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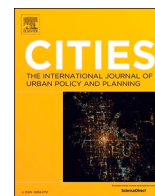Jaller, Miguel
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Publication Date

2023-06-01

DOI

10.1016/j.cities.2023.104290

Peer reviewed

Exploring the potential role of bikeshare to complement public transit: The case of San Francisco amid the coronavirus crisis

Xiaodong Qian [a,*], Miguel Jaller [b], Giovanni Circella [c,d]

[a] Department of Civil and Environmental Engineering, College of Engineering, Wayne State University, Detroit, MI 48202, USA
[b] Department of Civil Engineering and Environmental Engineering, Sustainable Freight Research Program, Institute of Transportation Studies, University of California, Davis, One Shields Avenue, Ghausi Hall 3143, Davis, CA 95616, USA
[c] 3 Revolutions Future Mobility Program, Institute of Transportation Studies, University of California, Davis, One Shields Avenue, Davis, CA 95616, USA
[d] Department of Geography, Ghent University, Krijgslaan 281, S8, 9000 Ghent, Belgium

A B S T R A C T

The recent worldwide SARS-CoV-2 (COVID-19) pandemic has reshaped the way people live, how they access goods and services, and how they perform various activities. For public transit, there have been health concerns over the potential spread to transit users and transit service staff, which prompted transportation agencies to make decisions about the service, e.g., whether to reduce or temporarily shut down services. These decisions had substantial negative consequences, especially for transit-dependent travelers, and prompted transit users to explore alternative transportation modes, e.g., bikeshare. However, local governments and the public in general have limited information about whether and to what extent bikeshare provides adequate accessibility and mobility to those transit-dependent residents. To fill this gap, this study implemented spatial and visual analytics to identify how micro-mobility in the form of bikesharing has addressed travel needs and improved the resilience of transportation systems. The study analyzed the case of San Francisco in California, USA, focusing on three phases of the pandemic, i.e., initial confirmed cases, shelter-in-place, and initial changes in transit service. First, the authors implemented unsupervised machine learning clustering methods to identify different bikesharing trip types. Moreover, through spatiotemporally matching bikeshare ridership data with transit service information (i.e., General Transit Feed Specification, GTFS) using the tool called OpenTripPlanner (OTP), the authors studied the travel behavior changes (e.g., the proportion of bikeshare trips that could be finished by transit) for different bikeshare trip types over the three specified phases. This study revealed that during the pandemic, more casual users joined bikeshare programs; the proportion of recreation-related bikeshare trips increased; and routine trips became more prevalent considering that docking-station-based bikeshare trips increased. More importantly, the analyses also provided insights about mode substitution, because the analyses identified an increase in dockless bikeshare trips in areas with no or limited transit coverage.

1. Introduction

The SARS-CoV-2 virus responsible for the worldwide COVID-19 pandemic has affected every aspect of daily life and resulted in a number of strategies, e.g., shelter-in-place, quarantine, social distancing, to minimize exposure and the spread of the virus around the world (Friedson et al., 2021; Taghrir et al., 2020). This pandemic has caused significant impacts to the transportation industry, including airline (Subramanya & Kermanshachi, 2021), railway (Wang et al., 2021), public transit (Parker et al., 2021), ride-hailing (Morshed et al., 2021), and shared micro-mobility (Li et al., 2020). However, different transport

modes were affected, and are recovering, at different paces. Some modes are still struggling to attract more ridership and protect the health of both staff and passengers, particularly modes that cannot provide enough social distance while serving passengers. As reported by the National Association of City Transportation Officials (NACTO), the eight largest docking-station-based bikeshare systems in the USA experienced a 44% ridership decrease in March–May 2020 and transit ridership had a 80% downturn compared with the same period in the previous year (Nacto, 2020). The significant drop in transit ridership (Walker, 2020) led several cities to reduce their public transit frequency, time availability, or coverage. These decisions have had substantial negative

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consequences, especially for transit-dependent residents. Some of them, especially those in front-line occupations, have had to decide whether or not to risk infection by traveling in public transit for essential purposes (e.g., working and food shopping), or find other options. Especially for shopping for basic necessities, some people relied on online shopping (Ali Taha et al., 2021), which may not available to residents with limited access to internet and smart communication devices. With a lack of alternatives such as private vehicles available to some population groups, e.g., low-income households, micro-mobility has emerged as a promising mode to complement or replace traditional transit services. In New York City, for example, bicycle sales have increased significantly with long waiting times (Goldbaum, 2020); thus, individuals have found bikeshare as an option, without the need to own bikes. This shows the potential role of bikeshare to complement transit services and to improve the resilience of urban transport systems during an emerging situation, e.g., the coronavirus pandemic.

Traditional bicycle-transit integration trips represent different proportions of total transit ridership: 27% in Netherlands, 26% in Copenhagen, 13% in Munich, and 2% in the UK (Martens, 2004, 2007). According to a survey report by the NACTO, over 50% of docking-station-based bikeshare users are reported to use bikeshare to connect to transit in the USA (NACTO, 2019). As bikeshare services expand, their features of flexibility, including obviating the need for onboard storage, could further promote the connection between micro-mobility and transit (Ma, Ji, Yang, et al., 2018). However, there is a long debate about substitution and complementarity between bikeshare and transit (Kong et al., 2020; Song & Huang, 2020). Based on current studies, there is no global consensus on the relationship between these two modes, which is complicated and highly dependent on the study areas, the features of trips and other building environment factors. In addition, most current research applies stated preference surveys, which ask participants their choice of modes in hypothetical situations given a specific set of conditions. It is very difficult to implement a real-world test to see how people actually would behave given a specific restriction on transport modes. The unexpected outbreak of the coronavirus pandemic, however, provides a unique lens through which we can observe the relation between transit and bikeshare, and even gain insights into the role of bikeshare in improving the resilience of urban transportation systems.

The pandemic has provided a unique opportunity to evaluate the resilience of our transportation systems, and the impacts of disruptions on travel-related choices. Since the outbreak of the pandemic, some studies have noticed that bikeshare ridership has nearly returned to normal while transit ridership still struggles below the pre-COVID19 levels (Padmanabhan et al., 2021; Wang & Noland, 2021). Meanwhile, bikeshare trip distance becomes longer, and the rate of recreational trips increases (Padmanabhan et al., 2021; Tokey, 2020). Understanding travel and use patterns allow us to better prepare transit and other transport services. Local transit agencies and bikeshare operators can learn from this period to adjust their planning strategies for future developments. Consequently, the objective of this work is to apply machine learning and visual analytics to explore the travel patterns of bikeshare users to identify how bikeshare has addressed travel needs during a disruption, and finally, whether bikeshare improves urban transportation resilience.

This study uses San Francisco as an example considering its particular case of reduced transit time availability and coverage after the virus breakout. The study identifies three key phases of the pandemic, i.e., initial confirmed cases, shelter-in-place, and the initial changes in transit service to conduct comparative analyses. Unlike survey-based studies, this study combines unsupervised machine learning and visual analytics to study the relationship between bikeshare and transit. Moreover, this study spatiotemporally matches transit and bikeshare by feeding General Transit Feed Specification (GTFS) into the OpenTripPlanner (OTP) tool. In doing so, the authors analyze the change of the spatial distribution of bikeshare trips caused by the geographic change in transit service areas for the different bikeshare trip types over the three

specified phases. Based on the findings and analyses, the authors provide planning recommendations for bikeshare and transit after the pandemic.

2. Literature review

This study mainly focuses on the relationship between bikeshare and transit during the pandemic. We investigate previous related research from two aspects: 1) the relationship between bikeshare and transit, and 2) mobilities during pandemics.

2.1. Bikeshare and public transit

Since the arrival and growing popularity of bikeshare services, practitioners and researchers have been interested in their relationship with public transit. Academics have approached the topic using survey-based and data-driven analytical methods including spatial and visual analytics. Wang and Liu (2013) analyzed the characteristics of bike-transit trips using the National Household Travel Surveys (NHTS) and noticed a clear concentration of bicycle-transit integrators in large and high-density urban areas where most transit-dependent users lived. In their results, around 40% and 60% of bicycle-transit trips are for home-based work in 2001 and 2009 respectively, which shows an increasing trend. Another survey study in San Francisco shows that bikeshare and shared e-scooter can support local transit usage in different ways (Barnes, 2019). In San Francisco, bikeshare is more likely to replace e-hailing trips to relieve traffic congestion in urban areas and improve the travel time reliability of transit services at the same time, while shared e-scooters are more likely to provide first/last mile transit access to promote transit ridership (Barnes, 2019). Similarly, in the Netherlands, Villwock-Witte and van Grol (2015) found that some private vehicle trips could be replaced by transit-bikeshare trips. Moreover, survey results indicate a slight competition between dockless (free-floating) bikeshare and transit trips (Barnes, 2019). A study in Washington DC found that survey participants in less-dense areas (e.g., suburban) are more likely to connect transit with bikeshare than participants in city center areas (Martin & Shaheen, 2014). As stated in the introduction, most of the current survey studies applied stated preference questionnaires, which do not reflect the exact responses of participants when one mode is unavailable.

The other direction of research uncovers the relationship between bikeshare and transit through data-driven analyses. Ma et al. (2015) developed a statistical regression model to test this relationship. Their results show that a 10% increase in bikeshare trips will lead to a 2.8% increase in Metrorail ridership in Washington DC. Wu et al. (2020) developed a parsimonious, continuous model to analyze the benefits of feeding transit by bikeshare. Their analytic results show that bikeshare can save costs for both transit users and agencies as a transit-feeder service compared to other transit-feeder services, e.g., feeder-bus. Tang et al. (2018) proposed a solution to match the demand of bikeshare trips connected to transit with an optimal capacity of bikeshare stations near transit stops. Among those data-driven analyses, spatial or visual analytics play an important role. Through spatial analyses and a spatial error model, Ma, Ji, Jin, et al., 2018 found that the proportion of local residents, job density, and the distance to the central business district (CBD) have significant effects on the space of metro-bikeshare trip activities. Using bikeshare smart card trip data and online points of interest, Bao et al. (2017) visualized the spatial distribution of bikeshare trip patterns and found that the most popular bikeshare trip purpose is for eating in New York in the U.S. Similarly, Bargar et al. (2014) combined interactive visual analytics and algorithms to conduct analyses on bikeshare usage and system design, which can provide useful insights to policymaking or future research. Visual analytics is also applied to show the spatial-temporal differences of bikeshare travel patterns by gender (Beecham & Wood, 2014; Zhao et al., 2015). In the previous data-driven analyses, a spatial-temporal matching between bikeshare trips and transit services has not been fully considered, i.e.,

combining both trip locations and transit schedule information.

From the research above, the primary relationship between public transit and bikeshare is that bikeshare serves as a feeder to promote public transit. However, research by Ma et al. (2019) found that an increase in bikeshare ridership near a bus stop will lead to reduction of bus ridership of that stop on weekend. Another study by Kong et al. (2020) used bikeshare trip data from four cities in the USA to investigate the relation between bikeshare and transit. Their results showed that bikeshare is more likely to replace transit at weekend and when bikeshare users are day-pass members. Thus, the relationship (substitution or complementarity) between bikeshare and transit is complex, and highly dependent on the features of trips, including trip time, trip length, trip cost, and travel time reliability, and cycling environment (Ma et al., 2015; Ma et al., 2019; Kong et al., 2020). Moreover, the connection between cycling and transit depends on the cycling facility, e.g., street connectivity and bicycle lanes (Akar & Clifton, 2009; Duthie et al., 2010; Krizek et al., 2009).

