Impact of COVID-19 Outbreak on Travel Behaviour: Evidences from early stages of the Pandemic in India

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Abstract: This study demonstrates the impact of COVID-19 outbreak on travel behaviour in India during the early stage. A questionnaire, consisting of five stages, was designed for collecting responses with respect to various aspects of travel and distributed through various online modes. A total of 3,830 refined responses obtained from various cities across India were analysed. The analysis brings out several interesting findings related to the travel characteristics including the trend of 'work from home', modal shift, infection risk perception about travelling on different modes, and expected mode preferences once the restrictions are eased. The results bring out evidences of higher infection risk perception for public transport, intermediate transport, and flights, modal shift in favour of personal vehicles during the initial stage, and expected delayed recovery of ridership on public transport (PT) and intermediate public transport (IPT) modes during post-COVID era.

Keywords: COVID-19, Travel behaviour, Mode share, Perceived infection risk, Work from Home

1 INTRODUCTION

The world has faced multifaceted challenges due to the outbreak of highly infectious COVID-19 (Corona Virus Disease 2019). The first known case of COVID-19 was reported from Wuhan city of China in December 2019 (WHO 2019), and, since then, the virus has grasped all over the world and, subsequently, the WHO (World Health Organization) declared COVID-19 as a pandemic on March 11, 2020. As of July 30, 2020, total reported cases of infection stood at 15,48,824, and reported number of deaths stood at 34,968 (MoHFW, 2020). In terms of reported deaths, United States of America (USA) has been the worst affected country with total reported deaths of 1,48,866 (CDC, 2020) followed by Brazil (88,539 deaths), United Kingdom (UK) (45,961 deaths), and Mexico (44,876 deaths) (WHO, 2020). Since March, the cases of infection have seen a steady growth in India. The public health emergency aroused from COVID-19 outbreak has been compared with the outbreak of Spanish Flu pandemic in 1918.

Despite countering several infectious diseases in the recent past (example, Ebola outbreak in 2019, Zika fever during 2005 and 2016, Ebola haemorrhagic fever in 2014, H1N1 Influenza in 2009, and SARS in 2003), the world has largely failed to contain the spread of COVID-19 at its early stage. In absence of adequate knowledge about the virus and unavailability of pharmaceutical treatment, countries have relied upon adoption of preventive measures such as travel restriction and lockdown of activities such as business, academic institutions, and public gatherings which have severely impacted the economy as well as peoples life. The transport sector, especially the public transport has been considered as one of the potential spreader of the virus as it limits the opportunity of maintaining social distancing. This is more critical in case of emerging economies such as India, where a significant share of the society is captive to public transport modes. Moreover, due to significant imbalance of demand and supply of transport in the urban areas, a shift from public transport to other personalized modes of transport due to perceived higher risk of infections would aggravate the already existing issues of congestion, pollution, and accidents in the cities. Therefore, it is important at this stage to make informed future decisions based on the evidences with respect to peoples' reaction to travel and related activities. The experts and policymakers would be greatly benefitted if they can use such information to formulate workable policies for managing the transport systems during the post pandemic "New World" and strategize interventions for managing transport during the expected second and possible third waves of the pandemic.

Several studies are available in the literature dealing with behavioural aspects and strategic interventions with respect to past pandemics such as Spanish Flu pandemic in 1918, Ebola outbreak in 2019, Zika fever during 2005 and 2016, Ebola haemorrhagic fever in 2014, H1N1 Influenza in 2009, and SARS in 2003 (Apolloni et al., 2014; Brug et al., 2009; Cooper et al., 2006; Ferguson et al., 2006; Garske et al., 2011; Soper, 1919; Van et al., 2010). Soper (1919) and Zhang (2020) highlighted that the nature of virus varied across different pandemics, thus, same set of interventions could not be successful in arresting the spread of virus due to lack of knowledge about the virus at its early stage. Zhao and Chen (2020) also pointed out that the COVID-19 virus has multiple distinct characteristics (say, "high infectivity during incubation, time delay between real dynamics and daily observed number of confirmed cases, and the intervention effects of implemented quarantine and control measures") than other infectious diseases. Therefore, it was important to adopt interventions derived from case-specific evidences. Thus, a clear understanding about the peoples' travel patterns and perceptions of various travel modes amid COVID-19 outbreak is necessary for formulation of effective policies for operating and managing the transportation systems.

Since the outbreak of COVID-19, so far, limited research findings are available concerning the passenger transport system which restricts the scope for comprehensive policy making. Several studies have been carried out in the strategic front to understand the impact of travel restrictions on spread of virus in the context of China (Chinazzi et al., 2020; Kraemer et al., 2020; Tian et al., 2020). These studies have found a strong association between human mobility data and spread of virus during the early stage (Kraemer et al., 2020) and travel restrictions played a significant role in delaying or reducing the spread of the virus across different cities (Chinazzi et al., 2020; Tian et al., 2020). Gao et al. (2020) developed a GPS-based system for mapping passenger mobility patterns in the Unites States of America with an aim to tracking peoples' movement and increasing awareness about social distancing. However, the GPS-based tracking system was not effective for tracking compliance to social distancing norms due to 'GPS horizontal error and uncertainty'(Gao and Mai, 2018). Alternatively, Zhang (2020) documented reactions of the people of Japan during the early stage of the outbreak. A few other studies had focused on behavioural changes and associated possible interventions (Bavel et al., 2020; West et al., 2020). It may, therefore, be mentioned that, as of date, there has been only a few attempts to capture the behavioural changes, especially in terms of travel-related activities, rising from the COVID-19 outbreak.

In order to provide a basis for formulation of new passenger transport policies and to address the future change in travel behaviour in emerging nations, an attempt has been made in this paper to bring out the evidences of changing travel patterns in Indian cities, and peoples' perceptions with respect to their travel during the early stages of COVID-19 outbreak in India. A survey instrument was designed to capture the public attitude towards COVID-19 outbreak, specifically in terms of their reactions to various travel advisories made by the administration, and regarding their preferences of mode for both urban and long-distance trips. An attempt was further made to investigate the risk perception of transmission of virus across various modes and the temporal impact on the perceptions. This has helped to develop an understanding on how people intend to use different modes for urban travel during the post-lockdown period. People from various sections of the society across various cities in India were approached virtually through various online media to provide their inputs. The evidences derived from the analysis of the obtained data are discussed in the present study. Implications from the evidences would help to formulate travel-related policies with respect to strategic interventions during post-COVID-19 scenarios and the early stages of second wave and possible third wave of COVID-19.

The remainder of the paper is structured in four sections. The following section (Section 2) presents a brief outline COVID-19 spread in India and the reactive measures taken by the Governments. The next section (Section 3) demonstrates the details about the design of survey instrument, database development, and an outline of the database. Subsequently, in Section 4, the data analysis and results are presented with relevant discussions. Finally, the paper is concluded by highlighting the major contributions of the paper along with discussions on policy implications of the findings.

2 COVID-19 SPREAD IN INDIA AND INTERVENTIONS

The first case of COVID-19 infection in India was detected on the January 30, 2020 in the State of Kerala. The infected patient was a student who returned from the then epicentre of COVID-19 Wuhan City of China (PIB Delhi, 2020). Subsequently, more cases were reported; however, all the initial cases were related to persons with international travel history. Starting from January to the end of February 2020, India relied upon thermal screening of international passengers at major airports. By early March, India started imposing partial restrictions on international travel including actions such as cancelation of visas and on March 13th India cancelled all visas, except diplomatic ones. On 19th March 2020, when the COVID-19 cases in India stood at 233 (death: 4 only), the Government of India asked all citizens to observe one day 'Jana Curfew' (people's curfew) on March 22, which was subsequently followed by nationwide lockdown including restriction on travel, closing of businesses, academic institutions, and all other activities, except emergency services. As of March 22, total number of cases reached to 468 (death: 9 only). The first lockdown continued until 14th April, which was followed by successive extensions of lockdowns; first it was extended until 3rd May (second lockdown), then until 17 May (third lockdown), followed by another extension until 31st May (forth lockdown). The final phase of lockdown (fifth lockdown) continued till 30th June; however, conditional resumption of services was started from 8th June (termed as "Unlock 1"). As on 8th June, the total cases of infection was over 2,65,000 (death: 7,473); and the numbers as on August 27th, 2020 crossed 3.24 million (deaths: 60,472) (MoHFW, 2020). With these figures, India stood at 3rd most affected country in the world in terms of total number of cases and at 4th in terms of total number of deaths. After taking into consideration the vast population (i.e., over 1.21 billion, (MHA, 2011)) of the country, it may be said that although the extended lockdown had slowed down the spread of the virus, but was only partially effective in containing it.

