Exploring the utility of Google(R) Mobility data during COVID-19 pandemic: A digital epidemiological analysis from India.

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Abstract

Background: Association between human mobility and disease transmission for COVID-19 is established, but quantifying the levels of mobility over large geographical areas is difficult. Google released Community Mobility Report (CMR) data collated from mobile devices and gives an idea about the movement of people.

Objective: Therefore, we attempt to explore the use of CMR to assess the role of mobility in spreading COVID-19 infection in India.

Methods: An Ecological study analyzed CMR for human mobility. The data were compared for before, during, and after lockdown phases with the reference periods. Another dataset depicting the burden of COVID-19 after deriving various disease severity indicators was derived from a crowd-sourced Application Programming software. The relationship between the two datasets was investigated using Kendall's tau correlation to depict the correlation between mobility and disease severity.

Results: At the national level, mobility decreased everywhere except residential areas during the lockdown period, compared to the reference period. Mizoram (minimum cases) depicted a higher relative change in mobility than Maharashtra (maximum cases). Residential mobility negatively correlated with all other measures of mobility. The magnitude of correlations for intra-mobility indicators was comparatively low for the lockdown phase compared to other phases. A high correlation coefficient between epidemiological and mobility indicators is observed for the lockdown and unlock phases compared to the pre-lockdown.

Conclusions: We can use mobile-based open-source mobility data to provide the temporal anatomy of social distancing. CMR data depicted an association between mobility and disease severity, and we suggest that this technique supplement future COVID-19 surveillance. Clinical Trial: NA

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With regards

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Abstract

Background

Association between human mobility and disease transmission for COVID-19 is established, but quantifying the levels of mobility over large geographical areas is difficult. Google released Community Mobility Report (CMR) data about the movement of people collated from mobile devices.

Objective

To explore the use of CMR to assess the role of mobility in spreading COVID-19 infection in India.

Methods

An Ecological study analyzed CMR for human mobility between March - October 2020. The data compared before (Between 14th -25th March 2020), during (25th March – 7th June 2020), and after lockdown (8th June 2020 - 15th October 2020) phases with the reference periods, i.e. (3rd January 2020 - 6th February 2020). Another dataset depicting the burden of COVID-19 as per various disease severity indicators was derived from a crowd-sourced Application Programming software. The relationship between the two datasets was investigated using Kendall's tau correlation to depict the correlation between mobility and disease severity.

Results

At the national level, mobility decreased from -38% to -77% for all but residential areas (an increase of 24.6%) during the lockdown compared to the reference period. At the beginning of unlocking, the state of Sikkim (minimum cases- seven) with a -60% reduction in mobility depicted more mobility compared to -82% in Maharashtra (maximum cases-1.59 million). Residential mobility negatively correlated (-0.05 to -0.91) with all other measures of mobility. The magnitude of correlations for intra-mobility indicators was comparatively low for the lockdown phase (corr ≥ 0.5 for 12 indicators) compared to other phases (corr ≥ 0.5 for 45 and 18 indicators in pre-lockdown and unlock phase, respectively). A high correlation coefficient between epidemiological and mobility indicators is observed for the lockdown and unlock phases compared to the pre-lockdown.

Conclusions

We can use mobile-based open-source mobility data to assess the effectiveness of social distancing in mitigating the disease spread. CMR data depicted an association between mobility and disease severity, and we suggest that this technique supplement future COVID-19 surveillance.

Keywords

COVID-19; Lockdown; Non-pharmaceutical Interventions soc;ial distancing; digital surveillance; Google community mobility reports; Community Mobility.

Manuscript

Exploring the utility of Google(R) Mobility data during COVID-19 pandemic: A digital epidemiological analysis from India.

Introduction

Infectious diseases have caused profound disruptions throughout the history of humanity. Despite a fall in the number of deaths attributed to contagious diseases, there is a constant rise in the number of outbreaks over the past few years due to emerging and re-emerging infectious agents.[1] Influenza, dengue, and HIV/AIDS have been the three leading contagious diseases that have infected millions globally.[2] Apart from them, approximately 215 different infectious agents have caused 12,102 outbreaks in 219 countries over the last 30 years.[3] In general, there are significant advances in treatment and cure for infectious diseases. However, infectious diseases pose a considerable challenge to the health system due to their frequency, infectivity, and mobility in today's extensively interconnected world. Therefore, early detection and prevention of infectious diseases continue to be a top priority among the global health community.

The current Coronavirus disease (COVID-19) pandemic has disrupted and overwhelmed global health preparedness. It is an infectious disease caused by a newly discovered coronavirus, and the main route of transmission is thought to be through respiratory droplets [4]. The index case of COVID-19 was traced to 1st December 2019, in Wuhan, China.[5] The aggressive nature of COVID-19 spread led to its declaration as a "public health emergency of international concern" and then pandemic by World Health Organization (WHO) on 30th January and 11th March 2020. As per the WHO, 216 countries reported more than 121 million cases and 2.6 million deaths due to COVID-19 as of 17th March 2021 [6]. There were 11.4 million confirmed cases in India alone, with 0.16 million deaths, and it is amongst the worst affected countries to date[7]. Due to a lack of effective treatment strategy, non-pharmaceutical interventions (NPIs), such as restricted mobility, home quarantine, and lockdown measures, were enforced worldwide to halt inter-human transmission of the virus.[8] Being the second-most populous country of the world - with sub-optimal investment - NPI was seen as the most crucial part of pandemic mitigation. Hence, the Government of India also implemented a country-wide lockdown to halt disease progression on 24th March 2020[9].

Research has demonstrated the association between mobility and disease transmission for various infectious diseases such as cholera, dengue, influenza, Ebola, malaria, measles, and COVID-19 [10–17]. NPIs are intended to slow down the rapid disease transmission and contain the disease burden until effective pharmacological management options become accessible [18,19]. Implementing NPI in response to infectious disease outbreaks is not a new method to limit mobility and is being used for centuries.[20,21] More recently, such measures were implemented during the containment of SARS and MERS epidemics, which occurred in the last decades.[22,23]

Although the connection between mobility and disease has been known for centuries, establishing such a causal association is challenging, as measuring and quantifying the levels of mobility at the population level is difficult. This can be attributed to surmounting challenges in getting access to mobility and disease data. However, numerous mathematical models have demonstrated such associations between mobility and infectious disease transmission dynamics.[24–26] But, during the current pandemic, the digital ecosystem has supplemented the traditional surveillance to provide data about disease severity and mobility in real-time.

