Mobility patterns before, during and after the COVID-19 pandemic in Singapore

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***Abstract*—Human mobility has been significantly affected by COVID-19 and associated travel restrictions imposed by government policies. This study examines changes in mobility patterns in Singapore during different stages of the pandemic using mobile phone data. Our results indicate that population mobility decreased over the COVID pandemic and is slowly increasing after the restrictions were lifted. However, there have been changes in the mobility patterns of the population. Despite the easing of COVID-19 measures, the population is making fewer trips and the trip distances are longer for some people. This change may be attributed to several factors. One of which is that the population has not quite come back to the pre-COVID working routine and has adopted a semi-work-from-home policy, where the staff is working in the office for a few days a week. The other factor is the habit of making more "purposeful" trips remains. Further, we investigate changes in mobility patterns among the classified explorers and returners. The results demonstrate that the change in mobility has a similar trend to the population as a whole. These observed changes in mobility patterns may become the new normal and should be taken into account for traffic management, business decision-making, policy-making, and urban or transport infrastructure planning.**

***Index Terms*—Human mobility, COVID-19 pandemic, mobile phone data, change in mobility, mobility classification**

I. Introduction

Human mobility plays an integral role in human life covering significant impacts on the spreading and control of diseases [1], [2], traffic volume [3], building intelligent transportation systems (ITS) [4] and shaping the form of cities [5]. Therefore, understanding human mobility is pivotal to studies of various fields ranging from urban planning to transport engineering [6]. [7].

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In recent years, the global impact of the Coronavirus disease (COVID-19 pandemic) caused by the Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV-2) virus has been substantial, affecting mobility patterns worldwide [8]. Numerous studies have shown that the COVID-19 pandemic has negatively affected the physical activity level of people worldwide [9]. Locally, the Singapore government has implemented measures throughout the years 2020 to 2022, such as social distancing, unnecessary travel banning, the closure of borders, working-from-home measures, and restriction of social gatherings outside of the household. These measures have direct and immediate impacts on individuals' mobility patterns [10]. However, the change in mobility in the Singaporean context has not been thoroughly investigated.

To bridge the gap, the present study aims to analyze the changes in mobility patterns and trends in Singapore to provide insights for a range of informed decision-making from business processes to government policy, e.g., location-based service, traffic management, and urban infrastructure planning. To achieve this goal, we analyze mobility across selected months of 2019, 2020, and 2022 using large-scale mobile phone data, to identify the changes in mobility trends and patterns before and after the local COVID-19 pandemic mobility restrictions. In addition, we identify patterns and trends specific to user types by classifying users into two categories: "explorers" and "returners", which helps us to recognize different patterns and trends in travel behavior and enable tailored mobility solutions to specific user needs.

II. Methodology

A. Data

For the mobility analysis, we make use of mobile phone data. The data set is from a commercial company, CITY-DATA.ai [11]. Three months of data are adopted in this paper: September 2019, September 2020, and June 2022, which correspond to the before, during, and after the COVID-19

TABLE I: Number of users in the data set

Data set	No. users after processing
Sep 2019	104,919
Sep 2020	121,246
Jun 2022	68,884

pandemic period, respectively. Location information of users is collected through various Apps such as social media Apps and gaming Apps mostly with a for-ground mode. The raw data are anonymized for privacy consideration. The raw data includes the anonymized user id, timestamp, location information, and GPS signal horizontal accuracy.

B. Data pre-processing

To prepare the data for analysis of human mobility, several pre-processing steps were conducted. First, for each data set, only the data points within Singapore were extracted, which contains 30 days of data for each month. Subsequently, the data points with low GPS signal accuracy were then discarded if the accuracy was lower than 250 m. Next, only the active users were selected as some users might have too few records to provide meaningful information. An active user is defined as a user who has at least one daily record for more than 5 days and has more than 120 records in a month.

The study area, Singapore, was partitioned into a regular grid of identical-sized cells measuring 250 m $\times$ 250 m, which aligns with the GPS accuracy threshold [12]. Each record was associated with a cell number which indicates the location of the grid cell. This removed the effect of noise due to GPS signal offset without compromising the granularity of the data.

C. Stay location detection

To obtain the stay locations of the users, detecting the stays made by the user is necessary [12]. The identification of stay locations is critical to identify trips (see Section III-D). In this paper, we defined a stay location as when a user spends at least 10 minutes within 500 m of spatial radius from a particular point. The choice of a 500 m threshold allows for GPS inaccuracies to be accounted for, while also avoiding misclassification of trips within the same neighborhood as stay locations.