3 SURVEY DESIGN AND DATABASE DEVELOPMENT

3.1 Design of Survey Instrument and Data Collection

A wide range of survey techniques have been used in travel behaviour studies for collecting peoples' responses. Such techniques include travel diary, face-to-face interview, telephonic interview, web-based survey forms, etc. (Axhausen et al., 2002; Carr and Worth, 2001; Schlich and Axhausen, 2003; Zhao et al., 2015). Traditional travel diary and face-to-face interview techniques are time consuming and the application is generally limited to data collection within a smaller geographic regions (Bolbol et al., 2010). Telephonic interview is relatively faster and may have a wider geographic coverage. However, the response rate in telephonic interview is generally low and it requires a large number of trained interviewers for collecting sufficient number of responses covering the whole country (Mancini, 2020). The COVID scenario was changing rapidly in the country. Therefore, it was felt necessary to adopt a survey technique which would be convenient to the respondents and on the other hand ensure a greater geographical coverage within a short period of time. Accordingly, a web-based survey was felt to be appropriate for the present work. The questionnaire was designed using 'google form' and circulated among the people for collecting their responses with respect to various aspects of travel amid COVID-19 outbreak in India. The survey was carried out during the early stage of COVID-19 outbreak in India and covered the period between 16th March 2020 (pre lockdown period) and 23rd March 2020 (immediate lockdown).

The survey questionnaire included five parts. In the first part (i.e., Part-A), the respondents were asked to provide details about their regular trips during last one years (before COVID-19 outbreak). The details included respondents' frequency of using different modes, predominant mode of travel to work, distance to work and corresponding travel cost and time. The second part of the questionnaire (i.e., Part-B) was designed to collect information regarding current trip characteristics (post-COVID-19 outbreak) of the respondents. Information such as work status (working from home/traveling to office), mode of travel, travel time and cost was collected in this part of the questionnaire. The Part-C, the third part of the questionnaire, was designed to collect respondents' perceptions about the impact of COVID-19 outbreak on various aspects of their life, measures against catching the virus during travel on various modes, and details regarding plans of long-distance travel. The respondents' infection risk perceptions were also collected based on cardinal scale (scale of 1 to 5, 1 being 'Highest Risk' and 5 being 'Lowest Risk). Respondents were further asked to express their willingness to cancel already planned long-distance trips due to COVID-19 outbreak. In the Part-D of the survey, respondents were asked to (i) express their perception regarding risk of infection on various modes during post-COVID scenario, and (ii) indicate the duration for which they would avoid travelling on various modes once the restrictions are removed. Finally, the Part-E of the survey was designed to record socio-economic and demographic information about the respondents.

Various online modes such as email, group chats, and social networking sites were used advantageously to increase the reach to the people across the country in a short period of time. However, such web-based survey showed some limitations. It generally excludes the economically disadvantaged populations who have very limited access to the internet and generally less proficient in responding to web-based survey.

3.2 Database

A total of 4,025 responses were collected from the people covering different geographic locations and socio-demographic characteristics. After the initial screening, nearly 2.7% (i.e., 106 Nos.) responses were rejected due to incompleteness of the survey. Out of remaining 3,919 responses, it was found that 89 responses were obtained from different countries across the globe other than India. This indicates a wide acceptance of the online survey during the study period. However, those responses from other countries were omitted from the database considering that the focus of the present work was on the Indian cities. Finally, 3,830 responses covering more than 100 cities in 26 States and 4 Union Territories (UTs) were used for the analysis. Highest numbers of responses were obtained from the State of Maharashtra (16.2%), which was followed by West Bengal (15.3%), Karnataka (11.2%), Uttar Pradesh (7.1%), and Telangana (7.0%), and others. Five metropolitan cities, namely Delhi, Bengaluru, Kolkata, Mumbai, and Hyderabad, contributed in 40% of total responses. The dominance of metro cities in responses was expected due to high internet connectivity and the urban population.

A summary of the sample characteristics is presented in Table 1. The sample covers respondents from different age groups, gender, profession, educational background, and income groups. It may be noted that the representation of female respondents appears to be low in view of the gender ratio in the entire population of the country. However, when the representation of female in working population is considered, the gender distribution in the sample may be considered as representative. It may be noted that the share of low-income population in the sample is 27.9%. However, a substantial share of these individuals is students.

Table 1 Descriptive characteristics of respondents in the sample

Factors	**Description**	**Sample (N)**	**Share (%)**	**Factors**	**Description**	**Sample (N)**	**Share (%)**
Age	<25	1377	36.0	Gender	Male	2959	77.3
	25-35	1890	49.3		Female	871	22.7
	36-45	371	9.7	Income (in thousands INR)	< 20	1063	27.8
	45-55	130	3.4		20 to 40	960	25.1
	>55	62	1.6		40 to 60	599	15.6
Education	Metric	14	0.4		60 to 80	422	11.0
	Higher Sec.	191	5.0		> 80	785	20.5
	Graduate	1923	50.2	Predominant mode of urban travel	Metro	268	7.0
	Masters	1397	36.5		Suburban Rail	231	6.0
	PhD	305	8.0		Bus	504	13.1
Profession	Student	1079	28.2		Motorized 3-Wheeler	215	5.6
	Academics	329	8.6		Shared Cab/Poolcar	163	4.3
	Business	293	7.6		Taxi/ Cab	213	5.6
	Doctor	97	2.5		Personal Car	588	15.4
	IT-industry	754	19.7		Motorized 2-Wheeler	1018	26.6
	Other Profession	720	18.8		Walk/Bicycle	568	14.8
	Unemployed	558	14.6		Other	62	1.6

4 RESULTS AND DISCUSSION

4.1 Change in Travel Characteristics

4.1.1 Work from home

Since WHO declared COVID-19 outbreak as a global pandemic on March 11, 2020, Indian population started reacting in terms of changing travel behaviour, working habits, and social conducts. The people were getting aware of the COVID-19 based on international news and awareness campaigns that were carried out by the Governments. Observing the global responses and increased emphasize on social distancing, industries and business groups started to adopt work from home. Based on the responses received in the survey, it is observed that almost 40% respondents started ‘work from home’ as of 16th March, 2020 (Figure 1). Figure 1 represents the trend of ‘work from home’ during the period before countrywide lockdown was announced. The share of ‘work from home’ reached to nearly 50% on 19th March, the day when the Government issued an official ‘work from home’ advisory to the companies. It may be observed that the share of ‘work from home’ increased gradually and became nearly 98% on the day before lockdown. Such observation indicates a gradual increase of awareness among the people about the need of social distancing for the protection from COVID-19. This increase in awareness and ‘work from home’ culture is also associated with the increase of COVID-19 cases in the country over the period (correlation coefficient 0.965).