Given the highly infectious nature of COVID-19, the importance of digital epidemiology could be felt in disease containment.[24–27] Digital Epidemiology is a branch of epidemiology that utilizes data generated outside the public health system[28]. Google flu® and Google Trends® have successfully studied various communicable and non-communicable diseases[29,30]. On similar lines, Google released Community Mobility Report (CMR) data collated from those accessing its applications using mobile and handheld devices. The restriction in mobility by the Indian government and the data availability provides researchers an opportunity to empirically study the relationship between social activity, mobility, and COVID-19 incidence. However, there is a shortage of scientific literature that has documented the use of such data for surveillance purposes. Very few have tried to correlate the mobility trends with the disease aggressiveness[31–34]. Sulyok M depicted negative correlations between CMR data and case incidence for major industrialized countries of Western Europe and the North Americas[31]. Wang H also depicted that model utilizing CMR data can describe the combined effects of mobility at the local level and human activities on the transmission of COVID-19[32]. Cot C et al. analyzed Google and Apple mobility data. They concluded a substantial decrease in the infection rate occurring two to five weeks after the onset of mobility reduction[33]. None of these studies explored the association of mobility with any other epidemiological indicators except disease incidence, when it has been established that just disease incidence is not an ideal measure for making comparisons[35]. Therefore, in the present study, we attempt to understand and explore mobility's role in spreading COVID-19 infection in India using mobility data from Google. During the pandemic, the central government has issued various health advisories, but since health is a state subject, the final implementation of those instructions depends on the state itself. Therefore, we hypothesize that the states with strict enforcement of lockdown would witness fewer cases and vice versa. Hence, we have also examined the states with a maximum and a minimum number of cases for changes in mobility as per CMR.

Methodology

Study design

An Ecological Study analyzed the secondary data available in the public domain between 14th March 2020 and 16th October 2020.

Study period

Many interventions were implemented at the national and sub-national during the lockdown period and were subsequently eased out in a phased manner. To begin with, India issued travel advisories and restricted international travel between January and March 2020. By early March, when cases started increasing, states scaled up movement restrictions. On 25th March, India went into a nationwide lockdown to ramp up preparedness.[36] The assessment of mobility data was done for three significant periods, based on the implementation of the social mobility restrictions by the Indian government to mitigate the pandemic [37]. Robust data for COVID19 disease burden was available in the public domain from 14th March, 2020. Hence, the three phases were labeled as the pre-lockdown (14th March - 24th March 2020), during lockdown (25th March, 2020-7th June 2020), and unlock (8th June 2020-15th October 2020).

Data sources

COVID-19 data: The datasets for COVID-19 cases in India are crowd-sourced and made freely available through Application Programming software (API) by a volunteer group. The API maintains the records of confirmed, active, recovered, and deceased records for all the Indian states and Union Territories (UT). The data in the API is gathered using state bulletins and official handles daily. After data validation, the same is available daily through google sheets.[7]

Mobility data: Google® collects and stores individuals' commuting information through a global positioning system (GPS) linked to google maps. This data has been made available online in the public domain after aggregating and anonymizing personally identifiable information as "COVID-19 Community Mobility Reports" (CMR) (**Appendix 1**).[38] The CMR compares the changes in activity and mobility during and after the lockdown compared to before lockdown. At the start of the study, the mobility data for 135 countries were available from Google®. The mobility data for India has been made available at states and union territories (UTs) levels since 15th February 2020.

Appendix 2 entails further details about this website. CMR provides the percentage changes in activity for six key categories (grocery and pharmacy, parks, transit stations, retail and recreation, residential, and workplaces) compared to baseline days before the advent of COVID-19 (5 weeks running from 3rd January 2020 to 6th February 2020)[39]. Daily activity changes are compared to the corresponding baseline figure day. For example, data on Monday being compared to corresponding data from the baseline series for a Monday. Baseline day figures are calculated for each day of the week for each country and are calculated as the median value.[38] The values represent the relative change in percentages compared to baseline days, not the absolute number of visitors. For instance, the -50 value in the workplace dataset on a Monday tells a 50% drop compared to the Monday in the reference period. Similarly, a positive value indicates the increase in mobility as compared to the reference period.

Primary outcome variables and covariates

The frequency of daily infected cases, deaths, and recovered cases were our study's primary variables. The disease burden data for India by individual states and Union Territories were depicted in Cases per million (CPM), Case Fatality Rate (CFR), and Doubling Rate (DR) that were calculated using the standard formulae.[40–42] We used the census population data of different states of India as a reference.[43] The mobility indicators pointing towards disease spread were the covariates of interest. CMR provides data for six mobility indicators used as covariates which give information on people's movement. It was significant to assess the variability in the mobility of the people during the unlocking phase in response to the case-load of each state during the lockdown. For the principle of parsimony, we report the frequency of cases using the median (min-max) value for the states with the maximum and minimum cases.

Data analysis

We downloaded the mobility and COVID-19 data in the ".CSV" format on 16th October 2020 and replaced the state codes for India COVID-19 data with state names using metadata. The mobility data at the national and states levels were filtered and stored. Subsequently, we merged mobility and COVID-19 data for India and respective states and union territories s by using the date variable and created a new spreadsheet. Finally, we arranged data for analysis in separate spreadsheets for further data analysis for the national and state levels. Subsequently, the relationship between mobility and COVID-19 spread for pre-and post-unlock phases was investigated using Kendall's tau correlation. It is more general and consistent with the ranking system and is the proportion of concordant pairs minus the discordant pairs. Tau ranges from +1 to -1 for identical and opposite ranking pairs, respectively. Since it is an initial empirical investigation of the relationship between mobility and epidemiological indicators, the emphasis is on the correlation's magnitude rather than the p-value. Further, we calculated and reported 95% CI with all the point estimates to give the readers an idea about the estimates range.

Results

Disease burden during different phases of lockdown

The line graphs display the mobility trend and rise in the number of cases during these phases (Figure 1). At the end of phase 1, i.e., just before the national lockdown, cumulative cases, cumulative death, and cumulative recoveries throughout India were recorded to be 567, 40, and 10. The lockdown was enforced for 75 days till 8th June 2020, but the surge in the cumulative case-loads continued (Table 1). This was followed by sequential unlocking that witnessed a further surge. As of 15th October 2020 (2nd unlock phase), the reported number of cumulative cases, cumulative death, and cumulative recoveries in India crossed 7.5 million, 0.1 million, and 6.6 million, respectively, with marked inter-state variations.