D. Home detection

For each user in the data set, the home location (i.e., home cell) was then identified. The home location of a user was determined by finding the cell where he/she cumulatively spent most of the time from 8 p.m. to 7 a.m. in a month [12], [13]. Table I summarizes the number of users included in data after this processing step. In addition, the detected home locations using mobile phone data are validated with the census data [14], and a comparison of home locations between the two is presented in Fig. 1, demonstrating a high level of consistency.

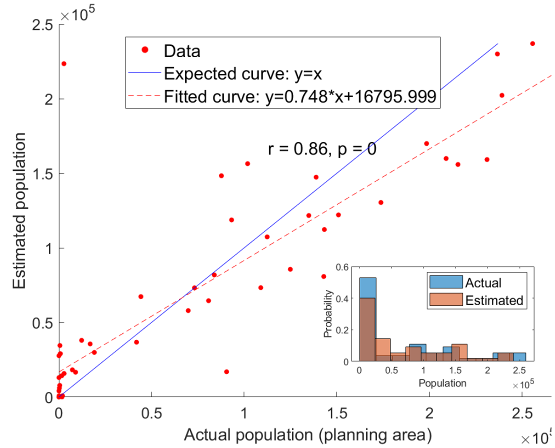

Fig. 1: Comparison of mobile phone data and census data (Sep. 2019).

III. Change in Mobility

A. Mobility metrics

To comprehend the shifts in mobility, mobility indicators are required to quantitatively assess human mobility and gain insights into collective mobility patterns [15]. In this paper, we choose three relevant mobility indicators to analyze changes in mobility, namely maximum displacement from home [16], trip frequency [17], and radius of gyration [18] for the sake of simplicity. The radius of gyration is a metric that measures how far an object travels from its center of gravity, which is used to evaluate the characteristic distance traveled by a user over a given time period [19], [20]. It is calculated by taking the root mean square distance of all other points visited by the user from the center of mass of the user's trajectory.

B. Mobility away from home

Firstly, we look at mobility away from home. The purpose is to examine the evolution of mobility outside of the immediate community along different stages of COVID-19 as the social distancing measures affect the activities of people [9]. While, short trips within the community, for example, where users buy food from a nearby food court, are not discussed here.

A threshold of 1 km is set to sufficiently accommodate the variations between acceptable walking distances to quantify displacement far enough from home [21]. The percentage of users that travel 1 km away from home is presented in Fig. 2. Generally, in comparison to 2019 (i.e., pre-pandemic), both 2020 and 2022 show a reduction in the percentage of users who traveled further away from their home locations. Even with most COVID-19 pandemic mobility restrictions lifted in June 2022, the proportion of users that went out more than 1 km from their homes remained slightly lower than that of September 2019, suggesting that the impact of mobility restrictions on user habits persisted over time.

These findings suggest that mobility levels have not fully returned to pre-pandemic levels. A possible explanation is that the population has not fully reverted to pre-COVID

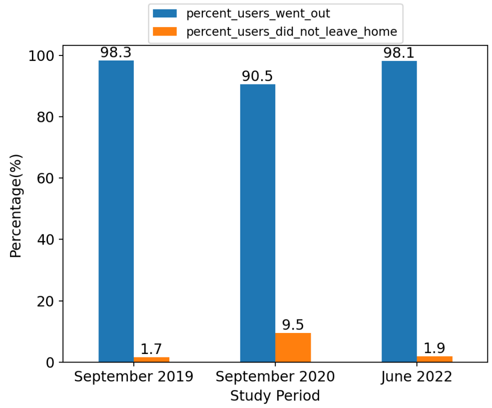

Fig. 2: Proportion of users that traveled >1 km and those who stayed within 1 km from the home location.

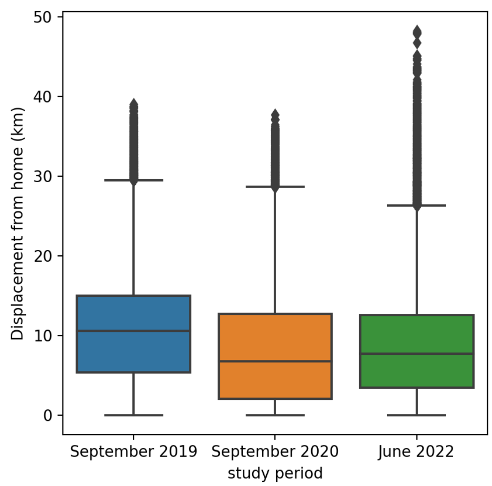

Fig. 3: Trip distance from home.

working routines and has adopted a semi-work-from-home policy, where the staff is working in the office for a few days a week. This may be particularly true for work-related mobility. For example, recent reports suggested that flexible work and hybrid working arrangements are becoming more common in Singapore despite the easing of COVID-19 measures [22].