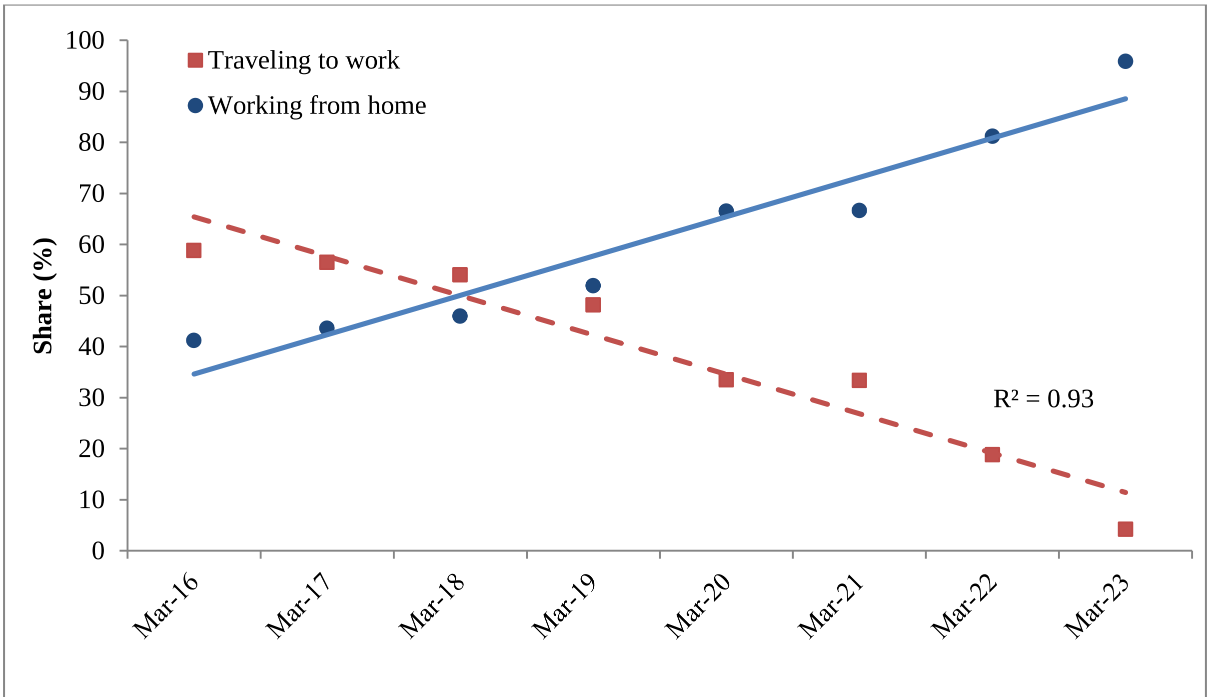


Figure 1 Change in the share of respondents 'Working from home’ over the period

In order to understand the impact of various socio-economic and demographic factors on the action of ‘work from home’, a probit model was developed considering the ‘work from home’ (Y) as response variable (Yes-1, No-0) and respondents’ socio-economic and demographic factors as independent variables along with other factor such as number of COVID-19 cases. While developing the model, the independent variables such as different levels of respondents’ profession and gender were entered into the model as dummy variable and income was entered as cardinal linear form. Age was grouped into three categories. Different classifications of age groups were investigated and the classification which gave statistically significant coefficient estimates was retained in the model. The final classification obtained includes younger people with age below 30 years, middle aged people with age between 30 and 55 years, and older people with age 55 years and above. It may be mentioned that for the profession variable 'other profession', for the gender variable, 'female', and for predominant mode of travel variable, 'personal vehicle' entered the model as the base levels. For the age variable, the youngest group, viz., 'younger than 30 years', was entered as base level, but for each of the other two levels (i.e., middle aged and older) age entered as linear variable. The final model specification is given in Equation 1 and the coefficient estimates are presented in Table 2. It may be observed from Table 2 that the coefficient estimates are statistically significant at 95% or higher level of confidence, except the coefficients for older age group and healthcare workers which are statistically significant at 90% level of confidence.

$$Y = \propto + \beta_{inc} * INC + \beta_{nc} * NC + \beta_a * D_a * AG + \beta_p * D_p + \beta_g * D_g + \beta_m * D_m \tag{1}$$

Where,

$\propto$	constant
β_{inc}, β_{nc}	coefficients associated with individual's monthly income and number of reported cases of COVID-19 (NC), respectively. INC= individual's monthly income in thousands.
β_a	coefficient associated with individual's age (takes different value depending on the age group, say, age group 30-55 years and above 55 years), AG=individuals age in years.
D_a	dummy variable associated with individual's age (equals to 0 for age group 30 years or less, 1 otherwise
D_p	dummy variable with respect to professions (equals to 1 for students, academic, business, healthcare, and IT Industry personals and 0 for other profession)
β_p	coefficient associated with individual's profession (takes different value for various professions)
D_g	dummy variable with respect to individual's gender (equals to 1 for Male and 0 for Female)
β_g	coefficient associated with individual's gender
D_m	dummy variable with respect to individual's gender, and equals to 1 for PT and IPT users and 0 for personal vehicle users
β_m	coefficient associated with individual's predominant mode of travel

The coefficient estimates with respect to professions such as student, academic, business, and IT industry shows positive sign, which imply that people with these professions showed higher propensity to 'work from home'. A close look at the coefficient estimates revealed that the coefficient estimate associated with IT industry is the second highest (after students) among all the professions indicating a faster adoption of 'work from home' in the IT industry. Although 'work from home' was not a new concept in the western world, especially for IT industry, it was not a very common practice in India. However, the findings show that the people adopted the 'work from home' quite quickly. On the other hand, it is interesting to note that the coefficient associated with the healthcare profession (i.e., doctor) shows a negative sign. This negative sign associated with doctors indicates that the people from medical profession, in general, continued to travel to their workplaces despite raising COVID-19 cases. This finding eventually reflects on the nature of the profession, viz. one of the indispensable services, during the pandemic.

It may also be observed that the coefficient estimates with respect to middle age groups (i.e., age between 30 to 55 years) showed a negative sign, which indicates that the people from this age group showed more propensity to travel to work as compared to the younger (age< 30 years) people. This finding reflects that this age group (‘age 30 to 55 years’), being most active and relatively independent, had a tendency to continue traveling. On the other hand, a portion of younger age group includes students who were adopting study from home as schools were suspending academic activities amid outbreak of COVID-19. However, as expected, the coefficient associated with the older people (i.e., ‘age >55 years’) shows a positive sign implying that older people generally preferred to stay at their home. This observation indicates that the older people became aware about more severe impact of COVID-19 on them. Intense campaigns and continuous news updates and expert analysis seem to have impacted their travel decisions.

The response of male and female population is also found to have differed from each other. The male population showed lesser propensity to adopt ‘work from home’ (showed negative coefficient estimate) as compared to the same by their counterpart. Further, it may be observed from Table 2 that the higher income groups had a higher propensity to work from home and an increased number of reported COVID-19 cases were positively related with the work from home. As the COVID-19 cases increased, people became more aware and concern about the virus which resulted in higher compliance to ‘work from home’ advisory issued by the Government. The predominantly used mode of transport also shows an indication to have impacted the decision of ‘work from home’. The coefficient estimates imply that the respondents, whose predominantly used mode was PT or IPT, had a higher propensity to work from home as compared to private vehicle users. However, distance between home and workplace did not show any significant impact on ‘work from home’ decisions.

Table 2 Probit model estimates with the factors influencing ‘work from home’

Variable		**Coefficient**	**Standard Error**	**b/St.Er.**	**P[|Z|>z]**
	Constant	-1.4959	0.1126	-13.289	0.0000
Profession	Student	1.3600	0.0769	17.678	0.0000
	Academic	0.3999	0.0941	4.250	0.0000
	Business	0.2175	0.0983	2.213	0.0269
	Healthcare	-0.3045	0.1743	-1.747	0.0807
	IT Industry	0.8952	0.0709	12.629	0.0000
Age (years)	30 to 55 years	-0.0037	0.0017	-2.157	0.0310
	>=55 years	0.0073	0.0035	2.071	0.0383
Gender	Male	-0.4320	0.0646	-6.691	0.0000
Income	Income ('000)	0.0069	0.0011	6.070	0.0000
COVID-19 cases	No. of COVID-19 cases	0.0046	0.0003	13.356	0.0000
Predominant mode	Public transport (PT)	0.1401	0.0605	2.314	0.0207
	Intermediate PT	0.3513	0.7236	4.856	0.0000
Log likelihood function		-1643.66			
McFadden Pseudo R-squared		0.183			

4.1.2 Mode of Travel

An analysis of respondents’ predominant modes of travel to work in last one year (i.e., pre-COVID-19 scenario) and during the initial stage of COVID-19 outbreak showed a considerable change in terms of modal share (Figure 2). It may be observed from Figure 2 that while the use of public transport modes such as metro, sub-urban rail, and bus was reduced by nearly 2% across each of the three modes, the use of Motorized 2-Wheeler (M2W) and cars increased by 4.8% and 3.9%, respectively. Such declined use of public transport modes may be attributed to peoples' higher risk perception about getting infected by the COVID-19 during travel in public transport as the public transport allows aggregation of a greater number of people inside a closed environment. On the other hand, lower risk perception about the spread of virus in personalized modes led to increase the modal share of M2W and personal car. It may also be noted that the share of para transit modes such as motorized 3-wheeler (M3W), shared cab/pool cars, taxi/ cabs also declined amid COVID-19 outbreak. This indicates that a section of people even considered travel by para transit modes as a risk.

