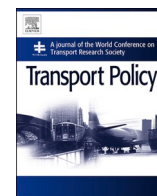




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Psychological impacts of COVID-19 pandemic on the mode choice behaviour: A hybrid choice modelling approach

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ABSTRACT

The COVID-19 pandemic is a pivotal moment in the history of mankind, which had a huge impact on the fast-paced world. The uncertainty associated with the plight of the pandemic, pushed the world towards a sense of insecurity and panic. Apart from the disease, the psychological problems connected to the lockdowns has caused an unprecedented change in the thought process of people towards travel. In the present study, we aim to statistically illustrate the change, the pandemic and lockdowns brought upon the travel mode choice behaviour. An Integrated choice and latent variable (ICLV) framework was adapted to understand the impact of the novel behavioural constructs, such as awareness of the disease and people's perception of the strictness of lockdown towards the mode choice in the post pandemic scenario. Different trip types were characterized according to the nature of the trip and their mode choice were assessed separately for the impact of the latent constructs. The results suggest that the awareness of the disease and the perception of strictness of the lockdown implemented play a major role in affecting the change of the mode choice of people. Further, the perception of safety in public transport, characterized by the social distancing and sanitization measures, determine the willingness of people towards the choice of public transit systems. The study concludes with a focus on the policies, which could be implemented for a safe travel in the post lockdown stage.

1. Introduction

The corona virus outbreak, which supposedly originated in the Wuhan, Hubei Province of China in December 2019, is one of the biggest pandemics that the humans have come across. Countries across the world have been implementing strict measures to contain the spread of virus including lockdowns, travel restrictions and curtailment of the commercial activities that restricts the movement of people. Social distancing, masks and personal sanitization have become the new standards of lifestyle. However, even now, there is an uncertainty regarding the persistence of the pandemic.

Currently, governments have set foot on the realization that the people might need to learn to live with the virus by following suitable precautionary measures. To reinstate the economy, countries are slowly moving towards a controlled relaxation of the strict lockdown rules.

As commercial activities need to restart, transportation services need to be resumed in a safe and systematic manner to support the daily movement of people. However, because of the influence of the pandemic and related lockdowns, one can expect a change in the travel behaviour

of people in the post lockdown scenario. Social distancing might be one of the major factors, which would help people assess their safety and the subsequent mode choice.

The effect of pandemic and lockdown could be expected to influence the safety perception among non-captive riders and their subsequent usage of public transport system for commute and non-commute trips. Even among captive riders, the awareness about new information related to the pandemic could be expected to modify their travel intentions (Bamberg and Schmidt, 2010). The influence of the psychological factors is in line with the theory of planned behaviour, which suggested that people's behaviour is regulated by their attitude, perceived behavioural control and existing subjective norms (Ajzen, 1991). Due to the ongoing pandemic, people's derived utility from different modes may be influenced by psychological aspects related with the new standards of safe, sanitized, socially distant and secure travel.

According to the level of safety presumed by the people, diverse changes can be expected from different transportation modes. Public transportation systems would require to match the psychological expectation of the people so that their demand is not affected. A rise in

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the usage of personal vehicles can be expected because of the sense of safety offered by these vehicles from the virus due to the personal sanitization measures taken. Private ride-hailing services may emerge as the new option for people for their daily commute, provided they offer the best safety with least compromise in conventional travel attributes such as travel time and travel cost.

In view of the expected changes in the travel behavioural patterns of people, this paper aims to understand the difference in the mode choice behaviour of the people before and after the lockdown. A statistical understanding of the change of mode choice is conducted, which helps in the initial leads for formulation of hypothesis. Further, the factors in the background causing the change are studied and analysed. An integrated Choice and Latent variable model will be used to understand the impact of the latent characteristics of awareness, social conformity, perception of strictness, subjective well-being of people, upon the intended change in the mode choice, due to the pandemic scenario.

The present study aims towards achieving the following objectives:

1. Evaluation of the change in the proportions of mode choice for private vehicles, public transport and NMT, before and after the lockdown using statistical techniques.
2. Modelling the impact of latent constructs such as awareness subjective wellbeing and social conformation on the mode choice of people in a post lockdown scenario.
3. Evaluation of the willingness among people to use public transportation after the lockdown depending on the safety measures introduced in these modes. The impact of different safety measures would be collected using a Stated Preference (SP) experiment.
4. Evaluation of the willingness of people to use non-motorised transport after lockdown.

