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Modelling work- and non-work-based trip patterns during transition to lockdown period of COVID-19 pandemic in India

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ABSTRACT

COVID-19 pandemic has significantly affected the transportation sector across the world. Implementation of lockdown (that includes restricted travel activities) is a prevention strategy executed by various governments to minimize the spread of COVID-19. India went into complete lockdown from 25th March 2020; however, change in commuter's travel behavior was observed from the third week of March (termed as transition to lockdown) due to pandemic fear. In total 1945 participants participated in the travel behaviour survey and their responses with respect to work-based and non-work-based trips during transition period were analysed to understand their adaptation towards COVID-19. The study also attempted to quantify the effects of influencing factors which can explain change in the commuters' travel behaviour. The findings revealed that one-year increment in traveller's age had 2% reduced probability of no travel during transition than pre-transition. For non-work-related travel, chances of lower travel frequency were significantly greater during the transition period as compared to pre-transition. Compared to the non-essential trips, the chances of reduced travel frequency for the essential trips were found to be lower by 92%. By examining these behavioural changes, the present study aims to assist the policymakers in understanding the dynamics of fluctuating travel demand with respect to trip purpose during pandemic situations like COVID-19.

1. Introduction

The war against novel coronavirus (SARS-CoV-2) has opened a battlefront across all the countries. The unprecedented lockdown in India has unsettled lives and halted the economy. The governments of various countries have implemented the lockdown protocol, where travel behavior of population is restricted only to essential services (such as food, healthcare emergencies, etc.). Since the vaccination of novel coronavirus is in the development and testing stages at present, public health authorities have advised people to practice social distancing and stay in their homes, and adopt precautionary measures such as using masks and sanitization (Wilder-Smith and Freedman, 2020).

Along with the threatening effects on public health, the COVID-19 outbreak has significantly impacted the travel behavior of individuals (Vos, 2020; Bogoch et al., 2020). Personal attitudes and individual perceptions are known to influence the travel-related choices and travel patterns (Kroesen and Chorus, 2020). Since the knowledge about the novel coronavirus is quite limited, it has inculcated pandemic fear among individuals. As a result, various countries (such as the USA, the UK, and South Korea) have observed significant decrements in their transit ridership (Badger, 2020; Carrington, 2020; Park, 2020).

China was the first country to implement lockdown to prevent the spread of COVID-19, where Wuhan city was put to lockdown on 23rd January 2020 for a period of 59 days after which travel relaxations were given (Langton, 2020). Following the steps of China, other countries majorly affected by the novel coronavirus (such as the UK, the USA, Italy, France, India, etc.) started putting their population into lockdown or mass quarantines (Kaplan et al., 2020). In India, the lockdown period of 68 days was implemented across the country by the government in five phases. The first phase was of 21 days from 25th March to 14th April; the second phase was of 19 days from 15th April to 3rd May; the third and fourth phases were of 14 days from 4th May to 17th May; and from 18th May to 31st May 2020 respectively, and the fifth phase began from 1st June 2020 (Ministry of Home Affairs, Government of India).

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However, with every subsequent phase of lockdown, some relaxations in the restrictions of travel behaviour are provided, but the situation is still far from normal.

Though India went into lockdown from 25th March 2020, the change in travel pattern of the commuters was noticed from the third week of March (i.e., between 15th and 24th March 2020) due to self-awareness and pandemic fear. This phase between no lockdown and lockdown is termed as transition phase for Indian population. During the transition period, people started reducing their daily commute to workplace and elsewhere, after perceiving the safety threats of COVID-19. Therefore, there is a need to investigate the variations in the travel behaviour and mobility patterns of individuals during the transition period to understand and model their adaptation mechanisms towards such pandemic scenarios, and also to identify the influencing factors which can explain these travel behaviour changes.

The present study has societal contributions linked to mobility and urban sustainability, which impacts the quality of life of individuals. By examining the variations in travel behaviour, the present study aims to assist the policymakers and transport authorities in understanding the dynamics of fluctuating travel demand along with time during pandemic situations like COVID-19. In the post-COVID era, the transport policies and infrastructure may require adequate makeover in order to meet the revised demands of travellers, due to the inclusion of social distancing in their travel routine. Therefore, it is important to understand the extent of deviations in travel patterns during the transition to lockdown period in comparison with pre-transition period, i.e., business as usual situation before the transition to lockdown period of COVID-19. In this aspect, the outcomes of the present study have policy implications on the urban transportation planning while accounting for effects of COVID-19 in a developing country like India.

2. Literature review

2.1. Individual travel behaviour and travel-related characteristics

The literature on travel behaviour dynamics research can be categorized into micro-dynamics and macro-dynamics (Wang et al., 2017). The micro-dynamics research deals with day-to-day scheduling of activity travel (Krygsman et al., 2006; Arentze et al., 2011), whereas the macro-dynamics research examines the temporal variations in the travel behaviour of individuals, from the perspectives of long-term and short-term travel patterns. The long-term travel behaviour dynamics research analyses the changes in travel patterns over a period of many years using panel data (Lin et al., 2018; Parkes et al., 2016; Srinivasan and Bhargavi, 2007; Roorda and Ruiz, 2008), while the short-term travel behaviour changes are observed with respect to different workdays for various activity types (Roorda and Ruiz, 2008; Habib and Miller, 2008).

Previous research had investigated the variations in travel behaviour of individuals subjected to various conditions such as residential relocation (Lin et al., 2018; Fatmi and Habib, 2017; Klinger and Lanzendorf, 2016), migration to other cities (Welsch et al., 2018), during recreational holidays (Wang et al., 2017), and during international sports events (Parkes et al., 2016). The selection of preferred mode of travel is generally a habitual decision and people continue to use the same mode of transport for commute unless there is a major change of state such as change in work site, change of residence, etc. which may force the commuters to change their mode of travel (Gardner, 2009; Zhang, 2006). The present situation of COVID-19 outbreak is also one such major situational changes of state which has influenced the travel behaviour of individuals (Vos, 2020). However, in such situations, individuals who do not have ownership of private vehicles, and are dependent on public transportation for their daily travel activities, may not have the flexibility of changing their mode of travel. This may lead to social exclusion and impact their quality of life (Kamruzzaman and Hine, 2012). It is observed that experience of day-to-day travel behaviour may significantly influence the overall well-being of individuals (Friman et al., 2017).

2.2. Factors influencing travel behaviour of individuals

Travel behaviour of individuals may depend on multitude of influencing factors, namely, (a) structural factors (e.g., transport operations, transport infrastructure, etc.), (b) demographic factors (e.g., age, income, education, etc.), (c) travel-related factors (e.g., travel purpose, travel cost, travel distance, etc.), and (d) psychosocial factors (e.g., individual attitudes, perceptions, etc.). Previous studies have reported significant differences in travel behaviour with respect to age, income, gender, and car ownership (Small et al., 1995; Pucher and Renne, 2003). However, a situation like COVID-19 pandemic would trigger a change in the social environment, which is likely to result in variations in travel behaviour and mobility patterns of individuals. The travel decisions taken during this changing social environment may not only depend on the traditional factors identified in the past studies, but may also take into account additional factors such as personal safety, and avoiding potential interactions generated due to the shift in the social environment of individuals.