Further analysis of the data clearly shows that the respondents who were predominantly using public transport modes shifted to either personal vehicles or para transit modes during the early stage of the COVID-19 outbreak. Figure 3(a) clearly shows that 11.5% respondents who were using metro rail shifted to personal modes (4.4 % to car and 7.1% to M2W). Similarly, over 8% of the bus users and 5.3% of the suburban rail users shifted to car or M2W during the initial stage. Considerable number of para transit users (i.e., over 7% of M3W users, 6% of the shared cab/pool car users, and nearly 8% of the Taxi/Uber/Ola Cab users) also expressed that they changed their mode and shifted to personal modes (i.e., car or M2W). These observations are noteworthy as an indication to potential challenges before the public transport system post COVID-19 era. The public transports may lose their ridership due to perceived infection risk in public transport and subsequent change in travel characteristic. On the other hand, increased use of personal vehicles is expected to aggravate traffic congestion and pose severe challenges for traffic management in many of the older cities, especially in the megacities in developing countries such as India.

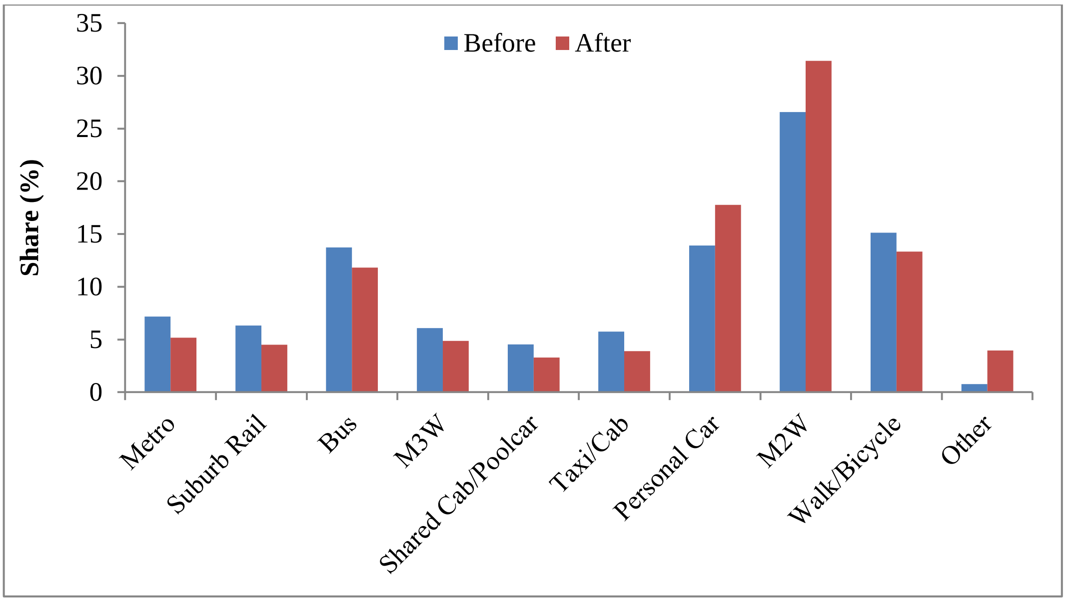
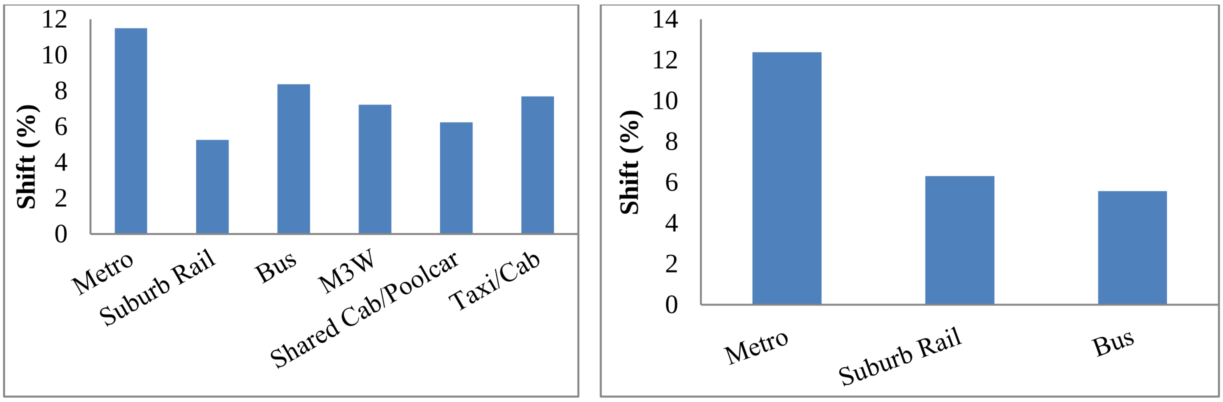


Figure 2 Mode share before and after COVID-19 outbreak



(a) (b)

Figure 3 Mode shift – (a) Shift from public and para-transit modes to personal modes (car + M2W); (b) Shift from public to para-transit modes (M3W + shared cab/pool car + taxi)

It was also observed that a section of the public transit users also shifted to para transit modes (say, M3W, shared cab/pool car, and taxi/app cabs). Over 12% of the metro rail users, 6.3% of the suburban rail users, and 5.4% of the bus users shifted to para transit modes. These people shifted to para transit modes possibly because of unavailability of personal vehicles (Captive riders) with them and they considered para transit as relatively safer than the public transit.

4.2 Perceived Infection Risk on Different Modes

The COVID-19 infection risk perceptions of the respondents during travel in various modes were analysed. The modes were classified into three groups based on their nature of use. The groups included International travel, Long distance (national travel), and Urban/Sub-urban travel. In order to understand the differences in perceptions across different modes in the same group, pairwise t-tests were conducted on the response data across different modes. The null hypothesis was defined as the "mean of the responses were equal". Based on the results of the hypothesis test, the modes which did not show significant differences in terms of mean perceived infection risk of the respondents were grouped together. For example, M3W and Cab are grouped together. The travel modes were also ranked based on infection risk perception about different modes. The ranking was done using Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The classified groups and rank of different modes bases on the perceptions are presented in Table 3.

Table 3 COVID-19 Infection risk perception during travel on different modes

Nature of travel	**Vehicle class**	**Mean Perceived Infection Risk***	**TOPSIS Score**	**Rank**
International	Flight-Int.	1.76	0.2172	10
Long distance (national)	Flight-dom., Train	2.02	0.2244,0.2319	8,7
Urban/Sub-urban	Sub-urban rail	2.00	0.2214	9
	Bus	2.06	0.2362	6
	Shared car/Pool car	2.23	0.2595	5
	M3W, Cab	2.52	0.3091/0.3060	4, 3
	Personal Car	3.75	0.7248	1
	M2W	3.54	0.6821	2

*1=most unsafe, 5= safest

It may be observed from Table 3 that while highest risk (most unsafe) of infection was perceived for the travel in International flight (mean score = 1.76, median = 1, stdev. = 1.16, rank = 10), the perceived infection risk was found to be least (safest) for the travel in Personal car (mean score =3.75, median =4, stdev. = 1.34, rank = 1). The origin of COVID-19 is believed to be in other country and it reached India through international travel (first victim was an international traveller), which justifies the high infection risk perception about the travel in international flight during the early stage. For the long distance (national) travel the infection risk perceptions were found to be similar for Domestic flight and Train (average score 2.02, rank 8 and 7). Among the Urban/Sub-urban travel modes, personal modes such as M2W (rank =2) and Personal Car (rank =1) were seen as relatively safer modes, whereas public transport modes such as bus (rank 6) and sub-urban rails (rank 9) were seen as higher risk modes. Para-transit modes, namely M3W and App cabs (viz., Ola, Uber), are considered to be safer than transit modes but riskier as compared to the personal modes. It may be noted that there is no significant differences in the infection risk perception about travel in M3W and cabs (viz., Ola, Uber).

4.3 Response to Long-Distance Travel

More than 20% respondents expressed that they had long distance travel plans during the early stage of COVID-19 outbreak in India. Among the planned trips, family/social trips and work trips were predominant, covering 39.4% and 32.9% of the total planned trips respectively (Figure 4a). Only little over 3% respondents had planned long distance trips for healthcare purposes. Flight was the predominant selected mode with a share of over 40% of the total trips (Figure 4b) and it was followed by personal car, rented car, bus, and train.