2.2. Mobility and disrupting events

Regarding the relationship between mobility and pandemics, to the authors' knowledge, the literature remains scant on the subject of bikeshare under pandemics. Teixeira and Lopes (2020) analyzed bikeshare and transit ridership during the first wave of COVID-19 in New York in the USA, and uncovers evidence of substituting bikeshare for the subway. However, the analyses only provide an aggregated view, i.e., the ratio between the daily subway and bikeshare ridership, instead of based on every single trip.

Beyond virus pandemics, there are many other disrupting events that influence travel behaviors, e.g., public transit disruptions and weather-related disruptions. Saberi et al. (2018) uncovered that daily bikeshare ridership increased by 85%, and the average trip duration rose to 43 min from 23 min by comparing bikeshare trips after and before a public transportation disruption in London in 2015. van Exel and Rietveld (2001) found that, in the short-term effect caused by public transport strikes, 10–20% of commuter trips were canceled due to either no alternative transport modes or inflexibility in their departure/arrival times. In Chicago, Saxena et al. (2019) conducted a joint revealed preference cum stated preference survey to estimate the value of travel time due to public transit cancellation and disruptions, which can provide reference information for local governments to plan remedial action. Besides public transit disruptions, there are a considerable number of studies on the effects of extreme weather events on transportation. In general, Markolf et al. (2019) summarized existing research on transportation systems under extreme weather events and pointed out that indirect pathways of disruption (e.g., signal outage disruptions of traffic communication and routing services) are often ignored in traditional resilience analyses of transportation systems. Another example is that Pregnolato et al. (2017) fitted a curve to represent the relationship between the depth of standing water and vehicle speed, and finally, analyzed the disruptive impact of flooding on road transport.

2.3. Research contribution

This study aims to develop a trip-level analysis framework including unsupervised machine learning and visual analytics to understand the relationship between bikeshare and public transit throughout the COVID-19 pandemic. Specifically, this study applies an unsupervised machine learning method to group bikeshare trips and exactly matches those trips with transit services using GTFS and OTP. After the classification and matching, this study measures the space-time change of shared bikeshare travel behaviors before and after transit services were affected by the virus crisis, interprets the results, and provides practical planning recommendations.

3. Case study and data description

This study chose San Francisco in California of the United States as the case study city, considering it provides an example for analyzing the bikeshare behavior changes before and during COVID-19. While the exploring study used a single case, the proposed analysis framework can be applied for other shared micro-mobility services, e.g., shared e-scooter and be implemented in any city around the world. The data used in the study is open source and does not need any permit, further increasing the adaptability of the analysis framework. This paper will introduce the details of the case study city and publicly available data in the following paragraphs.

Currently, the bikeshare system named "Bay Wheels" in San Francisco operates 244 bikeshare stations (Fig. 1) and approximately 3000 bikes. The bikeshare program provides publicly historical bikeshare trip data, including trip start day and time, trip end day and time, trip start/end location, user type (Lyft, 2021). Bikeshare users can choose to park bikes from sharing systems at bikeshare stations, i.e., docking-station-based bikeshare trips, or at public bike racks at the cost of two dollars, i.e., dockless bikeshare trips. Note that the company's open historical database changed the resolution for GPS information of bikeshare trip start/end locations. Meanwhile, dockless bikeshare trips represent a substantial proportion of the total trips. Thus, this study uses data from before the data policy change in June 2020, which can support the following spatial and visual analyses. The "Bay Wheels" system committed to providing equitable access to bikeshare and providing affordable membership plans, e.g., a $5 first-year annual membership (Bay Wheels, 2019). Based on the data in 2019, 20% of Bay Wheels users came from this affordable membership program (SFMTC, 2019).

Following the outbreak of COVID-19 on March 5, 2020, in San Francisco, bikeshare travel significantly plummeted, as shown in Fig. 2. The Governor of California issued a state-wide "shelter-in-place" order on March 19, except for essential businesses (CA Gov., 2020). In San Francisco, 21 days later on April 10, the San Francisco Municipal Transportation Agency (SFMTA) restricted its Muni transit service areas into a reduced operational plan (with only 17 of the previous 79 transit lines in service, and with changes in frequency and time availability, as shown in Fig. 3) considering both transit staff's health conditions and reduced ridership (Krogh, 2020). The authors developed Fig. 3 using GTFS data, which will later be explained in detail. Based on the latest census data before COVID-19 in the USA, the percentage of commuters who traveled by public transit was 20% in San Francisco, second to New York (approximately 35%) (Tan et al., 2020). This percentage is higher among low-income or other underserved populations (Tan et al., 2020). While a large percentage of the population changed their travel patterns, especially through remote work, many public transit commuters are front-line workers that have still been required to mobilize to their work locations during the pandemic. Thus, the reduction in transit services, including coverage, frequency, and time availability, affected these essential workers and other transit-dependent users.

Considering the two critical dates, i.e., March 19 and April 10, and the timeframe when the initial cases were reported, this study selected three phases for the analyses. Phase 1, from February 1 to 21, represents the period when new cases were identified, but ridership was not affected; Phase 2, from March 19 to April 9, includes the period between the shelter-in-place mandate and when transit services were not changed; and Phase 3, from May 1 to 21, accounts for the period after transit services were reduced amid the pandemic. The team selected consistent periods before and after the start of these phases to match the 3-week long period represented in Phase 2. In summary, Phase 1 is a normal period before COVID-19, while Phases 2 and 3 are after the virus outbreak and shelter-in-place order. Phase 3 is particularly after the reduction of transit services and when bikeshare activities are stable during the pandemic. These three phases offer different conditions and allow for identifying the potential effects of the pandemic and the change in transit services. The study analyzes the changes in bikeshare
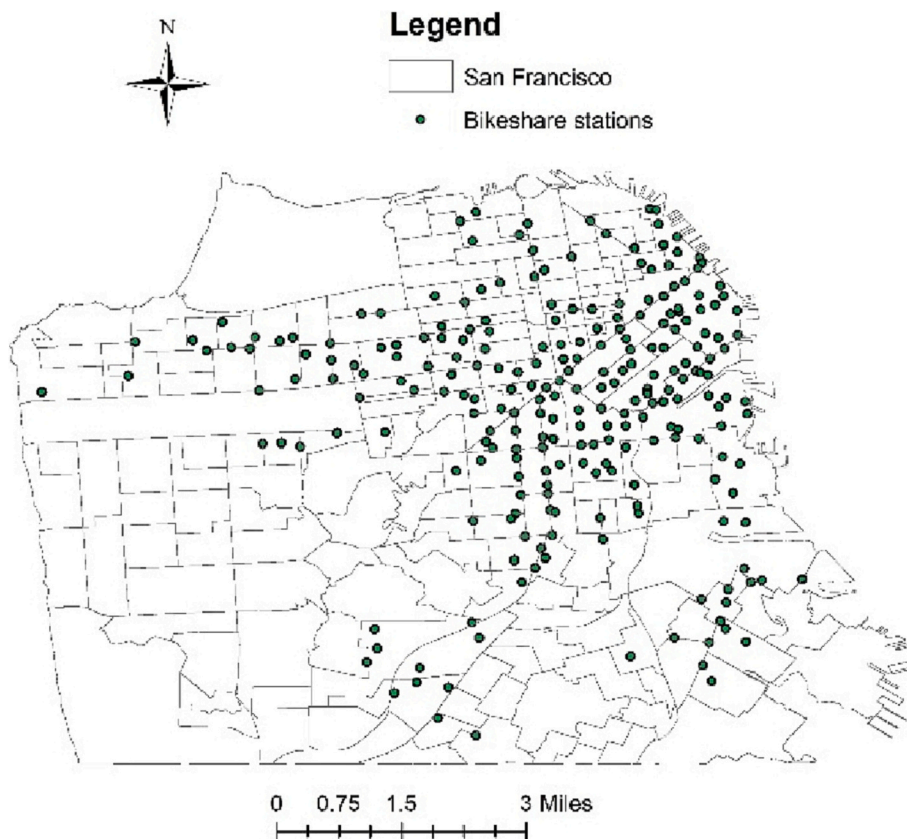
Fig. 1. Bikeshare stations in San Francisco.
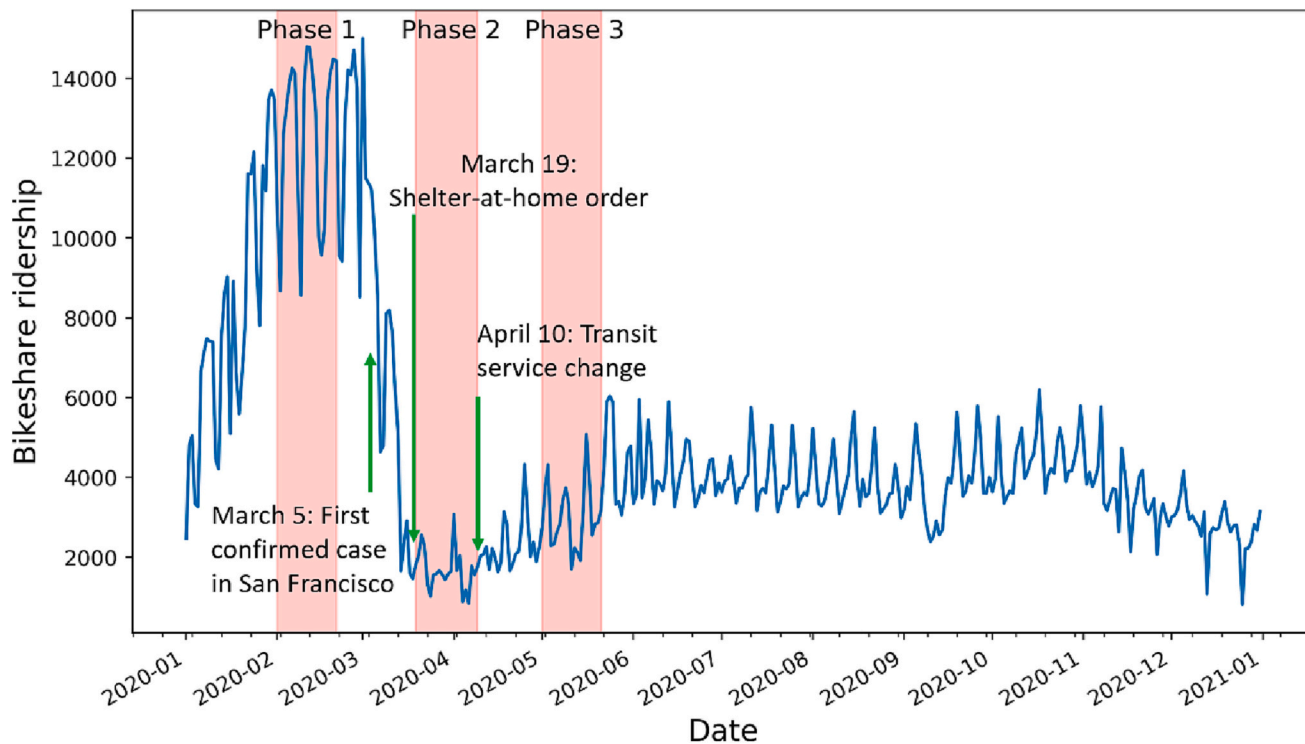
Fig. 2. Bikeshare ridership in San Francisco in 2020.

ridership between the three aforementioned phases. In sum, there are 249,595 trips in Phase 1, 36,873 in Phase 2, and 59,967 in Phase 3. These numbers show the significant impact of COVID19 on bikeshare ridership; however, even with the pandemic, there is still a slow increase of ridership before the reopening policy. For the distance between a bikeshare station and its nearest transit station, the average distance is

Fig. 3. Transit coverage before and after April 10, 2020.