According to the authors' knowledge, the present study is first of its kind that has applied a hybrid choice framework in defining the psychological impacts of a pandemic on the travel behaviour of people. The present study aims to capture these psychological impacts, in the context of a change in the mode choice behaviour of the people because of the lockdown.

The present study is organized as follows. Section 2 describes the literature reviewed for the study, and section 3 explains the conceptual framework and the thought process behind the study. Section 4 explains the data collection procedure adopted and the different variables used in the present research. Section 5 gives a description of the methodology, and section 6 presents a discussion on the results obtained. Section 7 elaborates on the policy implications of the results, and section 8 concludes the study.

2. Literature review

The onset of corona virus has filled the world with a sense of fear, and have forced the governments to implement strict lockdowns around the world. The social, economic, and psychological effects because of the pandemic can be expected to last long. From a behavioural modelling perspective, the information and experiences gathered during the lockdown can be expected to act as psychological factors that influence the way in which individuals take decisions regarding their daily activities. This may act as new information that affects the behaviour of people as perceived by a modeller (Bamberg and Schmidt, 2010). In this context, the current literature review initially highlights how the pandemic can influence the behaviour people in general. Further, it elaborates how different aspects associated with pandemic awareness, social conformation and lockdown strictness, which comes under the ambit of theory of planned behaviour (TPB) by Ajzen (Ajzen, 1991) could impact the mode choice of people.

Social distancing, sanitization and usage of masks are the only accepted practices currently proposed against the spread of novel corona virus (Coronavirus disease COVID-19 advice for the public), as the

mobility patterns of individuals are found to influence the spread of infectious diseases (Funk et al., 2010). Further, transportation sector has been proven to be a vector in the spread of past pandemics such as influenza (Zhang et al., 2011), shifting the focus of authorities towards lockdowns to curtail travel of people. Due to these lockdowns imposed, movement of people is greatly reduced resulting in boredom and depression (Brooks et al., 2020). As TPB suggests, interventions in the situation have a possibility of altering the intentions and behaviour, where disruptive events are understood to influence the travel behaviour greatly (Parkes et al., 2016). The change in the mood and well-being, imparted by the lockdown play an important role in travel (De Vos et al., 2013). Further, normative beliefs in form of social norms play an important role in shaping the behaviour of people during and post lockdown (Bavel et al., 2020). Social compliance or conformity acts as a leverage to assess the spread of awareness and stigma as well, as people tend to care about conforming to social norms (Shadmehr and Bueno De Mesquita, 2020), which reflects in the travel behaviour such as trip frequency (Aaditya and Rahul, 2021), shopping behaviour (Eger et al., 2021) etc. These normative beliefs, measured through the social conformity, can help in understanding the perceived societal pressure to conform to societal beliefs.

Perceived behavioural control is another aspect of the TPB, which explains a person's perceived ease or difficulty of performing a behaviour (Heinen et al., 2011). In the lockdown period, this perception of ease of travel or any outdoor task is influenced by the level of lockdown outside. Apart from the zones declared by the government for containment of virus, the perception of strictness of the lockdown imposed, influences the decisions made by the people. If an ease of movement is perceived in the lockdown period, the perception of the spread of the virus and the fear level might decrease, resulting in the past experiences dominating the decision. If the perception of the lockdown is towards a stricter side, new information perceived about the lockdown and spread of virus impacts the decision. Further, the psychological burden upon the people affects the recreational travel or short term usage of non-motorised modes, as physical activity might yield a sense of freedom and result in mental stress relief and happiness (Ettema et al., 2016; Mondal et al., 2020; Won et al., 2020).

Discrete choice models have been conventionally used to model the choices of consumers, from a distinct set of mutually exclusive and collectively exhaustive set of alternatives, based upon a complex combination of socio economic and psychological attributes of an individual (Ben-Akiva and Lerman, 1985; Bouscasse, 2018). Conventional choice models focussed more upon the observable attributes of people such as their demographics, past experience and market trends, neglecting the sociological and psychological attributes (McFadden, 1986). But, inclusion of psychological constructs into the analysis can be fruitful to assess their role in the mode choice decisions of an individual (De Witte et al., 2013). Acquiring a deeper knowledge and understanding about these latent psychological variables can be used to frame adequate policy measures (Bhat, 1998). Integrated Choice and Latent Variable (ICLV) models provide a robust structure to include these behavioural constructs as variables into the conventional framework of discrete choice analysis (Vij and Walker, 2016).