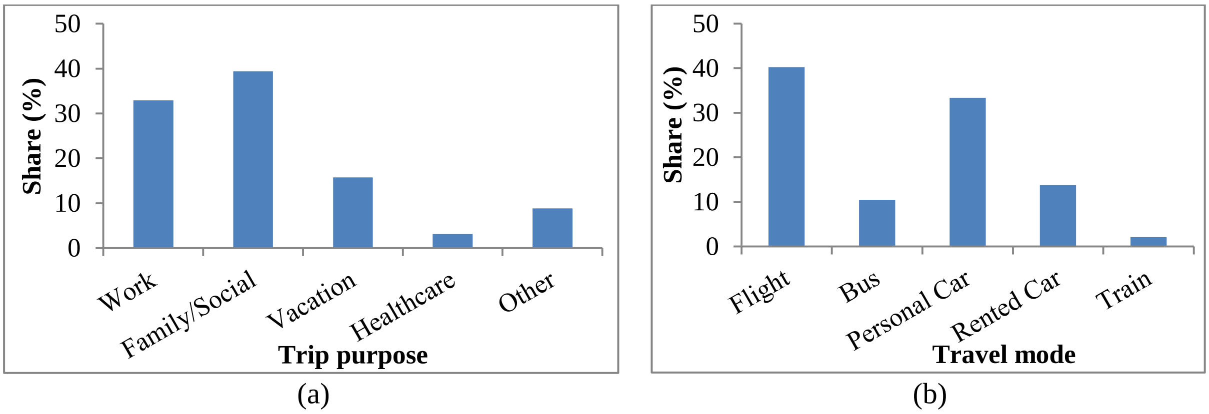


Figure 4 Characteristics of long distance planned trips (a) trip purpose, (b) travel mode

The share of respondents who had long distance travel plan dropped steadily over the time as the reported COVID-19 cases increased (Figure 5). While on 17th March 2020 reported COVID-19 cases stood at 143 only and over 28% respondents expressed that they had long distance travel plan, the share of such respondents dropped to mere 9.6% on March 22-23, 2020 as the reported COVID-19 cases increased to 396. This observation indicates that a section of people cancelled their long distance travel plans out of safety concerns and their concern grew over the period as the COVID-19 cases increased.

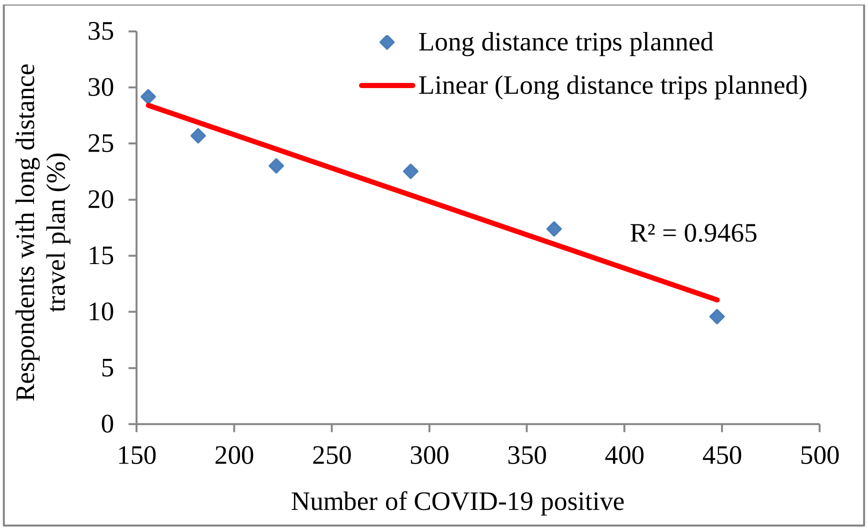


Figure 5 Change in long distance travel plan over the time

The analysis of respondents' reaction to cancelling the long-distance trips revealed that large number of respondents favoured cancellation of long-distance travel plans. The average score with respect to cancellation of long-distance trips was found to be 3.98 (1 being highly disagree and 5 being highly agree). However, the respondents' reactions were found to vary significantly based on trip purposes. While respondents strongly agreed in favour of cancelling vacation trips (average score 4.40), their agreements for cancelling healthcare trips were found to be relatively lesser (average score 3.32). Lower average score for cancelling healthcare trips signifies the emergency nature of such trips. At large, the respondents' views in favour of cancelling work tips and Family/Social trips were found to be statistically similar at 95% confidence level (average score 4.08 and 4.11, respectively). It is interesting to observe from Figure 6 that average score for cancelling long distance trips for different purposes increased over the time as the COVID-19 cases increased. A correlation analysis revealed that average scores for cancelling work trips, vacation trips, family/social trips are strongly positively correlated with the reported COVID-19 cases (correlation coefficients 0.825, 0.885, and 0.862 respectively) and, on the other hand, a weak correlation (correlation coefficient 0.013) was observed between the score in favour of cancelling healthcare trips and reported COVID-19 cases. The results show that the respondents were less willing and less sensitive to cancel healthcare trips even with rising cases of COVID-19 infection. This is a very critical aspect and establishes the need to formulate policies for such long-distance trips as, with the present pandemic, there are strong evidences of higher risks of infection with people having existing health complications.

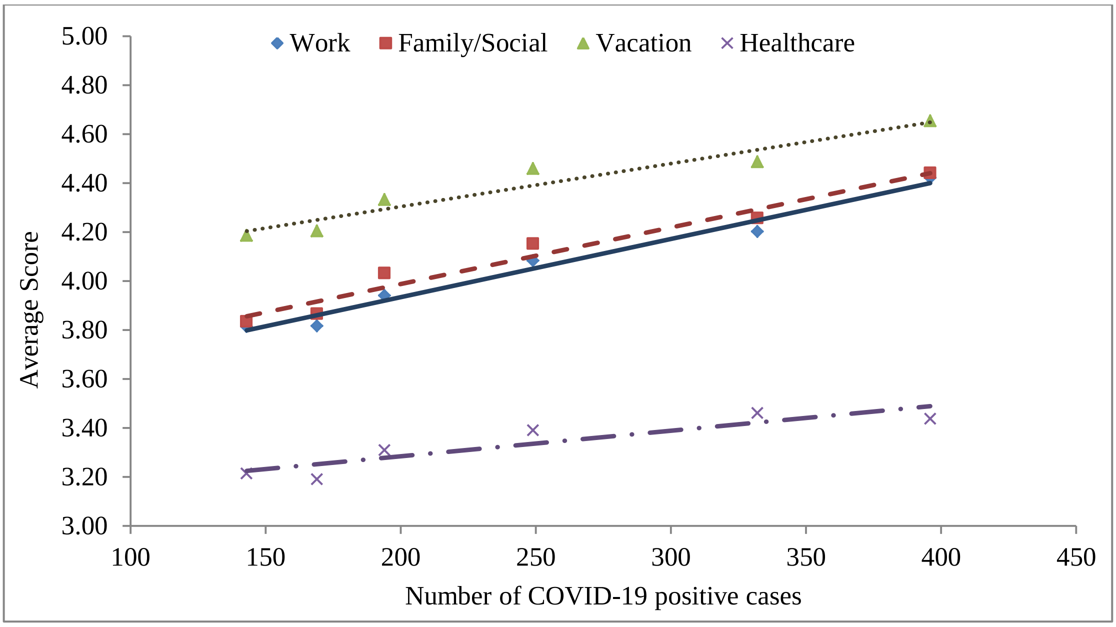


Figure 6 Reaction to cancellation of long-distance trips (1: highly disagree to 5: highly agree)

4.4 Impact of COVID-19 on Mode Preferences for Future Travel

4.4.1 Preference of Modes

It has been a critical question to the transportation professionals and policy makers that how people will react in terms of their travel behaviour post-COVID-19 world. It is now clear that the perceived risk regarding spread of virus vary across different modes (Section 4.2). The analysis of peoples' response to their preferred modes in post-COVID environment indicates that the infection risk perceptions regarding different modes are likely to play an important role in their mode choice behaviour. Figure 7 represents the shares of respondents who expressed their willingness to resume travelling by different modes during different periods after the travel restrictions are lifted. The observations indicate that, given the alternatives are available, people are likely to avoid public transport and flights during the initial periods after the restrictions are lifted.

The international flights are expected to get worst affected as only 4% respondents expressed that they would consider travelling by international flight immediately after the removal of restrictions (Figure 7). However, the international flight is expected to increase its ridership over the period. Almost 37% respondents expressed their willingness to consider international flight within one month after the removal of restrictions and the same share increases to 58% in three months, and 70% in six months after the removal of restrictions. It is expected to that the international flights will take more than six months of time to return to the normalcy. However, the domestic flight is expected to recover its normalcy faster than international flight.