Disease Severity/Epidemiologic Indicators

Table 2 presents crucial epidemiologic indicators that estimate disease burden in terms of CPM, DR, and CFR of COVID-19. CPM increased to 40 (36.6-43.3) at the national level by the end of unlock-phase 3. The disease doubling rate also increased to 33.4 (30.3-36.5), while CFR -a vital indicator of the severity of the disease in an epidemic-drops to 2.3% (CI; 1.9% to 2.6%) on 15th October 2020. The state of Punjab 4.6% (CI; 4.0% to 5.3%) and Maharashtra 4.1% (CI; 3.4% to 4.8%) reported the highest CFR. Whereas Mizoram, Lakshadweep and Daman, and Diu reported nil CFR.

Figure 1: Line diagram depicting COVID-19 cases and mobility trends for India from 14-03-2020 till 14-10-2020.

Table 1: State-wise burden (cumulative total) of the Coronavirus disease (COVID-19) pandemic in India during the different phases of the lockdown (March- October 2020).

ponse to the demic	**Pre-lock** (Before 25th March 2020)			**Lockdown** (25th March – 7th June 2020)			**Unlock** (8th June 2020 - 15th O	
atus	C	D	R	C	D	R	C	D
	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)
	567(100)	10(100)	40(100)	257478(100)	7205(100)	123848(100)	7546965(100)	114042(100)
	30(5.3)	1(10)	6(15)	28,936(11.2)	812(11.3)	10,999(8.9)	331,017(4.4)	6,009(5.3)
	30(5.3)	0	11(27.5)	4,448(1.7)	28(0.4)	1,473(1.2)	150,033(2.0)	1,640(1.4)
	29(5.1)	1(10)	0(0)	2,608(1)	51(0.7)	2,106(1.7)	127,154(1.7)	3,999(3.5)
d Kashmir	6(1.1)	0	0(0)	4,087(1.6)	41(0.6)	1,216(1)	87,942(1.2)	1,379(1.2)
nd	4(0.7)	0	0(0)	1,355(0.5)	13(0.2)	528(0.4)	58,024(0.8)	927(0.8)
Pradesh	3(0.5)	1(10)	0(0)	411(0.2)	6(0.1)	219(0.2)	18,967(0.3)	263(0.2)
rh	7(1.2)	0	0(0)	314(0.1)	5(0.1)	274(0.2)	13,646(0.2)	208(0.2)
	13(2.3)	0	0(0)	103(0)	1(0)	50(0)	5,598(0.1)	66(0.1)
a								
lesh	35(6.2)	0	11(27.5)	10,536(4.1)	275(3.8)	6,185(5)	455,146(6.0)	6,658(5.8)
	32(5.6)	0	3(7.5)	10,599(4.1)	240(3.3)	7,754(6.3)	173,266(2.3)	1,747(1.5)
arh	1(0.2)	0	0(0)	1,073(0.4)	4(0.1)	266(0.2)	160,396(2.1)	1,478(1.3)
Pradesh	7(1.2)	0	0(0)	9,401(3.7)	413(5.7)	6,331(5.1)	160,188(2.1)	2,774(2.4)
tra	107(18.9)	2(20)	0	85,975(33.4)	3,059(42.5)	39,314(31.7)	1,595,381(21.1)	42,114(36.9)
	34(6)	1(10)	0	20,097(7.8)	1,249(17.3)	13,643(11)	159,725(2.1)	3,637(3.2)
	0	0	0	300(0.1)	0	65(0.1)	40,587(0.5)	544(0.5)
l Nagar Haveli	0	0	0	20(0)	0	2(0)	3,176(0)	2(0)
d Diu	0	0	0	0	0	0	0	0
radesh	8(1.4)	0	0	4,659(1.8)	75(1)	2,669(2.2)	782,123(10.4)	6,425(5.6)
a	41(7.2)	1(10)	3(7.5)	5,452(2.1)	61(0.8)	2,132(1.7)	765,586(10.1)	9,889(8.7)
du	18(3.2)	1(10)	1(2.5)	31,667(12.3)	272(3.8)	16,999(13.7)	687,400(9.1)	10,642(9.3)
	109(19.2)	0	4(10)	1,915(0.7)	16(0.2)	803(0.6)	341,860(4.5)	1,162(1)
a	37(6.5)	0	1(2.5)	3,650(1.4)	137(1.9)	1,742(1.4)	221,601(2.9)	1,271(1.1)
ry	1(0.2)	0	0	119(0)	0	49(0)	33,143(0.4)	574(0.5)
and Nicobar	0	0	0	33(0)	0	33(0)	4,104(0.1)	56(0)
eep	0	0	0	0	0	0	0	0

gal	9(1.6)	1(10)	0	8,187(3.2)	396(5.5)	3,303(2.7)	0	6,056(5.3)
	2(0.4)	0	0	2,856(1.1)	11(0.2)	1,894(1.5)	268,364(3.6)	1,188(1.0)
	3(0.5)	1(10)	0	5,070(2.0)	30(0.4)	2,405(1.9)	204,212(2.7)	996(0.9)
	0(0)	0	0	1,103(0.4)	7(0.1)	490(0.4)	96,327(1.3)	39(0.7)
	0	0	0	2,682(1.0)	3(0)	637(0.5)	200,607(2.7)	872(0.8)
	0	0	0	802(0.3)	0	192(0.2)	29,465(0.4)	326(0.3)
	1(0.2)	0	0	172(0.1)	0	52(0)	15,463(0.2)	116(0.1)
l Pradesh	0	0	0	48(0)	0	1(0)	13,348(0.2)	30(0)
a	0	0	0	36(0)	1(0)	13(0)	8,404(0.1)	75(0.1)
	0	0	0	116(0)	0	8(0)	7,816(0.1)	21(0)
	0	0	0	7(0)	0	0	3,610(0)	60(0.1)
	0	0	0	34(0)	0	1(0)	2,253(0)	0

Where C: Confirmed cases of COVID-19; R: Recovered number of COVID-19 cases; D: Deceased due to COVID-19

Table 2: Inter-state comparison of the Coronavirus disease (COVID-19) related statistics during the different phases of lockdown in India (March- October 2020).