2.3. Effect of travel restrictions on activity-travel behaviour

Travel restrictions are enforced in various countries from time-to-time by their governments, where people have to adapt to such travel-related policy measures (Gu et al., 2017; Parkes et al., 2016). Gu et al. (2017) investigated the adaptation mechanisms of people during travel restrictions in China during Beijing Olympics in 2008, and found that restrictions on private vehicles led to 4.3% increase in the use of bus transit system, and 2.2% increase in bicycle use. Additionally, they reported that non-drivers (individuals who do not have private vehicle ownership) significantly reduced their trip frequency on days with travel restrictions compared to no-restriction days. Another study examined the variations in travel behaviour during London Olympics and Paralympic games in 2012, and compared the behavioural responses during the events with the behavioural responses before the event (Parkes et al., 2016). Researchers found that about 54% of the individuals who did not contemplate making any change in their travel behaviour during pre-event stage, had to undergo changes in their travel patterns during these events (Parkes et al., 2016).

Investigations on such disruptive events (either planned or unplanned) showed that variations in travel behaviour during the event, may also lead to behavioural changes in travel patterns after the event. For instance, a study by Shires et al. (2016) examined travel behaviour changes after the closure of a road bridge in Edinburgh, which resulted in doubling of travel time of car users. This event triggered the travel behaviour changes in such a way that about 60% of the car users switched to rails, resulting in overcrowding in some of the rail services (Shires et al., 2016). These studies demonstrate that such disruptive events bring prominent changes in the operation of transportation systems in order to cater to the varying public travel demands. However, in contrast to these disruptive events, COVID-19 outbreak resulted in significantly reduced ridership of public transportation (Carrington, 2020; Park, 2020). Therefore, it is important to understand the underlying factors that influence the adaptation behaviour of individuals concerning their transportation habits in an unplanned disruptive incident like COVID-19 pandemic is required.

2.4. Impact of COVID-19 outbreak on travel behaviour

Social distancing due to COVID-19 outbreak has resulted in travel demand reduction, which has impacted the road transport system (Vos, 2020). As the novel coronavirus poses a threat to personal safety, people are likely to avoid public transportation to prevent potential exposure, as there are high chances of human contact while travelling in public transport systems (Troko et al., 2011). A recent survey highlighted that about 74% of the people are anxious about their travel, with older population having higher travel anxieties (Glusac, 2020). Moreover, multinational corporations such as Google, Amazon, Nestle, Ford, etc. have restricted work-related travel for their employees (Brownstein Client Alert, 2020). However, people working in cargo and goods industries have no choice than to continue work-related travel even during COVID-19 outbreak (Brownstein Client Alert, 2020). Many companies have deployed technological solutions and online meeting platforms to enable digital interactions to minimize social gatherings and work-related travel wherever possible (Mathur, 2020). Further, COVID-19 has altered the way people make non-work-related trips. Due to the pandemic fear and travel restrictions, it is anticipated that consumers would be likely to buy more of essential items (such as grocery) and reductions would be observed in case of luxury goods and leisure items (Singh and Razdan, 2020). These differences in travel likelihood would have influenced the travel behaviour patterns for essential and non-essential trips. As trip purpose is likely to impact the travel behaviour of individuals, it is important to understand the contrasts in travel behaviour with respect to work-based and non-work-based trips during the transition to lockdown period.

2.5. Research motivation and objectives

The influence of COVID-19 outbreak on the travel behaviour of individuals needs to be understood and has received very little attention till date. As COVID-19 is likely to have substantial implications on transport-related policies in the coming days, understanding the variations in activity-travel behaviour induced by COVID-19 outbreak compared to pre-lockdown period, may provide detailed insights into the modelling, prediction and management of travel-related demands during post-COVID period. In this regard, the present study focuses on the following objectives:

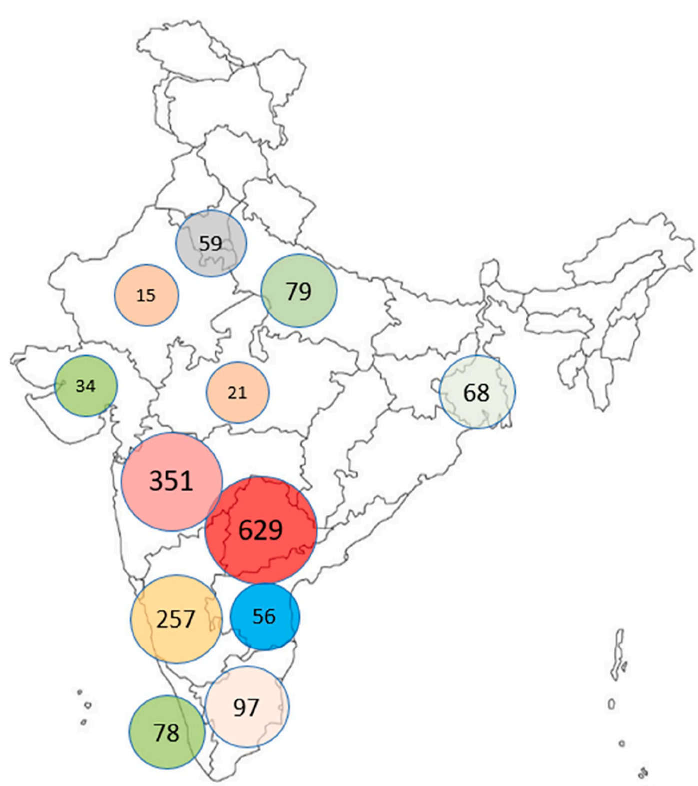
(a) To analyse the variations in travel patterns of individuals (with respect to work-based and non-work-based trips) during the transition to lockdown period due to COVID-19 outbreak in India, and
(b) To identify and quantify the effects of potential socio-economic and travel-related factors influencing behavioural changes in travel patterns during transition to lockdown.

3. Method

Based on the extensive literature review on travel behavior and COVID-19 impacts on transportation sector, a detailed questionnaire survey was designed, target study population was determined, and data analysis approaches were identified. Based on the questionnaire survey, travel behavior data was obtained with respect to work-based trips and non-work-based-trips of individuals during transition to lockdown period due to COVID-19 outbreak. The obtained survey data was then subjected to preliminary analysis where descriptive statistics were observed to analyze the travel behavior variations. In the next stage, statistical models were developed independently for both work-based and non-work-based trips. Further, the interpretations of study outcomes are presented and the policy and planning implications of the study are discussed.

