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Modelling the effects of COVID-19 on travel mode choice behaviour in India

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A R T I C L E I N F O

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A B S T R A C T

The COVID-19 pandemic has resulted in unprecedented changes in the activity patterns and travel behaviour around the world. Some of these behavioural changes are in response to restrictive measures imposed by the Government (e.g. full or partial lock-downs), while others are driven by perceptions of own safety and/or commitment to slow down the spread (e.g. during the preceding and following period of a lock-down). Travel behaviour amidst the stricter of these measures is quite straightforward to predict as people have very limited choices, but it is more challenging to predict the behavioural changes in the absence of restrictive measures. The limited research so far has demonstrated that different socio-demographic groups of different countries have changed travel behaviour in response to COVID-19 in different ways. However, no studies to date have either (a) investigated the changes in travel behaviour in the context of the Global South, or (b) modelled the relationship between changes in transport mode usage and traveller characteristics in order to quantify the associated heterogeneity. In this paper, we address these two gaps by developing mathematical models to quantify the effect of the socio-demographic characteristics of the travellers on the mode-specific trip frequencies before (January 2020) and during the early stages of COVID-19 spread in India (March 2020). Primary data collected from 498 respondents participating in online surveys have been used to estimate multiple discrete choice extreme value (MDCEV) models in this regard. Results indicate – a) significant inertia to continue using the pre-COVID modes, and b) high propensity to shift to virtual (e.g. work from home, online shopping, etc.) and private modes (e.g. car, motorcycle) from shared ones (e.g. bus and ride-share options). The extent of inertia varies with the trip purpose (commute and discretionary) and trip lengths. The results also demonstrate significant heterogeneity based on age, income, and working status of the respondents. The findings will be directly useful for planners and policy-makers in India as well as some other countries of the Global South in better predicting the mode-specific demand levels and subsequently, making better investment and operational decisions during similar disruptions.

1. Introduction

The COVID-19 pandemic has caused enormous disruption in the lifestyle, day-to-day activities and travel behaviour around the world. The impacts of COVID-19 at a national or sub-national level have likely been realized in several stages – especially in countries where the virus started spreading at a faster rate and much later compared to the West, such as in India (ECDC, 2020). This meant that there was some awareness about the deadliness of the virus and the need for social distancing quite early on in these countries. This, in turn, led to some 'natural' behavioural responses to the spread of the virus – primarily arising from one's self-protection concerns, even before any of the stringent government restrictions on travel (i.e. partial or full lock-down) were imposed. Understanding such 'natural' changes in travel behaviour is crucial for transport planning, especially in the context of devising plans for the relaxation phases of the lockdown as well as for planning targeted interventions during any similar future disruption. Mathematically modelling these changes in travel behaviour is also vital for forecasting future demands for different transport modes and to guide infrastructural investment and operational decisions – including but not limited to the reallocation of road-space, fare structure and frequencies of public transport, special exemption (or not) for ride-hailing, ride-sharing or micro-mobility services, especially in the context of similar disruptions in future. Quantifying the natural changes are also important to understand potential longer-term shifts – since the emergency regulation induced shorter-term changes can be

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difficult to sustain over a long time. Further, information on the differences in travel response among different socio-demographic groups can help understand and address any potential inequity in the travel-related impacts of such pandemics.

Given this importance of understanding the travel behaviour during COVID-19, there has been significant ongoing research in this area, although results are still sparse. In particular, there have been some descriptive data analyses on how different socio-demographic groups of different countries have changed travel behaviour in response to COVID-19 (e.g. Beck and Hensher, 2020; Molloy et al., 2020; Almlöf et al., 2020; etc.). However, to the best of our knowledge, no studies to date have looked at the changes in travel behaviour in India (or other countries in the Global South), where the modal attributes, socio-demographic characteristics of the travellers, etc. are expected to lead to substantially different responses. More importantly, none of the studies to date has mathematically modelled the relationship between the traveller characteristics and the changes in the transport mode usage to quantify the heterogeneity associated with the mode switch behaviour. In this paper, we address these gaps by developing mathematical models to quantify the relative effect of different socio-demographic characteristics of the travellers on the mode-specific trip frequencies before and during the early stages of COVID-19 spread in India. Primary data collected from online surveys is used to estimate multiple discrete choice extreme value (MDCEV) models (Bhat, 2008) in order to quantify the heterogeneity associated with the travel behaviour.

The rest of the paper is organised as follows: Section 2 provides a review of studies on travel impacts of COVID-19 and other disruptive events in the past. Section 3 presents the details of the survey and the sample characteristics. The model structure is presented in Section 4, followed by the results in Section 5. The last two sections summarize the findings and discuss the policy implications.

2. Review of studies exploring the impact of COVID-19 and other disruptive events on mobility

2.1. COVID-19 related studies and its mobility impact

There is a range of studies from different countries focusing on the preliminary impact of COVID-19 on mobility. De Vos (2020) outlined the potential implication of the current social distancing norms on daily travel patterns and suggested that travel demand is likely to reduce and so is the use of public transportation (De Vos, 2020). This has also been reflected in the aggregate mobility data from different countries (Apple, 2020; Google, 2020). For example, Google Mobility Data (Google, 2020) from European countries suggests that there has been a substantial decrease in trips to all locations except to parks (Falchetta and Noussan, 2020). In the UK, the use of motor vehicles fell by about 20% before the lockdown was imposed and more than 60% during the lockdown - the drops being the largest for the London Underground Services (DfT, 2020). In Switzerland, smartphone app data collected from 3700 users indicated that in March, the number of trips fell by 40% (from about 5 to about 3 per day) and the activity spaces (measured as the 95% confidence ellipse around the home) collapsed by 80% - with work from home contributing the most in the reduction of total-miles travelled (Molloy et al., 2020). The same study also looked at mode-specific frequencies and reported the reduction of distance travelled by all other models except bicycles. The travel behaviour variations among different socio-demographic groups have also been investigated in the study. The percentage changes in distance travelled was not found to vary substantially with gender and language-spoken but varied with income (up to 8%), employment status and car-ownership. In the context of Australia, a survey conducted among 1078 respondents indicated that there was a decline in the total use of all modes of transport – however, there was a higher percentage of travel by the private car (Beck and Hensher, 2020). The respondents of this study were also asked to state the modes they are most and least 'comfortable' using in the midst of the pandemic - the private vehicle was referred as the most comfortable one (in the event of a requirement to travel physically) and train and bus were referred as the most negative ones with 33% and 42% of respondents rating these modes as their least comfortable modes respectively. A study conducted in Chicago, USA among 900 respondents indicated that there was a large increase in telecommuting (from 15% to 48%) (Mohammadian, 2020). Majority of the respondents of this survey (93%) viewed public transit, taxis and ride-hailing services as a potential risk for exposure to the coronavirus while personal cars, bikes and walking were viewed as the safest modes of transportation. The same study also noted a rise in shopping online for groceries with roughly two-thirds of the online shoppers stating they had not used online shopping before the pandemic. Multimodal data in the context of UK and Budapest indicated that the most important development in the modal split is the declining share of public transport and the substitution by road transport including cycling (Bucsky, 2020; Hadjidemetriou et al., 2020). Data from the Netherlands indicated that COVID-19 approximately 80% of people reduced their activities outdoors, with a stronger decrease for older people (de Haas et al., 2020). Interestingly, de Haas et al. (2020) also analysed preference data in addition to behavioural data which revealed a strong indication of structural behavioural changes which is likely to lead to long-term shifts post-COVID-19. Although the statistical analyses of these studies clearly show evidence of change in mode usage patterns, none of these has investigated the mode-specific trip frequencies in detail and the associated 'shift' of trips between the modes (e.g. how many bus trips have been converted to a private car vs. to ride-hailing modes). More importantly, to the best of our knowledge, the effect of different factors driving these mode shifts have not been mathematically modelled. This gap has been addressed in this research.

Moreover, the modal attributes and socio-demographic characteristics of the users (and subsequently their preferences are substantially different in India and other countries in the Global South (see Appendix C for a review of mode choice models in India). However, the overwhelming majority of research pertaining to COVID-19 in India to date has focused on three areas, viz. developing a cure or method of prevention, forecasting the number of cases and the eventual peak of the disease, and the impact it is likely to have on the economy (e.g. Mandal et al., 2020; Tiwari et al., 2020; Agarwal et al., 2020; etc.) as opposed to predictive models of changes in activity and travel behaviour. The current paper fills in this research gap as well and is of immense global importance given that the number of diagnosed COVID-19 cases in India is currently the highest in the world (ECDC 2020, Appendix A).

2.2. Mobility impact of disruptive events

Several planned and unplanned special events have impacted mobility in the past, albeit the scale of such disruptions may have been different from the on-going COVID-19 pandemic. As specific studies on COVID-19′s impact on mobility are still being carried out, it is important to put the current disruptions in perspective. There is a decent amount of literature on travel behaviour during planned (e.g. van Exel and Rietveld, 2001; Clegg, 2007; Eliasson et al., 2009) and unplanned transport disruptions (e.g. Wesemann et al., 1996; Giuliano and Golob, 1998; López-Rousseau, 2005). The unplanned disruptions primarily include transit trade union strikes, natural disasters and extreme weather events, terrorist attacks, pandemics and epidemics, etc. which lead to complete closure or demand reduction of the full/part of the transport network. Marsden et al. (2016) measured the impact of bridge and road closure due to flooding, which saw 14% commuters reducing their work trip frequency. Zhu and Levinson (2012) studied the travel behaviour impact of the bridge collapse in

Minneapolis, USA, which predicted 7% of the commuters shifted their mode of travel from personal car to public transport.