125 m with a standard deviation of 88 m during Phases 1&2; while the average number increases to 182 m with a standard deviation of 214 m.
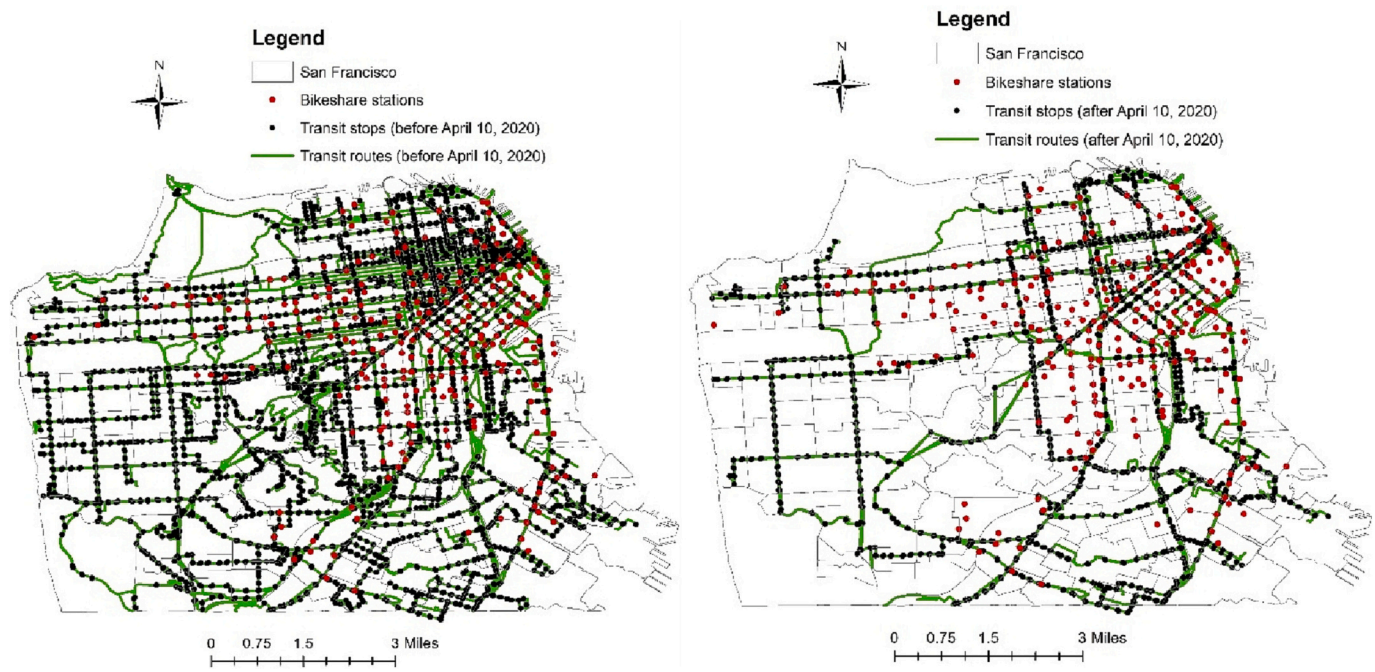
Besides the publicly available bikeshare trip data, this study also collected transportation network data through OpenStreetMap, land use information from government open database, and public transit service data from OpenMobilityData. The OpenStreetMap is a collaborative database to provide free geographic data, including road networks and transit stops (OpenStreetMap, 2020). Land use information in San Francisco can be downloaded from U.S. Government open database (Data.gov, 2020). To retrieve the transit service schedules during these three phases, the authors downloaded the historical official GTFS from OpenMobilityData (OpenMobilityOrg, 2020). The GTFS provides historical or current transit service schedules, including operating transit lines, transit stops, and service frequency. The following section will introduce the proposed methodology to analyze those data in detail.

4. Methodology

The authors propose a 4-step analysis framework (Fig. 4) comprising: data compilation, data analysis (clustering), data visualization, and behavioral change analysis. The proposed analysis method is replicable and could be used to monitor and further evaluate changes in micro-mobility services.

4.1. Bikeshare trip data compilation

First, the study compiled bikeshare data, as well as other data sources. For the bikeshare data, the authors removed the bikeshare trips longer than 2 h and shorter than 1 min, which are used as thresholds to clean bikeshare trip data in research by McKenzie (2020). Moreover, this study also set the maximum speed for a bike as 20 miles/h. Thus, bikeshare trips with a speed faster than 20 miles/h will be treated as bikeshare operator-related activities, e.g., rebalancing.

As mentioned in the case study section, this study has information about trip start/end date and time, trip start/end location, and user types. Additionally, this research included land use information, and classified the land use categories into seven main groups, as shown in Table 1. This study mainly listed land use for medical care as a separate land use category since trips for medical care may increase during this pandemic.
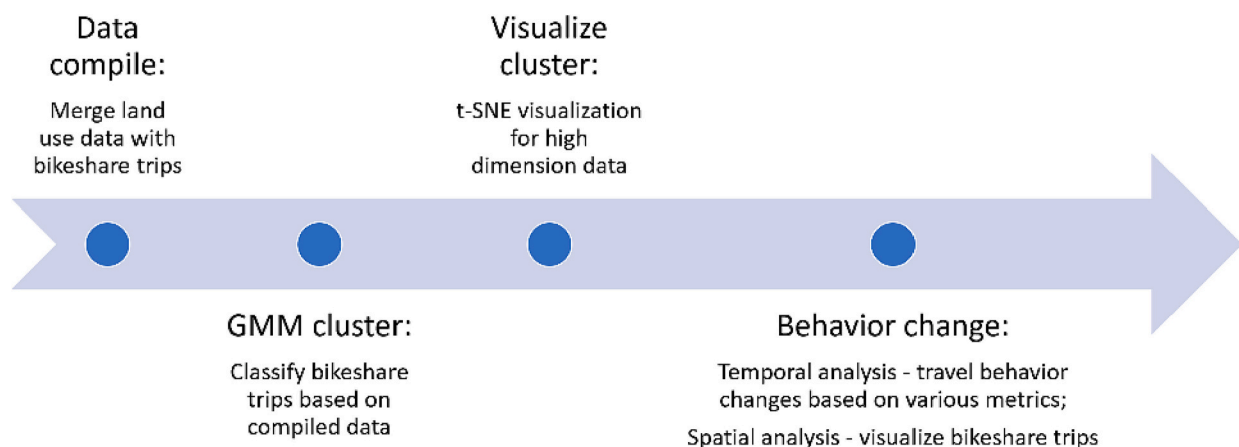

Fig. 4. Flowchart of analysis framework.

Table 1
Description of land-use groups.

Land use group	Code	Details
Office work locations	1	Cultural and educational institutions, offices for management, information, professional services
Industrial facilities	2	Facilities for production, distribution, and repair
Medical facilities	3	Hospitals and dentists' offices
Residential	4	Residential facilities
Recreation	5	Retails, entertainment, open space, hotels, visitor services
Mixture	6	Mixed land use
Others	0	For example, traffic roads and vacant space

For bikeshare trips starting or ending in bikeshare stations, the land use information was collected within 400-meter buffers, which is suggested by Qian and Jaller (2020), and calculated the proportion of different land-use groups within the buffers. However, for bikeshare trips parking at public racks (dockless bikeshare trips), the study assumed the closest land use to the bicycle trip start/end location as the only land use category.

Qian and Jaller (2020, 2021) have identified differences in bikeshare travel and use patterns between annual members and day-pass users. Due to these differences, the type of user could serve as a proxy for the type of trip. However, considering that the pandemic may have changed travel patterns, and induced new bikeshare users, the authors do not consider user type to make a priori assumptions about the trip purposes. Table 2 lists the key data used in the following cluster analyses.

Figs. 5 to 7 show the distribution of all of the data listed in Table 2. As we can see, there are clear differences in the patterns of travel behaviors among the three phases in terms of trip start day, trip start time, trip duration, and start/end location land use. Most of the trips happened during weekdays in Phases 1 and 2, while the proportion of weekend trips became the greatest in Phase 3. Trips were more likely to happen in the afternoon in Phases 2 and 3, instead of showing two obvious peaks (morning and afternoon) in Phase 1. For the trip duration, the average bikeshare trip duration is 12.8 min (Phase 1), 17.9 min (Phase 2), and 20.8 min (Phase 3) respectively. Trip time in Phase 3 tended to be longer than that in Phase 1, which is verified by a *t*-test (Phase 1 vs Phase 3: P-value 0.0). In Phase 1, the three most frequent land uses for both start and end locations are residential, mixture areas, and others (including traffic roads and vacant spaces). In Phases 2 and 3, residential areas dominated both trip start and end locations. However, medical-related land use is the least frequent land-use type no matter the phase.

4.2. Data analysis through Gaussian Mixture Model (GMM)

The authors proceeded to analyze the data, implementing an unsupervised machine learning algorithm based on Gaussian Mixture Model (GMM) clustering. GMM has been widely used in unsupervised machine learning (e.g., clustering) since it does not need labeled data (Han & Sohn, 2016; Maugis et al., 2009; Ouyang et al., 2004). GMM is a combination of multiple Gaussian distributions, each of which is distinguished from other components by its mean and covariance. Thus, the

Table 2
Summary of data used.

Trip features	Explanation
Trip start day	1: start on weekday; 0: start at weekend
Trip start time	Start time in hh:mm:ss format
Trip actual duration	Time difference between trip start time and end time in seconds
Start location land use	The percentage of areas in different land use categories for trip start location
End location land use	The percentage of areas in different land use categories for trip end location

probability of a sample is a weighted sum of its probability under a specific Gaussian distribution, as shown in Eq. (1).

$$f(\mathbf{x}_i) = \sum_{k=1}^{K} \pi_k f_k(\mathbf{x}_i | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k), for\ i = 1, ..., N \tag{1}$$

where $\mathbf{x}_i$ is the ith sample in our data, $f(\mathbf{x}_i)$ is the mixture probability, K is the total number of Gaussian distributions, π_k is the probability or weight of the kth group in the whole model, and $f_k(\mathbf{x}_i)$ is the single probability when $\mathbf{x}_i$ is in k^{th} group, $\boldsymbol{\mu}_k$ is mean vector, and $\boldsymbol{\Sigma}_k$ is the covariance matrix of variables in k^{th} group since $\mathbf{x}_i$ is a high-dimension vector in this study.