3.1. Data collection

The researchers disseminated an online travel behavior survey to the general Indian population through social media websites, personal interactions and public communications (Pawar et al., 2020). The geographic spread of collected data is shown in Fig. 1. The survey captured the travel patterns of individuals in terms of frequencies of making work-related and non-work-related trips during the transition to lockdown period of COVID-19 (i.e., 15th to 24th March 2020). Further,



State	No. of Data
Telangana	629
Maharashtra	351
Karnataka	257
Tamil Nadu	97
Uttar Pradesh	79
Kerala	78
West Bengal	68
Delhi	59
Andhra Pradesh	56
Gujarat	34
Madhya Pradesh	21
Orissa	17
Rajasthan	15

Fig. 1. Geographic spread of collected data.

non-work-based trips were categorized into essential and non-essential trips, where travel for purchasing grocery was considered as an essential trip, and other trips such as shopping trips, restaurant trips or inter-city travel were considered as non-essential trips. Further, the demographic information (e.g., age, income, etc.) as well as travel-related characteristics (e.g., preferred mode of travel, travel distance, travel time, etc.) and safety perceptions of individuals with respect to each transport mode were enquired. The responses from the participants were collected between 18th to 28th March 2020, however the participants were asked to fill the travel pattern data pertaining to the 3rd week of March only.

3.2. Respondents

A total of 1945 participants filled the travel behavior survey. About 65% of the participants belonged to Tier-1 cities, 20% belonged to Tier-2 cities and 15% were the residents of Tier-3 cities (In India, the cities are divided into these three categories based on the population density and cost of living. Tier-1 are the cities with the highest cost of living and population density, whereas Tier −3 cities have the lowest cost of living and population density). There was no compensation provided for participation and the participants were ensured about data confidentiality. Further, incomplete and inconsistent responses were removed from the analysis. Table 1 shows the descriptive statistics for work-based trips (N = 1505) and non-work-based trips (N = 1529) obtained from the travel behavior survey. The responses for annual income indicate that the sample is fairly distributed among all the different income groups. The mean age of respondents was 32.56 (±10.64) years in case of work-based trips (Table 1A), and 32.53 (±10.71) years in case of non-work-based trips (Table 1B). The preliminary analysis of questionnaire survey revealed that, during the transition to lockdown period, about 45% of the respondents did not travel to work, 23.6% reported reduced travel, while 31.4% said that they travelled to work similarly as during pre-transition period (normal course of the daily activities/business as usual). With respect to non-work-based trips, the frequency of making essential and non-essential trips before and during lockdown period is shown in Fig. 2.

It can be observed that there was a slight decline in regular travel to essential trips during the transition period compared to pre-transition period. However, there was a drastic reduction in non-essential trips during the transition period (81.04% reported zero travel during the transition period as compared to 42.24% in the pre-transition period).

3.3. Data analysis

During the questionnaire survey, the travel frequencies were directly enquired from the responders for both the work and non-work trips, and they were ordinal in nature. On the other hand, the change in trips were not ordinal in nature as they were derived by differentiating the trip frequencies. In case of the work trips, the change in trip patterns was categorized into the following categories: 'same as before', 'reduced travel' and 'no travel', whereas for the non-work trips, the change was categorized into the following categories: 'same as before', 'increased travel' and 'decreased travel'. Because the travel behaviour was presented in terms of change in travel frequency for work trips and their absolute travel frequency for non-work trips, the models were chosen as multinominal and ordinal regressions respectively (with k-fold cross validation technique).

As the work-related travel patterns involved three distinct choices, Multinomial Logit (ML) models were developed for quantifying the effects of socio-economic factors and travel characteristics of individuals on their travel patterns (Bansal et al., 2018; Basu et al., 2017; Fatmi and Habib, 2017). Here, the "Same as before" condition was considered as baseline, i.e., the ML model results were presented in terms of factors leading to "Reduced travel" and "No travel". All the variables listed in the Section A of Table 1 were considered as independent factors. In a multinomial logit model, the mathematical structure for the probability of selecting a travel pattern alternative '*i*' by a traveler with '*j*' alternatives and '*V*' as perceived utility, can be expressed as Eq. (1) shown below (McCafferty and Hall, 1982).

Table 1
Descriptive statistics for work-based and non-work-based trips obtained from survey.

Section (A): Summary statistics of work-trips (N = 1505)		
Variable	Levels	% or Mean (SD)
Age		32.56 (10.64)
Travel distance (kilometers)		13.37 (14.57)
Travel time (minutes)		37.15 (38.09)
Safety perception for public transport	Not safe	92.36
	Safe	7.64
Safety perception for private vehicle	Not safe	8.31
	Safe	91.69
Safety perception for taxi	Not safe	72.49
	Safe	27.51
Safety perception for active modes (Bicycle/Walk)	Not safe	32.4
	Safe	67.6
Frequency of work travel before transition period	<5 days a week	13.29
	Five days a week	39.87
	Six days a week	34.02
	Whole week	12.82
Annual income*	Up to 3 lakh rupees	25.65
	3 to 6 lakh rupees	27.04
	6 to 12 lakh rupees	27.38
	More than 12 lakh rupees	19.93
Preferred mode of transport	Private Vehicle	51.83
	Public Transport	21.73
	Non-shared Taxi/Auto	11.56
	Active modes (Bicycle/Walk)	14.88
Frequency of travel to work during transition period	Same as before	31.36
	Reduced travel	23.65
	No travel	44.98
Section (B): Summary statistics of non-work-trips (N = 1529)		
Variable	**Levels**	**% or Mean (SD)**
Age		32.53 (10.71)
Safety perception for public transport	Not safe	92.54
	Safe	7.46
Safety perception for private vehicle	Not safe	8.18
	Safe	91.82
Safety perception for taxi	Not safe	72.53
	Safe	27.47
Safety perception for active mode (Bicycle/Walk)	Not safe	32.44
	Safe	67.56
Annual income*	Up to 3 lakhs rupees	25.77
	3 to 6 lakh rupees	26.88
	6 to 12 lakh rupees	27.34
	More than 12 lakh rupees	20.01
Frequency of travel to essential non-work-based trips before transition	Regular travel	75.48
	Sometimes	12.52
	No travel	11.99
Frequency of travel to essential non-work-based trips during transition	Regular travel	62.71
	Sometimes	13.33
	No travel	23.97
Frequency of travel to non-essential non-work-based trips before transition	Regular travel	22.99
	Sometimes	34.77
	No travel	42.24
Frequency of travel to non-essential non-work-based trips during transition	Regular travel	10.32
	Sometimes	8.65
	No travel	81.04

*1 lakh = 0.1 million.