Planned disruptions include road or rail link closures due to maintenance/construction, mega-events such as major sports, political and religious gatherings, discontinuation of ride-hailing or ridesharing services (e.g. Uber, Lyft, etc.). Econometric models developed by Pnevmatikou et al. (2015), Sadri et al. (2014) and Hampshire et al. (2018) revealed that the modal shifts due to such disruptions are strongly influenced by the modal attributes (e.g. number of transfers, travel costs) and network characteristics (e.g. residential location, public transport accessibility). However, they also vary substantially among different socio-demographic groups – gender, income and vehicle ownership in particular.

It may be noted that though these studies (detailed in Appendix B) provide some initial insights, the results are likely to be substantially different in the case of COVID-19. This is because the travel behaviour changes before the introduction of the Government restrictions were driven by personal health/safety concerns as opposed to closure or capacity reductions of the transport modes or network (as investigated in the studies presented in Appendix B). On the other hand, after the introduction of the restrictive measures, the travel behaviour changes are likely to be driven by both sets of factors.

3. Data

3.1. Data source and survey design

The information used in this study was captured using an online survey questionnaire where we received responses from 498 individuals across various cities in India. The survey was administered between 24th March 2020 and 12th April 2020 (3 weeks). Respondents were asked about their weekly commute and discretionary travel patterns during pre-COVID (regular days) and early-COVID (beginning of March) period which lead to a panel data, with two sets of observations per respondent. Respondents were recruited using various social media platforms (Facebook, LinkedIn, Twitter, WhatsApp and Instagram) using both unpaid (individual social circles, professional groups such as Transport Research Group of India, etc.) and paid (Facebook marketing) campaigns to enhance the reach of the survey as well as to minimize sampling bias as far as possible. Such dissemination technique was deemed as the best feasible option in the view of country-wide lockdown (initiated from 25th March onwards) which made the face-to-face survey option infeasible. In particular, the Facebook (paid) advertisement campaign allowed us to reach the intended target group both spatially and based on socio-demographic information and aided in obtaining a more diverse sample across the country as opposed to a mere convenience sample.

The survey questionnaire has 3 major sections – (a) travel modes with their weekly usage-frequency for regular day situation (pre-COVID infection i.e. January 2020 in Fig. 1); (b) travel modes with their weekly usage-frequency for the early-COVID situation (with COVID-19 infection i.e. beginning of March 2020 in India); and (c) person-level and household-level socio-demographics. In the questionnaire, the respondents (18 years or older) were asked to provide information about both commute and discretionary activities.

3.2. Sample characteristics

The socio-demographic characteristics of the respondents in the sample are presented in Table 1. Comparison of the relevant fields with the corresponding values of the latest census (Ministry of Home Affairs Govt. of India, 2011) revealed that there is some over-representation of males and young millennials (18–25 years) and salaried workers. This is not unexpected given that the data has been collected using online surveys and there is a demographic bias associated with the people who are more internet savvy. The income and vehicle ownership values are not available at the national level, but overall substantial diversity is observed in the sample.

In terms of spatial distribution, the data used in our sample entirely constitutes of urban population with a 60–40 split between big cities (population > 10,00,000) and small cities (population < 10,00,000). The data thus has a fairly balanced coverage of big and small cities but does not cover rural areas. As such our results are more relevant to urban areas in India, rather than to rural areas.

The distribution of trip lengths for commute and discretionary activities are presented in Fig. 1. The trip length is assumed to be 0 for virtual activities. When individuals did not work from home, the destination is assumed to remain unchanged between pre-COVID and early-COVID for commute trips. So the change in commute trip length only reflects the change due to increased share of work from home (leading to a decrease in the share of the physical trips of different lengths). Around 20% of the commute trips comprised of trips > 15 km which dropped to around 13% in early-COVID.

The trip length associated with discretionary activities pre-COVID (which included social trips in addition to shopping trips) included a large share of trips less than 10 km (80% of all discretionary trips). It is interesting to note that the share of longer discretionary trips (>15 km) increased in the early-COVID, potentially due to individuals apprehending a lock-down and availing the last opportunity to visit family members and friends who live far.

4. Model structure

The dependent variable in the model is the weekly frequency of choosing each mode for commute and discretionary activities reported separately by the respondents. The alternatives include ten modes for both commute and discretionary activities: work from home (or online shopping, leisure activities in case of discretionary ones), non-motorized transport (NMT), auto-rickshaw, car, motorbike, taxi, ride-hailing, ride-sharing, bus, and railway (suburban train and subway/metro rail). Six categories of trip frequencies have been used for each of these ten modes (1–5 and > 5 times in a week). Moreover, the respondents who selected the option 'more than 5 times in a week' were asked to state the exact number of trips. Apart from that non-availability of the mode was also considered to create respondent specific choice sets instead of a universal one. The dependent variable is hence a multiple discrete–continuous (MDC) variable with two components: (1) discrete mode choice (i.e. individual-level choice of the 10 modes) and (2) continuous mode-specific weekly trip frequencies.

The mode choices of travellers are influenced by three major categories of factors: (a) characteristics of the trip maker (e.g. income, car availability); (b) characteristics of the journey (e.g. trip purpose, time of day of the trip); and (c) characteristics of the transport facility (e.g. travel time, monetary cost, reliability, availability). In typical mode choice models, discrete choice models based on Random utility maximisation (RUM) principles are used to quantify how each of the influencing factors affects the choice of the mode. However, the multiple discrete–continuous nature of the choice, in this case, prompted us to use Multiple Discrete Choice Extreme Value (MDCEV) models.

MDCEV models, first proposed by Bhat (2005) and extended in different directions (Bhat, 2008; Castro et al., 2012; Enam et al., 2018; Pinjari and Bhat, 2010) simultaneously estimates the discrete and continuous components of the choices. The model is derived coherently with the RUM theory, and it differs from traditional choice models in the fact that, by allowing the choice of multiple products, it relaxes the assumption of the alternatives being mutually exclusive. The additive but non-linear formulation of the utility function guarantees that the consumption of one good does not affect the utility of the others and that these goods are imperfect substitutes. It may be noted that in this case, the attributes of the alternatives were unobserved in the

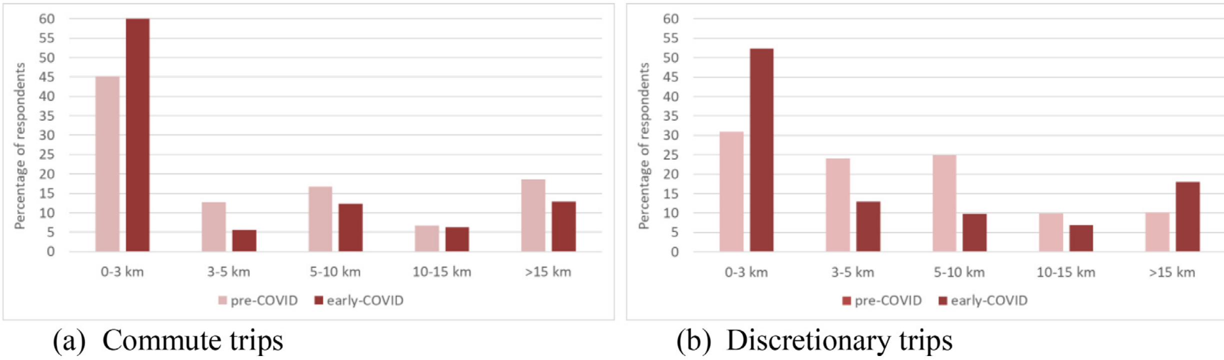


Fig. 1. Trip length distribution.

Table 1
Sample characteristics of socio-demographic variable.

Independent variables: *categorical variables*	Sub-categories	Sample distribution[#] (%)	Census distribution[#*] (%)
Gender	Male	64.0	51.5
	Female	36.0	48.5
Age (years)	Young millennial (18–25)	35.2	15.5
	Old millennial (25–40)	53.2	22.8
	Middle age (40–60)	11.6	17.5
	Old age (>60)	0.1	7.1
Monthly household income (INR[**])	Low income HH (0–10 K)	10.0	NA
	Low-middle income HH (>10–25 K)	14.2	NA
	Middle income HH (>25–50 K)	28.6	NA
	High-middle income HH (>50–75 K)	20.8	NA
	High-income HH (>75 K)	26.4	NA
Occupation	Salaried worker	56.4	39.8
	Non-salaried worker	43.6	60.2
Household vehicle ownership	Car ownership – 0	65.2	NA
	Car ownership – 1	31.8	NA
	Car ownership – >1	3.0	NA
	Motorbike ownership – 0	49.8	NA
	Motorbike ownership – 1	43.0	NA
	Motorbike ownership – >1	7.2	NA
	Bicycle ownership – 0	61.6	NA
	Bicycle ownership – 1	36.0	NA
	Bicycle ownership - >1	2.4	NA

*source: Census Data India, 2011
[#] The percentages are rounded off to one decimal places
[**] 1 INR = 0.013 USD

data as was also the case of MDCEV applications regarding various time-use decisions (Bhat, 2018; Enam et al., 2018), communicating medium related decision (Calastri et al., 2017) etc.

The other advantage of using MDCEV framework is that one can incorporate diminishing marginal utility (satiation) in the consumption (frequency of usage) of an alternative (Bhat, 2008) although the satiation parameters have been kept constant across alternatives in this study for better interpretation of the model. The functional form of the utility function as proposed by Bhat (2008) is as following:

$$U(x) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \psi_k \left\{ \left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} \tag{1}$$

where U(x) is a quasi-concave, increasing, and continuously differentiable utility function; ψ_k is the baseline marginal utility (i.e. marginal utility at the point of zero consumption) which can be represented as following:

$$\psi(z_k, \varepsilon_k) = \exp(\beta' z_k + \varepsilon_k) \tag{2}$$

where z_k is the set of attributes characterizing the individual and the alternative k; and ε_k is the unobserved attributes that impact the baseline utility of alternative k.