Phased response to the pandemic	**Pre-lock** (Before 25th March 2020)			**Lockdown** (25th March – 7th June 2020)			U
Status	**CPM**	**DR**	**CFR**	**CPM**	**DR**	**CFR**	
	Mean (95% CI)	**Mean (95% CI)**	**Mean (95% CI)**	**Mean (95% CI)**	**Mean (95% CI)**	**Mean (95% CI)**	**Me**
India	0(0,0.1)	4.1(2.8,5.5)	22.0(0,47.6)	2.5(2,3)	10.6(9.6,11.5)	12(9.7,14.3)	40
North India							
Delhi	0.1(0,0.2)	2.3(0,4.8)	0	20.6(15.6,25.6)	12.6(10.6,14.6)	12.6(7.2,18)	121.
Haryana	0.1(0,0.2)	4.3(0,8.9)	0	2.1(1.3,2.9)	20.9(14.7,27.2)	4.3(0.9,7.6)	38.8
Punjab	0.1(0,0.2)	2.3(0,5.3)	0	1.1(0.7,1.5)	50.8(8,93.7)	12(6.3,17.7)	31.2
Jammu and Kashmir	0(0,0.1)	0.8(0,2.3)	0	4(2.6,5.4)	14.4(12.1,16.8)	5.9(1.7,10.1)	46.3
Uttarakhand	0(0,0.1)	0.5(0,1.3)	0	1.6(0.8,2.4)	11.2(7.6,14.7)	4.8(,0.4,10)	37.9
Himachal Pradesh	0(0,0.1)	0	10.0 (0,32.6)	0.7(0.5,1)	11.5(8,14.9)	2.9(,1.1,6.8)	18.7
Chandigarh	0.5(,0.2,1.2)	0.5(0,1.6)	0	3.5(2.3,4.8)	24.7(12.2,37.2)	8.8(1.2,16.4)	86.5
Ladakh	4.1(,1.7,9.9)	0	0	4.2(1.5,6.8)	3.9(1.4,6.4)	1.6(,1.6,4.8)	143(
Central India							
Uttar Pradesh	0.1 (0.0,0.2)	6.2(3.5,8.8)	0	0.6(0.5,0.7)	13.7(12,15.5)	6.7(3,10.3)	14.1
Rajasthan	0(0.0.1)	2.5(0.7,4.2)	0	1.7(1.5,2)	14.6(12.7,16.5)	7.3(3,11.7)	15.1
Chhattisgarh	0	0	0	0.5(0.3,0.7)	7.4(4,10.8)	0.4(,0.1,0.8)	40.7
Madhya Pradesh	0.1	0.9(0,2.5)	0	1.5(1.2,1.7)	18.2(12.7,23.7)	16.1(10.4,21.8)	13.3
West India							
Maharashtra	0.1(0,0.1)	5.8(3.6,8.0)	33.3(0,87.5)	9.3(7.4,11.2)	10.7(9.4,12)	19.1(14.2,24.1)	92.2(
Gujarat	0(0,0.1)	1.7(0,4.0)	0	4.2(3.5,4.9)	14(11.5,16.4)	22.1(16,28.1)	16.4(
Goa	0	0	0	2.5(0.8,4.2)	6.2(2.5,9.9)	0	191 (
Dadra and Nagar Haveli	0	0	0	0.4 (0.1,0.9)	0.4(,0.1,0.8)	0	25.3
Daman and Diu	0	0	0	0.4(0,0.9)	0	0	38.5
South India							
Andhra Pradesh	0.1	2(0,4.2)	0	1.2(1,1.3)	17.3(14.6,19.9)	7.5(3,11.9)	108.4
Karnataka	0.1(0,0.1)	3.2(0,5.7)	0	1.1(0.7,1.4)	16.5(13,20.1)	8.4(4.2,12.5)	84.6
Tamil Nadu	0	1.2(0,2.1)	0	5.4(4.2,6.7)	11.9(10.3,13.6)	5.1(1.8,8.3)	63.3
Kerala	0.3(0.1,0.4)	4.9(0,9.9)	0	0.7(0.5,0.9)	42.4(26.5,58.4)	2.2(0.5,4)	71.6
Telangana	0.1(0,0.1)	3.3(1.9,4.8)	0	1.2(1,1.5)	34.4(22.3,46.5)	10.9(5.4,16.4)	41.6
Puducherry	0.1(0,0.2)	0	0	1.1(0.6,1.7)	2(0.8,3.2)	0	175.
Andaman and Nicobar Islands	0	0	0	1.1(0.4,1.7)	0.4(,0.2,0.9)	0	73.
Lakshadweep	0	0	0	0	0	0	

East India							
West Bengal	0.1	0.7(0,1.9)	0(0,0)	1.1(0.8,1.4)	9.9(8.6,11.1)	14.5(8.7,20.2)	23.6
Odisha	0.0	0	0	0.8(0.6,1.1)	10.5(8,13)	3.6(0,7.9)	43.1
Bihar	0.0	0.3(0,1)	0	0.5(0.4,0.7)	12.8(9.7,15.8)	1(0.3,1.6)	12(1
Jharkhand	0	0	0	0.4(0.2,0.5)	13.6(9.3,17.9)	2.1(,1.5,5.6)	18.6
Northeast							
Assam	0.0	0	0	1(0.6,1.5)	6.4(4.2,8.7)	4.7(,0.6,10)	41.
Tripura	0.0	0	0	2.6(1.2,3.9)	8.8(2.5,15)	0	51.
Manipur	0(0,0.1)	0	0	0.7(0.4,1.1)	1.4(0.1,2.8)	0	37.
Arunachal Pradesh	0.0	0	0	0.4(0,0.8)	0.8(0.1,1.5)	0	64.
Meghalaya	0.0	0	0	0.1(0.1,0.2)	1.6(0.5,2.8)	0	18.
Nagaland	0.0	0	0	0.7(0.2,1.2)	0.5(0.1,0.9)	0	25.
Sikkim	0.0	0	0	0.1(0,0.3)	0(0,0.1)	0	39.
Mizoram	0.0	0	0	0.4(0,0.7)	0.2(,0.1,0.6)	0	13.

*****values less than 0.1 are rounded off to 0.*

CPM: Cases per million; DR: Death rates; CFR: Case Fatality Rate; CI: Confidence Interval.