C. Trip displacement from home

The impact on mobility is more profound when investigating the distribution of displacement from home, as shown in Fig. 3. September 2019 witnessed the highest median, with a reduction in September 2020 and an increase in June 2022 but it did not return to what it used to be in pre-pandemic levels. It is also observed that June 2022 sees a more varied level of maximum displacement from home with more outliers traveling further away from their home locations. An explanation is that the habit of making more "purposeful" trips still remains after the pandemic.

TABLE II: Average number of trips

Data set	Weekday	Weekend
Sep 2019	4.10	4.05
Sep 2020	2.62	2.65
Jun 2022	3.20	3.15

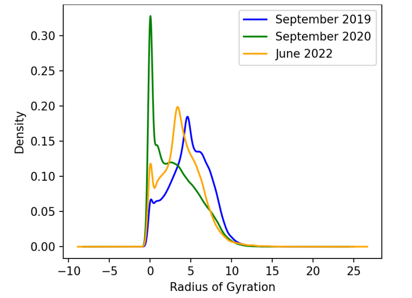

Fig. 4: Distribution of the radius of gyration

D. Trip frequency

The number of trips is investigated in this section. For each individual, a trip is counted between two consecutive stays. To better understand travel behavior, the data were divided by weekdays and weekends. Table II depicts the average trip frequency for weekdays and weekends. Interestingly, the results indicate a similar trend for weekdays and weekends. Nevertheless, mobility on weekdays suffers a larger negative impact from COVID-19 but recovers faster, compared with mobility on weekends.

E. Radius of gyration

The radius of gyration (ROG) is formulated as

$$r_g(x) = \sqrt{\frac{1}{n_x}\sum_{i=1}^{n_x} dist\big(r_i(x) - r_c(x)\big)^2} \tag{1}$$

where $r_g(x)$ is the ROG of individual x, $r_i(x)$ and $r_c(x)$ denote the i^{th} of n_x positions recorded for individual x and the center of x's trajectory, respectively.

Fig. 4 plots the distribution of radius gyration of the 3 periods of study. From Fig. 4, comparing the peaks at the smaller radius of gyration, we observe that September 2020 and June 2022 see more users with small radii of gyration, which means that in these two months, users tend to travel between locations that are close to one another as compared to September 2019. This could be a manifestation of users making their trips more purposeful by visiting nearby locations to complete their errands.

F. Comparison with Google Mobility Reports

To further validate our findings, we compared the Google COVID-19 pandemic Community Mobility Report [23]. The Google COVID-19 pandemic Community Mobility Report for Singapore provides data to show the changes in mobility to six different place categories. As both the baseline period (i.e., 5-week period of Jan 3 – Feb 6, 2020) and the 2019 study period in this report are before mobility restriction periods, it

TABLE III: Mean change in mobility from baseline based on Google mobility data

Place category	Mean change from baseline (%)	
	Sep 2020	Jun 2022
Retail & recreations	-19.23	-8.73
Grocery & pharmacy	1.93	-3.93
Parks	-17.40	-10.73
Transit stations	-31.27	-15.10
Workplaces	-20.00	-9.00
Residential	16.07	9.17

is rational to assume that the mobility level of the baseline is representative of the mobility level of the 2019 study period.

According to Table III, we see that mobility has decreased from the baseline in September 2020 across all place categories except residential as more people are staying at home due to mobility restrictions. In June 2022, even as the percentage of mobility change has increased from September 2020, all the place categories except residential still experience a gap in mobility levels from pre-pandemic levels.

Summarizing the findings above, we can infer that mobility levels have yet to return to pre-pandemic levels and there are some changes to mobility patterns that differ from pre-pandemic periods. Additionally, the results obtained are coherent with the findings from the Google Mobility Reports.

IV. Mobility classification: user type

A. Mobility classification

Rather than combining various user mobility patterns into a single class, mobility classification can help to segment users into groups that have common traits and might be modeled similarly [24]. More importantly, user classification enables us to understand the change in mobility for different groups.