After the initial conceptualisation of ICLV structure in the 1980s (McFadden, 1986; Train et al., 1987), there has been a great amount of research upon the formulation and specification of ICLV models (Walker, 2001; Bhat, 2008; Kamargianni et al., 2015; Enam et al., 2019). These models have been successful to a great extent to incorporate the latent nature of psycho-attitudinal variables and subjective perceptions of individuals. ICLV models have been used to model travel time (Varela et al., 2018), mode choice (Kamargianni et al., 2015), route choice (Sener et al., 2009) and ownership patterns (Daziano and Bolduc, 2013; De Luca et al., 2020) of individuals. Various studies have used diverse perceptible and behavioural variables such as willingness (Kamargianni and Polydoropoulou, 2013), environmentalism (Sottile et al., 2015), climate (Motoaki and Daziano, 2015), habits (Kamargianni et al., 2014)

etc. Analysis was done on Revealed preference data (Kang et al., 2017), Stated preference data (Giansoldati et al., 2020), combined RP and SP data (Morikawa et al., 2002). Till date, various kernels such as multinomial probit (Kamargianni et al., 2015), multinomial logit (Bhat, 1998), mixed probit and logit (Walker et al., 2002) were used for the discrete choice part in the framework. Brisk simulation and optimization provided by recent advent of software and packages such as Biogeme (Bierlaire, 2020) helped many researchers to experiment upon the framework.

3. Conceptual framework

Fig. 1 below presents the conceptual framework adopted in the study. It is formulated based on the proposition that there would be a change in mode share after the lockdown because of the COVID scenario. In the first step data is collected regarding various socio-demographic variables and mode share before and after lockdown across India. In the next step, a Z-test for proportions is conducted, to check the statistical significance of the change in the mode choice in a pre and post lockdown scenario. In the third step, an ICLV framework is formulated for understanding the specific impact of latent variables such as the awareness regarding the disease, social conformity of the people, and the perception of strictness of the lockdown on the mode shift between pre and post lockdown scenario. The model is developed for work and non-work trips with non-work trips further categorized in to essential and recreational trips. In the fourth step, a stated preference experiment is devised for eliciting the influence of safety perception, in the context of COVID, on the willingness to use public transport after the lockdown. For this, eight hypothetical scenarios are framed based on different safety standards, and the corresponding travel cost and travel time. An ICLV model is then employed to identify the influence of the latent variable defining safety perception on the willingness to use public transport. In the final step, the effects of lockdown on the willingness to choose non-motorised transport was determined using a binary logit model.

4. Data collection

A web-based survey was adopted for the data collection. The data was collected across India during the time period between May 20th to June 31st, 2020. The survey was conducted through Google forms. Different social media platforms such as Facebook, WhatsApp, LinkedIn were used to distribute the form. The questionnaire consisted of details

on demographics, indicator variables, the current and future mode choice and the SP experiment for the evaluation of public transport. A total of 58 questions were asked in five different languages. After preliminary sorting and data cleaning, a data set consisting of 410 data points was finalised for the analysis. Demographic variables can be used to describe the disaggregate diversity in the data sample used for the empirical analysis. The demographic variables for which information was collected in the current study include age, gender, occupational status, educational status. Age is considered as an important factor, as an increase in age may be responsible for a change in the attitude and perceptions of people. Gender has been conventionally used to distinguish between the views and helps in better interpretation of psychological constructs. Income and occupation can be used to assess the socio-economic characteristics of the sample. The respondents were provided with six different occupation types to choose from. Out of these, time bound workers such as public and private sector employee and contract basis employees were merged to form a dummy variable called occupation category 1 (occu1), and all other occupations such as students, business, work from home and retired were considered to be the base level and called occupation category 2.

Education level helps in understanding the level of awareness of people. It is represented as a dummy variable in the current study with respect to categories - respondents having their highest educational qualification till graduation (0) and respondents having their highest educational qualification above graduation (1).