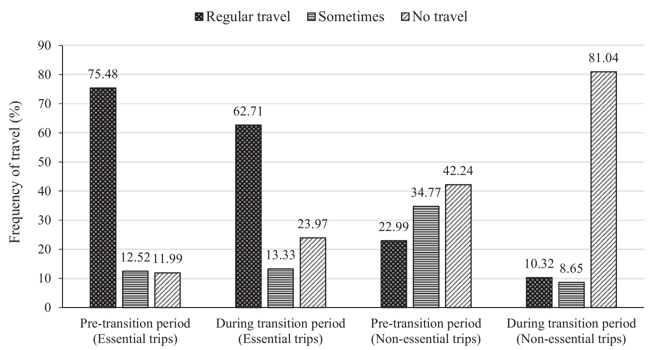


Fig. 2. Travel frequencies for non-work-based trips before and during the transition to lockdown period.

$$Pr(i) = \frac{exp(V_i)}{\sum_{j=1}^{J} exp(V_j)} \quad (1)$$

For non-work trips also, the change in travel frequency was modelled initially, but it was not able to explicitly explain the travel behavior as none of the factors except purpose of the trip appeared significant. Moreover, travel behaviour was better explained by the travel frequency rather than change in trip frequency. Hence, to better understand the travel behaviour for non-work trips, the travel frequency model is presented. Keeping in the view of ordered response of the travel frequency, an Ordered Logit Model was developed to explore the significant factors associated with travel patterns for non-work-based trips (Rezapour et al., 2019; Kropat et al., 2017; Yasmin and Eluru, 2013). All the variables indicated in Section B of Table 1, were considered as potential factors affecting travel patterns for the non-work-based trips. The mathematical formulation of ordered logit models for modelling the probability of selecting z can be expressed as Equation (2) shown below. Here, j ε {1, …, J-1}, i ε {1, …, M}, α is constant, x_i are the predictor variables and β_i are their parametric coefficients (Kropat et al., 2017).

$$logit(P(z_i \le j)) = \alpha_j + \sum \beta_i x_i \quad (2)$$

4. Results

The present study aimed to explore the changes in travel patterns and potential factors leading the changes in these patterns of work-based and non-work-based trips during the transition period as compared to before the transition period. The study findings are presented separately for work and non-work-related trips in the subsequent subsections.

4.1. Change in travel patterns for work-based trips

The results of best fit ML model are shown in Table 2. The findings revealed that in case of 'no travel' category, the variables such as age, city type, income and frequency of travel significantly influenced the change in the travel pattern of commuters during the transition to lockdown period. Whereas, in case of 'reduced travel' category, only frequency of travel appeared as the major influencing factor. Moreover, mode of travel to work did not significantly impact any of the travel categories. Though the safety perceptions of the travellers were also considered as potential factors for prediction of change in their travel patterns during the transition period, they did not appear to be significant and therefore, are not discussed further.

Fig. 3 shows the effects of age on probability of travel patterns for work-based trips indicating that age was a potential factor leading to reduced probability of "no travel" during the transition period. The model revealed that one-year increment in the age of traveller had 2% reduced probability of no travel during transition vs same as before transition. Further, the commuters residing in Tier-3 cities showed 32% and 71% lower probabilities of 'reduced travel' and 'no travel' respectively, compared to those residing in Tier-1 cities. The people residing in Tier-2 cities displayed 35% reduced probability of 'no travel' compared to Tier-1 dwellers; however, their probability of 'reduced travel' was not significantly different from the Tier-1 residents.

Table 2
Multinomial logit model results showing factors associated with change in work-based trips during the transition period.

Variable	Coefficients	OR	SE	z-value	p-value
Reduced Travel					
(Intercept)	0.595	1.813	0.379	1.568	0.117
Age	0.004	1.004	0.007	0.549	0.583
City type (Ref = Tier-1)					
Tier-2	0.061	1.063	0.181	0.337	0.736
Tier-3	−0.380	0.684	0.199	−1.903	0.057
Income (Ref = Up to 3 lakh rupees)					
3 to 6 lakh rupees	0.028	1.029	0.206	0.138	0.890
6 to 12 lakh rupees	−0.560	0.571	0.215	−2.610	0.009
More than 12 lakh rupees	−0.316	0.729	0.256	−1.234	0.217
Mode of travel (Ref = Private vehicle)					
Taxi	0.011	1.011	0.237	0.048	0.962
Public Transport	−0.105	0.900	0.193	−0.546	0.585
Bicycle or Walk	−0.451	0.637	0.244	−1.843	0.065
Frequency of travel (Ref = <5 days a week)					
Five days a week	−0.420	0.657	0.285	−1.474	0.140
Six days a week	−0.924	0.397	0.278	−3.320	0.001
Whole week	−0.870	0.419	0.321	−2.713	0.007
No travel					
Variable	**Coefficients**	**OR**	**SE**	**Z-value**	**p-value**
(Intercept)	2.876	17.736	0.340	8.449	<0.001
Age	−0.020	0.981	0.007	−2.922	0.003
City type (Ref = Tier-1)					
Tier-2	−0.433	0.648	0.170	−2.552	0.011
Tier-3	−1.223	0.294	0.198	−6.173	<0.001
Income (Ref = Up to 3 lakhs)					
3 to 6 lakh rupees	−0.589	0.555	0.185	−3.179	0.001
6 to 12 lakh rupees	−0.931	0.394	0.189	−4.928	<0.001
More than 12 lakh rupees	−0.369	0.691	0.224	−1.646	0.100
Mode of travel (Ref = Private vehicle)					
Taxi or Auto	0.216	1.241	0.213	1.013	0.311
Public Transport	0.294	1.342	0.169	1.737	0.082
Active modes (Bicycle or Walk)	0.156	1.169	0.200	0.781	0.435
Frequency of travel (Ref = <5 days a week)					
Five days a week	−0.973	0.378	0.246	−3.962	<0.001
Six days a week	−1.804	0.165	0.245	−7.369	<0.001
Whole week	−1.594	0.203	0.281	−5.664	<0.001
AIC value	3054.627				

OR = Odds Ratio; SE = Standard Error; Ref = Reference category; AIC = Akaike Information Criterion.

As shown in Fig. 4, the results also showed that generally, the travellers with higher income (3 to 6 lakh rupees or 6 to 12 lakh rupees) were less likely to switch to no travel during transition period as compared to travellers with income up to 3 lakhs (1 lakh = 0.1 million). As compared to travellers with income <3 lakh rupees, the chances of switching to no travel reduced by 45% and 61% for travellers with income of 3–6 lakh rupees and 6–12 lakh rupees, respectively.

The models revealed that working days in a week had a significant effect on travellers' choice to switching to reduced travel and no travel during the transition period as compared to the same travel pattern observed before transition (Fig. 5). The likelihood of having reduced travel was around 58–60% lower for people travelling more than 5 days a week as compared to people who travelled less than five days a week. The chances were worsened for opting to no travel as model showed that the likelihood of switching to no travel was 62–84% lower for people travelling more than 5 days a week as compared to people who travelled less than five days a week.