Before implementing this algorithm, the authors needed to decide the number of K in our GMM. Since the ground-truth data is not available, this study applied other criteria to decide the optimal value of K. In general, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) are used to decide the number of clusters in unsupervised machine learning. Moreover, this study also applied the idea of the elbow method to identify the optimal number of clusters (Liu & Deng, 2020). The elbow point is the value of K at which improvement in criterion values declines the most and this study will stop dividing the data into more clusters.

After deciding the value of K, there are three sets of parameters to estimate π_k, $\boldsymbol{\mu}_k$, $\boldsymbol{\Sigma}_k$ for i from 1 to K. To estimate the parameters (π_k, $\boldsymbol{\mu}_k$, $\boldsymbol{\Sigma}_k$) in the GMM, this study applied the Expectation-Maximization (EM) algorithm, which has been broadly used in calibrating GMMs (Liu et al., 2017). The EM algorithm consists of two steps: Expectation and Maximization, and the details of this algorithm are discussed in a book by Gupta and Chen (2011). To be simple, the EM algorithm starts with an initial random guess of these parameters (π_k, $\boldsymbol{\mu}_k$, $\boldsymbol{\Sigma}_k$). Then, this algorithm will decide these parameters through the iterative loop of E-step and M-step. In the E-step, we need to calculate the probability that a sample belongs to a group as show in Eq. (2). The value of $r_k(\mathbf{x}_i)$ will be higher if $\mathbf{x}_i$ is assigned to the right group.

$$r_k(\mathbf{x}_i) = \frac{\pi_k f_k(\mathbf{x}_i | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{k=1}^{K} \pi_k f_k(\mathbf{x}_i | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}, for\ k = 1, ..., K \tag{2}$$

In the M-step, we need to update π_k, $\boldsymbol{\mu}_k$, and $\boldsymbol{\Sigma}_k$ by considering the probability $r_k(\mathbf{x}_i)$ from E-step using Eqs. (3)–(5). Finally, this iterative loop will converge and reach a threshold.

$$\pi_k = \frac{\sum_{i=1}^{N} r_k(\mathbf{x}_i)}{N}, for\ k = 1, ..., K \tag{3}$$

$$\boldsymbol{\mu}_k = \frac{\sum_{i=1}^{N} \mathbf{x}_i * r_k(\mathbf{x}_i)}{\sum_{i=1}^{N} r_k(\mathbf{x}_i)}, for\ k = 1, ..., K \tag{4}$$

$$\boldsymbol{\Sigma}_k = \frac{\sum_{i=1}^{N} (\mathbf{x}_i - \boldsymbol{\mu}_k)^T (\mathbf{x}_i - \boldsymbol{\mu}_k) * r_k(\mathbf{x}_i)}{\sum_{i=1}^{N} r_k(\mathbf{x}_i)}, for\ k = 1, ..., K \tag{5}$$

In this study, the main objective was to try to identify and classify different bikesharing use patterns. GMM can estimate the category of a bikeshare trip based on the maximum value of $r_k(\mathbf{x}_i)$.

4.3. Data visualization for clustering validation

After classifying bikeshare trips, this study visualized bikeshare data in different groups to validate the cluster results. This study applied the state-of-art visualization method for high dimension data: t-Distributed Stochastic Neighbor Embedding (t-SNE) (van der Maaten & Hinton, 2008). The core idea behind t-SNE is measuring the similarity between
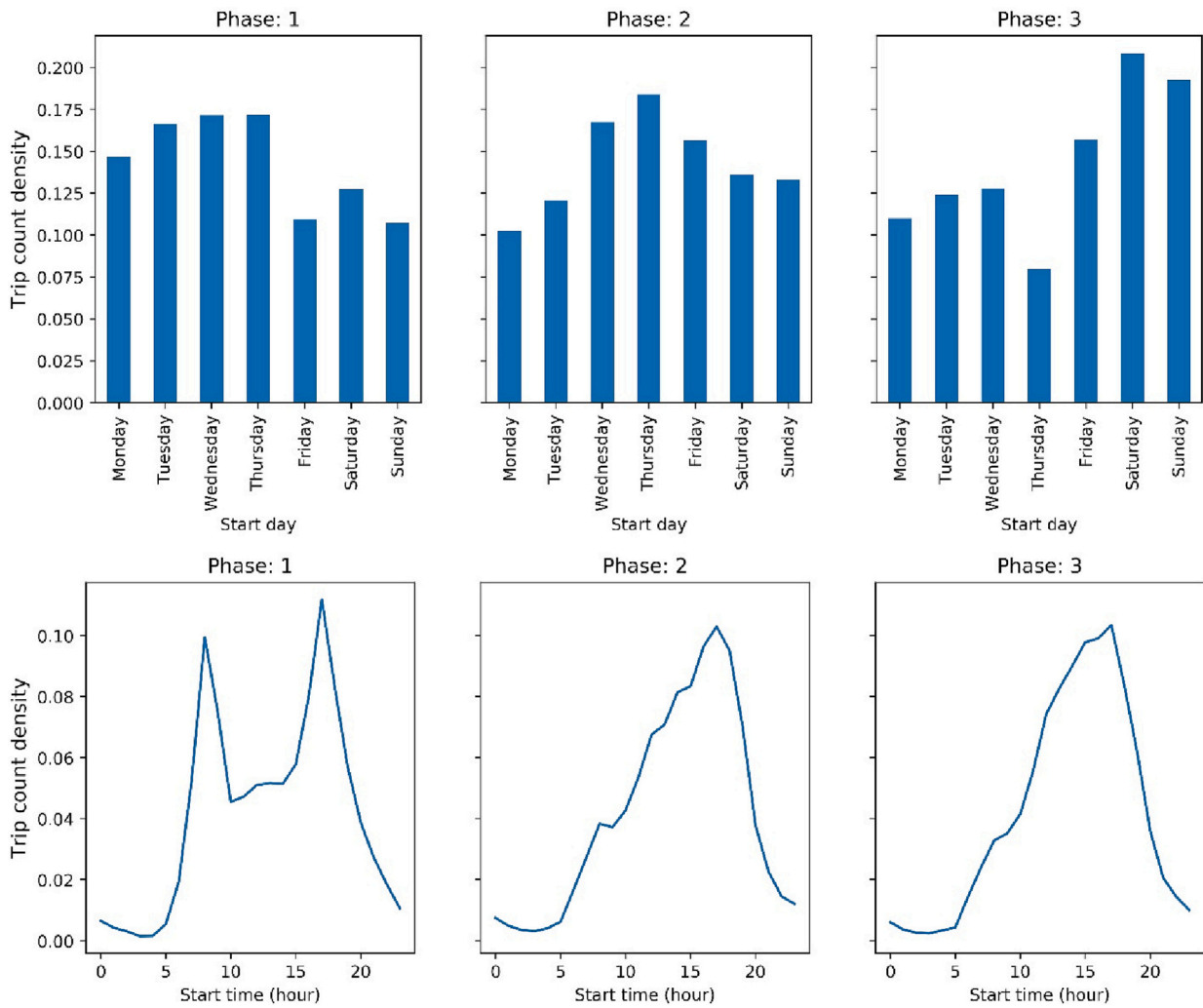
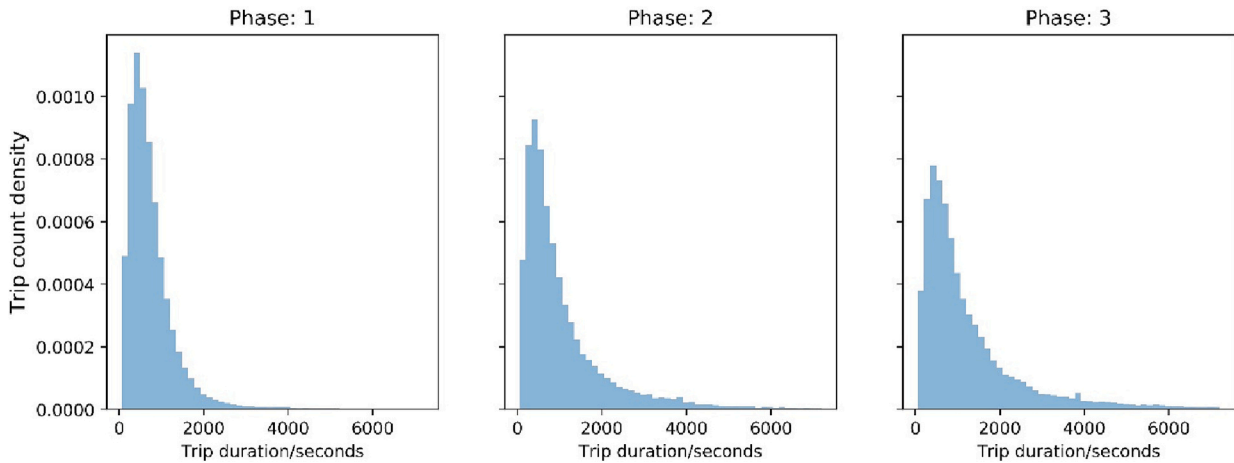**Fig. 5.** Distribution of trip start day and time.

Fig. 6. Histogram for trip duration (seconds).

two data points by the Euclidean distance under high and low dimensional space. The similarity in high dimensional space is measured by pair-wise datapoint (x_i and x_j) as show in Eq. (6). Likewise, the similarity in low space (y_i and y_j) is calculated using Eq. (7).

$$p_{j|i} = \frac{exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma_i^2}\right)}{\sum_{k \neq i} exp\left(\frac{-\|x_i - x_k\|^2}{2\sigma_i^2}\right)} \quad (6)$$