Apart from demographics, geographic attributes play an important role in the mode choice. The zone of residence, type of regionality and distance of travel are the variables used to study the geographical diversity, and its impact upon the behavioural and mode choice variables.

The zone of residence pertains to the containment zones divided for control of spread of the virus. As the country is divided into three different types of zones (red, orange and green), impact of red zone and orange zone, upon the dependent variable was determined by assigning each of them a value of one. Green zone was the base level and was assigned a value of zero.

The type of regionality is an important factor to assess the reach of transportation services and information and is treated as a dummy variable in the current study. The impact of regionality in the analysis was assessed by allotting a value one for the respondents (urban) who are urban/semi urban -dwellers, considering rural region respondents as the base level. Three different types of trips were considered in the study. Work trips include the daily commute trips of the employees to their work places along with school and college trips of students. Essential

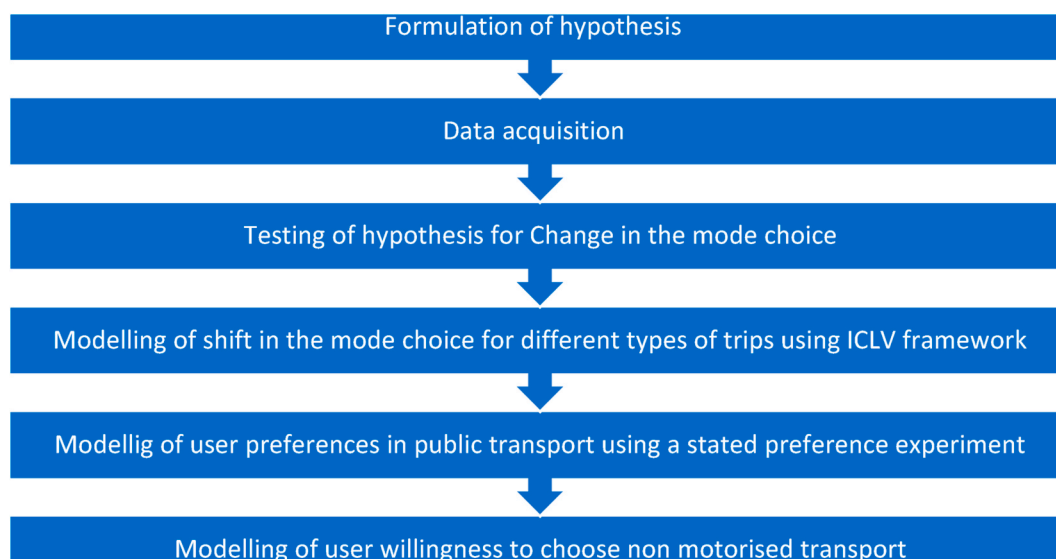


Fig. 1. Conceptual framework.

trips are made for essential purchases such as groceries, vegetables and other essential commodities. Recreational trips include weekend shopping, long rides and other trips made for recreational purposes.

For each different type of trip, 4 different mode choice options were provided in the questionnaire to choose from-Public transport, Personal vehicle, Cab or auto and Non-Motorised Transport. Public transport includes buses, metro and local trains. Personal vehicles may be two wheelers or 4 wheelers, which the respondents own. Cab or Auto is the ride hailing service, which may be individual or under an organisation such as Ola and Uber. Non-Motorised transport includes walking or cycling.

Table 1 describes the demographic and geographical variability of the data. 60.8% of the respondents are female and 55.9% of the respondents are concentrated in the age of 24–40 years. Among all respondents, majority are urban dwelling (83%), and around half of the respondents have their education level above graduation (52.2%). Further, 31.6% of respondents have their income in the range of 25000–50000 rupees. Vehicle ownership is dominated by two-wheeler (64%) followed by four-wheeler (41.3%). A majority of the respondents are confined to the red zone (constricting their travel activities to essentials only). Fig. 2 represents the geographical spread of the respondents across all states of India, where the majority of respondents belong to Jammu & Kashmir(25%), closely followed by Telangana(24%) and Tamil Nadu(20%), and a scarce representation of respondents from Arunachal Pradesh, Bihar, Goa and Orissa(0.02%).