Several methods of user classification have been explored in the studies. For example, the authors in [18] proposed the classification of users into returners and explorers by the radius of gyration of users. Returners have a radius of gyration dominated by recurrent movement between a few preferred locations while explorers have the tendency to move between a large number of locations. The bisector method was applied in [18], which was based on the k-radius of the gyration factor defined as

$$r_g^{(k)}(x) = \sqrt{\frac{1}{n_k}\sum_{i=1}^{n_k} dist\big(r_i(x) - r_c^{(k)}(x)\big)^2}. \qquad (2)$$

For user classification, we adopted the bisector method proposed in [18], where the population was divided into two classes. More specifically, we choose $k = 2$ for the k-radius of the gyration factor, which indicates that returners would be defined as users whose trajectories are dominated ($>= 50\%$) by the two most frequented locations. The reason for this choice is to aid the study of the effects of mobility changes, especially during weekdays when users in Singapore would most likely travel between home and work locations.

In addition, the K-means clustering method [24] was also used for user classification, according to the ratio of k-radius

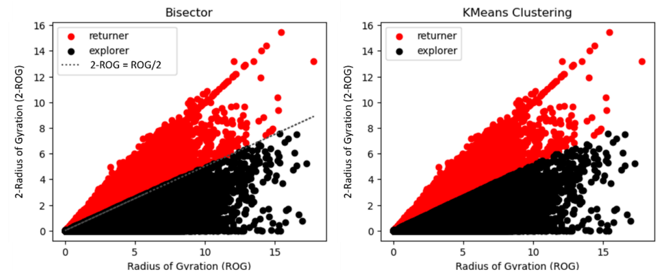

Fig. 5: Classification of returners and explorers of k=2 using bisector method and K-means clustering method.

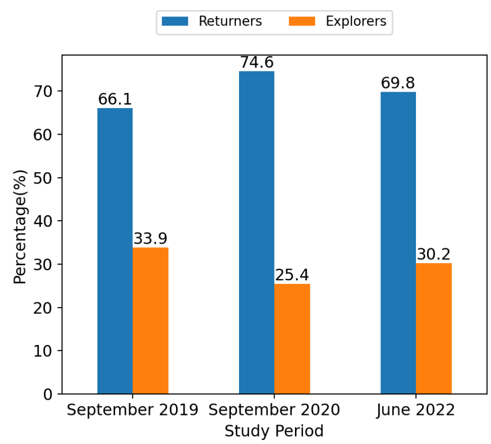

Fig. 6: Proportion of returners and explorers.

of gyration and total radius of gyration [24], i.e., $s_k = \frac{r_g^{(k)}(x)}{r_g(x)}$. The ratio quantifies the influence of an individual's recurrent mobility on the individual's overall mobility. The higher the ratio, the greater the weight of the top k locations in the trajectories of an individual. The results in Fig. 5 demonstrate that the two classes are clearly separated and well-defined and the two classification methods produce similar results.

B. Percentages of returners and explorers

From Fig. 6, we can see that in 2019, there are more users traveling to many other places beyond just their home and work locations during the pre-pandemic period. In the case of 2020, the high number of returners could mean that the 2 most frequented locations may be the place they run errands and their home locations instead of work and home location as default remote working measures were in place. In June 2022, we observe an increase in the number of explorers from 2020. In general, the increase in the percentage of returners and the decrease in the percentage of explorers from 2019 to 2022 means that the users' trajectories are concentrated between 2 locations, with lesser users venturing to more locations. This is consistent with our findings in section III.

C. Mobility of returners and explorers

To examine if explorers visit more locations, we visualize the probability of daily distinct locations by returners and explorers in Fig. 7. From Fig. 7, it is not hard to see that for

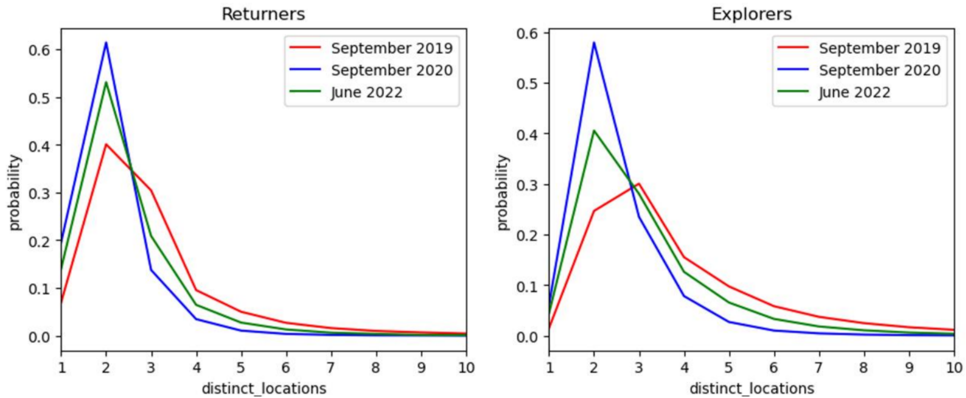

Fig. 7: Distribution of the number of distinct locations.

