COVID-19 and transportation of India: influence on infection risk and greenhouse gas emissions

Arti Roshan Soni1 · Kumar Amrit2 · Amar Mohan Shinde3

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Abstract
COVID-19 have significant impact on travel behaviour and greenhouse gases (GHG), especially for the most affected city in India, Mumbai metropolitan region (MMR). The present study attempts to explore the risk on different modes of transportation and GHG emissions (based on change in travel behavior) during peak/non-peak hours in a day by an online/offline survey for commuters in Indian metropolitan cities like MMR, Delhi and Bengaluru. In MMR, the probability of infection in car estimated to be 0.88 and 0.29 during peak and non-peak hour, respectively, considering all windows open. The risk of infection in public transportation system such as in bus (0.307), train (0.521), and metro (0.26) observed to be lower than in private vehicles. Furthermore, impact of COVID-19 on GHG emissions have also been explored considering three scenarios. The GHG emissions have been estimated for base (3.83–16.87 tonne), lockdown (0.22–0.48 tonne) and unlocking (2.13–9.30 tonne) scenarios. It has been observed that emissions are highest during base scenario and lowest during lockdown situation. This study will be a breakthrough in understanding the impact of pandemic on environment and transportation. The study shall help transport planners and decision makers to operate public transport during pandemic like situation such that the modal share of public transportation is always highest. It shall also help in regulating the GHG emissions causing climate change.

Keywords COVID-19 · Greenhouse gas emissions · Travel behaviour · Transport modal share · Metropolitan cities

The original article has been corrected: The reference Meena S (2020) has now been cited correctly.
1 Introduction

The modal share of transportation in the Mumbai metropolitan region (MMR), Bengaluru and Delhi are entirely different from any other place in India, with the highest share contribution from public transport. The suburban rail (51% is the highest contributor to the modal share, followed by a bus (14%). Other modes also share 21.3% (car and two-wheeler) and 11.7% (auto-rickshaw and taxi) in the total modal share of MMR (CMP, 2016). Delhi has significant reliance on its public transportation infrastructure. Buses in Delhi carry more passengers than in MMR. The buses in Delhi travel 10% of the total vehicle kilometre; they, however, cater 54% of the total passenger–kilometres (Khanna et al., 2011; Jain and Tiwari, 2016). With the expansion of Bangalore Metropolitan Transport Corporation (BMTC), the public transportation sector of Bengaluru changed drastically with an increase in the share of a public bus in the modal share by double (IIHS, 2015). Nearly 50% of the population in the city commute through BMTC buses (Badami et al., 2009). The urban districts in Bengaluru show a modal split with the dominance of bus (28%) followed by a walk (29%). The remaining share in the modal split is shared by two-wheeler (23%), four-wheeler (10%), autos-rickshaw + taxi (3%), cycle (5%), and train (1%) (Baindur et al., 2016).

The modal share of cities is observed to be changing due to various factors as reported by different kinds of literature, resulting in the changing pattern of greenhouse gas emissions (GHG) which shall be covered in following sections. Change in the modal shift was observed on the specific route in MMR due to the implementation of the Mumbai metro (Soni et al., 2018). In Delhi, modal shift towards the metro was observed due to overcrowding in buses and congestion on roads (Chauhan et al., 2016). Literatures highlighted the savings in travel time as the main attraction towards shifting from buses to Delhi metro line apart from other issues like connecting modes, cleanings at stations (bus and train), and other amenities (Kumar et al., 2014). In addition to travel time, in Bengaluru, a congestion charge was also a factor influencing people’s mode choice (Sarkar et al., 2017). COVID-19 pandemic has emerged as a new reason for the modal shift in vehicles since 2020. The perception of higher risk in public, intermediate, and flights, results into switching towards private cars in India (Dandapat et al., 2020). However, the choice of mode selection was utterly dependent upon the respondent’s age, income, and working status in Indian cities (Bhaduri et al., 2020). It was observed that the shared mobility option in India dropped by 35% due to the unavailability of vehicles during the lockdown. Other modes of transport like walk and bicycle saw a significant increase in the contribution to the total modal share for short trips (Meena, 2020). In Istanbul, a substantial reduction in usage of public transportation and simultaneous shifting towards private vehicles have been observed during unlocking period (Shakibaeei et al., 2021).