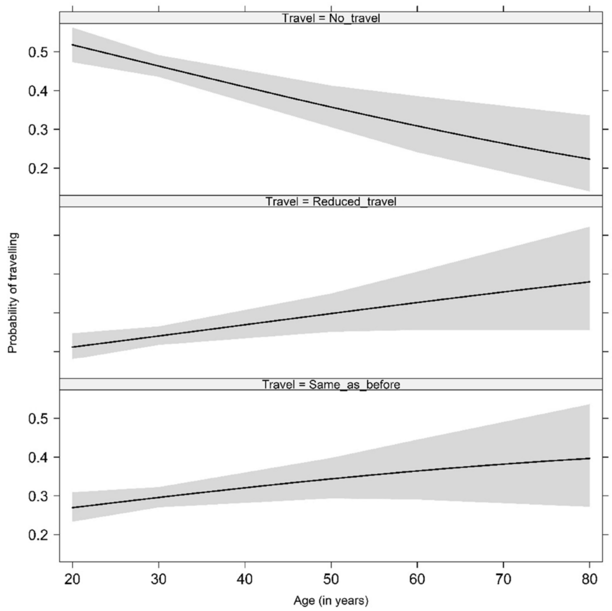


Fig. 3. Effect of traveller's age on work-related travel frequency (Note: The gray band indicates the 95% confidence intervals around the estimated probabilities).

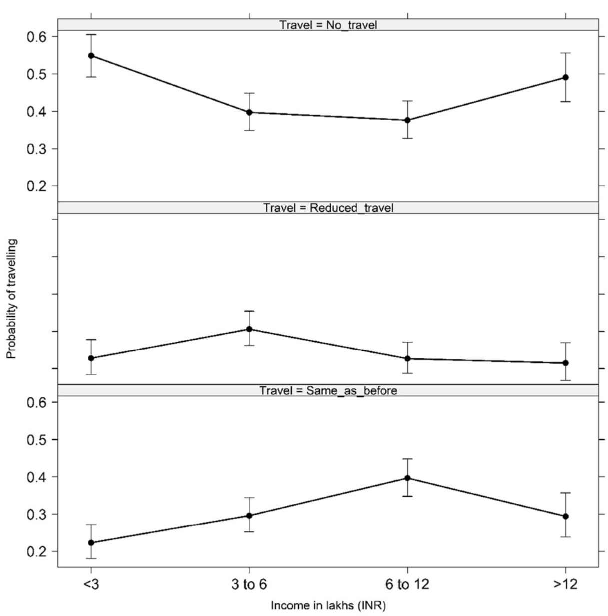


Fig. 4. Effect of traveller's income on work-related travel frequency (Note: Error bars indicate 95% confidence intervals around the estimated probabilities).

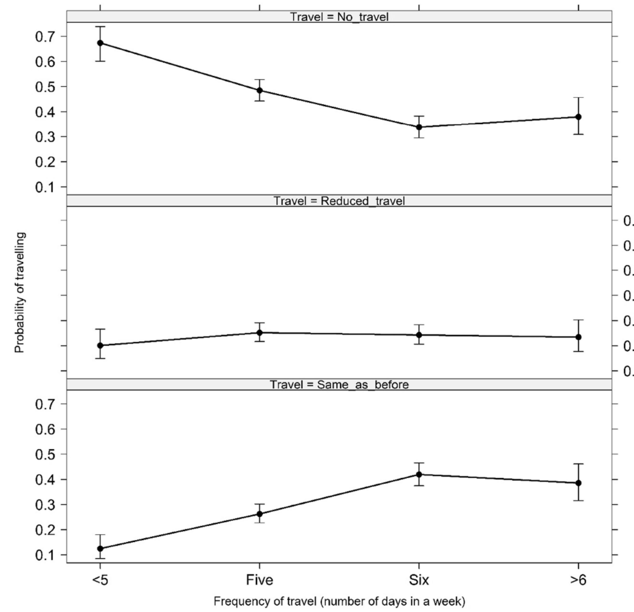


Fig. 5. Effect of working days on work-related travel frequency (Note: Error bars indicate 95% confidence intervals around the estimated probabilities).

Table 3
Model results of order logit model predicting likelihood of travel patterns for non-work-based trips.

Variable	Value	OR	SE	t-value	p-value
Trip period (Ref = Before transition)					
During transition	1.431	4.182	0.041	35.128	<0.001
Type of trip (Ref = Non-essential)					
Essential	−2.552	0.078	0.050	−51.450	<0.001
Income (Ref = Up to 3 lakh rupees)					
3 to 6 lakh rupees	−0.152	0.859	0.054	−2.802	0.005
6 to 12 lakh rupees	−0.291	0.747	0.054	−5.386	<0.001
More than 12 lakh rupees	−0.308	0.735	0.059	−5.184	<0.001
Safety perception (Ref = Note safe, for all modes)					
For Public Transport (Safe)	−0.135	0.874	0.076	−1.782	0.075
For Private Vehicle (Safe)	0.295	1.343	0.074	3.999	<0.001
For Non-shared taxi/auto (Safe)	0.077	1.080	0.045	1.723	0.085
Type of city (Ref = Tier 1)					
Tier 2	−0.068	0.934	0.050	−1.359	0.174
Tier 3	−0.017	0.984	0.057	−0.292	0.771
Intercepts					
Frequently | Sometimes	−0.892	0.410	0.081	−11.063	<0.001
Sometimes | No travel	0.282	1.326	0.080	3.528	<0.001
AIC	20354.07				

OR = Odds Ratio; SE = Standard Error; Ref = Reference category; AIC = Akaike Information Criterion.

4.2. *Travel frequency for non-work-based trips*

The best fit ordered logit model for non-work-based trips with all significant factors is presented in Table 3. The model results revealed that income, trip period (before/during transition), type of trip (essential/non-essential) and safety perception towards different modes were significantly associated with their frequency of travel to non-work-based trips.

The results showed that chances of reduced travel frequency were significantly higher during the transition period as compared to before the transition (odds ratio for reduced travel during transition vs before transition = 4.18). Further, type of trip had a significant effect as the chances of reduced travel frequency were 92% lower for essential trips as compared to non-essential trips. The effects can be easily predicted from the probabilities plotted with respect to time and type of trips (Fig. 6). From Fig. 6, it can be seen that probability of no travel for essential trips was substantially lesser than the non-essential trips, indicating that chances of having essential trips were significantly higher than non-essential trips. Whereas, the chances of no travel were significantly higher for both essential and non-essential trips while comparing the trips with respect to period of trip. However, travel patterns were not drastically different for sometimes travel category. The probability of regular travel was higher for essential trips as compared to non-essential trips, but the travel was less likely to be regular for both essential as well as non-essential trips during the transition period as compared to before transition.