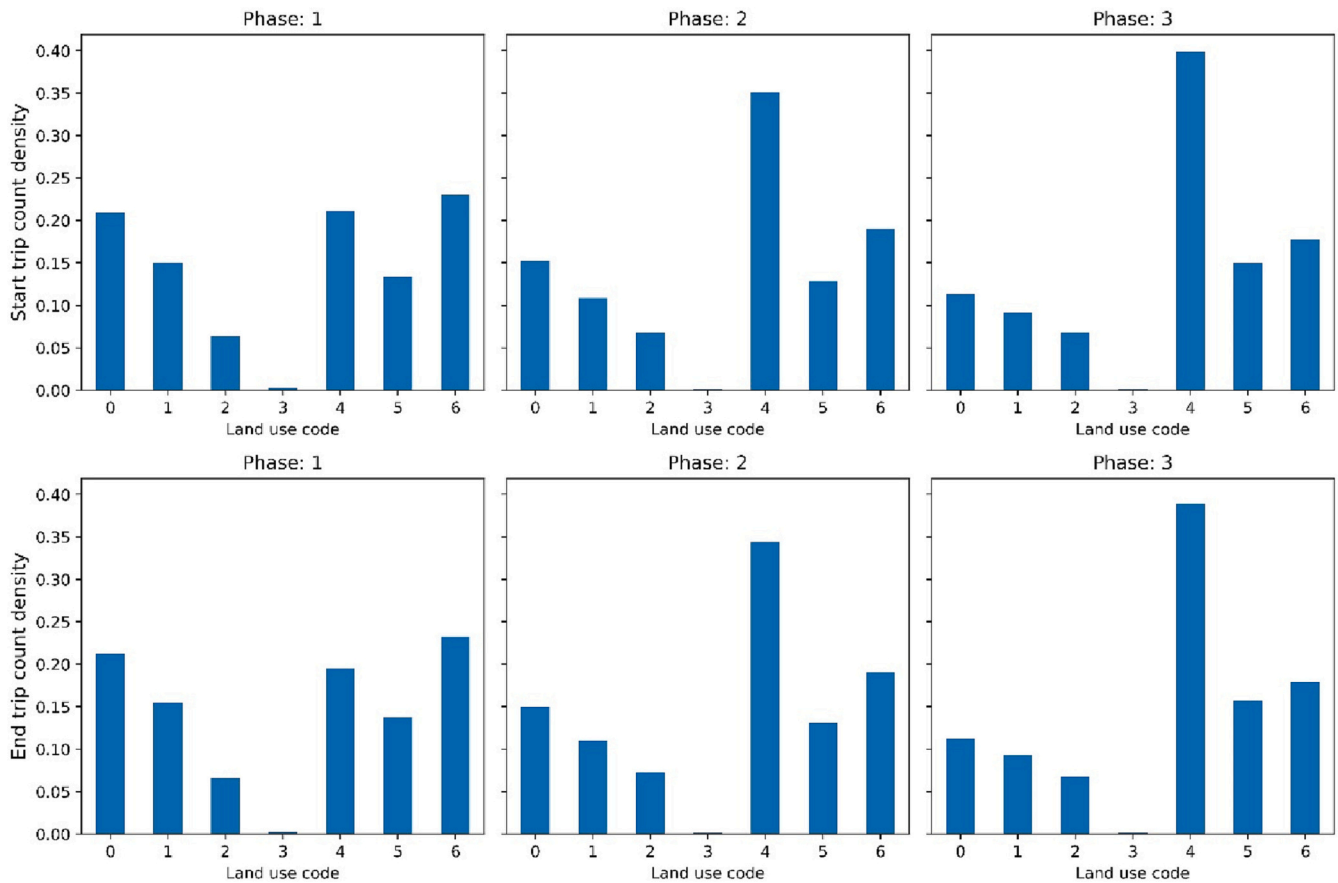where σ_i is the variance on datapoint x_i.

Fig. 7. Distribution of dominant land use of trip start/end locations.

$$q_{j|i} = \frac{exp\left(-\left\|y_i - y_j\right\|^2\right)}{\sum_{k \neq i} exp\left(-\left\|y_i - y_k\right\|^2\right)} \tag{7}$$

Finally, through minimizing the cost Eq. (8), which combines Eqs. (6) and (7), this study can find a low-dimensional cluster to maximize the similarity between high and low dimensional spaces. In the end, this study can visualize the high dimension bikeshare trip data and show the performance of the previous clustering.

$$C = \sum_i KL(P_i \| Q_i) = \sum_i \sum_j p_{j|i} log\frac{p_{j|i}}{q_{j|i}} \tag{8}$$

4.4. Identifying behavioral changes

To identify the behavior changes, this study conducts both spatial and temporal analyses under various dimensions. For the temporal comparison, this study shows how travel behaviors, e.g., starting from a bikeshare station or not, change over the three phases. In the spatial analysis, both direct visualization and quantitative measurement are applied to display the change in trip spatial distributions. The following paragraphs will introduce those comparisons in detail.

After clustering bikeshare trips, this study analyzed how travel behaviors changed across the three phases. In addition to the trip characteristics (e.g., user types and start/end in bikeshare stations or not) directly from the "Bay Wheels" bikeshare system, this study explored metrics related to transit information for bikeshare trips. By comparing those metrics, we can uncover how bikeshare trips change according to the change in transit services.

Since the available bikeshare trip data does not provide trip purposes, this study required the identification of another proxy to represent the relation between bikeshare trips and transit services. Making

the most of the spatial-temporal information in bikeshare trips, this study matches them with transit services. The connection includes: 1) whether a bikeshare trip starts/ends near transit stops; 2) whether this bikeshare trip can be finished by transit if starting at the same location and time; and 3) what is the ratio between trip time by transit if possible and by bikeshare. The following paragraphs will introduce the process of matching.

First we analyzed if a bikeshare trip starts or ends near transit stops. Currently, there is limited research analyzing the walking distance for people to transfer between bikeshare and public transit. To overcome this limitation and identify whether a trip starts or ends near a transit station, this study estimated the average distance between bikeshare stations and their closest transit stations (Fig. 8). The average of the shortest walking distance is 182 m. Without any other supporting data, the team used 200 m as the threshold to classify if a docking-station-based bikeshare trip starts or ends near a transit station. For bikeshare trips parked in public racks, the distance threshold was selected as 50 m. It is important to consider these different transit networks between Phases 1&2 and Phase 3 due to the change in transit coverages (Fig. 3). Thus, the study conducted the threshold analysis for each phase separately.

This study retrieved public transit information using OTP. OTP is an open-source software project that provides route information combining pedestrian, bicycle, and transit using OpenStreetMap and GTFS data. Moreover, the platform provides an Application Programming Interface (API) to programmatically calculate numeric routes at the same time. Because San Francisco had a change in transit services on April 10, as previously mentioned, this study retrieved the transit information before and after April 10 and matched that with bikeshare trips based on trip start dates. Phases 1 and 2 share the same transit service plan, while Phase 3 has a separate, reduced transit schedule.
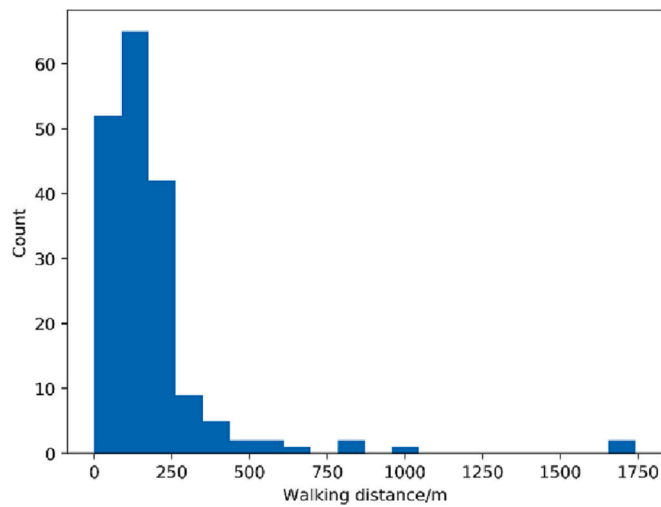
Fig. 8. The histogram of the shortest walking distance between bikeshare stations and transit stops (before April 10).

Additionally, the study estimated two travel times for each bikeshare trip using the OTP platform. These were the travel times between origins and destinations using transit (if transit service was available), at the same start date and time, and the estimated shortest trip time and trip distance by cycling (Fig. 9). Table 3 lists the information used for the comparative analyses. Those comparison features make the most of the information reflected by bikeshare trips and transit services, and can help researchers identify the changes in travel behaviors across the three phases.

Besides the visual analytics, the study also quantitatively compares the spatial difference between the distribution of transit service and bikeshare trips. In detail, this study applies the Wasserstein metric (i.e., earth mover's distance (EMD)), which has been widely applied to compare spatial similarity (McKenzie, 2020). The Wasserstein metric is a distance function to measure the difference between two probability distributions. In this study, these two probability distributions refer to the spatial distributions of public transit stops and bikeshare trip start/ end locations. The distance can be viewed as the smallest "cost" or effort, to transform one distribution into another, like shaping one terrain into another in a sand table. The spatial analyses are conducted at the census tract level. We estimate the number of transit stops per census tract, as well as for bikeshare trip start/end locations. Considering that the number of bikeshare trips is larger than the number of transit stops, we normalize both distributions and estimate the Wasserstein metric to indicate the similarity or difference.

5. Empirical results

5.1. GMM clusters

The first step involves identifying the optimal K value, through the analysis of the AIC and BIC scores (the left panel in Fig. 10). It is obvious that the greater the cluster number, the better the GMM fits the data in terms of the AIC/BIC score. However, the gradient of AIC/BIC score (the right panel in Fig. 10), shows that to avoid over-fitting, the optimal
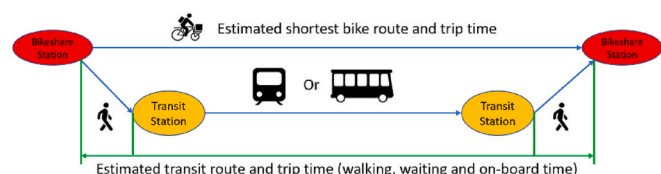

Fig. 9. OTP estimation for bikeshare trips.

Table 3
Comparison features.

Comparison features	Explanation
User types	1: Member (annual or monthly); 0: casual user (single ride)
Start in bikeshare stations (or not)	Self-explanatory
End in bikeshare stations (or not)	Self-explanatory
Start near transit stops (or not)	Self-explanatory
End near transit stops (or not)	Self-explanatory
Transit service availability	Check whether this bikeshare trip can be replaced by a transit trip under the constraint that maximum walk distance to a transit stop is 850 m (Zhao & Li, 2017)
Trip time ratio 1	The ratio between the actual bikeshare trip time and shortest trip time by cycling
Trip time ratio 2	The ratio between the total trip time (including walking time, waiting time, and on-board time) by transit (if possible) and shortest trip time by cycling

value of clusters K is 14, based on the elbow method.

Therefore, the authors grouped the bikeshare trip data into 14 clusters. Table 4 lists the trip features of every group. For the column "Weekday code," the value is the mean of all values (1 or 0) of trips belonging to this group. The "Start time" column is the average trip starting time of all trips in a specific group. The number of trips in most clusters is approximately 20,000, except for Clusters 3, 5, 8, and 12. Some clusters have a similarity in several trip features, e.g., trip duration and start/end location land uses. For example, Clusters 3 and 10 have a longer trip duration and a later trip start time compared with other clusters.

Referring to the study by Han and Sohn (2016), this study further classified all of these 14 clusters into a smaller number of trip types for the convenience of the following comparison. Based on previous survey studies, the primary trip purposes for bikeshare trips are work commuting, personal or recreational purposes (Buck et al., 2013; McNeil et al., 2017). Moreover, based on the features of bikeshare trips (i.e., trip start time, duration, and land use) in Table 4, and for tractability purposes, the authors aggregated the 14 clusters into three main trip types and assigned corresponding labels: typical work trip, mix-purpose trip, and recreational trip. These three types are distinct from each other across trip start time, duration, and land use (Table 5) and follow previous studies, though the number of trip types may change for other case studies.

It is important to note that directly selecting the value of K to be three and re-running the model, is not adequate. This is because the cluster results from GMMs are not stable when the K value is small. When K is small, one record will be more likely to be randomly classified into any cluster when the boundary of clusters is not clear.