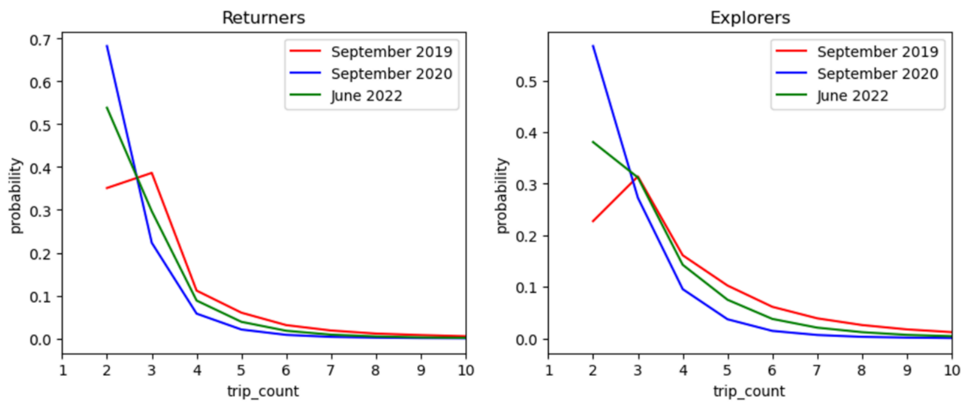

Fig. 8: Distribution of the number of trips. Here the users who stay at home are not counted.

both returners and explorers, daily distinct locations visited decreased from 2019 to 2022. In general, there is a higher probability of an explorer visiting more distinct locations as compared to a returner, which is in line with our expectations.

In Fig. 8, we present the number of daily trips of returners and explorers, respectively. Overall, comparing June 2022 and September 2019, it is obvious that lesser daily trips were made in June 2022. Similarly, a comparison between returners and explorers shows that explorers have a higher daily trip count compared to returners. This is as expected as explorers are classified as users whose movements are not dominated by the 2 most frequented locations and it is inherent that explorers would make more trips as they possibly visit more locations.

Although the results of the brief analysis of returners and explorers in this section give us similar overall conclusions for both types of users. However, it is worthwhile to note that categorizing users into returners and explorers can be a valuable approach for future analyses as it can enable the identification of potential differences between them across various measures.

D. *Practical implications*

This paper investigates the changes in mobility at different stages of the COVID-19 pandemic. This study suggests that the mobility patterns have been changed and mobility levels have not returned to pre-pandemic COVID-19 levels. The emergence of these new mobility patterns may represent a "new normal" that should be taken into consideration in the planning of transport infrastructure, business processes, and policy-making. Specifically, for planning urban infrastructures and operating public transport (or taxi fleet), it is significant to understand the change in mobility patterns. In addition, it is suggested that implementing a hybrid working mode may be a promising solution to reduce travel demand, so as to alleviate traffic congestion and enhance the level of service of public transport (e.g., reduce crowding on public transport), especially for countries like Singapore where public transport is the most commonly used mode of transport. As such, policies and incentives can be deployed to encourage the adoption of hybrid working arrangements, which in turn can reduce the demand for workplaces. Additionally, this study also provides valuable insights into the decision-making of business processes, particularly for those that are highly affected by human mobility.

V. Conclusions

Through analyzing the changes in mobility across the three indicated months in 2019, 2020, and 2022, we found that the level of mobility has not reached pre-pandemic 2019 levels, even though mobility has increased after the easing of COVID-

19 travel restrictions. This could be because individuals are used to the new mobility habits that could have developed from mobility restrictions and stay-at-home mandates, which caused them to make more purposeful trips once they have traveled out of their homes, reducing the need to make multiple trips to multiple locations.

This study, however, is subjected to some data limitations. As the data recording mode is mostly foreground and the recording is limited by the phone permission of each user, records of users in the data tend to have low and uncertain frequencies. The sparseness of data makes it difficult to identify the exact trajectory of users. In addition, the data coverage is still limited, which can be augmented with mobility models such as TimeGeo [25]. This will be of great significance for a more comprehensive mobility evaluation of the whole population and a more in-depth modeling of travel behavior.

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