For this study, we assume ε_k to have an extreme value distribution, independent of z_k, and independently distributed across alternatives. In general, MDCEV framework assumes the existence of a budget constraint which is mostly related to either time (Bernardo et al., 2015; Salem and Nurul Habib, 2015) or money budget (Ferdous et al., 2010; Lu et al., 2017) and in a few instances combination of both (Castro et al., 2012). But the authors have increasingly recognised difficulties with such assumptions and recent studies in this field brings up estimation (like regression) approaches to compute a latent budget (Augustin et al., 2015). In the present study, we opted for a simpler approach (similar to (Calastri et al., 2017)) for deciding on the budget as there was no such hard constraint for trip frequencies, specifically for discretionary trips. The *budget* for a given individual is then simply given by the total number of trips observed, across all alternatives (modes) in a week. In an extension to this, we also assume there is no outside good (or alternative) (i.e. a good which has non zero consumption for all respondents) so that the corner solutions (zero consumption) are allowed for all the alternatives. For modelling purpose, we opted to work with the panel formulation to hold the error component correlated across observations (pre-COVID and early-COVID) from the same individual. The overall activities were similar in both periods (no strict restrictions in early-COVID) so the variation in the total budget was assumed to be negligible.

In Eq. (1), γ_k is a translation as well as satiation parameter whereas α_k governs only satiation. As the objective of this study is to investigate the change in mode choice behaviour from pre-COVID days to early-COVID period, no price variation among alternatives have been assumed and the satiation parameters have been constrained which corresponds to fixing α values of all alternatives to be equal to 0, and γ values for all alternatives to be equal to 1. Although the advantage of γ_k is that even when fixed, if it has a positive value it will allow corner solutions. Therefore, for this study the utility can be written as follows:

$$U(x) = \sum_{k=1}^{K} \psi_k \ln(x_k + 1) \tag{3}$$

Finally, the probability that an individual consumes the quantities $x_1^*, x_2^*, \ldots, x_M^*, 0, \ldots, 0$, where M of the K goods are consumed in positive amounts, can be expressed as follows (Bhat, 2008):

$$P\left(x_1^*,x_2^*,\cdots,x_M^*,0,\cdots,0\right)=\frac{1}{p_1}\frac{1}{\sigma^{M-1}}\left[\prod_{i=1}^{M}f_i\right]\left[\sum_{i=1}^{M}\frac{p_i}{f_i}\right]\left[\frac{\prod_{i=1}^{M}e^{V_i/\sigma}}{\left(\sum_{i=1}^{K}e^{V_i/\sigma}\right)^M}\right](M-1)! \quad (4)$$

where σ is an estimated scale parameter, V_i is the systematic utility of the alternative i and $f_i=\frac{1-\alpha_i}{x_i+\gamma_i}$.

The scale parameters and the other coefficients of the model are estimated jointly using the Maximum Likelihood Estimation (MLE) technique within the software Apollo (Hess and Palma, 2019). The panel formulation was used in this regard to account for the correlation between the error terms of the same individual. It may be noted that MDCEV models have been applied in many different empirical contexts, both in transport and beyond. Examples include applications to the choice of vehicle type and mileage (Bhat and Sen, 2006), time-use (Bhat, 2005; Calastri et al., 2020; Enam et al., 2018; Pendyala and Bhat, 2004; Srinivasan and Bhat, 2005); multi-buy alcohol promotions (Lu et al., 2017), patterns of social interaction between people and their social contacts (Calastri et al., 2017). But, to the best of our knowledge, this is the first application of the MDCEV framework in modelling mode and trip frequencies.

5. Results and discussion

5.1. Descriptive analysis

This section summarizes the responses and provides us with insights about the variables tested in the model specifications in 5.2.

In response to a direct question, majority of the respondents (95%) state that their daily commute, as well as discretionary travel behaviour, have been affected due to COVID-19 pandemic. The respondents were asked specifically if they had worked and/ or conducted discretionary (e.g. non-work) activities during the previous week. The responses are summarised in Figs. 2 and 3. As seen in the Figures, the reduction (non-participation) in work and/ or study related activities in early-COVID days as relative to pre-COVID period is 13% while the reduction in discretionary activities (e.g. shopping, exercise, leisure, social visits, etc.) is 26%. This is expected given shopping, exercise or leisure trips and social visits are discretionary in nature, and are typically the first ones that are curtailed in the event of a disruption (Zhu et al., 2012; De Vos, 2020).

For work/commute activities*,* there are substantial variations in participation depending on income and gender. Fig. 2a depicts that women reduced their work participation by 17% which was more compared to men (−9%). Respondents from low household incomes have reduced working the most (−29%) while those from the high-income group barely show any decline (−1%, Fig. 2a). This effect is most likely due to greater opportunities for work from home for respondents from high-income households as well as their higher personal vehicle ownership (which makes it easier for them to avoid the crowd and maintain social distancing). As seen in Fig. 2b, among those who continued to work, a large share shifted to work from home. The shift is slightly larger for women (+19%) relative to men (+16%). As expected, the shift toward work from home increases with income (+11%, +17%, and +20% for low, middle, and high-income households respectively).

In terms of discretionary activities*,* women reported more discretionary trips pre-COVID compared to men (Fig. 3a); this is quite common in travel behaviour literature (Vance and Iovanna, 2007). However, similar as in the case of work activities, during the early-COVID days, women have a larger drop in the number of discretionary activities (−34%) compared to men (−28%) (Fig. 3a). While there are clear reductions in discretionary activities for all three income groups, a clear relationship with income (as in case of work trips) cannot be observed and non-participation in discretionary activities for the high-income group is observed to be almost equal as that of the low-income group (around −29% for both groups). For those who continue to participate in discretionary activities (Fig. 3b), the share of online activities has actually decreased. This reduction is larger for men (−13%) compared to women (−7%). The reduction in the usage of online discretionary activities is observed in all three income groups, but again, a clear trend is missing.

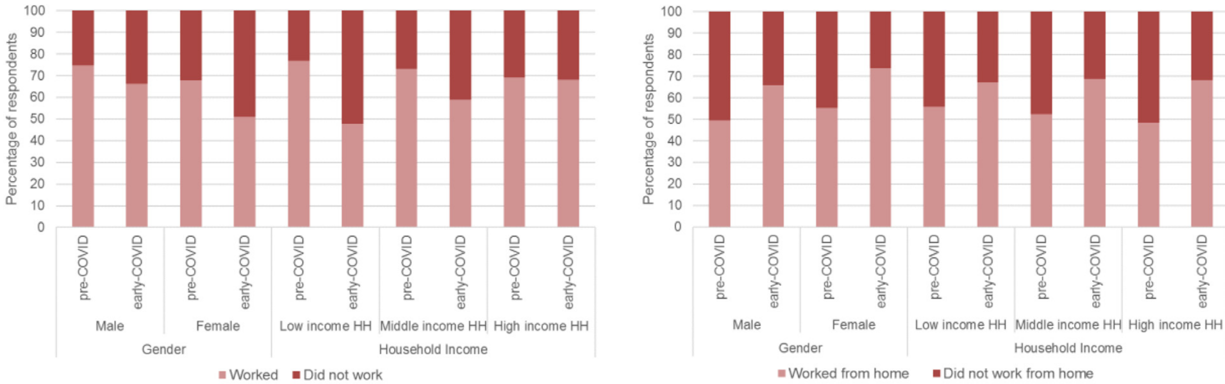
To facilitate the understanding of mode choices we have grouped the modes into five categories – (1) *virtual medium* (work from home (WFH) and conducting discretionary activities online), (2) *personal vehicle* (PV) (car and motorbike), (3) *on-demand private vehicles* (ODPV) (auto-rickshaw, taxi, ride-hailing), (4) *shared vehicles* (SV) (bus, rail, ride-sharing or pooled ride-hailing), (5) *non-motorized transport* (NMT) (walk and cycle). The first two categories, i.e. the virtual medium, and PV modes are where users are likely to be able to maintain the required social distance, while the three categories of OPDV, SV and NMT include modes where there is likely to be higher levels of crowding, and as such maintaining the required social distance may be difficult[1].

Table 2 provides descriptive statistics of the weekly frequency of mode choice to provide an overview of how the average weekly use of the respective modes has changed in the early-COVID situation as compared to pre-COVID days. As seen in the table, for work activities, the share of users who have used a mode at least once have decreased and so have the corresponding mean fraction values (average number of uses in a week) – the only exception being WFH where the trend is opposite. However, for discretionary trips, the share of users and mean fractions have decreased for WFH in addition to all other modes.

The change in share of different category of modes has been explored in further detail in Fig. 4. As seen in the figure, for work activities, modes that experience higher crowding levels, i.e. lower levels of social distancing, experienced a sharper decline in trip share in the early-COVID period. For example, NMT trips (i.e. walking, bicycling, etc.) saw the sharpest decline of approximately 5%, although after excluding those who switched to work from home, NMT share remains almost the same (−1% from pre-COVID). Trips on SVs and ODPVs decline by 4% and 1% respectively. On the other hand, the share of WFH (i.e. virtual medium), where the likelihood of maintaining a social distance is high, skyrockets by as much as 15%. However, the trip share of PVs goes down (−6%) which is likely because PV users may have shifted to WFH, where the likelihood of maintaining a social distance is even greater. The same trend is also observed for discretionary activities i.e. modes where users are likely to encounter greater levels of crowding witnessed a decline in mode share. The share of ODPVs (−6%) and SVs (−6%) experienced an almost similar decline in trip share. On the other hand, there is an increase in the share of PVs (+5%) and the virtual mediums (e.g. online shopping, online food delivery, etc.) (+3%), as both of them offer greater social distancing. However, there is an increase in NMT trips for discretionary activities (around +4%) in early-COVID days relative to pre-COVID days. This may be due to a greater proportion of people work from home in the early-COVID days and hence making short NMT trips for shopping, exercise, etc. where they may be exposed to crowding only for a short duration.