Mobility Indicators and Intra-mobility correlation

Table 3 depicts the changes in the mobility pattern at all the six places reported under CMR for India, Maharashtra (leading cases), and the Sikkim (minimum cases) state of India. At the national level, mobility at the five places except residential areas was reduced during the lockdown period, compared to the reference period. During the lockdown, maximum restrictions were seen at retails and recreation areas, followed by transit, Parks, and workplaces. The leading drop of -77.2% (CI; -78.7% to -75.8%) at the national level happened for retail and recreation during the lockdown. In contrast, residential mobility increased by 24.6% (CI; 23.4% to 25.8%) during the lockdown. During unlock, the areas with mobility in their increasing order were residential areas, groceries and pharma, workplace, transit, parks and retails, and recreation centers. With the maximum number of cases, Maharashtra state displayed the highest restriction in the movement with a drop of -82.4% (CI; -83.3% to -81.5%) in the lockdown phase for retail and recreation. Sikkim depicted higher mobility compared to Maharashtra for all the six places reported under CMR. The state of Sikkim displayed a drop of -65.4% (CI; -67% to 63.9% points during lockdown for retail and recreation. The spiral bar charts in **Figure 2(a-f)** display the change in mobility for the state of Sikkim, Maharashtra and the national level across the different phases of the lockdown. **Table 4** exhibits the intra-mobility correlation. In general, residential mobility negatively correlated with all other measures of mobility.

The magnitude of correlations for intra-mobility indicators was comparatively low for the lockdown phase compared to pre-lock and unlocked stages.

Table 3: Percentage Changes in mobility patterns during different stages of lockdown during the COVID-19 pandemic as per the google community mobility reports for India (March-October 2020)

	Pre-lockdown (Before 25th March 2020) Median (95% CI)	**Lockdown** (25th March – 7th June 2020) Median (95% CI)	**Unlock** (8th June - 15th October 2020) Median (95% CI)
India			
Retail & recreation	-29.6 (-46.7, -12.4)	-77.2 (-78.7, -75.8)	-50.5 (-52.1, -48.9)
Transit	-25.7 (-42, -9.4)	-59.5 (-62.0, -57.1)	-35.2 (-36.4, -34)
Parks	-18.3 (-31.2, -5.3)	-56.8 (-58.0, -55.6)	-49.0 (-49.7, -48.2)
Workplace	-21.1 (-36.2, -5.9)	-51.9 (-55.2, -48.6)	-28.2 (-29.5, -27)
Groceries and Pharma	-14.0 (-31.4, 3.4)	-38.0 (-42.4, -33.6)	-5.7 (-7.2, -4.1)
Residential	9.4 (3.8,15)	24.6 (23.4, 25.8)	13.9 (13.6,14.3)
State with maximum cases at the end of lockdown (Maharashtra)			
Retail & recreation	-40.3 (-58.8, -21.8)	-82.4 (-83.3, -81.5)	-29.4 (-33.5, -25.3)
Transit	-35.6 (-53.8, -17.3)	-71.3 (-72.8, -69.8)	-44.3 (-46.2, -42.4)
Parks	-30.7 (-45, -16.5)	-70.4 (-71.5, -69.2)	-52.2 (-54.1, -50.2)
Workplace	-31.8 (-50.1, -13.6)	-65.3 (-68, -62.6)	4.4 (-0.5, 9.3)
Groceries and Pharma	-20.1 (-38.6, -1.6)	-48 (-50.9, -45.2)	-52.5 (-55.7, -49.4)
Residential	14.5 (7.3,21.6)	31.8 (30.6,32.9)	22.2(21.3,23.2)
State with minimum cases at the end of lockdown (Sikkim)			
Retail & recreation	-8.6 (-23.3,6.1)	-65.4 (-67.0,-63.9)	-52.3 (-55.1,-49.6)
Transit	-22.4 (-38.8,-5.9)	-65.2 (-67.3,-63)	-54.5 (-57.1,-51.9)
Groceries and Pharma	-12.5 (-30.8,5.8)	-48.3 (-52.5,-44.1)	-39.3 (-43,-35.6)
Parks	-16.4 (-29.9,-2.8)	-43.5 (-44.1,-42.8)	-43.6 (-44.1,-43.1)
Workplace	0.8 (-8.1,9.7)	-20.2 (-23.3,-17.1)	-15.6 (-17.8,-13.4)
Residential	3.6 (0.4,6.7)	12.8 (12.1,13.5)	13.5 (12.7,14.3)

Figure 2 (a-f): Spiral bar charts displaying change in mobility pattern for states of Sikkim and Maharashtra compared to India across the different phases of lockdown.

Table 4: Intra-Correlation plots between the mobility indicators during the Coronavirus disease (COVID-19) pandemic in India (March- October 2020).

Indicators		Pre-lockdown (Before 25th March 2020)			Lockdown (25th March – 7th June 2020)			Unlock (8th June 2020 - 15th October 2020)		
Mobility	Epidemiological	India	Maharashtra	Sikkim	India	Maharashtra	Sikkim	India	Maharashtra	Sikkim
Retail & Recreation	Grocery &Pharmacy	0.60	0.93	0.90	0.40	0.40	0.17	0.37	0.68	0.38
	Parks	0.96	0.99	0.81	0.45	0.48	0.32	0.69	0.81	0.17
	Transit	0.97	0.96	0.95	0.38	0.29	0.27	0.77	0.79	0.52
	Workplace	0.85	0.82	0.72	0.29	0.20	0.14	0.26	0.43	0.25
	Residential	-0.91	-0.84	-0.85	-0.44	-0.33	-0.29	-0.30	-0.50	-0.33
Grocery & Pharmacy	Parks	0.67	0.95	0.85	0.03	-0.07	-0.11	0.46	0.75	0.25
	Transit	0.56	0.96	0.96	0.91	0.80	0.69	0.47	0.66	0.59
	Workplace	0.47	0.82	0.71	0.63	0.51	0.70	-0.08	0.27	0.63
	Residential	-0.58	-0.81	-0.74	-0.60	-0.40	-0.71	-0.05	-0.34	-0.80
Parks	Transit	0.90	0.99	0.87	-0.04	-0.23	-0.15	0.67	0.72	0.10
	Workplace	0.77	0.84	0.60	-0.18	-0.27	-0.22	0.10	0.34	0.24
	Residential	-0.91	-0.85	-0.73	0.07	0.14	0.11	-0.08	-0.36	-0.19
Transit	Workplace	0.88	0.86	0.67	0.70	0.70	0.72	0.35	0.57	0.37
	Residential	-0.89	-0.84	-0.79	-0.69	-0.61	-0.79	-0.35	-0.64	-0.53
Workplace	Residential	-0.88	-0.99	-0.78	-0.84	-0.85	-0.66	-0.49	-0.74	-0.63