Personal modes such as motorized 2-wheelers (M2W) and Car are expected to become most popular mode of travel immediately after the removal of travel restrictions. Almost 70% respondents expressed that they would consider travel using personal vehicle safer immediately after the removal of restrictions (Figure 7). This observation gives a clear indication that the usage of personal vehicle is expected to increase during post-COVID times. Although such increased use in private vehicle shall essentially be helpful to revive manufacturing industry, which was under tremendous strain during pre-COVID times, it will pose additional challenges in terms of increased congestion and vehicular emission in the cities.

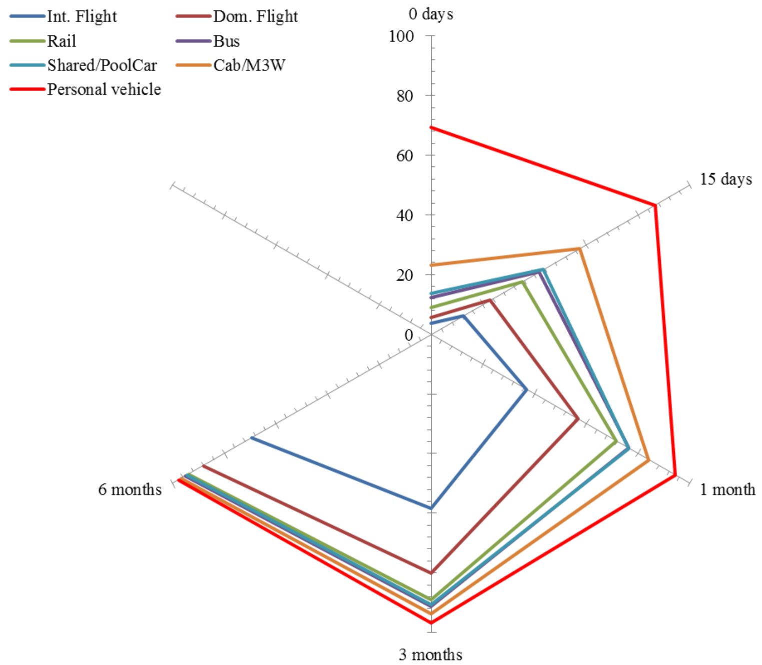


Figure 7 Expected travel pattern after removing the restrictions

For developing further insights, ordered logit models were developed to investigate the recovery of transportation systems during post-lockdown period. The ordered choices were based on the respondents answer to the question that indicated the duration, after travel restrictions are lifted, for which a respondent would prefer to avoid usage of specific modes for their trips. During the analysis the transport modes were considered in three groups, namely personal vehicles (PV), public transport (PT) and intermediate public transport (IPT). It is interesting to note that, majority of the respondents (more than 75%) expressed that they would feel comfortable using private vehicles, such as cars and two-wheelers, immediately after the restrictions are lifted. This behaviour indicates towards a possible surge in private vehicle usage during post-lockdown period. However, according to the respondents' reactions regarding their intended start of using public transport (PT) and intermediate public transport (IPT) modes during the post-lockdown periods varied across individuals. While nearly 17% respondents indicated that they would start using PT immediately after the restrictions are lifted, almost 19% respondents indicated that they would consider using PT only after three months after the relaxation of restrictions or later. Other respondents indicated their intention to start using PT during the intermediate periods. Similarly, wide variations were observed in respondents indicated time period to start using IPT modes. In order to develop an insight about respondents' potential behavior regarding the resumption of using PT and IPT modes during post-lockdown period and understand about the factors (such as, respondents' socio-economic, demographic, trip characteristics, infection risk perception about travel on different modes and COVID-19 scenario) that are influencing such behaviour, ordered logit models were developed considering the responses with respect to public transport (PT) and intermediate public transport (IPT) modes. Although the responses were collected based on six categories/time periods (i.e., zero day, fifteen days, one month, three months, six months, and more than six months), a few categories were clubbed together during the model development. Finally, three ordered categories, viz., immediately/within one month (0), within three months (1), and more than three months (2), were used for model development. Different socio-economic, demographic and trip characteristics were trialed and only the variables that returned statistically significant coefficient estimates were retained in the model. The ordered logit model specifications with finally obtained influencing factors for PT and IPT models are given in Equation 2 and Equation

3 respectively. It may be noted that during the model development one of the threshold parameter (i.e., μ_0) was normalized to zero. The findings specific to PT and IPT modes are discussed in detail in the following subsections.

$$Y_{iPT}^{*} = \propto + \beta_{inc} * INC_i + \beta_{nc} * NC_i + \beta_a * AG_i + \beta_{rc} * RC_i + \beta_m * D_{mi} \quad (2)$$

$$Y_{iIPT}^{*} = \propto + \beta_{nc} * NC_i + \beta_{rc} * RC_i + \beta_m * D_{mi} \quad (3)$$

The observed ordinal variable Y_is for each observation, for both models, is defined as

$Y_i = 0$ if $Y_i^* \leq \mu_0$ [within 15 days]

$Y_i = 1$ if $\mu_0 < Y_i^* \leq \mu_1$ [within three months]

$Y_i = 2$ if $Y_i^* > \mu_2$ [above three months]

$\propto$	constant
β_{inc}, β_{nc}	coefficients associated with individual's monthly income and number of reported cases of COVID-19 (NC), respectively. INC= individual's monthly income in thousands.
β_a	coefficient associated with individual's age, AG=individuals age in years.
β_{rc}	coefficient associated with individual's risk perception about catching COVID-19 while travelling on the given mode, RC =risk perception score (in 1 to 5 scale)
D_m	dummy variable with respect to individual's predominant mode of travel during pre-covid times, and equals to 1 for PT, IPT, and PV users and 0 for other modes
β_m	coefficient associated with individual's predominant mode of travel

4.4.1.1 Public transport

As summarized in Table 4, it is found that infection risk perception about public transport (PT), age, monthly income, and predominantly used mode had significant influence on respondents' choice of public transport during post-lockdown period. The negative sign corresponding to the coefficient of infection risk perception about PT indicates that people who are considering PT relatively safer are likely to start using it earlier. Therefore, strategies and measures to enhance public confidence regarding safety on PT may help in early recovery of PT ridership. Seating arrangements ensuring social distancing norms, regular sanitization, contactless ticketing system, enforcing use of mask are few such strategies which may improve infection risk perception of people and, thus, likely to encourage use of PT. The coefficient with respect to respondents age indicates that higher age groups (i.e., older people) are likely to avoid PT for relatively longer duration as compared to the younger population. The awareness about more severe impact of COVID-19 on the older people likely to delay their return to PT. Respondents' income has emerged as a significant factor that is likely to influence PT use. The positive coefficient estimate of monthly income indicates that people from the lower income individuals are likely to start using PT earlier than the people with higher income. This is essentially showing that the captive riders to PT, who are largely belonging to the low-income groups, are likely to use the PT services despite their concerns about infection risk on PT. It is, therefore, important to take adequate preventive measures during PT operations to protect these people. On the other hand, deterring attitude of higher income group may result in a paradigm shift in transportation mode usage and result in a increase of personal modes. It was also interesting to note that respondents, who predominantly used PT (before outbreak of COVID-19), are more likely to resume using PT earlier than others. This observation is commensurate with the general trend of PT users in developing countries, such as India, that majority share of PT users is captive in nature. On the other hand, the positive coefficient with respect to the variable 'Predominantly used mode PV' clearly indicating that the individuals, whose predominant used mode is personal vehicle (PV), are likely to take longer time before using PT. The COVID-19 cases were gradually increasing during the data collection period. The models indicate a statistically significant effect of the number of COVID-19 cases on peoples' attitude regarding considering PT for their travel. This shows that, with decrease in the COVID-19 infections, the confidence will increase towards use of PT modes.