After classifying bikeshare trips into three main types, this study applied the t-SNE visualization method to show the performance of the GMM in clustering (Fig. 11). These three different trip types are apparently separated even though small sub-groups exist within the large trip types, which, from another angle, is consistent with the split by the statistics of trip features in Table 5.

5.2. Changes in bikeshare trip patterns

The change of bikeshare travel behaviors was then further analyzed during the three phases. It is clear that the proportion of Type 3 trips significantly increases, whereas Types 1 and 2 decrease (Fig. 12). As expected, work-related bikeshare trips decreased because the shelter-in-place order came into effect. However, Type 3 bikeshare trips, mainly weekend recreational trips, increased, as people wanted to improve emotional health during this pandemic.

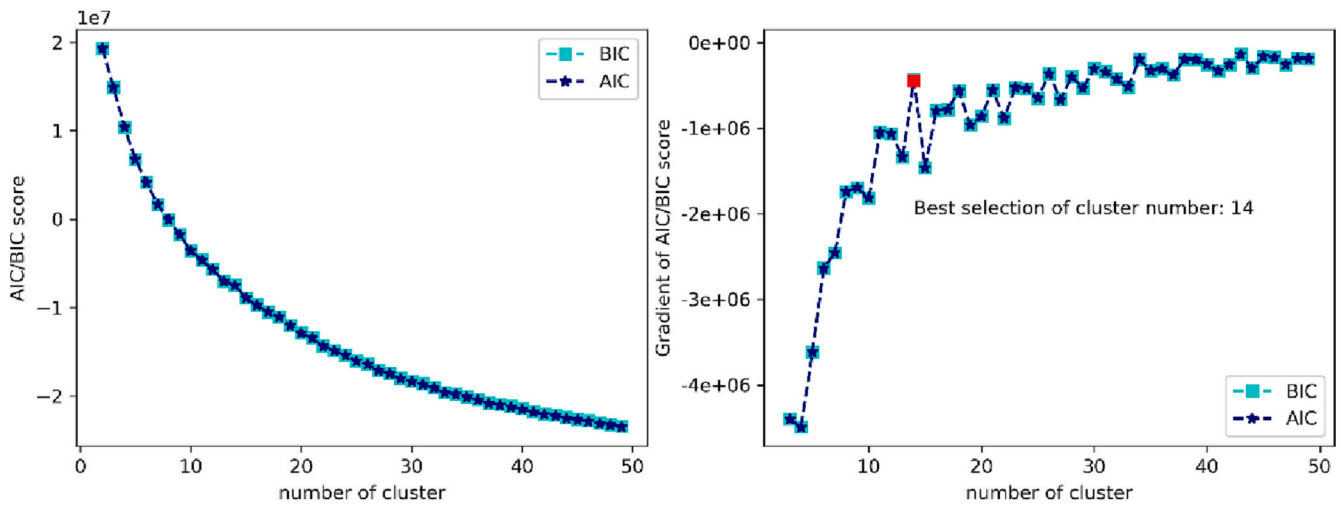The study then compared the potential change of these metrics for

Fig. 10. The AIC and BIC index of GMM.

Table 4
Mean values of bikeshare trips in every cluster.

Cluster	Number of trips	Weekday code (1: weekday; 0: weekend)	Start time (hh:mm:ss in 24 h)	Duration (seconds)	Domain land use in start location	Domain land use in end location
1	18,879	0.74	13:48:00	805	6	0
2	18,905	0.71	13:58:00	875	4	4
3	33,831	0.00	14:28:00	1223	4	4
4	14,459	0.73	14:26:00	844	2	6
5	46,874	1.00	14:01:00	826	4	4
6	27,976	0.67	14:54:00	898	5	6
7	24,615	0.82	14:25:00	735	0	6
8	53,810	1.00	14:07:00	829	4	4
9	25,060	0.84	14:13:00	743	1	6
10	21,718	0.60	14:39:00	1124	5	5
11	13,802	0.70	14:24:00	785	6	6
12	7366	0.78	14:21:00	754	2	4
13	21,866	0.70	14:31:00	842	6	4
14	13,274	0.70	13:46:00	834	4	6

Table 5
Description of the resultant clusters based on mean values.

Cluster group	Most likely description			Most likely title
	Trip start time	Duration	Dominant land use	
2, 4, 5, 8, 9, 12	Most weekday peak hour	Short	Resident/ industrial work/ office work locations	Typical work trip
1, 7, 11, 13, 14	Most weekday	Moderate	Mixture/ resident/other	Mix-purpose trip (e. g., work-related, transit connection, afternoon shopping)
3, 6, 10	Most weekend afternoon	Long	Recreation/ resident/ mixture	Recreation trip

Fig. 11. Patterns on t-SNE feature space for compiled bikeshare trip data.

the different trip types over the three phases. First, the authors examined the ratio of bikeshare trips by subscriber members and found that their trips keep decreasing for all trip types, though work trips decrease less than the other trip types (see Fig. 13). This may be because some new users may have joined as casual bikeshare users due to personal health concerns.

For transit service availability, the percentage of bikeshare trips with available transit services decreases significantly after the reduction of transit services. Even though the percentage decreases, it can still be as high as 94% during this period, bec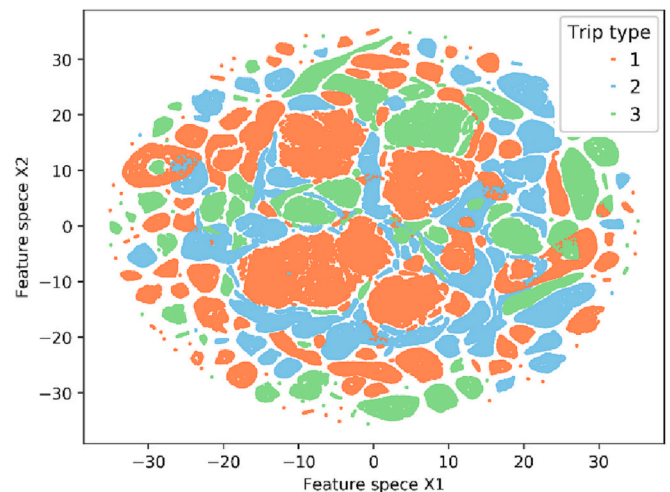ause people are allowed to walk as long as 850 m to get access to transit stops when this study applied the OTP API. Thus, transit service is still available for the majority of bikeshare trips after April 10. However, transit users have to walk longer distances, wait longer times, or transfer more times if they choose to make these bikeshare trips by transit. The drops in transit service availability (2% for trip Type 1, near 3% for Type 2, and 6% for Type 3)
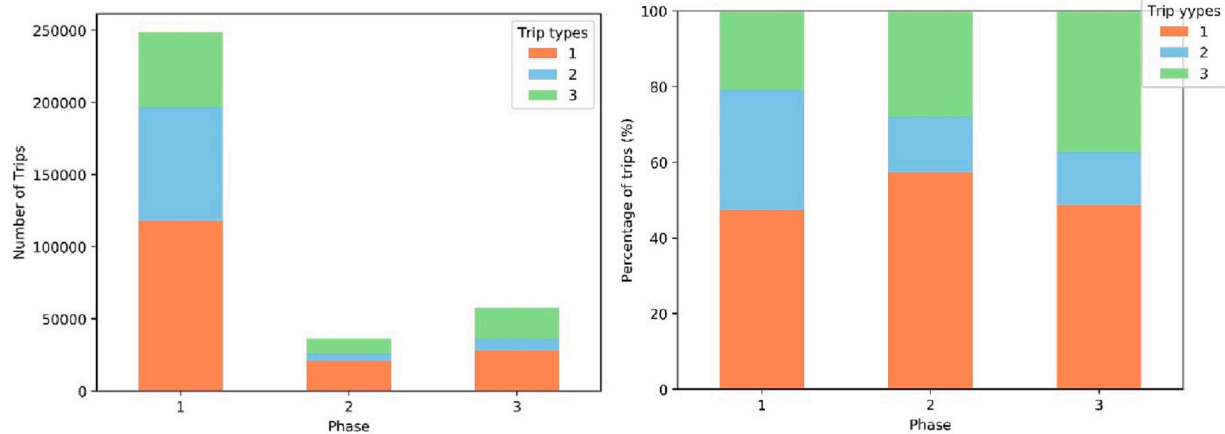
Fig. 12. The change in the number of different trip types among the three phases.

show that a certain number of bikeshare trips complement transit services when this service is completely unavailable.

For bikeshare trips starting/ending at bikeshare stations, the percentage increases between Phases 1 and 2; the only exception is the trips starting in bikeshare stations of Type 2. One reason is that the shelter-in-place reduced the majority of non-essential flexible trips (parked at public racks). Another potential reason is the change in operational rebalancing strategy, i.e., bikes are more likely to be relocated to physical bikeshare stations for management convenience. However, there are no data available to validate this assumption. Comparing Phases 2 and 3, there are not too many changes in the percentage of bikeshare trips starting/ending in bikeshare stations. Thus, bikeshare users' travel behaviors regarding choosing flexible bikeshare trips or not, are not significantly affected by the change in transit service on April 10.

For bikeshare trips starting/ending near transit stops, the percentage increases from Phase 1 to Phase 2. More trips started or ended in bikeshare stations and majority of bikeshare stations are within 200 m of transit stops. Thus, the percentage of bikeshare trips connected with transit stops or near transit stops increases. However, after April 10, fewer bikeshare trips are connected with transit services since fewer transit lines are operating, or there are transit frequency decreases.

The research team then examined the ratio between actual bikeshare trip time and planned (shortest) trip time by cycling (the top panel in Fig. 14). The distribution of this ratio is similar across all three different trip types over the three phases. However, when comparing the ratio between planned transit trip time and shortest cycling trip time (the bottom panel in Fig. 14), the distribution of this ratio is different, particularly between Phase 1 (or 2) and Phase 3. During Phase 3, more bikeshare trips are taken, which will take four-fold to six-fold time if by transit. Note that there is a peak of around 400% in Phase 3 for all trip types. The reason is that the OTP estimates transit travel time by combining walking time to transit stops, waiting time at transit stops, and on-board time. If a user can walk directly to a destination with less time than by taking transit, this trip will be finished by walking, which is true among short distance trips (less than 850 m, the maximum walking distance to transit stops set in OTP). Besides, cycling speed is four-times the walking speed in OTP.

5.3. Sensitivity analysis for walking distance to transit stops

Since this study set a maximum walking distance (850 m) to transit stops based on previous research (Zhao & Li, 2017), the authors wanted to test how this value influenced transit service availability. Thus, this study conducted a sensitivity analysis on the value of maximum walking distance to transit stops. Note that in this section, the authors focused on bikeshare trips in Phase 3, when transit services were affected by the

pandemic. Fig. 15 shows the change in the percentage of transit service availability for replacing bikeshare trips. As people are less likely to walk a long distance to transit stops, more bikeshare trips can not be finished by transit, even when people consider taking transit. This trend is true for all kinds of bikeshare trip purposes. Moreover, the slope of this curve is steeper when the maximum walking distance is between 200 and 400 m. Unfortunately, lack of access to bikeshare trip users (e.g., age and income) limits our ability to understand which segments of the populations are most affected by the change in transit services during the crisis.