Correlation between Mobility and Epidemiological Indicators

A general trend of a high correlation coefficient between epidemiological and mobility indicators is observed for the lockdown and unlock phases compared to the pre-lockdown phase. Besides few exceptions, the correlation coefficient between epidemiological and mobility indicators for India and Maharashtra are close. The highest correlation for India, Maharashtra, and Sikkim was observed in the unlocking stage for retail and recreation and all epidemiological indicators. It was interesting to see a substantial increase in correlation between park visits and epidemiological indicators from the lockdown phase to unlock phase. There were just seven cases in Sikkim before unlocking; therefore, inter-correlation for CFR and recovery are not available during the pre-unlock phase. **Table 5** gives details of correlation coefficients between mobility and epidemiological indicators. Initial exploration indicated that there is a substantially high correlation between various epidemiological and mobility indicators by google. Figure 1 displays the cumulative rise in the frequency of cases with the mobility indicators. There was a rapid surge in the number of cases in the unlock phase after a flat linear growth till the lockdown stage.

Table 5: Inter-Correlation between the mobility and epidemiological indicators during the Coronavirus disease (COVID-19) pandemic in India (March- October 2020).

Indicators		Pre-lockdown (Before 25th March 2020)			Lockdown (25th March – 7th June 2020)			Unlock (8th June - 15th October 2020)		
Mobility	**Epidemiological**	**India**	**Maharashtra**	**Sikkim**	**India**	**Maharashtra**	**Sikkim**	**India**	**Maharashtra**	**Sikkim**
Retail & Recreation	Doubling rate	0.00	0.11	-	0.29	0.29	0.15	0.72	0.66	0.27
	Case Fatality rate	-0.49	-0.55	-	-0.21	-0.33	-	-0.64	- 0.55	0.37
	Recovery	0.02	-	-	0.32	0.30	-	0.63	0.64	0.12
Grocery & Pharmacy	Doubling rate	0.00	0.16	-	0.78	0.62	0.19	0.15	0.43	-0.01
	Case Fatality rate	-0.44	-0.37	-	-0.69	-0.41	-	-0.05	-0.35	-0.16
	Recovery	-0.14	-	-	0.85	0.76	-	0.00	0.37	-0.30
Parks	Doubling rate	0.05	0.11	-	-0.06	-0.13	0.05	0.51	0.59	0.02
	Case Fatality rate	-0.41	-0.57	-	0.14	-0.06	-	-0.44	-0.48	-0.07
	Recovery	-0.06	-	-	-0.07	-0.20	-	0.43	0.55	-0.05
Transit	Doubling rate	-0.02	0.11	-	0.79	0.62	0.14	0.59	0.60	0.13
	Case Fatality rate	-0.53	-0.55	-	-0.68	-0.39	-	-0.51	-0.49	0.09
	Recovery	0.04	-	-	0.87	0.80	-	0.47	0.55	-0.08
Workplace	Doubling rate	-0.09	0.07	-	0.59	0.46	0.13	0.35	0.35	-0.10
	Case Fatality rate	-0.40	-0.55	-	-0.56	-0.23	-	-0.37	-0.35	-0.06
	Recovery	-0.02	-	-	0.70	0.57	-	0.35	0.38	-0.31
Residential	Doubling rate	0.05	-0.07	-	-0.55	-0.40	-0.16	-0.35	-0.41	0.02
	Case Fatality rate	0.36	0.57	-	0.51	0.23	-	0.30	0.34	0.08
	Recovery	0.06	-	-	-0.65	-0.48	-	-0.25	-0.36	0.31

Discussion

We used the CMR by Google to assess the national and subnational pattern of mobility before, during, and after the COVID-19 pandemic lockdown enforced by the government of India and its correlation with the disease severity. There are specific critical findings of our study. Firstly, there were marked inter-state variations in the disease burden during the three phases of our study period. By the end of the lockdown phase, though the cases per million and doubling rate kept increasing, disease severity, as depicted by case fatality rate, started decreasing. CMR data depicted that mobility decreased during the lockdown and then increased again during unlock phase. We observed intra-mobility solid patterns among the six mobility indicators. Residential mobility was seen to be inversely associated with mobility at public places. A significant correlation was seen between mobility and epidemiological indicators.

The inter and intra-mobility network plays a significant role in disease transmission dynamics in the modern era.[44] We observed wide subnational variations in the disease burden as depicted by various epidemiological indicators used in the study. The state of Maharashtra was among the worst-hit states of the country. This can be attributed to its large population size, as it is the second-most populous state of India after Uttar Pradesh. Then, COVID-19 was more or less an urban phenomenon during the study period, and Maharashtra is one of India's most urbanized (more than 50 percent) states. More than half of the COVID-19 cases in Maharashtra were reported from four major cities, Mumbai, Thane, Pune, and Nagpur. On the contrary, the proportion of urbanization in other populous states like Uttar Pradesh is 22 %. Also, Maharashtra attracts more people from other states for education and jobs and hence has a very high population density. This demographic profile has a significant impact on the COVID-19 transmission dynamics. However, if we look at total cases per million, then many other states like Goa, Delhi, and Andhra Pradesh had more cases than Maharashtra by the end of lockdown. Also, any state with an efficient and sensitive surveillance system in place will detect more cases during an epidemic. Maharashtra has always been amongst the top performers from India in this regard[45]. On the other hand, the state of Sikkim depicted a minimum number of cases throughout the country. It is a far-off state in a hilly area, with small population size and less population density, fewer migrations, more rural areas, and less inter-state trade and transit, which explains fewer cases during the study period.

In our study, residential mobility increased during the lockdown. It also correlated negatively with other measures of mobility. The findings are consistent with studies conducted by Saha et al., which found that people stayed at home during the lockdown [34,46]. The mobility trends display that mobility started decreasing even before the government implemented the lockdown measure. Although legal enforcement was the prime reason for reducing mobility, people also restricted their movements voluntarily and avoided crowded places due to apprehensions [47–49]. Mobility at other places was reduced during the lockdown and then gradually rescaled during the unlocking phase. The pattern in coherence with other studies found that people rescheduled or/and revoked travel and transport in the wake of public health emergencies[50,51].

