.47***	−0.21	0.23	−0.02	−0.05
	28	0.63	0.000	0.74	3.28***	−0.82	0.60	−0.39	0.01

Note: * significant at 0.1 level, ** significant at 0.05 level, and *** significant at 0.01 level.

Table B.2
The regression results of policy impacts on the number of changepoints.

Change direction	Time lag (day)	R^2	P	Factors					
				Intercept	RA	SD	PTP	ESD	$Case_J$
Up (travel frequency increase)	7	0.36	0.009	−0.05	−0.45	−0.01	−0.37	1.34***	−0.08
	14	0.56	0.000	−0.24	−0.34	0.19	−0.44	1.53***	−0.06
	21	0.54	0.000	−0.15	−0.46	0.34	−0.56	1.39***	−0.10
	28	0.51	0.000	−0.38	−0.27	0.39	0.02	1.34***	−0.07
Down (travel frequency decrease)	7	0.51	0.000	1.35	3.17***	0.21	−0.40	−0.28	−0.18
	14	0.57	0.000	1.10	2.93***	0.17	−0.11	−0.26	−0.15
	21	0.67	0.000	0.68	3.27***	−0.15	0.19	−0.06	−0.05
	28	0.65	0.000	0.79	3.09***	−0.73	0.53	−0.41	−0.01

Note: * significant at 0.1 level, ** significant at 0.05 level, and *** significant at 0.01 level.

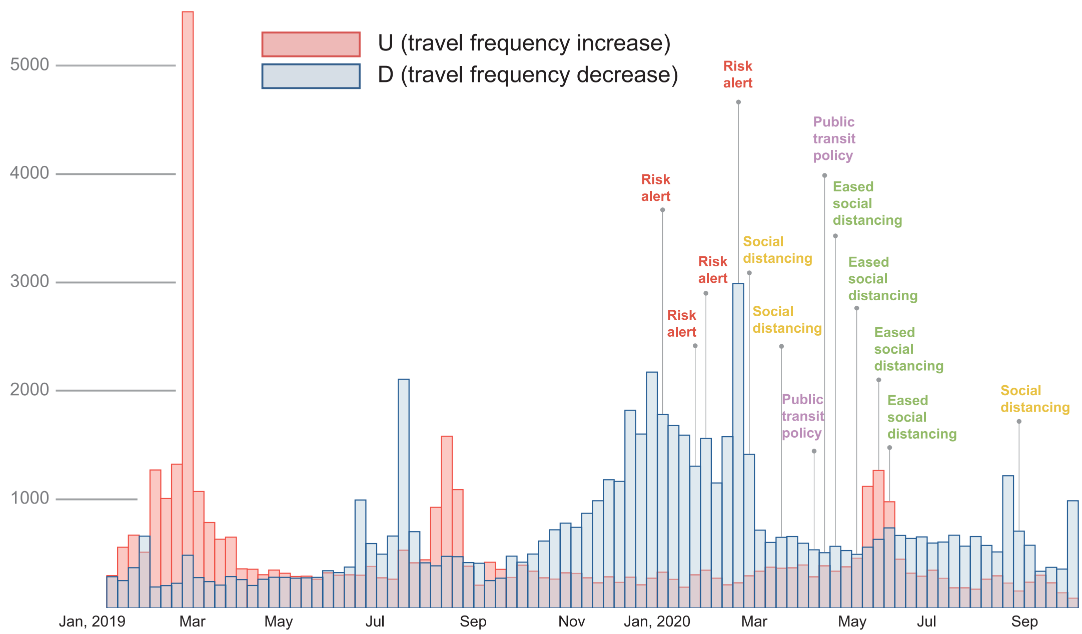

Fig. B.4. Number of changepoints with travel frequency increase (U) and decrease (D) in each week before and during COVID-19.

B.3. $\alpha = 1, \beta = 2$

See Fig. B.4 and Table B.3.

Table B.3
The regression results of policy impacts on the number of changepoints.

Change direction	Time lag (day)	R^2	P	Factors					
				Intercept	RA	SD	PTP	ESD	$Case_J$
Up (travel frequency increase)	7	0.35	0.011	−0.02	−0.48	−0.01	−0.38	1.39***	−0.08
	14	0.56	0.000	−0.23	−0.36	0.20	−0.45	1.60***	−0.06
	21	0.54	0.000	−0.12	−0.49	0.37	−0.60	1.46***	−0.11
	28	0.51	0.000	−0.36	−0.29	0.41	0.01	1.40***	−0.07
Down (travel frequency decrease)	7	0.51	0.000	1.35	3.17***	0.21	−0.40	−0.28	−0.18
	14	0.57	0.000	1.10	2.93***	0.17	−0.11	−0.26	−0.15
	21	0.67	0.000	0.68	3.27***	−0.15	0.19	−0.06	−0.05
	28	0.65	0.000	0.79	3.09***	−0.73	0.53	−0.41	−0.01

Note: * significant at 0.1 level, ** significant at 0.05 level, and *** significant at 0.01 level.

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