The major reason behind change in travel behaviour during COVID-19 pandemic may be due to the risk of infection in the transportation modes. In India, Das et al. (2021) estimated risk probability inside the vehicle, air-conditioned (AC) taxi observed to be highly risky ($6.10 \times 10^{-2}$), followed by Non- AC taxi ($1.71 \times 10^{-2}$), whereas risk probability in public buses ($1.42 \times 10^{-2}$) and auto rickshaws ($1.99 \times 10^{-4}$) were seemed to be relatively lower and least, respectively. The study concluded that the probability of infection inside a transport vehicle depends on the air change per hour. The probability of getting infection depends on ventilation system (fresh air requirement), the exposure time, and occupancy of the vehicle. Furthermore, a distance of 1.6 to 3.0 m while talking was observed to be safe to reduce the chances of catching the exhaled large droplets.
COVID-19 and transportation of India: influence on infection…

(Sun et al., 2020). In confined spaces as well a sound ventilation system has been considered to lower the risk of transmission of COVID-19. Therefore, to have risk probability of 1% in confined space, the ventilation rate to be in the range of 100–350 m³/hour (15 min exposure time) and 1200–4000 m³/hour (3 h exposure time) (Dai et al., 2020). In addition to, infection risk, migration of people comes out to be another reason for change in mobility pattern (Bemia et al., 2021). In a built environment, if we increase the open space the incident rate decreases and overcrowding results in increase in infection probability (Liu et al., 2021).

The modal change may have resulted in change in GHG emissions around the world in 2019. International energy agency (IEA) has forecasted a fall of 8% in global carbon dioxide (CO₂) emissions during lockdown (Scientific American, 2020) and a further fall of 5% is expected in 2020, highest so far (Scientific American, 2020). The CO₂ emissions for India were expected to drop by ~15% during March 2020 lockdown and by 20% during April month (Mylavirta & Dahiya, 2020). Studies have reported that knowledge of impact of COVID-19 on air pollution shall help in building future cities more resilient (Sharifi et al., 2020). Other major pollutants showed a reduction in 43, 31, 10 and 18% during lockdown for PM₂.₅, PM₁₀, CO and NO₂, respectively (Benchrif et al., 2021). Singh and Chauhan (2020) investigated the change in air quality due to lockdown in India during COVID-19 using ground and satellite observations. A significant reduction in PM₂.₅ and AQI was observed over metro cities, while tropospheric NO₂ concentration showed decreasing trend. The analysis indicated the significant improvement in air quality during lockdown.

Singh et al. (2020) assessed the diurnal and temporal change at 134 sites across India during lockdown due to COVID-19. A decline in PM₂.₅, PM 10 and NO was observed. The analysis revealed that PM₂.₅ and PM 10 reduced significantly to nearly 40–60%, while nearly 30–70% reduction in NO₂ was observed. Furthermore, a significant improvement in air quality with a marginal increase in O₃ was observed in Delhi. Sahraei et al. (2021a) investigated the effects of lockdown 2020 on public transport and air quality index (AQI) in 12 countries. The analysis revealed improvement in AQI and significant reduction in pollutants like PM₂.₅, PM₁₀, NO₂, SO₂, and CO.

In the literature, studies explored so far have been found to have gaps in terms of studying the impact of COVID-19, especially by considering the real-time transportation pattern of the city. The gaps identified from the literature review are as follows: the modal shift due to pandemic and probability of infection for all modes of transport is unexplored area, multiple factors for infection probability (speed, occupancy, travel time, peak/non-peak hour) estimation are lacking, rapid transport system are not studied, GHG emission for Indian cities are not quantified. Therefore, the present study aims to fulfil these gaps identified in literature for metropolitan cities of India considering real time scenarios of driving. The present study will be a breakthrough for transport planners and policymakers to regulate the transportation system during a pandemic to carry out essential activities with a minimum spread of the infection.

To achieve the desired objectives of the study, the article is divided into different sections. Introduction section elaborates the transport system of metropolitan cities in India. Methodology section describes the study area, data and procedure by which the study has been carried out. Furthermore, result and discussion section shall highlight the existing transport system of cities (pre and post COVID-19), GHG emissions due to pandemic and estimation of probability of infection. Lastly the conclusion section shall summarize the entire paper in brief followed by reference section. A flow chart (Fig. 1) shall clearly depict the main goal and aim of the paper.
2 Methodology

The present study has been carried out to understand the change in travel behaviour and its impact on GHG emissions due to COVID-19 for three metropolitan cities in India (Fig. 2). Furthermore, the study propagates an estimation of the risk of infection in different travel modes to explore the sustainable mode of transport during a pandemic like COVID-19. The risk probability has been computed for the different modes of transport in MMR as per data availability. Besides the data availability, MMR contributes the largest share of public transportation in India, which is one of the primary reasons for considering it as the main study area. In MMR, the driving cycle of all roads is not same, depending on the route the peak/off-peak hour varies for entire MMR (Soni et al., 2022). The following sections shall further elaborate on the methodology for each goal identified.