5.4. Spatial distribution of bikeshare trips under different categories

After temporally analyzing the change of bikeshare behaviors, this paper visualized those trips over three phases (Fig. 16). There is no noticeable difference in the geographic distribution of bikeshare trips between Phase 1 and Phase 2. The significantly less dense trip distribution in Phase 2 compared with Phase 1 is because of the plummeted ridership after the virus outbreak. Comparing Phase 2 and Phase 3, the data shows more bikeshare trips taking place in the southwest of San Francisco, where transit services were affected after April 10. Considering that some of those trips are of type 1 (work) and type 2 (mix purpose), it could be expected that most of those trips were previously taken by transit because the only change between Phases 1/2 and Phase 3 in transportation services is transit services. For Type 3 or recreational trips, there is not enough evidence to identify if the new bikeshare trips are because of mode substitution, or are the result of individuals trying to exercise or wander around as the shelter-in-place progressed.

Besides the direct visualization in Fig. 16, this study applied the Wasserstein metric (i.e., earth mover's distance (EMD)) to calculate the similarity between two spatial distributions, as suggested by McKenzie (2020). The smaller the Wasserstein metric values, the higher the similarity between different spatial distributions.

The authors measured the similarity of bikeshare trip distribution and transit stop distribution (Table 6). In this analysis, the transit stops refer to those before the shelter-in-place and reduced transit service. The similarity between these two distributions before the pandemic is not significant compared with after the virus outbreak. Before the pandemic, most of the bikeshare trips happened in the city center areas. The reason for this is that most of the bikeshare stations are in the northeast of San Francisco (covering city center areas), and the majority of the bikeshare trips are docking-station-based bikeshare trips. Before the pandemic, transit served most of San Francisco city with more frequent services in the city center areas. However, during the pandemic, particularly after the transit services were reduced, the bikeshare trips extend to other areas without bikeshare stations, and areas with transit services before the pandemic to meet travel demand there in Phase 3. This trend causes
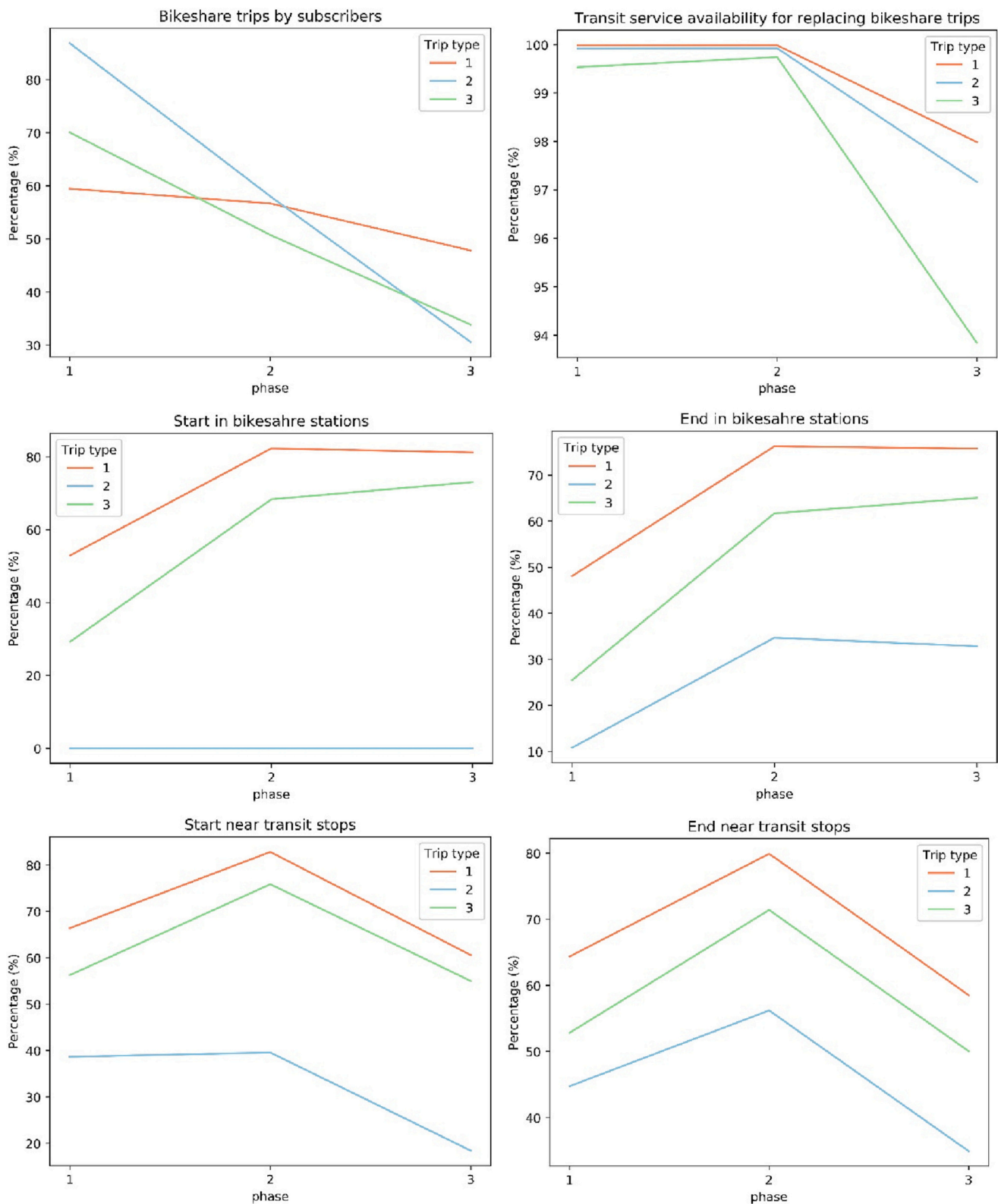
Fig. 13. The metric changes for different trip types over three phases.

the similarity between the spatial distributions of bikeshare trips during Phase 3 and transit stops in Phase 1 to be significant. Moreover, the similarity between dockless bikeshare trips and normal time transit services is more significant than that between docking-station-based bikeshare trips and normal time transit services. The reasons may be that bikeshare users could park bikes very close to transit stops for transit-bikeshare trips, or users took dockless bikeshare trips to substitute for transit trips that were unavailable after transit service was changed. However, the difference between the trips during 0 am–12 pm, and the trips during 12 pm–24 pm is not significant.
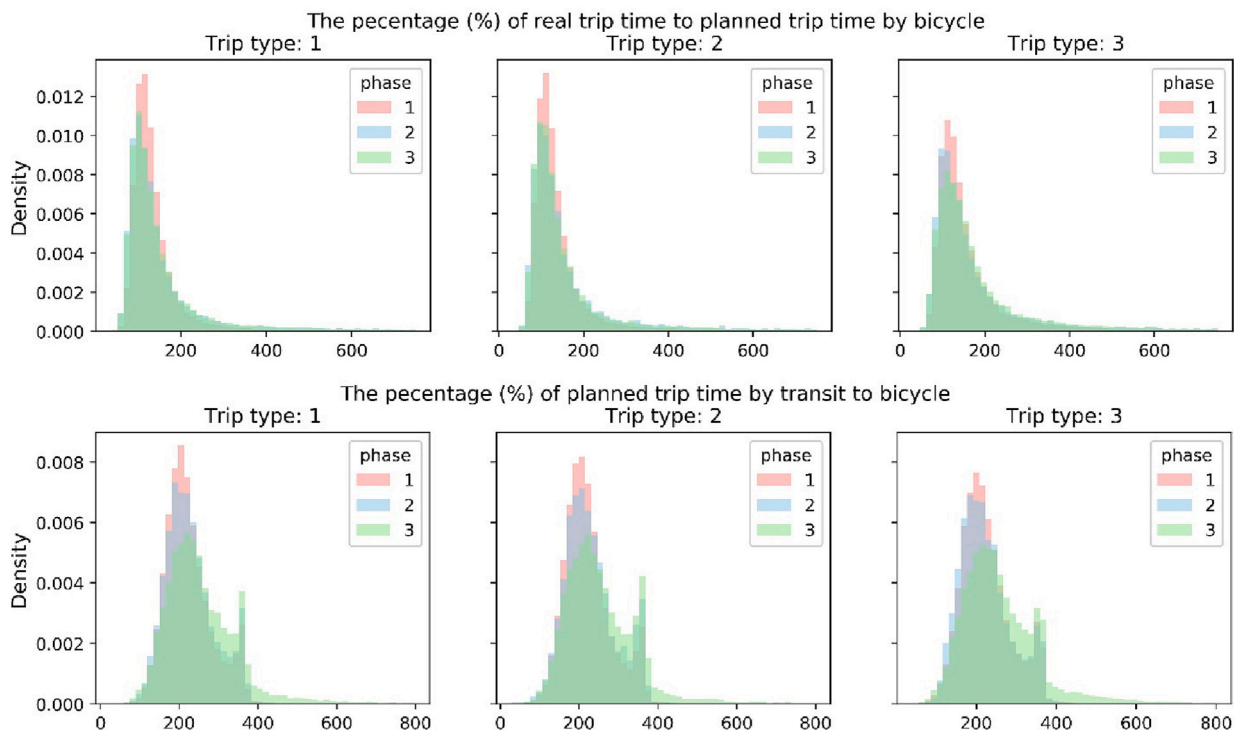
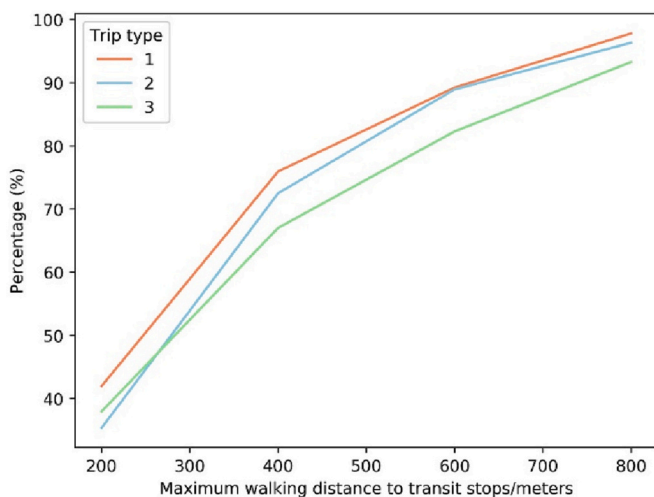Fig. 14. Histogram for two ratios (in the unit of percentage).

Fig. 15. The percentage of transit service availability for replacing bike-share trips.

6. Discussion and conclusion

6.1. Bikeshare activities during COVID-19

To analyze how other modes may help relieve the transportation challenges caused by disruptive events, this study develops a framework combining unsupervised machine learning and visual analytics to examine how bikeshare activities changed amid the COVID-19 pandemic. As reflected by the results, the proposed analysis framework can successfully group different trip types by merging various data sources, including bikeshare trip data and land use information. Even though previous survey-based studies can identify a similar trend, e.g., the increase in casual users and recreation trips, and longer trip times (Chibwe et al., 2021; Heydari et al., 2021; Shang et al., 2021; Wang & Noland, 2021), the proposed method does not require a time-consuming process to collect survey data and can provide timely and reliable insights during the early stage of unexpected disruptive events. In addition, our method can enhance other data-drive modeling (Song et al., 2022a; Tokey, 2020) to further predict the trip purposes of bikeshare trips.