We used Kendall Tau's correlation to quantify the relationship between mobility and epidemiological indicators, as the same is more robust and consistent for non-normal data. The mobility indicators depicted strong correlations with epidemiological characteristics for both the lockdown and unlock phases. This trend is consistent with many theoretical studies which have predicted the role of mobility for infectious diseases[10,52,53]. Previous studies have demonstrated the utility of mobility in the spread of COVID-19 data globally[31,54]. Our analysis indicates that mobility has the potential to monitor and predict the disease outbreak. However, the statistical analysis is exploratory and univariate and requires rigorous statistical evaluation before adopting mobility as an indicator of surveillance.

Moreover, our models depicted wide inter-state variations in mobility patterns. We discussed variations only in the state of Maharashtra and Sikkim as they depicted maximum and minimum cases at the end of lockdown to understand the relationship between mobility and disease dynamics. Dealing with diseases like COVID19 from a mathematical perspective can reveal the internal pattern and potential structure of pandemic control and help gain insights into the transmission dynamics of such diseases and the potential role of different public health intervention strategies[55]. The lockdown interventions to prevent the spread of infection lead to different patterns of mobility. However, lockdown measures only serve the purpose when strictly enforced. Our data suggest that the growth trajectory for the rise in cases was linear compared to the steep trajectory post lockdown. Many authors have previously discussed the impact of lockdown in controlling COVID-19 spread in India [56,57]. Although, lockdown measures to save lives were recommended and championed by WHO and other leading agencies. There are numerous discussions and debates in the literature regarding the appropriateness of total lockdown measures[58–60]. A group of medical researchers emphasized "Focused Protection" and gave the "Great Barrington Declaration" [61]. Simultaneously, the other disagreed and called for strict measures till the vaccine is available and came with the "John Snow Memorandum" [62]. However, it may take a long time to assess the overall strengths and shortcomings of the lockdown.

The present study is the first pan India empirical study quantifying the role of mobility in disease transmission. However, there are some obvious limitations in our study. The major limitation is the dynamic nature of the disease and the mobility patterns. Therefore, it is challenging to obtain robust estimates unless disease transmission stabilizes. Moreover, an ecological study used normative mobility data; the current study may suffer from the ills of ecological fallacy. The disease infection rate varies as per gender, accessibility to healthcare, and literacy level, but the data for the current study limit its generalization to these subgroups.

Similarly, no attempt can be made to examine the psychological and sociological issues affecting mobility. The data used by Google for generating the mobility estimates may be questioned for concordance with the actual mobility rates. The mobile-phones may not reflect the actual mobility in the community, more so in the rural areas as GPS enabled smartphone is not used by many. Similarly, apprehensions about data misuse may prevent many smartphone users from avoiding maps, undermining the actual estimates. Less frequent GPS usage may be a potential reason that we could not find inter-mobility patterns for Sikkim in analysis. Lastly, as per CMR, baseline dates do not account for the seasonality of movements. The lack of accounting of seasonality may also affect the accuracy and precision of estimates. Also, Google's CMR data do not directly equate to some specific COVID-19 control measures. We could not assess the reasons underlying the patterns observed in mobility.

To conclude, we can use mobile-based open-source mobility data to assess the effectiveness of social distancing. CMR data depicted an association between community mobility with disease severity indicators. We suggest that the data related to community mobility could be of utility in future COVID-19 modeling studies. With the declaration of COVID 19 as a pandemic, mobility levels declined, primarily attributed to legal enforcement or increased fear of disease leading to personal behavioral changes. Google's CMR depicts the effect of these measures on community movement. CMR can provide an effective tool for the authorities to evaluate the timing and impact of social distancing efforts, mainly related to movement restrictions. We recommend using this data whenever applicable to supplement the existing surveillance methods in any country. It does not involve any extra cost and can give quick action points about the adherence to such measures. This method can forecast mass movements during non-pandemic conditions like the famous gatherings in 'Kumbh-Mela of India' and can help us assess preparedness accordingly. An attempt can also be made to forecast the mass movements in need of making informed decisions. With the increase in mobile internet usage, the real-time data method is expected to increase accuracy. Future studies should focus on establishing cultural, social, and economic issues responsible for some of the differences in adherence to social distancing measures.