Table 4 Ordered logit model showing post-lockdown recovery of PT ridership

Variable	**Coefficient**	**St. Error**	**b/St. Er.**	**P[|z|>z]**
Constant	-0.053	0.190	0.276	0.782
Infection risk perception about PT	-0.288	0.036	-7.893	0.000
Age	0.009	0.006	1.650	0.116
Monthly income (in thousands)	0.007	0.002	4.213	0.000
Number of COVID-19 cases	0.001	0.000	2.582	0.000
Predominantly used mode PT	-0.964	0.102	-9.428	0.000
Predominantly used mode PV	0.359	0.085	4.213	0.009
Threshold parameter µ1	1.615	0.049	33.000	0.000
		Log likelihood		-2709.01
		Restricted log likelihood		-2875.32
		Pseudo R-squared		0.06
		$\chi 2$		332.62
		AIC		1.955

4.4.1.2 Intermediate public transport

The ordered logit model estimated for post-lockdown recovery of intermediate public transport (IPT) ridership is presented in Table 5. It may be observed that only the 'infection risk perception' about IPT, number of COVID-19 cases, and the predominantly used modes before COVID-19 outbreak showed association with post-lockdown resumption of IPT use by the respondents. As expected, the coefficient associated with the infection risk perception is found to be negative which is indicating a longer resumption time with increased infection risk perception and highlights the need for implementing adequate precautions and creating awareness about those measures to build public confidence. It may be noted that while the coefficients with respect to PT users (predominant mode) and IPT users (predominant mode) are negative, the same for PV users (predominant mode) shows positive sign. This implies PT and IPT users (generally captive riders) are likely to resume the use of IPT earlier than the personal vehicle (predominant) users. Like PT modes, the model also indicates a statistically significant effect of the number of COVID-19 cases on peoples' perception regarding considering IPT for their travel.

Table 5 Ordered logit model showing post-lockdown recovery of IPT ridership

Variable	**Coefficient**	**St. Error**	**b/St. Er.**	**P[|z|>z]**
Constant	1.766	0.154	11.476	0.000
Infection risk perception about IPT	-0.505	0.035	-14.598	0.000
Number of COVID-19 cases	0.001	0.000	2.680	0.003
Predominantly used mode PT	-0.322	0.107	-2.994	0.001
Predominantly used mode IPT	-0.390	0.120	-3.265	0.000
Predominantly used mode PV	0.599	0.101	5.925	0.007
Threshold parameter µ1	1.580	0.044	35.876	0.000
		Log likelihood		-3123.75
		Restricted log likelihood		-3325.42
		Pseudo R-squared		0.061
		$\chi 2$		403.35
		AIC		2.067

4.4.1.3 Marginal effects

The marginal effects of different variables are presented in Table 6. The estimates show that with increased sense of safety ('infection risk perception about PT'), respondents are over 7% more likely to start using PT and 10% more likely to start using IPT within one month of relaxing travel restrictions. With the similar improvement in infection risk perception, people are over 3% less likely to wait for three months and 4% less likely to wait for more than three months. Similarly, for IPT use, with unit improvement in risk perception, people are over 11% less likely to wait beyond three months to start using IPT. However, with increase of age, likelihood of resuming PT use during the initial period after easing the lockdown becomes lower. The individuals, whose predominantly used mode before COVID-19 outbreak was PT, are 23% more likely to start using PT within one month of removing the restrictions as compared to other travellers. On the other hand, PV users (predominant mode) are 9% less likely to start using PT and 12% less likely to start using IPT within one month of easing restrictions as compared to their counterpart.

Table 6 Marginal Effects

	Variable	**One month**	**Three months**	**More than three months**
PT model	Infection risk perception about PT	0.0719	-0.0306	-0.0413
	Age	-0.0022	0.0009	0.0013
	Monthly income (in thousands)	-0.0017	0.0007	0.0010
	Number of COVID-19 cases	-0.0003	0.0001	0.0002
	*Predominant PT users	0.2350	-0.1152	-0.1198
	*Predominant private vehicle users	-0.0894	0.0368	0.0526
IPT model	Infection risk perception about IPT	0.1055	0.0056	-0.1111
	Number of COVID-19 cases	-0.0002	0.0000	0.0002
	*Predominant PT users	0.0691	-0.0003	-0.0689
	*Predominant IPT users	0.0855	-0.0038	-0.0817
	*Predominant private vehicle users	-0.1218	-0.0117	0.1336

*Dummy coded variables

4.4.1.4 Scenario analysis

The ordered logit models presented in the previous section were further used to estimate the probability of public transit (PT) and intermediate public transit (IPT) use by different user groups over the period after easing of restrictions (Figure 8 and

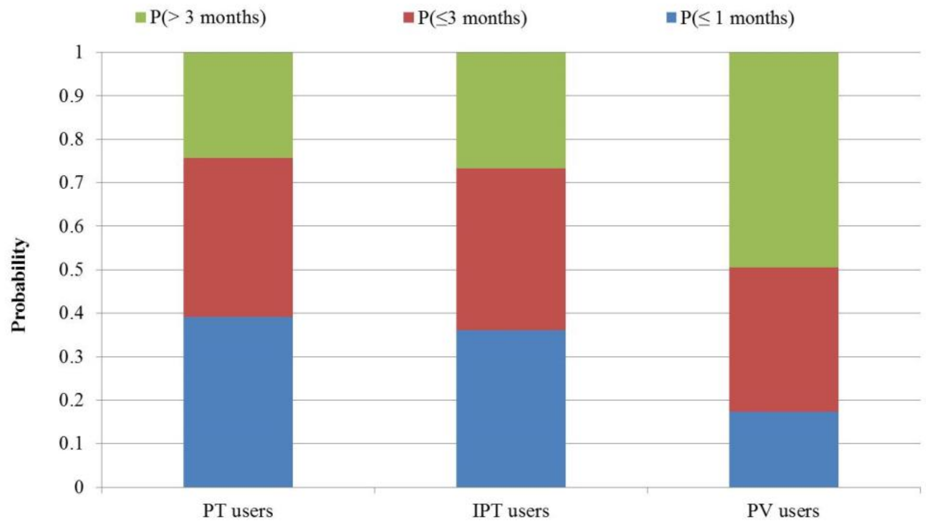


Figure 9). It may be observed from Figure 8 that with increase of age the probability of recovery of PT use during different time periods reduces in general for both PT and PV users (predominant mode). However, significant differences are observed in recovery between those two types of travelers. For example, for a younger age group (say, 25 year older) and predominantly PT users, the likelihood of starting the use of PT service within one month after easing of restrictions is over 69% which reduces to 65.8% for middle age group (say, 45 year older) and 62.7% for older age group (say, 60 year older). On the other hand, though the likelihood of starting the use of PT service shows a similar decreasing trend with increase of age for the predominantly private vehicle (PV) users, the likelihood values are substantially lower (i.e., only 38%, 34%, and 31% for 25 years, 45 years and 60 years older PV users respectively) for this group of travelers as compared to PT users. As the figures indicate the recovery of PT usage across age groups are likely to further improve with the time and it is likely to take more than three months to recover nearly to 90%. However, the predominantly PV users are likely to take even longer time and may only recover upto 70-75% in three-months' time or more. A full recovery may take longer time, sometimes even upto six months or more and a section of people may not even return to PT due to change in their riding behaviour.

A close look at the recovery trend across different income groups revealed a declining trend in likelihood of starting use of PT with the increase of income. This indicates that higher income groups across different age groups are likely to take longer time to start using PT services.

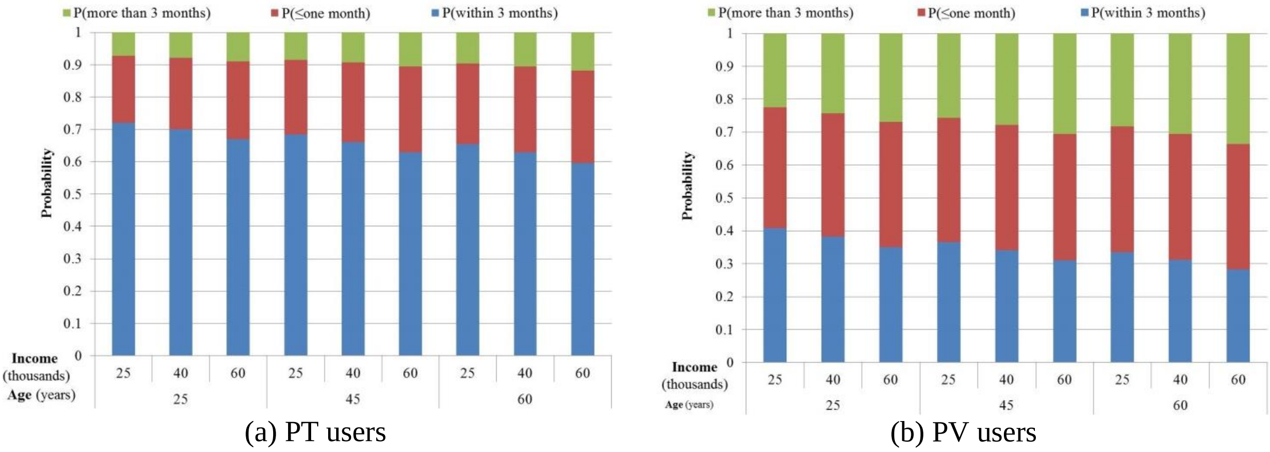


Figure 8 Use of PT modes by different user groups

Similarly, the likelihood of recovery of IPT ridership across different user groups is presented in