Income of the traveller was also a significant factor, revealing that

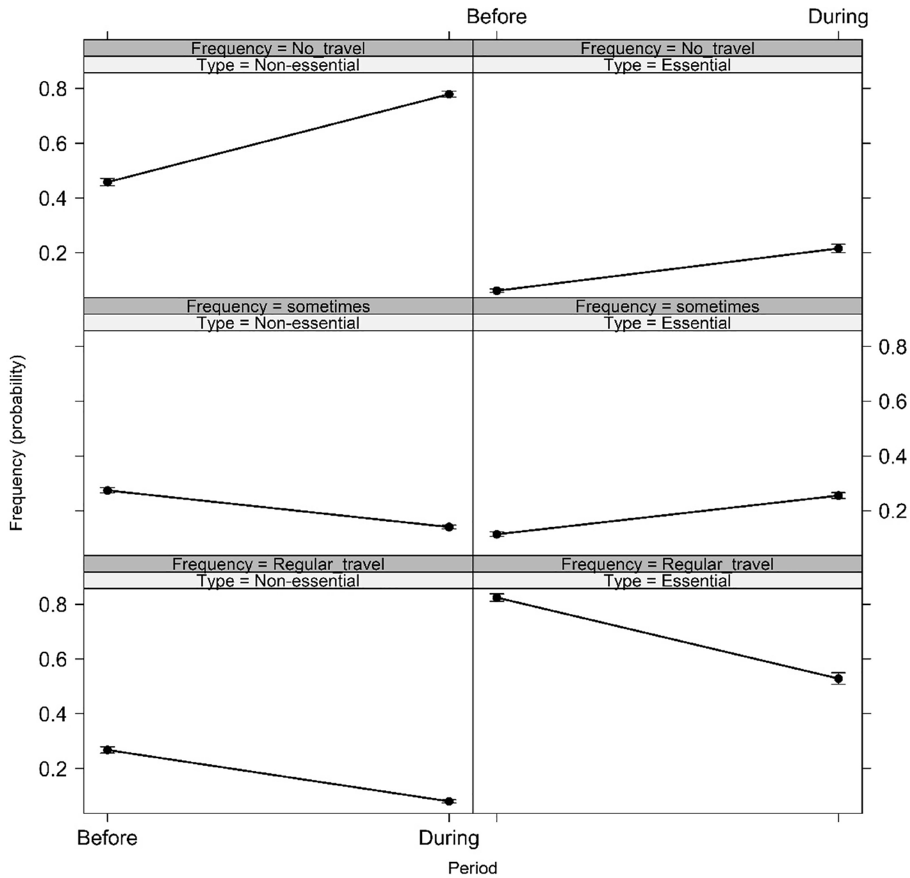


Fig. 6. Effect of type of trip on frequency of non-work-based trips (Note: Error bars indicate 95% confidence intervals around the estimated probabilities).

chances of opting to no travel were significantly lower for travellers belonging to higher income groups. There was approximately 14–25% reduction in chances of having reduced travel for higher income groups as compared to traveller who earned <3 lakhs rupees. Fig. 7 shows that higher income groups had higher probability of regular non-work-related trips as compared to low income groups. However, the graphs also indicate for all the income groups, there was substantial increment in probability of having no travel and significant reduction in regular travel during the transition period as compared to before the transition for all income categories.

Safety perception towards various modes of travel was also found to be affecting the travel pattern of the non-work-based trips. The results showed that the people who reported private vehicles (car, two-wheeler) and non-shared transit transport modes (taxi, auto-rikshaw) as safe options (i.e., less spreading of COVID-19) of travel, had more chances of no travel for non-work-based trips (Fig. 8). While the opposite effects were observed for safety perception towards public transport (PT) modes, because the chances were 18% lower for reduced travel for people who reported PT to be a safe option.

5. Discussion

This study examined the implications of COVID-19 pandemic on behavioral changes in travel patterns of individuals with respect to their work-based and non-work-based trips during the transition to lockdown period in Indian context. Further, the study identified the significant factors (among the socio-economic characteristics, travel characteristics, and safety perceptions) influencing the work-based and non-work-based travel behavior of individuals and quantified their effects on the behavioral changes.

5.1. *Impact of COVID-19 outbreak on work-based trips*

Commuting from home to work and vice-versa is a significant part of routine life for most of the individuals. However, during the transition to lockdown period of COVID-19, the present study found that travelers significantly reduced their work-related travel. Commuters of young age had higher probability of shifting towards no-travel during the transition to lockdown, probably because they might have higher opportunities of working from home (Vos, 2020). Further, low-income category people were more likely to shift towards no-travel compared to high-income group. A possible explanation for this observation is that low-income category people are favored towards public transportation, and since public transportation systems have higher chances of human contact resulting in viral transmission, they shifted towards no-travel (Troko et al., 2011).

Mode choice is known to be a crucial factor influencing the travel potential of individuals. However, in the present study, mode of travel did not show any significant influence on the travel patterns during the transition to lockdown period of COVID-19. Nevertheless, in the previous research, significant shifts have been observed from the public transport to the private transport modes, due to the associated risks of viral transmission (Hotle et al., 2020). Moreover, people with lower frequency of work-trips per week shifted towards reduced-travel or no-travel, compared to those who had to make frequent trips for work. This may be due to the reason that individuals who had to travel frequently to work, might have permanent/regular jobs and would have found it difficult to reduce their travel even due to associated risks of COVID-19. However, people who travel less frequently for work might consist of students or part-time workers/freelancers, etc. with flexible work schedule.