Our study compliments current discussion on the impacts of COVID-19 on bikeshare activities including docking-station-based and dockless services, which uncovers the different changes between them during this pandemic. During the pandemic, the proportion of docking-station-based bikeshare trips increase, which shows that bikeshare users are more likely to finish routine activities within fixed routes. Our study confirms the statement that the popularity of bikeshare increases during the pandemic (Nikiforiadis et al., 2020; Song et al., 2022b). However, for dockless bikeshare trips, different from the studies by Tokey (2020) and Song et al. (2022a) that the spatial distribution shows a significant centrality, we notice that the geographic distribution of dockless bikeshare trips has expanded compared to the pre-pandemic norm of concentrating in the city center areas. More dockless bikeshare trips are also generated in the southwest of San Francisco after Phase 3, where there are no bikeshare stations, and transit service was reduced (Fig. 3), which is due to the physical flexibility of dockless bikeshare. This insight brings an important policy or operation suggestion that city urban areas may focus more on docking-station-based systems while suburban areas can leverage dockless systems to enrich mobility options there.

There is still uncertainty for whether these trends observed are temporal or will be permanent during the post-pandemic period. In order to retain those casual users and keep replacing more vehicle trips with longer bikeshare trips, bikeshare operators need to monitor the change in their user profiles and identify the critical factors causing this trend. Then, targeted membership incentives or corresponding operation strategies can be adopted to keep this trend when some factors, e.g., health risk, do not exist in the future.
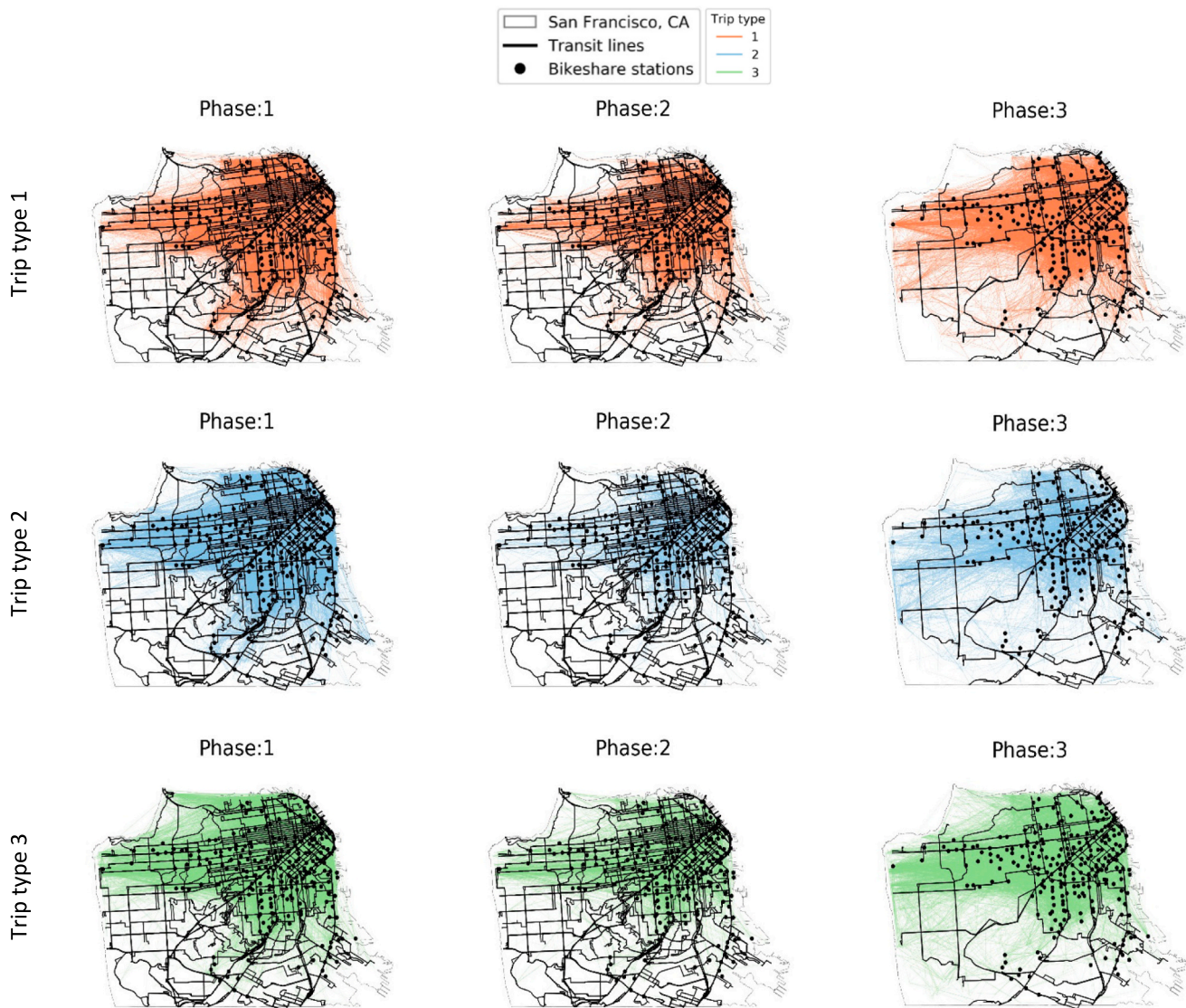
Fig. 16. Spatial distribution of bikeshare trips.

6.2. The relationship between bikeshare and transit

In this study, the flexibility of bikeshare and the resilience it provides in the context of disruptions (e.g., the virus pandemic), could help it grow in popularity in areas where transit services are limited or unavailable. There was a certain proportion of transit users switching to alternative modes including bikeshare due to safety considerations (Haque & Board, 2021). After the change in transit service, that proportion grew, especially among those who had no other mode besides transit previously. The result is similar to what Saberi et al. (2018) discovered in London (UK) during a public transit disruption, Wang and Noland (2021) found in New York City (USA), and Kim and Cho (2021) uncovered in Seoul (Korea) during this pandemic. These changes demonstrate the potential of bikeshare to improve the resilience of urban transportation systems, which can provide an international reference other than only for San Francisco. The studies by Wang and Noland (2021) and Kim and Cho (2021) draw a similar conclusion after examining the bikeshare activities during this pandemic. Besides, the expansion of bikeshare service in the southwest of San Francisco shows that shared micro-mobility can take a timely reaction during unexpected disruptions, e.g., transit service shutting down. The consistent trip

activities in those areas indirectly prove that rebalance operation happens there to meet those emerging demands. However, the study by Jobe and Griffin (2021) found that more communication between bikeshare operators and local communities is needed to make residents more aware of the operation. Especially, low-income populations may have limited access to smartphones and the internet. Thus, it is critical to timely inform them of this emerging mobility option. Due to the limitation of data sources, we cannot estimate the proportion of users from low-income or disadvantaged groups, who joined after the outbreak.

Different from previous research, this study directly uncovers how the distance between transit stops and bikeshare stations will boost the process of bikeshare substituting transit. The average distance between bikeshare stations and transit stops increased significantly after transit services were affected. This caused more bikeshare trips to switch from transit feeding into transit substitution. As indicated by Fig. 15, if residents are less willing to walk a long distance, e.g., over 400 m, approximately 30% of bikeshare trips cannot be replaced with transit trips. Considering the flexibility of bikeshare, e.g., trip start time or arrival time, and a much shorter trip time compared with transit (Fig. 14), this proportion could be higher. This phenomenon leads to suggestions for both transportation agencies and bikeshare operators.

Table 6
The spatial similarity between the distributions of bikeshare start/end locations and transit stops.

Phases	Trip types	Docking-station-based (1) or not (0)	Wasserstein metric value			
			Trip during 0 am–12 pm		Trip during 12 pm–24 pm	
			Trip start	Trip end	Trip start	Trip end
1	1	1	2.86	2.68	3.34	3.35
		0	2.76	2.97	3.09	3.09
	2	1	–	2.90	–	3.09
		0	2.64	2.62	2.78	2.75
	3	1	2.75	2.60	2.62	2.60
		0	2.41	2.44	2.55	2.53
2	1	1	2.45	2.40	2.42	2.37
		0	2.05	2.28	1.93	2.18
	2	1	–	2.43	–	2.41
		0	2.43	2.45	2.25	2.18
	3	1	2.33	2.25	2.18	2.03
		0	2.18	2.22	1.85	1.88
3	1	1	2.34	2.27	2.21	2.14
		0	**1.19**	1.66	**1.21**	1.49
	2	1	–	1.93	–	1.88
		0	1.72	1.62	1.47	**1.36**
	3	1	2.26	2.21	2.04	1.93
		0	1.41	**1.48**	1.94	1.55

Note: "–" means there is no bikeshare trip in this category. Numbers in red and bold are the smallest EMD.

Transportation agencies can require bikeshare stations closer to transit stops and allow greater service areas for bikeshare operators. Bikeshare operators can target this transit service gap by adding more dockless bikes/e-scooters or releasing restrictions on bike/e-scooter parking, e.g., no penalty fee for parking at public racks.

Envisioning the near future, we may leverage this fact to promote more bikeshare services in sub-urban areas or areas with limited transit services. Basu and Ferreira (2021) pointed out the critical points that we need to provide bicycle infrastructure and regulatory support for cycling to keep this trend. Combs and Pardo (2021) found that there is a trend of reallocating traffic lanes to walking and cycling during this pandemic. To take this chance to promote bikeshare activities in areas with limited mobility options, we also need to investigate more on bicycle infrastructure there, not to replace transit with bikeshare but to complement transit. Local governments may also consider promoting shared micro-mobility combined with on-demand transit services in areas where fixed-route transit is unavailable, the walking distance to transit services is very large, or disadvantaged populations resident.

6.3. The research limitations and future research directions

However, this research has several limitations, including its lack of access to real trip purpose data. In the future, one short question could appear in users' smartphones after every trip to collect their trip purposes since most of the bikeshare trips are reserved through cellphone APPs. With such information, this and future studies could develop a more accurate spatial and temporal correlation between transit ridership and bikeshare trips. Moreover, this study could further analyze how bikeshare serves traditional transit "desert" areas. Second, there is no information on whether the bicycles used were electric or not. As noticed in a study by Qian et al. (2020), electric bikes can help extend the service areas of bikeshare systems. The emerging technologies, e.g., electric bikes and e-scooters, could change the existing relationship between shared micro-mobility and transit, which could be an interesting research direction for the future. Lastly, whether populations from disadvantaged communities take advantage of share micro-mobility services during unexpected public transit disruption remains unclear. Further research in this direction can help understand the relationship between transportation equity and transport system resilience.

CRediT authorship contribution statement

Xiaodong Qian: Conceptualization, Methodology, Data curation, Writing-Original draft preparation, Visualization.
Miguel Jaller: Conceptualization, Methodology, Supervision, Writing-Reviewing and Editing, Funding acquisition.
Giovanni Circella: Conceptualization, Supervision, Writing-Reviewing and Editing, Funding acquisition.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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