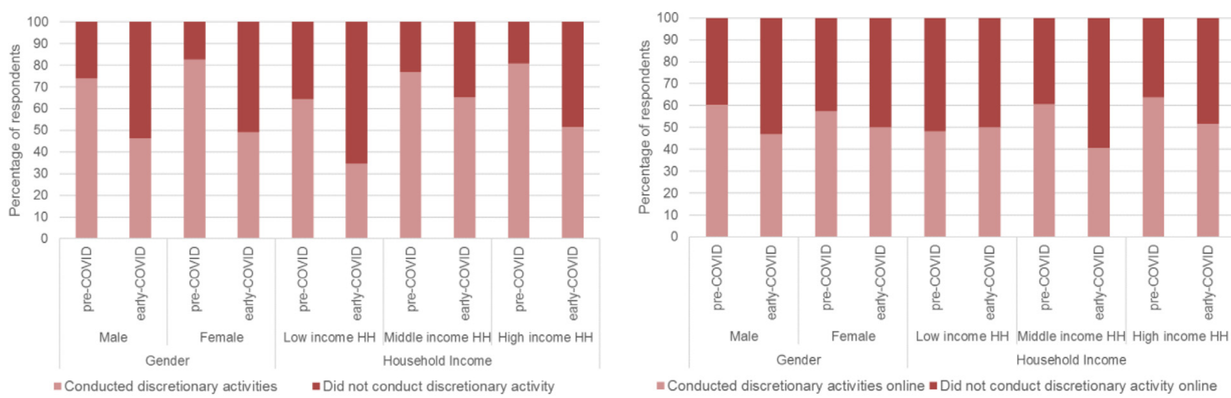
It is hypothesized that the travellers have a significant propensity (referred to as *inertia* hereafter) to continue using their pre-COVID modes. The level of inertia to retain pre-COVID mode as the major mode (the mode used most frequently by an individual in a week) has hence been examined. Interestingly, the inertia trend for discretionary activities differs in a few aspects as compared to commute activities.

[1] It may be noted that due to the level of crowding in the streets and pedestrian walkways, the level of social-distancing in NMTs in India are very different from countries in the Global North.



(a) (b)

Fig. 2. Response variation based on gender and household income for participation in work activity and (b) work from home.



(a) (b)

Fig. 3. Response variation based on gender and household income for participation in discretionary activities and (b) online discretionary activities.

Table 2
Weekly frequency of choosing different modes pre-COVID and early-COVID.

Mode	Category	Work				Discretionary			
		Users (%)		Mean fraction#		Users (%)		Mean fraction#	
		pre-COVID	early-COVID	pre-COVID	early-COVID	pre-COVID	early-COVID	pre-COVID	early-COVID
Non-motorized transport	NMT	27.80	22.00	4.40	3.22	35.80	25.00	3.21	2.08
Auto-rickshaw	ODPV	13.20	12.40	2.66	1.88	22.20	8.80	2.30	1.67
Taxi	ODPV	8.20	6.80	2.26	1.81	12.20	5.6	2.13	1.43
Ride-hailing	ODPV	10.20	9.80	2.33	1.83	19.40	6.20	2.03	1.68
Car	PV	20.40	17.80	3.85	2.56	30.80	17.00	2.88	2.24
Motorbike	PV	18.60	14.00	3.84	2.88	23.00	14.20	3.01	2.40
Ride-sharing	SV	8.40	4.40	2.12	1.90	11.20	4.60	1.83	1.56
Bus	SV	16.40	11.40	3.22	2.58	18.60	7.20	2.66	1.57
Railway	SV	14.40	11.60	3.00	2.49	18.80	7.40	2.65	2.13
In home execution of work or discretionary activity	Virtual	29.00	39.20	3.52	3.60	45.80	22.80	1.52	1.42

The mean fraction (average number of trips in a week) of mode use is mentioned only for those who opted for a respective mode at least once (e.g. during pre-COVID among the respondents who chose an NMT at least once a week, the mean usage on NMT was 4.4 trips)

For commute trips (see Fig. 5a), it can be observed that people have switched to work from home (WFH) instead of travelling, more so from low social distancing modes (i.e. SVs, ODPVs and NMT). On average, 40% of respondents shifted to WFH from low social distancing modes as compared to 32% in case of higher social distancing modes (i.e. PVs). Intuitively, the inertia for PVs is quite high and closely follow WFH inertia. Interestingly, SVs and NMT show higher inertia than ODPVs, which might be attributed to the reluctance of long-distance commuters (mostly rail users) in using ODPVs as they are more expensive (i.e. unaffordable for long trips) and may have spatially-restricted service coverage.

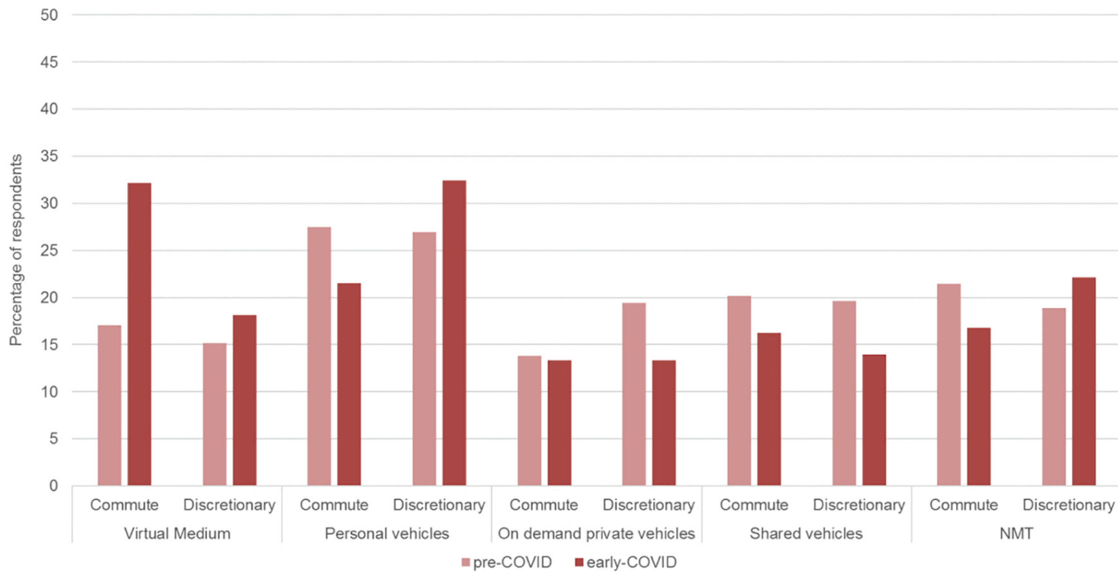


Fig. 4. Trip share of different modes for work and discretionary activities.

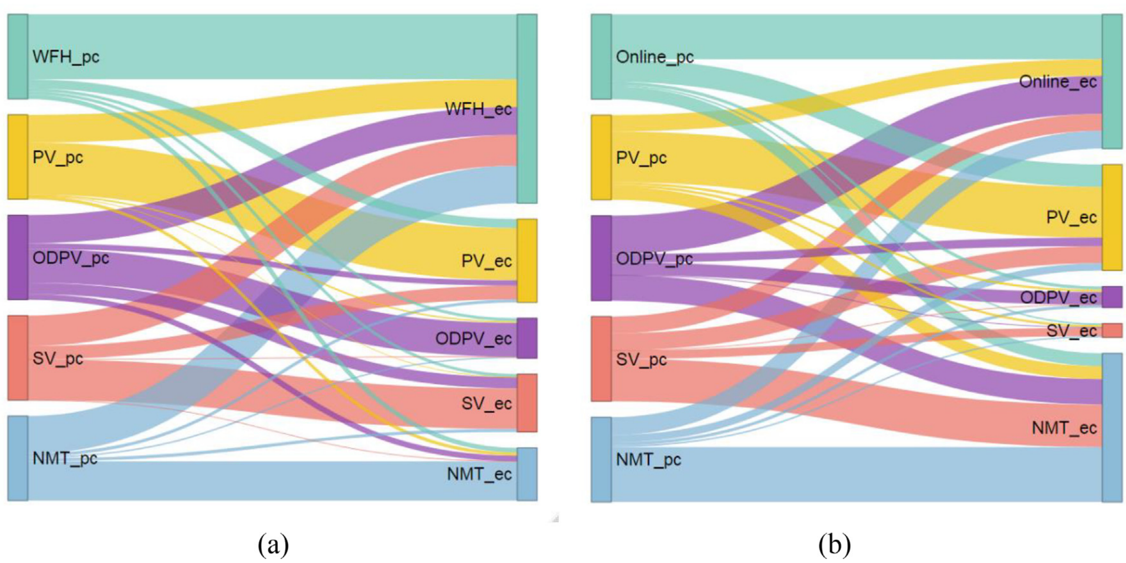


Fig. 5. Inertia (measured in major mode switching) of different mediums for (a) commute and (b) discretionary activities.

In the case of discretionary activities (see Fig. 5b), respondents tend to stick to their pre-COVID habit of using NMT modes (i.e. walking and cycling) rather than switching to online mediums. In fact, they show a strong tendency to shift to NMT modes especially from other modes with a lower level of social distancing (i.e. SVs). This might be an effect of their desire to procure essential items quickly in view of imminent lockdown instead of depending on e-commerce services. The reason why online activities do not see much hike could be longer than usual waiting times for the delivery and perceived risk of getting infected via the delivery persons. Apart from that, the trend for PVs and ODPVs follow the same pattern observed in case of commute activities.