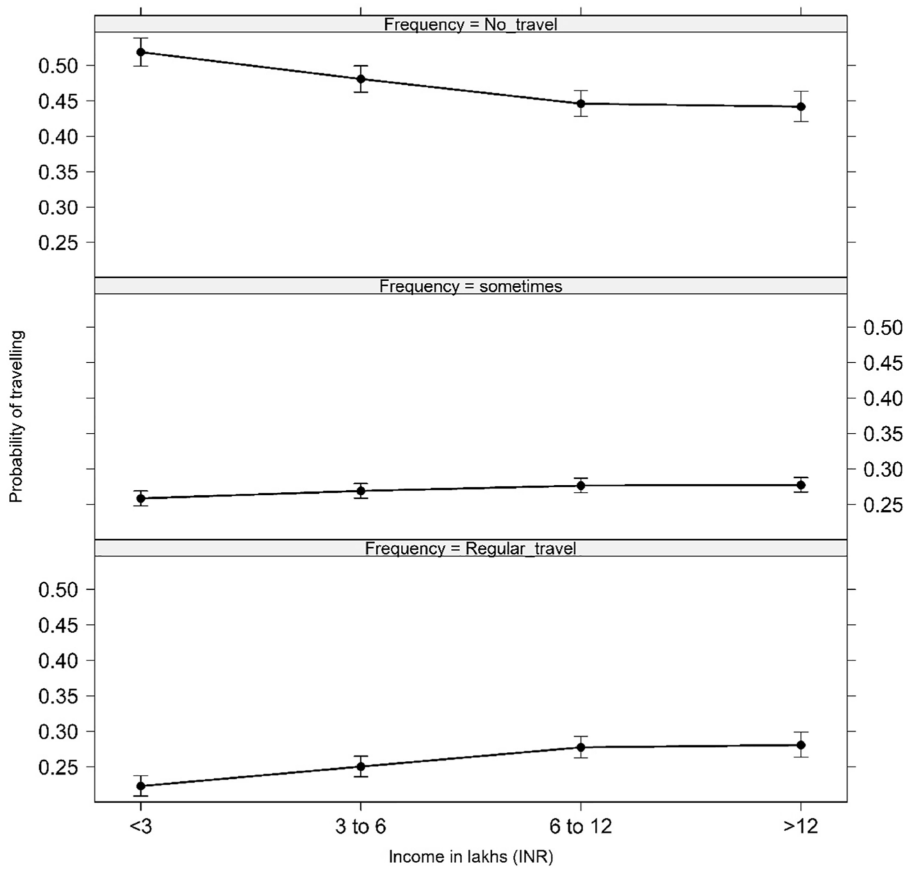


Fig. 7. Effect of income on frequency of non-work-based trips (Note: Error bars indicate 95% confidence intervals around the estimated probabilities).

5.2. Impact of COVID-19 outbreak on non-work-based trips

In the present study, non-work-based trips were divided with respect to trip type into essential trips and non-essential trips. Essential trips were the trips made to purchase essential items of livelihood such as grocery. Non-essential trips were basically leisure and recreational trips including shopping trips, restaurant trips and inter-city travel. Previous research has observed that after work-based trips, shopping trips are the second most frequented trips among the individuals (Shamim Al Razib and Rahman, 2017; Kikuchi et al., 2004). Besides, grocery trips are considered as an integral component of people's lives as they satisfy their basic daily needs (Guo and Peeta, 2020; Mouratidis et al., 2019).

Similar to the work-based trips, income was found to be significant factor influencing the travel frequency of non-work-based trips as well, where high-income category people were found to be less susceptible towards shifting to no-travel during the transition to lockdown period, compared to low-income group. Further, as expected, the travel frequency of non-work-based trips was significantly reduced during the transition to lockdown period than the pre-transition period. Moreover, travel frequency for essential trips was found to be significantly higher as compared to non-essential trips. This shows that people made most of the non-work-based trips with respect to essential grocery shopping, and avoided other recreational trips during the transition to lockdown period. Owing to the COVID-19 crisis, people may have got persuaded towards e-shopping which provides home-delivery of purchased items, which may also have affected their frequency of shopping trips (Xi et al., 2020; Shi et al., 2019).

An interesting observation in case of non-work-based trips in the present study was that the safety perception emerged as a significant factor influencing travel frequency. Previous studies have demonstrated an interrelated association between safety perception and risk mitigation (Jacobs et al., 2010; Barr et al., 2008). It has been observed that individuals with higher health-related safety perceptions are more likely to follow policy interventions to mitigate such virus outbreaks (Barr et al., 2008; Leung et al., 2003; Jacobs et al., 2010).

5.3. Policy recommendations

The outcomes of this study provide insights that have the potential to guide the design of future interventions aimed at providing safer travel as the relaxations in lockdown are provided. As lockdown cannot go on for an indefinite time, the government agencies would require research support in order to understand the variations in travel behavior and mobility patterns of individuals during these difficult times. The present study clearly indicated that people have drastically reduced their travel for both work-based as well as non-work-based trips during the transition period itself. However, in future, with lockdown relaxations, people have to resume their travel in due course. In this aspect, the insights from this study may help the transport authorities to understand the commuter's behavior and thereby easing the pressure gradually on transport infrastructure during the lockdown relaxations.

The study highlighted that people who are full time employed are less susceptible to stay at their home, and have to travel even in threatening scenarios like COVID-19 outbreak. In this regard, from the perspective of public health, the study suggests the provision of alternative work arrangements such as telecommuting and promotion of flexibility in work hours for the working population (Liao et al., 2012). However, it should be noted that work from home facilities are mainly available to the middle- and high-income category people (Beck and Hensher, 2020). As the present study observed that low-income category people significantly minimized their work-related travel, they may still not get benefitted from the flexible work arrangement systems.

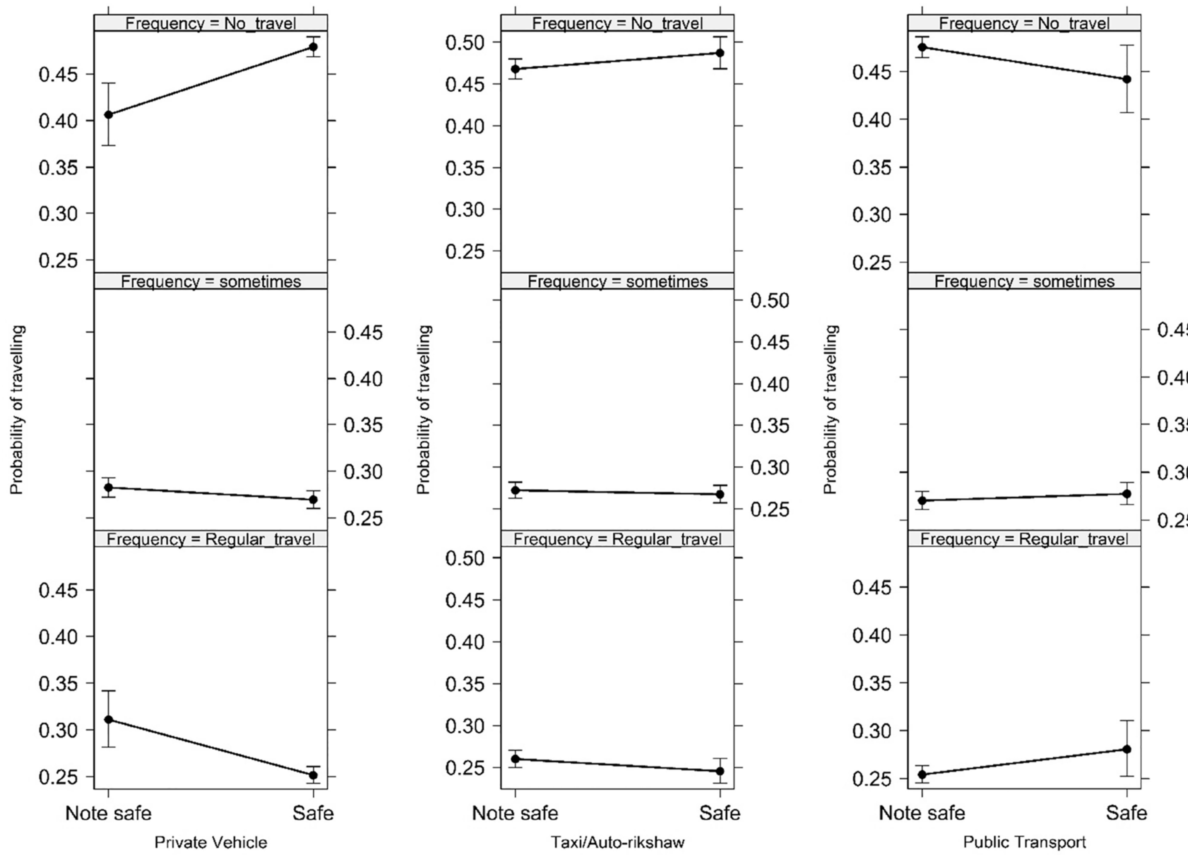


Fig. 8. Effect of safety perceptions on frequency of non-work-based trips (Note: Error bars indicate 95% confidence intervals around the estimated probabilities).