Declarations

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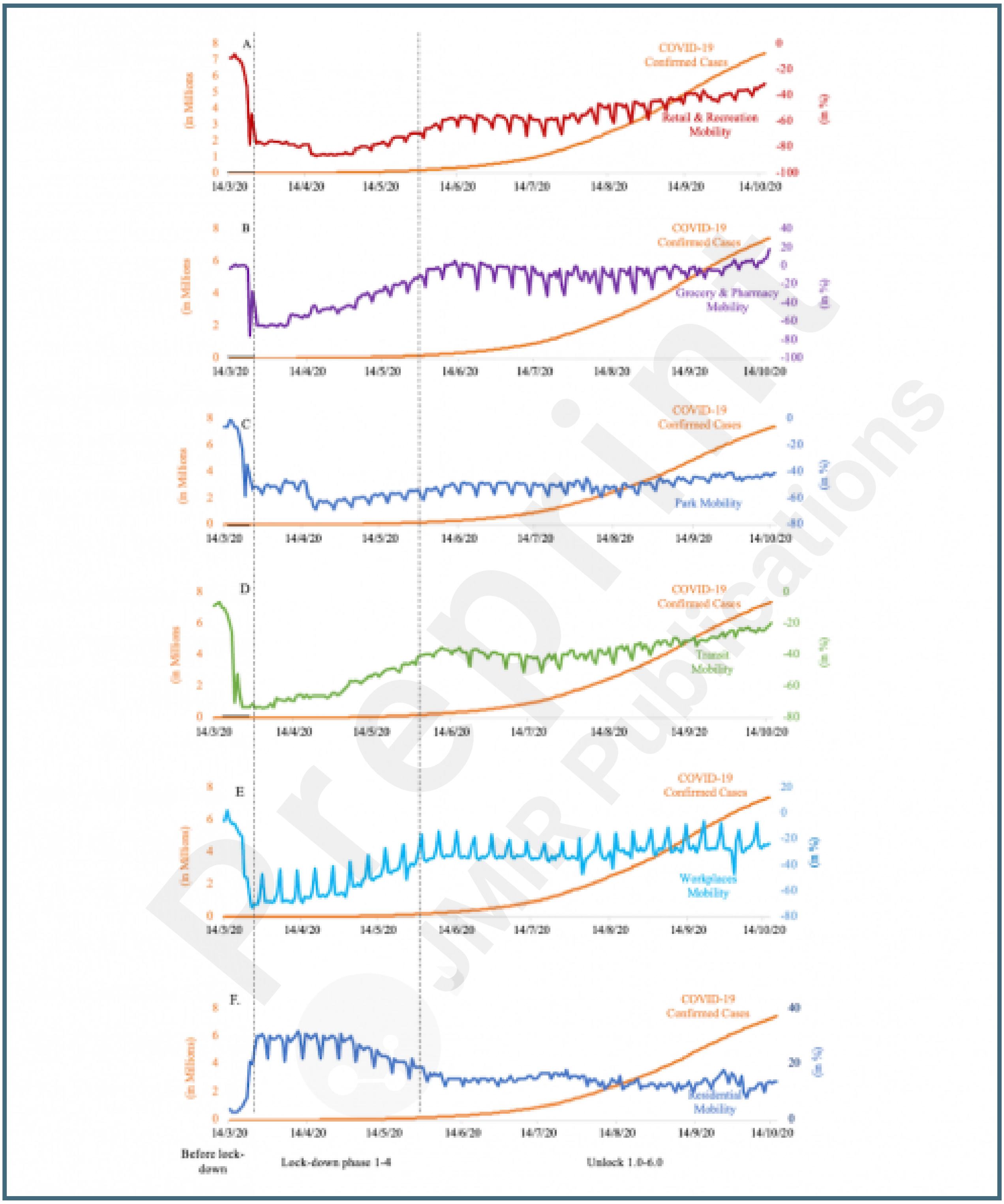
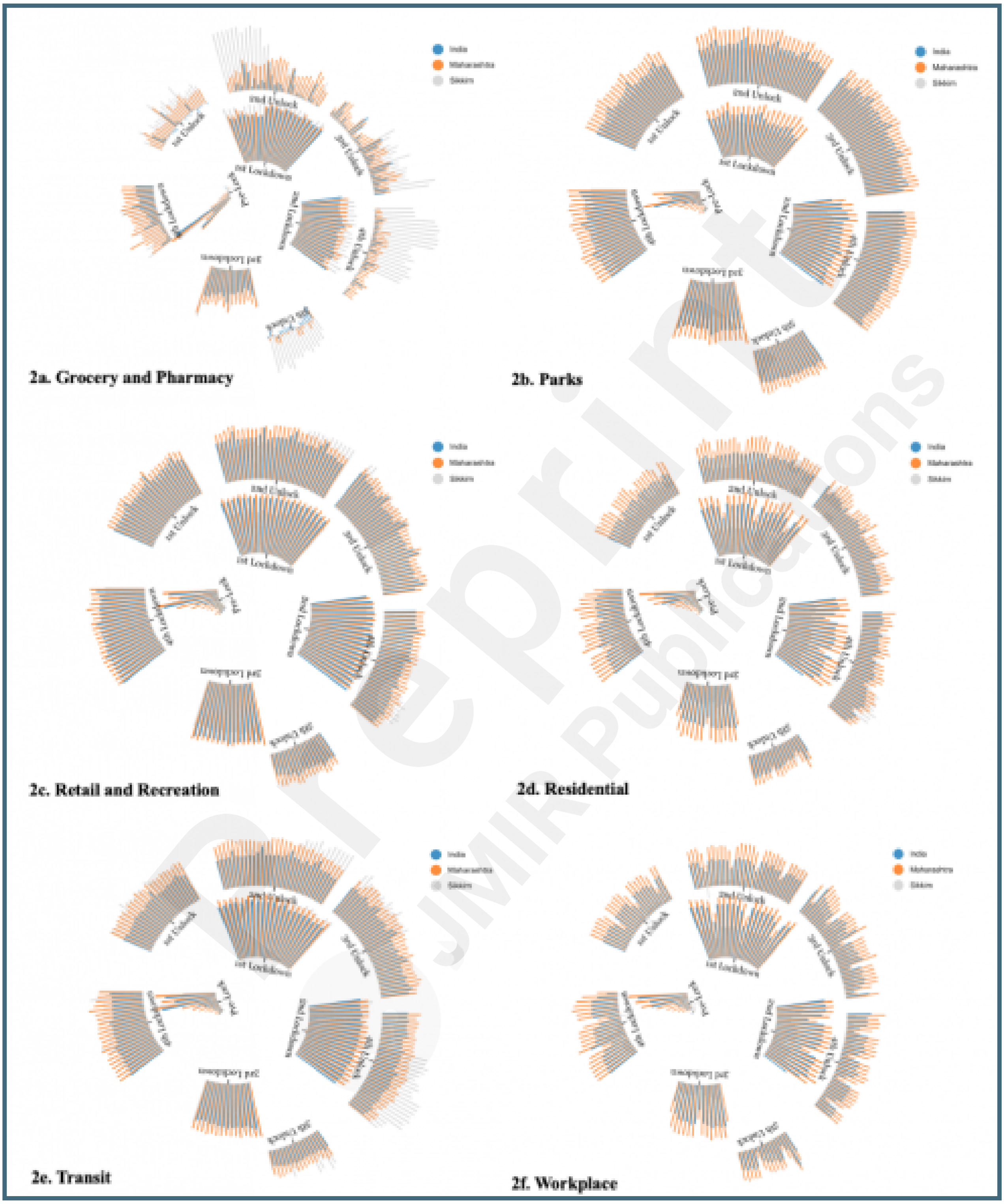
Supplementary Files

Figures

Line diagram depicting COVID-19 cases and mobility trends for India from 14-03-2020 till 14-10-2020.



Spiral bar charts displaying change in mobility pattern for states of Sikkim and Maharashtra compared to India across the different phases of lockdown.



Multimedia Appendixes

1- Summary of mobility reports generated by Google to combat the COVID-19 pandemic. 2-Snapshot of the process to download community mobility reports and data.
URL: http://asset.jmir.pub/assets/932d5afaa5b89ccc5c149fd682b69631.docx