Furthermore, the potential variation in inertia based on trip lengths have also been explored for both types of activities. For commute activities, respondents have greater stickiness for PVs in case of higher trip lengths (see Fig. 6b) compared to that associated with shorter trip lengths (see Fig. 6a) and this trend is also to some extent applicable for SVs. This effect might be attributed to the advantages of social distancing for PVs and captive ridership for SVs. Interestingly, for NMT and ODPVs respondents show less inertia if they have to travel more which might be due to higher risk associated with longer exposure to COVID-19. Intuitively, most of the respondents who had primarily worked from home during the pre-COVID period selected PVs in case they had to commute to their workplaces.

The inertia for the major mode is however more complex (and less meaningful) in case of the discretionary activities since the destination is no longer fixed as in case of commute trips.

Overall, the data trends indicate that the mode choices and shifts occurring in the early-COVID days vary substantially between different socio-demographic groups and are also influenced by the attributes of the modes (i.e. the ease of maintaining social-distancing) and inertia to continue using the pre-COVID modes. However, the interaction among different variables cannot be captured from these analyses. These are captured in the models presented in the next section where the trade-off among different influencing factors is captured using the MDCEV structure.

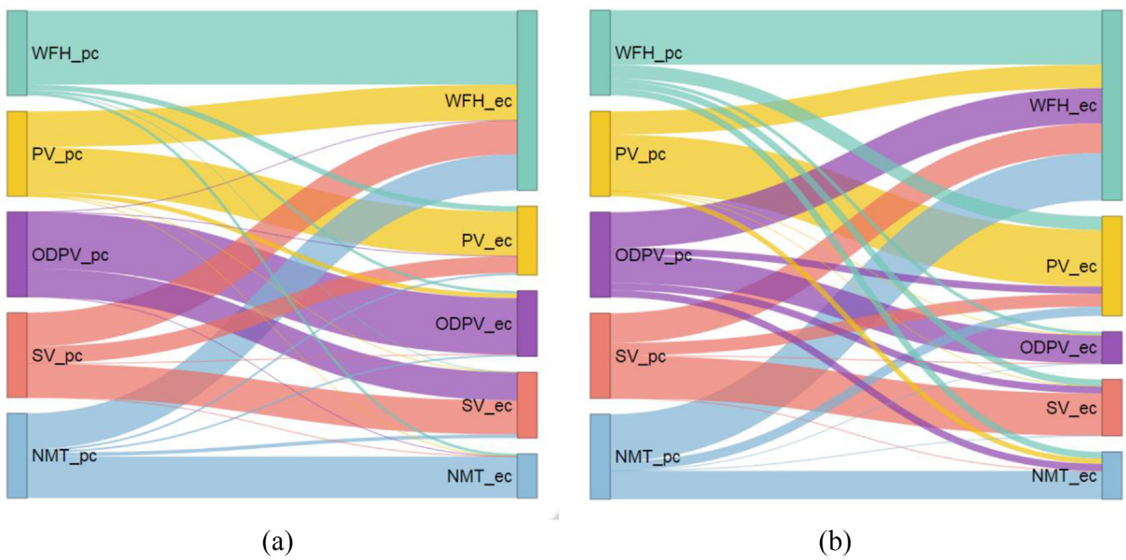


Fig. 6. Inertia of different mediums for commute activities for (a) shorter trip length (≤5 km) and (b) long trip length (>5km).

5.2. Modelling results

The choices of mode and frequency in pre-COVID days (regular days) and early-COVID days (the initial stage of COVID-19 spread in India) have been estimated jointly using the MDC framework accounting for the panel nature of the data (i.e. acknowledging the correlation between the two observations of the same individual). In this study, we assume the satiation effects (governed by α and γ parameters) to remain constant over different modes which is why in the estimation process both satiation profiles i.e. α-profile and γ-profile were kept fixed at 0 and 1 respectively. As in MDCEV framework, the total budget needs to be non-zero and positive, we removed the respondent data points who did not perform either of commuting or discretionary activities. Hence, the total number of data points used for estimation was lesser as compared to the actual sample size. Different model specifications have been tested and the final models are selected primarily based on the goodness-of-fit and statistical significance of model parameters. In terms of statistical significance, a variable is retained in the model if it is statistically significant at 90% level of confidence[2] in either the pre-COVID or early-COVID scenario even if it is not significant in both.

5.2.1. Model for commute activities

The estimation results for commute activities are presented in Table 3[3]. Globally, the signs and coefficient sizes are consistent with a-priori expectations. The alternative specific constants (ASC) for the modes indicate the relative preference for the modes when all else is equal. The results indicate that the ASCs of all modes, other than of NMT, are smaller than that of work from home (WFH) in both pre-COVID and early-COVID days indicating that all else being equal, NMT is the most preferred alternative, followed by WFH. In the case of pre-COVID days, the ASC is smallest for the bus (−1.25), closely followed by ride-sharing (−1.18) and ride-hailing (−1.17). Whereas, for early-COVID days, ASC is the smallest for the car (−2.21), followed by ride-sharing (−2.16) and bus (−2.00). However, it may be noted that due to the contribution of the inertia terms and other covariates, the ASCs do not possess any direct indication of absolute preferences.

The inertia variables indicate that in most cases (NMT, auto-rickshaw, car, motorbike, taxi, ride-hailing, and railway), there is significant positive propensity (inertia) in using the mode which had been most frequently used in pre-COVID days. It reveals that the respondents have some stickiness or habitual attachment with the mode they had previously used, however, but there is heterogeneity in the inertia terms across the modes. The private vehicles (i.e. motorbike and car) have a larger inertia relative to other modes, which is possibly expected due to their higher levels of comfort and flexibility. However, this large inertia is also a result of their higher ability to provide 'separation' and 'privacy' from other travellers and thus a reduced risk of COVID-19 infection. Furthermore, for car and motorbike, the inertia differs significantly depending on the commute distance. Respondents who have a longer commute distance (>5 km) are 2.5 times more likely to continue using car compared to those who have shorter commute distances. The opposite trend is observed for motorbikes (2 times higher inertia among respondents with shorter commute distances). This might be a reflection of perception regarding the potential risks of longer exposure to COVID-19 virus in a motorcycle. The interactions between inertia and trip lengths are not significant for other modes. The inertia values for different paratransit services (i.e. ride-hailing, taxi, and auto-rickshaw) closely follow each other, which may be an effect of the flexibility in terms of departure time and route of these services as well as the advantage of door-to-door pickup/drop-off (that minimizes being in contact with unknown co-passengers). Expectedly, the modes which are riskier from COVID-19 point of view (low social distancing) (i.e. bus, ride-sharing, NMT) display lower inertia values as commuters tend to prefer switching to high social distancing modes. It is interesting to note that while in some countries (e.g. see Beck and Hensher, 2020) the share of NMTs has seen an increase since the COVID-19 pandemic, in case of India the trend has been opposite. This may be due to the cultural differences aided by the high level of crowding and un-ordered movement as observed in prevalent NMT literature (Chattaraj et al., 2009; Rastogi et al., 2013).

Although, despite being a low social distance mode, railways show a higher inertia value. Rail transport is a lifeline for the low-income commuters in most of the Indian urban centres, for which few alternative modes are available, resulting in a larger inertia compared to other public transport modes (Kumar et al., 2017).

The next set of variables relate to various socio-demographic attributes of the respondents. Women have a lower propensity to use cars compared to work from home and other modes and this is significantly

[2] The 90% level of confidence has been used for 2 variables as the sample size was relatively small.

[3] In cases of socio-demographic variables, statistically insignificant parameters with intuitive signs have been retained in the model for comparison purposes.

Table 3
Estimation results for commute activities model.

Model details						
Number of observations	408					
Number of individuals	204					
Parameters	pre-COVID days			early-COVID days		
	Estimate	*t*-stat	Sig.	Estimate	*t*-stat	Sig.
Satiation parameters (α, γ)						
Alpha base	−6.8145	–		−6.8145	–	
Gamma base	1 *(fixed)*	–		1 *(fixed)*	–	
Alternative Specific Constants (ASCs)						
Work from home *(base)*	0.00 *(fixed)*	–		0.00 *(fixed)*	–	
Non-motorized transport	0.7278	3.34	***	−0.8275	−3.08	***
Auto-rickshaw	−0.7403	−3.44	***	−1.3432	−6.03	***
Car	−0.8271	−2.38	**	−2.2187	−5.73	***
Motorbike	−0.7206	−3.49	***	−1.8133	−7.55	***
Taxi	−1.1285	−4.56	***	−1.8511	−7.03	***
Ride-hailing	−1.1739	−4.23	***	−1.6608	−6.20	***
Ride-sharing	−1.1832	−4.75	***	−2.1615	−7.30	***
Bus	−1.2523	−3.33	***	−2.0027	−4.02	***
Railway	−0.6714	−3.21	***	−1.3967	−6.19	***
Inertia variables						
Inertia: Work from home	–	–		−0.107	−0.43	
Inertia: NMT	–	–		1.3914	4.86	***
Inertia: Auto-rickshaw	–	–		1.5811	3.13	***
Inertia: Car for long-distance trips (>5km)	–	–		2.6461	6.62	***
Inertia: Car for short-distance trips (≤5km)	–	–		1.0268	1.71	*
Inertia: Motorbike for long-distance trips (>5km)	–	–		2.2615	4.74	***
Inertia: Motorbike for short-distance trips (≤5km)	–	–		4.3824	6.10	***
Parameters	pre-COVID days			early-COVID days		
	Estimate	*t*-stat	Sig.	Estimate	*t*-stat	Sig.
Inertia: Taxi	–	–		1.7869	2.12	**
Inertia: Ride-hailing	–	–		1.6321	1.83	*
Inertia: Ride-sharing	–	–		0.8296	0.76	
Inertia: Bus	–	–		0.7967	1.31	
Inertia: Railway	–	–		1.8109	3.10	***
Socio-demographic variables						
Gender						
Female Dummy for Car	−0.3836	−1.14		−0.8379	−2.33	**
Monthly household income						
High Income Dummy[a] for Car	1.2335	3.92	***	0.8829	2.50	**
High Income Dummy[a] for Ride-hailing	0.9925	2.45	***	0.5438	1.27	
Age						
Young Millennial Dummy[b] for Bus	1.0937	3.12	***	0.8189	1.61	
Occupation						
Salaried Worker Dummy for Bus	0.6203	1.70	*	0.4887	0.98	
Salaried Worker Dummy for NMT	−0.8482	−3.13	***	−0.3158	−1.13	
Goodness-of-fit						
Log-likelihood value at convergence	−2240.28					
Log-likelihood value of the constant only model	−2348.48					
Teststatistic$\chi^2 = 216.40 > \chi^2_{24} = 36.42 at 95\% CI$						

*** 99% *significance* level, ** 95% *significance* level, * 90% *significance* level
[a] The high-income group corresponds to individuals from households with high monthly income (>75 K in a month)
[b] The young millennials include individuals in the age group 18–25 years

different from zero in early-COVID days. This may be due to the low percentage of women having driving licenses[4] (which affects both pre-COVID and early-COVID scenarios) and the higher propensity of women provided with the flexibility to work from home during the rise of the pandemic (Deshpande, 2020).