Moreover, as the economy hit low due to COVID-19, many of the low-income category people lost their jobs and their source of earning. Therefore, the first policy suggestion of the present study is that the government interventions should target the low-income category group by providing them adequate work opportunities/alternatives to sustain their livelihood, where they can work from their home or common working space by ensuring social distancing and using precautionary measures to combat COVID-19 transmission.

Moreover, safety perception during travel played a major influencing role in case of non-work trips, but no significant role was observed in case of work-trips. This indicates that people are afraid of going out of their homes for non-mandatory trips. However, they have to move out for the purchase of essential items (such as grocery). In this regard, the second policy suggestion of the study is that the shift towards no-contact purchase of the goods should be encouraged in order to ensure the safety of the vendors as well as the customers.

5.4. Conclusions

As far as the authors are aware, this is the first study in India which analyzed the influence of COVID-19 pandemic on the travel patterns of individuals with respect to work and non-work trips during the transition to lockdown period. The prevalent variations in travel behavior observed in the present study indicate that people substantially adapt their travel behavior and change their travel patterns in short-term owing to the perceived risk of contamination. Moreover, the outcomes of the study provide detailed insights into the various socio-demographic, travel-related factors and risk perceptions influencing the behavioral changes in travel patterns with respect to work-based and non-work-based trips during the transition to lockdown period in India. The study conclusions are listed as follows:

- About 45% of the individuals reported ‘no-travel’ and 23.6% reported ‘reduced travel’ for work-based trips during the transition to lockdown period of COVID-19 outbreak.
- In case of work-based trips, travellers’ age, income, city type and frequency showed significant influence on changes in their travel pattern during the transition to lockdown period.
- With respect to non-work-based trips, compared to pre-transition period, significant reductions were observed in regular travel to essential (from 75.5% to 62.7%) as well as non-essential trips (23% to 10.3%) during the transition to lockdown period.
- Travellers’ income, trip period (before/during transition), trip type (essential/non-essential) and safety perception towards transport modes showed significant influence on their travel frequency to non-work-based trips.

Having recently come into existence, this study examines the mobility patterns of individuals during the transition to lockdown period of COVID-19, and identifies the travel attributes associated with their travel behavior changes. Overall, it can be emphasized that pandemic fear has significant potential in impacting the travel-related decision-making process of individuals. Future transport policies would require to better address the travel needs of people, in order to restore their trust in safe transport systems post-COVID period.

The present study observed that more than 67% people reported positive safety perceptions towards active mode of transport (walk and bicycle). However, people using active mode during pre-transition period showed significant shifts towards no-travel during the transition to lockdown period. A possible reason could be the lack of existing pedestrian and bicycle friendly transport infrastructure in a developing country like India. Thus, the policymakers should consider encouragement of active transport usage among the travelling population, at least for short-distance travel, and improvement of existing road infrastructure facilities for cyclists and pedestrians. This will act as a significant step towards promoting public health and environmental benefits, shifting towards sustainable, equitable and green travel, and easing the road congestion and facilitating interpersonal distance (Vos, 2020). Moreover, the policy interventions would be more effective if the intervention strategies understand the target community and its people. In this aspect, the present study highlighted the characteristic traits of individuals which impact their travel-related decision-making process with respect to their purpose of travel. The short-term and long-term policy decisions would require to inculcate the new set of travel habits induced due to COVID-19 pandemic.

5.4.1. Research contribution

After the onset of COVID-19, researchers around the world have studied the influence of the pandemic on various aspects of travel behaviour (Dzisi and Dei, 2020; Irawan et al., 2020; Mogaji, 2020; Beck and Hensher, 2020; Jenelius and Cebecauer, 2020). However, the policy implications of the findings from other countries may not be directly applicable to the Indian conditions since the influence of the pandemic on commuters' travel behaviour tends to vary across the countries due to the inter-country differences with respect to the transport infrastructure, policy implementations, planning approaches, population size, economic conditions, government strategies to combat COVID-19, and public attitudes towards the pandemic. For instance, many of the developed countries were better equipped in minimizing the spread of the pandemic (such as New Zealand), whereas the large size developing nations (such as India) were struggling to control the situation during the pandemic. In this aspect, the present study contributes to the existing literature on the COVID-19 impacts on transport-related decisions by showcasing the perspective of a developing country like India with respect to work- and non-work-based trip behaviour. From this study, the research community will get a detailed insight into the attitudinal behaviour of the Indian commuters with respect to travel-oriented decisions, and the significant influencing factors behind their intention to travel during the transition to lockdown period in India. Even though the findings of the present study are primarily specific to India, but they can also be applicable to the other developing countries with similar level of transport infrastructure and policy regulations. The study observations will be helpful in developing the future interventions to combat such pandemic situations in the coming future, at the country level as well as at the global level.

5.4.2. Limitations

This study encountered certain limitations, which should be considered while interpreting the results. The present study examined the change in commuters' travel behavior only during the transition to lockdown period when the people may not have settled to the new travel patterns due to COVID-19. As the findings were obtained using a questionnaire survey, it cannot be devoid of the non-responder bias. The study did not capture the regional variabilities in travel behavior of commuters during the transition to lockdown period. Also, the study findings cannot be generalized to the population which is not compatible with the technology, as such people were left out during the online questionnaire survey. Future research shall look into developing large-scale models to monitor the travel behavior and public participation in handling such viral outbreaks efficiently. Further, the links between travel patterns, perceived risks and actual risk of exposure can also be examined. Additional studies shall also investigate the effectiveness of policy interventions, media campaigns and social media in reducing the spread of COVID-19 among the global population.

CRediT authorship contribution statement

Digvijay S. Pawar: Conceptualization, Data curation, Methodology, Writing - review & editing. **Ankit Kumar Yadav:** Validation, Visualization, Writing - original draft. **Pushpa Choudhary:** Formal analysis, Validation, Writing - review & editing. **Nagendra R. Velaga:** Supervision, Validation, Writing - review & editing.

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