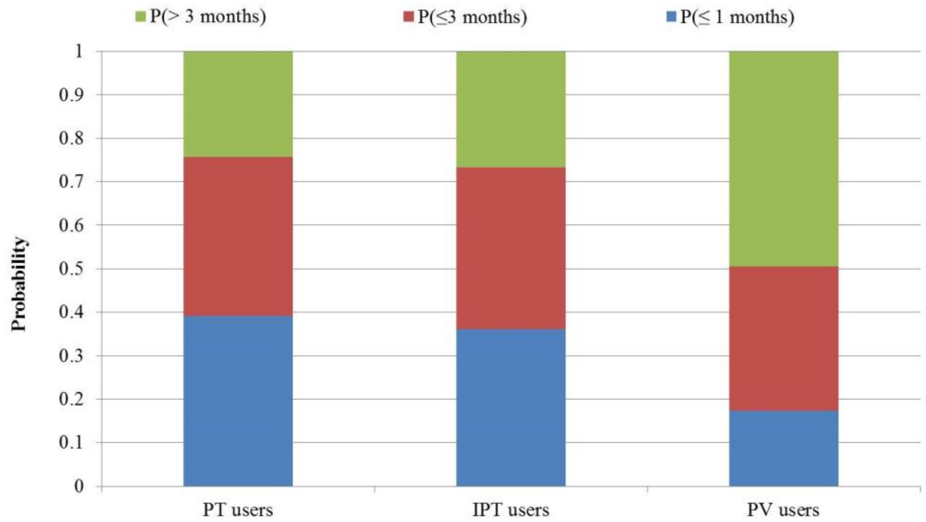


Figure 9. It may be clearly observed from the figure that the likelihood of PV users starting to use IPT modes within one-month period after easing of restrictions is lowest (i.e., only 17%) among all the travelers. The recovery may reach only upto 50% for the PV users until three months after the easing of restrictions. However, predominant PT users and IPT users are expected to start using IPT relatively earlier because of their captive nature to PT/IPT modes.

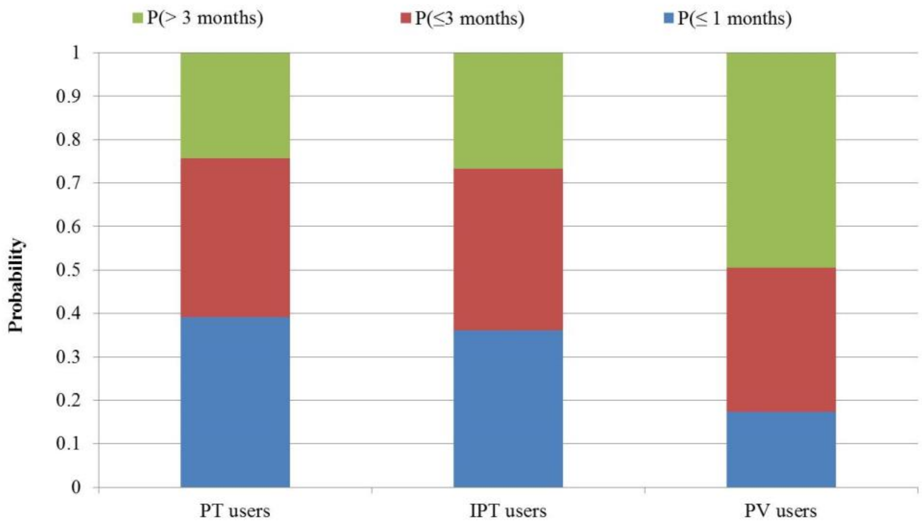


Figure 9 Use of IPT modes by different user groups

5 CONCLUSION

The present paper brings out several interesting findings regarding impact of COVID-19 outbreak on travel behaviour in India in terms of reaction to 'work from home' advisory issued by the Government, change in preferences of mode of travel and long distance travel plans, perceived risk of infection from travel on different modes and how the infection risk perceptions changed over the time, and future use of different modes.

The findings with respect to 'work from home' advisory indicates that the compliance to this policy gradually increased over the time with the increase of reported COVID-19 cases which may be attributed to higher degree of awareness about the dangers of COVID-19. Almost 98% respondents reported that they started 'work from home' even before the lockdown was announced. Such high compliance to work from home policy certainly helped to maintain social distancing and reduce the spread of the COVID-19 virus. People also cancelled their planned long-distance trips due increased awareness and/or occasionally were forced to cancel the trips due to unavailability of realistic alternatives. The findings encourage the application of 'work from home' policy as an effective and acceptable instrument to reduce travel and subsequently the spread of the pandemic.

The work brings out different infection risk perceptions across different modes of transport with high degrees of risk observed for common carrier modes. Highest perceived risk of infection from travel was observed for international flights indicating a long recovery period for the resumption in international travel and related economic recovery. In terms of urban travel, personal vehicles were perceived as safest mode of transport among all the modes followed by intermediate public transport (IPT) modes and public transport (PT) modes. This finding was also reflected in the change of travel modes during the initial periods of the COVID-19 outbreak. Almost 25% respondents changed their travel mode from PT to personal vehicle (i.e., car/M2W) and the change to personal vehicle from IPT was over 21%. These findings clearly indicate towards a paradigm shift in terms of expected mode choice during post-COVID-19 era – the personal vehicles are likely to be more favourable than PT or IPT modes. This may result in aggravated congestion and emission issues in urban India. Therefore, a substantial level of interventions for the common carrier modes is necessary on a priority basis to regain the confidence of road users towards use of such modes and restrict the modal shift towards more personalized modes of transport. The study also indicates a change in the perceived infection risk of different modes over the time with the rise in COVID-19 cases.

The study further reflects on the future of transportation system post COVID-19 era based on infection risk perceptions about travel in different modes, and their stated willingness to potential use of different modes over the period after the restrictions are lifted. It is clear from the study that the international flight is likely suffering challenges to return to normalcy for a longer duration than other modes. The study shows that while the use of private transport modes is likely to start as soon as restrictions are removed, PT and IPT modes are likely to take a longer time to regain their ridership. However, the choice of PT and IPT modes over the period may get influenced by various factors such as infection risk perception, prevailing covid situation, and predominant mode choice behaviour during pre-COVID times. Additionally, travellers' age and income level may also influence the traveller's choice of PT modes over the time. The riders captive to PT and IPT models are likely to start using these modes earlier than others, and these modes may take more than six months to regain their ridership given the COVID-19 scenario is controlled. It is expected that use of personal vehicles will increase during post-COVID times and it may result in increased congestion, emission, and traffic management challenges in the cities. More worrisome is that the public transport may not be able recover their ridership to pre COVID-19 levels for a longer period in post COVID-19 era unless the concerns related to infection risk perception are addressed adequately. It is also a possibility that a section of people who were using PT/IPT modes during pre-COVID-19 era may get adapted to personal vehicle and may not return to PT/IPT mode. Strategic interventions to reduce risk of COVID-19 infection during travel in PT and IPT modes and awareness to build public confidence may help in early recovery of PT and IPT ridership. The study also emphasises on the potential challenges in rejuvenating the use of public transport modes for urban travel as the personal modes seem to be a clear favourite among the people during post COVID-19 era.

It is evident from the study that the behaviour with respect to the travel decisions were changing over the period and the present paper considers the responses during the early stage of COVID-19 outbreak in India. It would, therefore, be interesting to investigate the responses over other time periods during the post-COVID-19 outbreak and also study the impact of various policies adopted in the subsequent periods by the administration on travel behaviour.

ACKNOWLEDGEMENTS

Authors express their sincere thanks to the COVID-19 Task Force of World Conference on Transportation Research Society (WCTRS) for motivation and encouragement to carry out this work.

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