2.1 Study area

The Study area includes MMR along with other megacities, Bengaluru and Delhi (Figure 2). MMR covers an area of 6355 km² consists of Mumbai and its satellite cities of Konkan, Maharashtra, having population of more than 26 million. MMR is centre for the major economic activities of the country and therefore called as economic capital of India. The region has tropical climate with average annual rainfall of ~2500 mm. Delhi officially the national capital territory (NCT) of Delhi extends over the area of 1484 km² and having
the population of 11 million. Delhi shared its boundary with Uttar Pradesh in east and with Haryana from remaining three sides. Delhi receives annual rainfall of ~ 750 mm, about 80% of total annual rainfall occurs in monsoon season (Das et al., 2021). The city becomes very hot during summer and very cold during winters. Bengaluru is located in Deccan plateau at an elevation of 900 m above sea level. It is the capital and biggest city of Karnataka. The city has an area of 741 km² and accommodates over 8 million population (Kumar et al., 2020). Bengaluru has tropical climate with mean annual rainfall of about ~ 900 mm. The city is also known as information technology (IT) capital of India. These three cities

Fig. 2 Study area
provides job opportunities to people from all the parts of the country which contributes the major part of Indian economy.

2.2 Change in travel behaviour due to COVID-19

To understand the impact of COVID-19 on travel behaviour and GHG emissions, a survey (online/off-line) was carried out for three metropolitan cities in August 2020. A questionnaire was shared among ~ 500 people. The main goal behind the survey was to gather data related to the choice of travel mode (before COVID-19, during lockdown and unlocking) and distance travelled. The survey was only carried out for work-related trips. Since work-related trip share in MMR is > 50% and similar pattern was assumed for other metropolitan cities under consideration (Transform, 2008).

2.3 GHG emission estimation due to COVID-19

The GHG emissions for different cities were estimated by multiplying the CO₂ emission factor of the respective vehicle with the number of vehicles and distance (Eq. 1). The data on emissions factor were obtained (Table 1), and the distance/number of the vehicle was obtained from the survey carried out.

The steps followed to estimate CO₂ emissions from vehicles in MMR, Delhi and Bengaluru are as follows:

Total emissions (tonne) = CO₂ emission factor (EF) X number of vehicle X distance (km)(1).

2.4 Infection risk probability inside different modes of transport

In addition above impacts, the risk probability of different modes of transport was also estimated (Eq. 2) to understand the most suited sustainable mode of transport during a

| Type of vehicle       | CO₂ emission factor (gm/km) | Source                           |
|-----------------------|-----------------------------|----------------------------------|
| Car                   | 144.13                      | Chandel et al. (2018)            |
| Two Wheeler (2 W)     | 36.33                       | Chandel et al. (2018)            |
| Auto (3 W)            | 85.51                       | Chandel et al. (2018)            |
| Bus                   | 611.48                      | Chandel et al. (2018)            |
| Metro                 | 21.45                       | Table 4                         |
COVID-19 and transportation of India: influence on infection…

The probability of infection was estimated for the following conditions due to local conditions of the city under consideration i.e. MMR.

1. The probability of infection is based on the speed, occupancy, and travel time and congestion level of MMR.
2. For four wheeler (4 W), which includes private car and taxi (Uber/Ola/Kaali-Peeli). The probability of infection is considered concerning windows (open and closed).
3. The results of train and metro are calculated only for one coach and not for the entire train (which includes a number of coaches). The reason behind it is that each coach has a different volume and may not be interconnected. Thus risk probability calculation is beyond the scope of work for the entire train/metro
4. The emission rate, which is \( q \), is also considered as minimum \( ~ 10 \). However, the value of \( q \) for Severe Acute Respiratory Syndrome (SARS) varies from \(~ 10\) to \(~ 300\) (Dai et al., 2020)
5. Since it is mandatory to wear a mask in MMR, especially in public spaces. Our study has also assumed the effectiveness of the mask. Thus particle penetration rate \( (R_m) \) and filtration rate \( (F_m) \) both are considered (Fennelly et al., 1998 & Furuya, 2007)

\[
P = 1 - \exp \left( -\frac{I(F_m X_p)(R_m X_q)I}{Q} \right)
\]  

(1)
Where, $P$ is the infection risk probability, $F_m$ is the particle filtration rate, $p$ is the pulmonary ventilation rate per person (m$^3$/hour), $q$ is the emission rate, $R_m$ is the particle penetration rate, $t$ is travel time in the respective mode of transport (Hour), and $Q$ is the ventilation rate of clean air (m$^3$/hour). All the above input parameters for estimation of $P$ are taken from Tables 2, 3, 4 and 5. Thus the infection risk probability was estimated using Wells-Riley Eq. 2 (Wells, 1955; Riley, 1978).