In pre-COVID situation, individuals from affluent households have a preference of using cars and ride-hailing services as compared to less affluent individuals, which is consistent with the mode choice literature in India (Ashalatha et al., 2013; Devaraj et al., 2020). Although, in early-COVID days they have been found to move away from those modes, which is possibly related to the WFH opportunities that the affluent household individuals are likely to avail due to the type of profession and job profile (Narayan, 2015; Krishnan, 2017).

The young millennials prefer using public transit in pre-COVID days, which agrees with previous findings (Verma et al., 2016), but they tend to avoid such modes during the early-COVID days. For salaried workers, an increased propensity to use the bus and decreased propensity to use NMT is observed during pre-COVID which reflects similar findings in Indian mode choice context (Ramakrishnan et al., 2020). However, during early-COVID days no such additional preference for buses can be observed, again indicating the lower attractiveness of this mode during the pandemic. The statistical significance of NMT mode for salaried workers also diminishes during early-COVID days.

[4] The number of female license holders is as low as 5% in some states (Parashar, 2019)

5.2.2. Model for discretionary trips

The estimation results for discretionary activities are presented in Table 4[5]. The ASCs indicate that all else being equal, the utility of all modes except NMT (+1.09 and +0.57) decreases compared to work from home (WFH) in both pre-COVID and early-COVID days. In the case of pre-COVID days, the ASC is smallest for the motorbike (−2.83), closely followed by car (−2.54). Whereas, for early-COVID days, the ASC of motorbike (−1.56) is the smallest, followed by ride-sharing (−1.51). However, it may be noted that due to the contribution of the inertia terms and other covariates, the ASCs do not possess any direct indication of absolute preferences.

The inertia variables for discretionary activities indicate that respondents have a significant level of stickiness for fewer modes as compared to commute trips (NMT, car, motorbike, taxi, and ride-hailing). For car and motorbike, the respondents who have longer travel distances (>5 km) show higher inertia which is different from the inertia values obtained in case of the commute activities. It might be a reflection of the perceived (positive) utility of personal vehicle in executing multiple discretionary activities at different locations (for example, a person going to the bank, buying medicine, and then going for shopping – all at different locations). Interestingly, in a close similarity with the commute model, modes with lower levels of social distancing (bus, rail, ride-sharing) have lower inertia. However, in the case of the discretionary trips, they are in fact not statistically different from zero. Unlike the commute activities model, the inertia for NMT modes is found to be larger. This may be driven by the fact that due to the flexibility offered by the work from home, people have a larger propensity to exercise more and make more local trips on foot or by cycle.

The next set of variables relate to various socio-demographic attributes of the respondents. Similar to the trend for commute activities, the individuals from affluent households have an increased propensity to use car and ride-hailing modes. But a decrease in the propensity to use such modes is observed during the early-COVID days (though not statistically different than zero at a 90% level of confidence). There is a decreased propensity among high-income households to use auto-rickshaws which become statistically different from zero in the early-COVID period. Overall, this effect may be attributed to greater affordability of this group which enables them to continue using car, ride-hailing and other modes and do online shopping.

The association between age and decreased use of NMT as a discretionary trip mode is intuitive because young adults are more tech-savvy and have an affinity for virtual mediums which leads to curtailing their NMT trips. Whereas middle-aged adults have an increased propensity to increase their use of car compared to other groups - possibly to avoid crowding in shared modes (bus, rail, ride-sharing) and NMTs. It may be noted that in most of the Indian households, the middle-aged adults enjoy priority access to household cars.

Finally, the effect of vehicle ownership at household levels has been also explored. It is interesting to note that though car and motorcycle ownership has a substantial effect on mode choice pre-COVID – with the propensity to use car and motorcycle being high for car and motorcycle owners respectively and propensity to use NMT being low among motorcycle owners, the effect diminishes in early-COVID days. This may be driven by the overall propensity to use online mediums and/or execution of the discretionary activities within their neighbourhood instead of travelling to distant destinations using motorized modes.

6. Policy implications

The social distancing measures which have been applied globally to avert the risk of spread of COVID-19 pandemic has resulted in an unprecedented transformation of urban mobility. As the world navigates through multiple waves of the disease, its impacts can well transcend to 'new normal', i.e. long-term change in daily travel pattern and mode choices. The study results highlight three potential aspects of changes in travel behaviour (1) changes in trip characteristics (mode, frequency, and destination) of low social distancing modes, (2) variations in travel pattern based on activity purposes (commute and discretionary), and (3) variations in the inertia for different modes. All these have implications for transport planning and policymaking.

Transport planners, especially infrastructure operators, need to be cautious about the likely increase of single-occupancy PVs (especially for discretionary trips, car and motorbike ASC increase by 1.46 and 1.27 respectively) as they offer a greater sense of safety due to higher social distancing. Reduced congestion in the cities due to restricted travel may pose favourable conditions for PVs, and a persistent change toward such behaviour is likely to increase traffic congestion in the long run. Along with the increase in the propensity of choosing PVs, the modelling results also show that there is a decrease in the likelihood of people walking to work (ASC decreases by 1.10 and 0.52 respectively for commute and discretionary trips), which will likely compound the vehicular congestion issues in the future. Hence, planners and policymakers may attempt to not only encourage active use of NMT modes through an accelerated provision of NMT infrastructure but at the same time employ restrictive measures for single occupancy PV users. A greater NMT modal share for commute purposes may be achieved through strategies including, but not limited to, allocation of more street space to pedestrians, developing NMT infrastructure (such as pedestrian benches, shades, etc.), and improving safety-security (automatic pedestrian crossings, grade-separated walkways, etc.) as observed in earlier studies (Aziz et al., 2018; Rahul and Verma, 2018). Such measures to increase NMT capacity and helping in maintaining a social distance is also likely to further encourage the use of NMT for carrying out discretionary activities (which has emerged as the most preferred mode during pre-COVID days in our data). In addition, policies such as restricted vehicle entry, parking pricing, or congestion pricing in the central business districts of the urban areas, which have shown encouraging results in VKT reduction, may be implemented.

Transit operators will have to upgrade their services both in terms of hygiene and operational quality (service period, headway, etc.) to regain public trust, as the results show low inertia among the current bus users to continue using it both for commute (0.79) or discretionary activity (0.18) purposes. In fact, the younger generation who have significant propensity (especially for commute trips (1.09)) to use public transits (in pre-COVID) can be re-attracted by integrating various smart measures which can reduce physical contact and resultantly, the risks of COVID-19 infection. Candidate measures can include the online availability of bus schedules, contactless ticketing, etc., which have been documented to enhance transit ridership (Brakewood et al., 2020; Sharaby and Shiftan, 2012). In the short term, several strategies that enhance hygiene, such as automatic hand-sanitizers on-board buses, disinfecting transit units and stops frequently may be implemented to assure potential users about the safety of using such modes and make public transits attractive again. At the same time, transit operators would need additional financial support from state authorities as their revenues are already plummeting.

Transport network companies (TNC) need to adapt to the 'new normal' in a sustainable manner. For example, the results show low inertia (especially for commute trips in a range of 1.58–1.78) to continue the use of ODPVs, which might have to be encouraged for shared use but maybe only with known co-passengers (say, family members, colleagues, etc.), such that there is trust among fellow riders about each other's COVID-19 infection. In addition, various protective arrangements may be installed (such as separator between driver and passenger seats, maximum carrying capacity to 2 persons at a time, mobile tracking of individual's COVID-19 infection status, etc.). TNCs in India

[5] In cases of socio-demographic variables, statistically insignificant parameters with intuitive signs have been retained in the model for comparison purposes.

Table 4
Estimation results for discretionary trip model.

Model details						
Number of observations	424					
Number of individuals	212					
Parameters	pre-COVID days			early-COVID days		
	Estimate	*t*-stat	Sig.	Estimate	*t*-stat	Sig.
Satiation parameters (α, γ)						
alpha_base	−16.3614	–		−16.3614	–	
gamma_base	1 *(fixed)*	–		1 *(fixed)*	–	
Alternative Specific Constants (ASCs)						
Online *(base)*	0.00 *(fixed)*	–		0.00 *(fixed)*	–	
Non-motorized transport	1.0953	3.23	***	0.5771	1.50	
Auto-rickshaw	−0.5158	−2.74	***	−0.7898	−3.40	***
Car	−2.5475	−6.85	***	−1.0854	−2.89	***
Motorbike	−2.8357	−5.96	***	−1.5661	−3.21	***
Taxi	−1.299	−6.21	***	−1.3736	−5.57	***
Ride-hailing	−0.9011	−4.26	***	−1.0485	−4.10	***
Ride-sharing	−1.4626	−6.62	***	−1.5131	−5.77	***
Bus	−0.8299	−4.66	***	−1.1382	−5.00	***
Railway	−0.8522	−4.69	***	−1.0358	−4.63	***
Inertia variables						
Inertia: Online	–	–		0.1351	0.52	
Inertia: NMT	–	–		0.7468	2.96	***
Inertia: Auto-rickshaw	–	–		0.5571	1.03	
Inertia: Car for long-distance trips (>5km)	–	–		1.7539	4.50	***
Inertia: Car for short-distance trips (≤5km)	–	–		1.674	4.24	***
Inertia: Motorbike for long-distance trips (>5km)	–	–		2.4627	3.97	***
Inertia: Motorbike for short-distance trips (≤5km)	–	–		1.8795	5.50	***
Parameters	Pre-COVID days			Early-COVID days		
	Estimate	*t*-stat	Sig.	Estimate	*t*-stat	Sig.
Inertia: Taxi	–	–		3.6459	3.56	***
Inertia: Ride-hailing	–	–		3.2485	2.21	**
Inertia: Ride-sharing	–	–		–	–	
Inertia: Bus	–	–		0.1794	0.23	
Inertia: Railway	–	–		0.9427	0.82	
Socio-demographic variables						
Monthly household income						
High-income dummy[a] for Auto-rickshaw	−0.0482	−0.14		−0.9607	−1.75	*
High-income dummy[a] for Car	0.4832	1.78	*	0.4490	1.57	
High-income dummy[a] for Ride-hailing	0.5847	1.81	*	−0.3344	−0.68	
Age						
Young millennial dummy[b] for NMT	−0.1594	−0.65		−0.4505	−1.82	*
Middle age dummy[c] for Car	0.5127	1.65	*	0.5476	1.59	
Vehicle ownership						
VOC[d] for Car	1.4606	7.1	***	0.3430	1.56	
VOM[e] for NMT	−0.6609	−2.97	***	−0.3867	−1.96	**
VOM[e] for Motorbike	1.3361	5.53	***	0.3191	1.30	
Model fit information						
Log-likelihood value at convergence	−2362.80					
Log-likelihood value of the constant only model	−2501.99					
$Test statistic \chi^2 = 278.38 > \chi^2_{27} = 40.12 at 95\% CI$						

*** 99% *significance* level, ** 95% *significance* level, * 90% *significance* level
[a] The high-income group corresponds to individuals from households with high monthly income (>75 K in a month)
[b] The young millennials include individuals in the age group 18–25 years
[c] The middle-aged persons include individuals in the age group 40–60 years
[d] The variable VOC corresponds to the number of cars in a household
[e] The variable VOM corresponds to the number of motorbikes in a household

are diversifying their businesses, providing online food delivery services, which is likely to encourage more e-commerce activities, enabling greater social distancing for end users.

This study attempts to shed light on the changing travel behaviour due to fear of contagion, albeit long term impacts are hard to forecast at this stage. In general, longer the social distancing norms and subsequent mobility restrictions last, its effect will be more profound. As work from home and online discretionary activities are likely to change the dynamics of activity-travel behaviour, further research is necessary to interpret time-use pattern changes, both at the individual as well as household level.

7. Directions of future research

The data used in this paper is limited to urban areas. The changes in mode behaviour in rural areas is expected to be substantially different. It will be interesting to apply a similar model for rural areas as well if suitable data is available. However, since the choice set of modes is

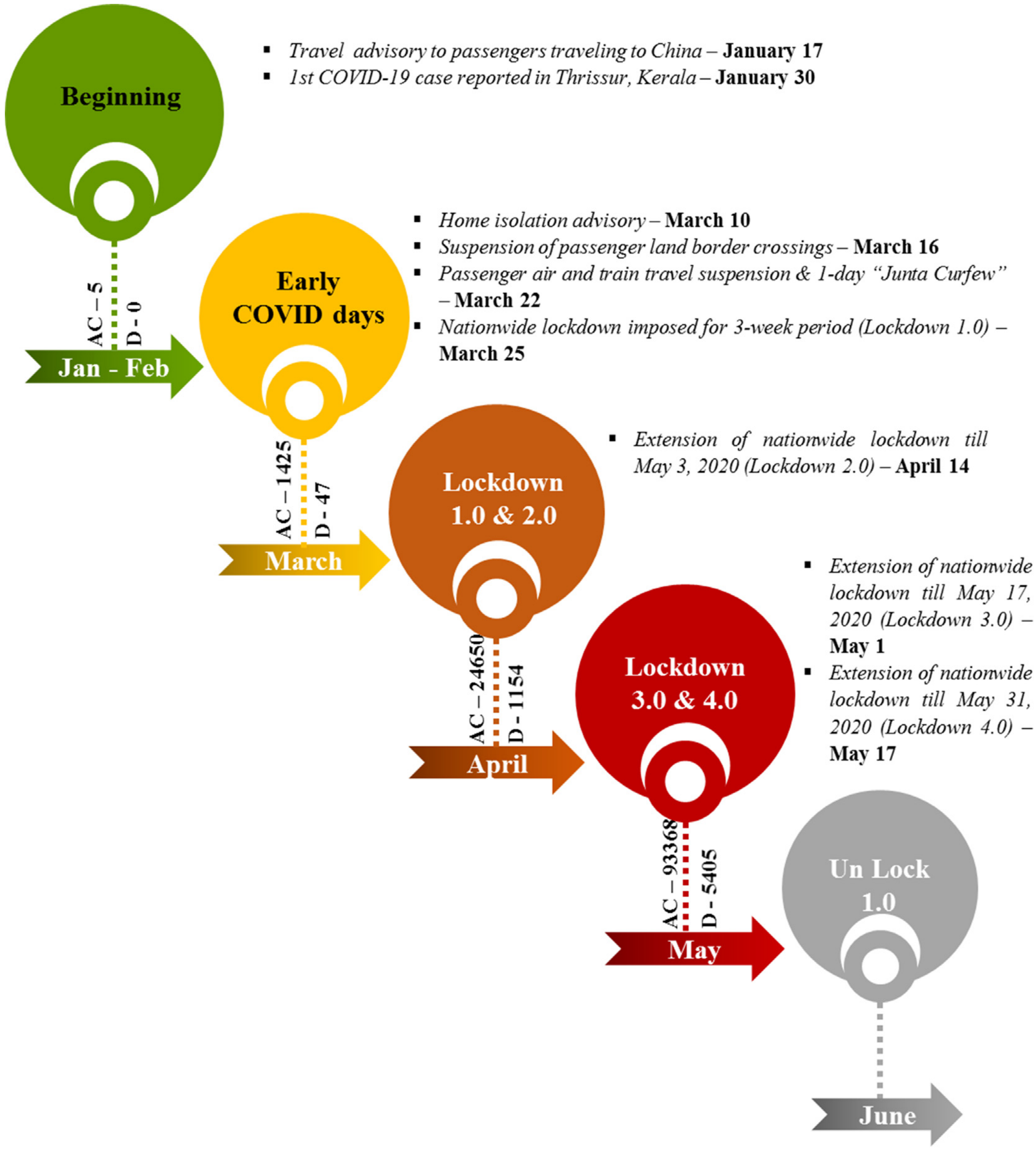


Fig. A1. Timeline of travel-related steps taken due to COVID-19.

very small and typically, majority of the travellers are captive to a specific mode in rural areas, the extent of mode switching due to Covid-19 is expected to be very small in these areas.

Further, the pre-COVID data (and the early-COVID data to some extent) involved recalling past behaviour. Combining the survey data with large-scale passive data (e.g. mobile phone records for example), which have a better representation of travel behaviour of the mass population, but typically lack socio-demographic information, may help in accounting for these biases.

On the other hand, the preference for travel modes can be significantly affected by attitudes and perceptions of the respondents as well as their risk-taking propensity. Although such information was collected on a limited scale in this survey, it has not been incorporated in the present study due to the limited sample size and lack of clear trends. In terms of model structure, the model does not incorporate responses from individual who have declined to participate in an activity (zero budget/consumption). Extending the choice dimensions even further to include such responses can provide more robust results. Developing methods to extend the MDCEV framework to accommodate this can be a direction of future research. More flexible model structures like Multiple Discrete-Continuous Nested Extreme Value (MDCNEV) and mixed MDCEVs are also worth testing.

8. Concluding words

In this research, the mode choice behaviour has been estimated in two temporal dimensions – pre-COVID and early-COVID, both in the context of India. The objective was to assess the impact of such pandemic on the daily commute as well as discretionary travel behaviour without any government restriction in place. The effects have been estimated simultaneously in terms of mode choice and weekly usage of the modes, with a comprehensive array of modes including virtual mediums and conventional ones. The policy implications of the results have been highlighted in Section 6.

In terms of the methods, the research extends the use of MDCEV modelling framework for quantifying the change in travel preference by simultaneous modelling of mode choice (discrete component) and weekly frequency (continuous component). The results demonstrate a finer level of details that can be obtained through multiple discrete–continuous modelling as opposed to simpler discrete choice models. For example, it highlights the influence of inertia dimension that allows us to get insights about what will be the extent of change in frequency of using different modes (as opposed to change in the major mode, or change in the mode for a specific trip), while a simpler logit model would fail to reveal such subtle effects.

The online survey – only safe option during the pandemic – prevented us from getting a fully representative sample (see Section 4.2). However, while sample representativeness is a must for descriptive and simple statistical analyses of the data, for econometric models, a fairly 'balanced' sample is sufficient in the estimation stage – but adjustments need to be made during forecasting.