3 Results and discussion

To understand the impact of COVID-19 on transportation and environment, it is very important to understand (a) change in travel behaviour, (b) GHG emission due to changing travel behaviour and, (c) risk of getting infected in different travel modes.

3.1 Modal share before COVID–19

This section shall present the preliminary findings of the individual opinion towards the preferred mode of transport before COVID-19. The mode choice of people in three cities of India before the outbreak of the pandemic has been obtained from the survey (Fig. 3). The mode choice was only for work/office purposes. It has been observed based on survey outcomes that the bus (23%) has the significant modal share in MMR which is in agreement with the CTS report (CTS, 2008).

In Delhi, modal share was dominated by four-wheeler (4 W) includes own car, Ola, Uber and taxi. The second most preferred mode choice was common for MMR and Delhi, the two wheeler (2 W). As per high powered committee report for 2014, Delhi was dominated by bus (27%) followed by two-wheeler (14%) (Report, 2014). In Bengaluru, survey findings indicated metro (27%) as the dominant mode, followed by 4 W (24%). However, literature revealed that bus (28%) followed by scooter (23%) to be major mode used in Bengaluru urban district (Baindur et al., 2016).

3.2 Change in modal share due to COVID-19

During the survey respondents were asked preferred mode of transport if called to work which shall be described in this section. For MMR, there was reduction in the share of bus (13%), metro (2%) and train (4%) as the choice of transport during unlocking (Fig. 4a). The share of car and two wheeler was increased by 12 and 5%, respectively. In Bengaluru,
| Title | Auto | Car | Taxi | Bus | Train | Metro |
|-------|------|-----|------|-----|-------|-------|
| A     | Volume (m³) | 12.93 | 2.2 (Ott et al., 2008) | 56.81 (Kale et al., 2007) | 161.40 (MRVC, 2015) | 141.12 (MRVC, 2015) |
| B     | Ventilation rate per passenger (l/sec) (MRVC, 2015) | Mentioned as air change per hour in row C | 7 |
| C     | Air changes per hour (Hour-1) | (Das et al., 2021) | Windows closed (Ott et al., 2008) | Windows open | 9.9 (Das et al., 2021) | Mentioned in row B |
|       | Peak | Non-Peak | Peak | Non-Peak | Peak | Non-Peak |
|       | 1.9 | 4.1 | 30.8 | 51.7 |
| D     | Ventilation rate of clean air (m³/hour) (C * A) | 42.66 | Peak | Non-Peak | Peak | Non-Peak | Peak | Non-Peak |
|       | 4.18 | 9.02 | 67.76 | 113.74 | 522.08 | 187.47 | 14,000 | 4760 | 7560 |
Fig. 3  a, b & c Pre-pandemic modal share for three cities in India based on survey findings

(a) Mumbai Metropolitan Region

(b) Delhi

(c) Bengaluru
Fig. 4  a, b & c Change in travel behaviour in different metropolitan cities in India due to COVID-19
before lockdown (Before COVID-19), metro followed by car were the dominant share as
given by survey respondents. However, Bengaluru is also dominated by cars and 2 W, both
the mode share 90% of the total registered vehicles in the city. Two-wheeler population
was also recorded to increase by 17% per annum in 2003–2004. The outcomes of the ques-
tionnaire indicated that the modal switch towards 2 and 4 W justifies the change in travel
behaviour. COVID-19 for Bengaluru will act as a trigger to use private vehicles to already
sorted choice of 2 and 4 W (Fig. 4c). Delhi, showed a completely different mode choice
behaviour from the impact of COVID-19. In Delhi, private modes had a dominant share
before COVID-19 with a share of the car as 52% and 2 W as 22%. This share was reduced
by 16% (Car) due to COVID-19, but 2 W saw an increase in mode choice by 14%. Public
transport buses also saw an increase in share by 23% due to COVID-19, which is a posi-
tive sign and may be due to restriction policies. Rest other modes had zero/no share due
to the impact of COVID-19 on travel behaviour (Fig. 4b). TERI (2020) investigated the
change in travel behaviour of India and it was observed that 35% of the people shall likely
change the mode of transportation from public to private mode. The increase in share post-
COVID was found in private car, taxi, cycle, walking, carpooling and company vehicle.
Similar change in travel behaviour and reduction in usage of public transportation have
been observed also in other parts of the world. The cities like Istanbul and Ankara in Tur-
key observed more than 80% reduction in the usage of public transportation (Sahraei et al.,
2021b).