The current models provide useful policy insights for transport planners in India (as summarised in Section 7), especially in terms of predicting the extent of 'spontaneous' behaviour change without strict measures like lockdown in place. Though travel behaviour, particularly behaviour during an unusual situation as in the COVID-19 pandemic, is not likely to be transferable to other countries, the findings provide some insights which may be useful to other countries. In particular, the estimates show evidence that even in the absence of restrictive measures as full-lockdown, awareness among the people does lead to substantial voluntary shifts in travel behaviour. It also highlights the potential gains from doing an MDCEV based model to disentangle the effect of socio-demographics, inertia, trip characteristics (purpose and length) in addition to mode-specific attributes. Incorporating these models in an agent-based framework and linking it with epidemiological models can be also beneficial for improving the prediction of the spread of the virus.

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Appendix A

COVID-19 timeline in India

The World Health Organization (WHO) published their first disease outbreak news on the Corona Virus Disease (COVID-19) on January 5, 2020, even though it is believed to have been circulating from December 2019 (and possibly earlier) (WHO, 2020a). In India, the first case of COVID-19 was officially reported on January 30, 2020, and as of today (6 July 2020), WHO reports a total of 410,461 confirmed cases, out of which 13,254 have succumbed to the virus – indicating a nationwide mortality rate of 3.2%. The total number of confirmed cases in India have been rising exponentially of late, wherein a rise of 115% has been witnessed in June 2020 (WHO, 2020b).

As a preventive measure, and also a means of reducing the spread of the virus, several nations have imposed a variety of restrictions on the movement of people and goods during the past 6 months. India began taking travel-related precautions from January, when the first travel advisory was issued to passengers travelling from China on January 17, 2020. A timeline of the COVID-19 spread and important travel-related steps taken by the Ministry of Health and Family Welfare (MoHFW), Government of India are encapsulated in Figure below (MoHFW, 2020).

As can be observed in the Figure above, India witnessed 4 contiguous stages of travel restrictions, spanning from March 25 – May 31, 2020. While the 1st stage of restrictions, i.e. Lockdown 1.0, was the most stringent, where the movement of only essential manpower and goods were permitted, the subsequent phases witnessed gradual relaxations. During Lockdown 2.0, the nation was classified into 3 zones, i.e. red, orange, and green, which was based on the number of cases of coronavirus, and the travel restrictions were also graded in the same fashion. Small retail shops, banks, etc. were allowed to operate with limited staff, and strict social distancing norms, which stipulated a 1-meter distance between customers. Subsequently, in the next phase, i.e. Lockdown 3.0, further travel relaxations were made, where buses were allowed to ply with 50 percent capacity in green zones. Orange zone would also witness the resumption of travel by private and hired modes, all the time taking precautions and maintaining social distance, however, no public transport was allowed. Finally, in Lockdown 4.0, the reclassification of zones was carried out by individual states, and more travel relaxations were issued. However, mass rapid transit systems were still not allowed to operate in any of the cities in India, which continues to be the case as of today, when we are in the Unlock 2.0 phase. It is further anticipated that a decision on re-opening mass rapid transit systems for the public is scheduled to be taken in August 2020.

It may be noted that as in other countries, the Indian economy has also been hit hard by the pandemic. The Asian Development Bank (ADB) has estimated that COVID-19 outbreak could cost the Indian economy alone between US$ 387 million and US$ 29.9 billion in personal consumption losses while Moody's has predicted a 4% reduction in India's GDP growth forecast in 2020 (IANS, 2020)[6].

Appendix B

Effects of other disruptions in transport

Temporary or sustained disruptions affect the routine travel behaviour of people and consequently lead to substantial changes in the demand patterns, both at the city and regional scales. The behavioural adaptations and innovations can be both in the short and long run (Marsden and Docherty, 2013). In the short run, these include re-evaluation of whether to continue the activity or not and if continued, whether or not to change the destination, mode, departure time and/ or duration (Zhu et al, 2012). In the longer run, they may lead to changes in working patterns, vehicle ownership, the extent of multimodality and lifestyle in general (Parkes et al., 2016).

Given the dearth of literature on the impact of pandemics on travel behaviour, we have focused on the review of papers on planned and unplanned disruptions that are associated with some lead time and/ or are sustained for the substantial duration to allow the travellers to make some adjustments in their activity and travel decisions. The summary of the review is presented in Table B1 below (see Marsden et al., 2016; Zhu and Levinson, 2012 for a more comprehensive review).

Appendix C

Modal share/ mode choice in India

Also relevant to this work is understanding the "normal" modal share and their influencing factors in Indian cities. The rapid growth of urbanization has profoundly influenced the travel patterns in the majority of the Indian metropolitan cities (MoUD (GoI) (2016))[7]. The share of public transport has steadily decreased and is expected to fall from 46% in 2007 to an estimated 26% in 2031. Alternately, the share of personal vehicles, like car and motorbike has increased, from 24% in 2007 to an estimated 46% in 2031 (MoUD (GoI) (2008)). The mode share is associated to a number of factors ranging from travellers' individ-

[6] IANS – Indo Asian News Service

[7] MoUD (GoI) – Ministry of Urban Development, Government of India

Table B1
Example of studies on the impact of disruptions on travel behaviour.

Authors	Focus	Disruption	Key findings
Type of disruption: Planned			
Pnevmatikou et al. (2015)	Behaviour and travel pattern of metro users	Metro service, Athens, Greece	Transfer inconvenience and travel cost are important factors when making mode related decisions Female commuters have less propensity to shift to car mode and low-income group people prefer to travel by bus during metro disruptions
van Exel and Rietveld (2001)	Travel behaviour of users	Railway strike, Netherlands	10–20% of the public transport users cancelled their trips 15% of the users shift to personal vehicles
Hampshire et al. (2018)	To evaluate the impact of disruptions on travel demand	Uber/Lyft disruptions, Austin, TX	45% of the users switched to personal cars and 3% to public transport 14% increase in the trip frequency of an individual who shifted to personal vehicle post disruptions
Type of disruption: Unplanned			
Marsden et al. (2016)	Behavioural adaptation during disruptive events	Road and bridge closure due to flooding	14% of the commuters' work trips frequency reduced 11% of the commuters cancelled their one of the trips 10% to 28% shifted to other modes to complete their trips over a travelled distance of 0–2 miles to 51 + miles
Zhu and Levinson. (2012)	Behavioural response after network disruptions	Bridge collapse, Minneapolis	9% of the respondents considered they would be considering moving further from work, whereas 11% reported that they would be considering taking a job further from home 7% of the commuters shift their mode of travel from personal car to public transport
Sadri et al. (2014)	Mode choice behaviour	Hurricane evacuation, Miami	Majority of the evacuees are more likely to take evacuation bus A single evacuee is less likely to use personal vehicle Higher-income people are more likely to use taxi
López-Rousseau (2005)	Public transport response after the terrorist attack	Train Bombing in Madrid, Spain	6% decrease in the train commuters after the bombing There is not much significant increase in the highway traffic share

Table C1
Review of key studies on factors influencing mode choice in India.

Authors	Focus	Case study city	Method	Significant Variables
Arasan et al. (1998)	Mode choice of urban travellers owning motorised vehicles	Chennai	Disaggregate multinomial logit	Travel time, travel cost, relationship to the head of household, age, gender and ownership of motorcycle
Pulugurta et al. (2013)	Mode choice analysis using artificial intelligence	Port Blair	Fuzzy logic	In-vehicle travel time, out-vehicle travel time, comfort index and travel cost
Kumar et al. (2013)	Travel patterns of commuters and their willingness to pay for an alternate mode	Delhi	Fuzzy logic	Income, in-vehicle travel time, out-vehicle travel time, comfort level and travel cost
Manoj and Verma (2015)	Travel behaviour of non-workers in the different income group	Bangalore	Binary logit model	Gender, age(retired age > 65), income, personal vehicle ownership, health care activity, trip distance and land-use mix
Kedia et al. (2015); (Kedia et al., 2017)	Mode choice model for educational trips and transit choice behaviour of urban commuters	Surat	Fuzzy logic	Household income, trip length, comfort and convenience level Walking distance to a bus stop/accessible distance to bus stop, waiting time at a bus stop and bus schedule reliability
Sarkar and Mallikarjuna (2018)	Attitudinal and perception variables on mode choice behaviour	Agartala	Integrated choice and latent variable method	Gender, age, income, vehicle ownership, educational qualifications, size of the family, land use mix, comfort and flexibility
Kunhikrishnan and Srinivasan (2019)	Behaviour heterogeneity of mode choice on work trips	Chennai	Binary logit model	Age, gender, income, work duration, congestion level, road quality and the presence of co-passengers
Dinda et al. (2019)	Accessibility and suitability on mode choice	Jamshedpur	Analytic hierarchy process	Frequency, purpose of trips, educational qualification, trip duration, vehicle ownership, age, family size and gender

ual mode choice decision to perform their activities, which in turn depends upon individual and mode characteristics, the density of population, and lastly to land use (Santos et al., 2013). A summary of some of the earlier research on to mode choice in India is presented in Table.

As seen in Table C1, the socio-economic parameters (like age, income, gender and vehicle ownership), mode characteristics (like travel time, cost, waiting time and reliability of public transport), land-use and network characteristics (like accessibility and level of mixed land-use) are found to be significant in most of the previous researches. Typically, the mode choice studies covered a particular city. However, it is interesting to note that the irrespective of the method used and the geographical location, the variables significantly affecting the mode choice of the individuals are largely found to be similar - though the model coefficients often varied in magnitude.

Overall, though there is a considerable volume of literature on mode choice behaviour in India – they are not likely to be useful in the context of the pandemic since the findings of Section 3.1 reveal significant differences in mode choice behaviour in the event of disruptions. However, the findings of these studies can provide the internal validity of the parameters of the pre-COVID models developed in this research.

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