### 3.3 GHG emissions from change in travel behaviour due to COVID-19

The emission load of GHG emissions on environment from change in travel behaviour due
to COVID-19 will be elaborated in this section. In Delhi, from the number of respondents,
the emissions before COVID-19 were estimated to be 6.42 tonne which reduced to 2.19
tonne during unlocking and had dropped to 0.24 tonne during the lockdown. The reduc-
tion in emission during lockdown has justification of all activities being stopped, however
during unlocking only essential activities were open which may be reason for reduction
in emissions. Bengaluru and MMR observed a similar highest reduction in CO₂ emission
during a lockdown of 16.57 tonne and 3.83 tonne, respectively (Fig. 5b & c). Emissions
were higher in Bengaluru in base scenario because public transport had no share in trans-
portation mode for work. It was dominated by 4 and 2 W, whereas in MMR, emission load
was less compared to Bengaluru because MMR has highest mode share of public transport
(48%) in base scenario. Amongst all three cities, MMR had the least emission load because
of its balanced state of public and private transport. Although public transport in MMR
was reduced during unlocking but it had a share of 39% compared to other cities which had
0 (Bengaluru) and 42% (Delhi).

### 3.4 Infection risk probability in different modes of transport

The analysis revealed that highest risk of getting infected due to COVID-19 during peak
and off peak hours is in 4 W. The probability of infections varies based on the conditions
of windows closed/open. When the windows are open, the risk varies from 0.24 (off-peak
hour) to 0.84 (peak hour). The chance reaches 1 for both peak and off-peak hours when
windows are closed with no ventilation. The reduction in probability from 0.84 to 0.29 is
due to the following factors off-peak hours, when the speed increase to 40 km/hour and
exposure time also reduces to 30 min (Fig. 6a & b). 4 W in our study refers to the private
vehicle carrying two passengers (1 infected) for both peak/off-peak hours of the day. Similar findings observed for taxi which includes Ola/Uber/Kaali-peeli in MMR. Similarly, for non-peak hour, the probability was 0.21 (windows open) and 0.95 (windows closed). There is also an observed reduction in the probability of risk between 4 W (private) and taxi which may be due to a reduction in an exposure time of 10–15 min between each.

For public transport modes like buses in MMR, which normally run with open windows, the probability estimated as 0.31 for peak hours and 0.09 for off-peak hours of day. In MMR, the risk probability in train and metro for peak hour were computed as 0.54 and 0.27, respectively (peak hour) which is lower than 4 W/taxi. The results estimated for metro and train are only for one coach. The probability seemed to be least for Auto rickshaw in both peak (0.07) and off-peak (0.05) hours.
4 Conclusion

The paper analyses the impact of COVID-19 on transport sector of major metro cities of India. The survey revealed that mode share of public transport (bus, train and metro) reduced to 18 to 100% for all three cities. Delhi, however, observed an increase in the share of public buses but in Bengaluru, the share reduced by 100% (bus + metro). The modal share of car and 2 W increased by 10 to 20%. The survey indicated a significant rise in the share of 2 W for all three cities due to COVID-19. The behavioural change in travel patterns shows the subsequent reduction in GHG emissions relative to the base scenario. The reduction of 6 tonne, 17.61 tonne and 5.86 tonne in GHG emission were observed in Delhi, Bengaluru and MMR, respectively, due to COVID-19 restrictions. Further, the analysis propagates with the estimation of risk probability for different travel modes in MMR. The highest risk probability of 0.84 (non-peak hour) and 1 (peak hour) observed to be in four Wheeler (4 W), whereas auto rickshaws are observed to have the lowest risk probability of 0.07 (peak) and 0.05 (off-peak). Occupancy of the vehicle, vehicle speed, and travel time were found to be the major factors that influence the probability of getting an infection. The study provides an impact of COVID-19 on GHG emissions and transport pattern of major cities. Similar study with survey from different economic and social background shall provide further information. There is a room for the further research with the inclusion of factors such as travel time, waiting...
time at bus/train stations, age of vehicle and rate of vaccination drive, to get clear understanding of impact of COVID-19 on transportation sector.

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