Awareness regarding the disease (COVID-19), social conformity and strictness of the lockdown were the latent variables employed in the ICLV framework developed for modelling the shift of modes happening between the pre lockdown and post lockdown period. Awareness regarding the disease measures the people’s knowledge about the pandemic scenario. If the participant is more aware, he/she is more likely to avoid risk by taking a wise decision in the mode choice. Social conformity can be used to assess a person’s susceptibility to his perceived social norm. More susceptible a person is to the conformity pressure, more likely are they to change their opinion based on the norm set by the society (Mallinson and Hatemi, 2018). Strictness of the lockdown is the perception of the people regarding how strict the lockdown was implemented in their housing locality. It would influence their perception of the spread of the disease, which would subsequently influence their mode choice.

Table 1
Demographics.

		Percentage
Gender	Male	60.8
	Female	39.2
Regionality	Urban/Semi Urban	83
	Rural	17
Age	18-24	30
	24-40	55.9
	40-56	10.2
	56-65	3.9
Education	Post graduate and above	52.2
	Graduate and below	47.8
Occupation	Category 1	45.9
	Category 2	54.1
Income	Less than 5000	3.4
	5000 to 10000	6
	10000 to 25000	10.4
	25000 to 50000	31.6
	50000 to 75000	15.4
	75000 to 100000	15.9
Vehicle ownership	Above 100000	17.2
	Bicycle	25.84
	2-wheeler	64
	4-wheeler	41.3
Zone	Red Zone	48.8
	Orange Zone	24.3
	Green Zone	26.9

Awareness regarding the disease was measured using 3 specified indicators pertaining to the symptoms of illness caused by the virus, the age groups affected by the virus, and the precautionary measures to avoid the transmission of the virus. Knowledge regarding these indicators were measured using a scoring system as proposed by Almutairi (Almutairi, 2015) and were later converted into a scale between 1 and 5. This awareness was measured by using the knowledge of the respondents on the symptoms of COVID-19, the age groups affected by COVID-19 and the precautionary measures to prevent the spread of COVID-19.

Social conformity of the people (Mehrabian and Stefl, 1995) was measured using two indicators - the people’s reliability on others for their actions and the role of their friends or family in their decision making. This measurement was done on a 5-point Likert scale of agreement that included the options strongly agree, agree, no opinion, disagree and strongly disagree.

Strictness of the lockdown was measured using the indicator ‘perception of strictness’. The individuals were asked to indicate their opinion regarding the extent of strictness adopted in their locality on a scale between 1 and 5.

A stated preference experiment is employed for modelling the influence of safety perception of individuals on the willingness to use public transport. This perception depended on the different safety standards that could be adopted in the context of COVID-19. The questionnaire consisted of 8 hypothetical scenarios with varying combinations of sanitization, crowd management and social distancing, along with repercussions for each scenario on travel time and travel cost (Table 2). The increase in travel time or travel cost was obtained with respect to the current travel time and travel cost obtained for the public transport modes. The current travel time and travel cost was taken as an average of their values across work, non-work essential and non-work recreational trips.

Besides the perception of safety, attitude towards the public transportation (Popuri et al., 2011) also affects the choice of public transport. Attitude towards the public transport was measured using two indicators, which measured the agreement of respondents to statements: “The present infrastructure for public transport such as bus stops, shelters or bus lanes are not sufficient or comfortable enough” and “I believe using motorised modes are a sign of prosperity compared with non-motorised modes and public transport”, on a likert scale from 1 to 5. For each scenario framed in the stated preference experiment, a variable of safety was included to assess the safety, the respondent perceives, and was measured on a likert scale between 1 and 5, from most safe to least safe.

A binary choice model with a logit kernel was adapted for modelling the mode choice of Non-motorised transport. Attitude towards the infrastructure of NMT, attitude towards NMT as a mode compared to motorised modes and the strictness of lockdown were taken as the indicators for the latent variables. Due to a lack of correlation between the attitude indicators, single indicator exists for each latent variable for incorporating them into the ICLV framework. Hence, the indicators were taken directly as observed variables in the utility, rather than taking them as the latent variables in ICLV framework.

Table 3 presents the mean perception ratings of the indicators used in the study against the demographics. The mean awareness of urban dwellers is higher compared to rural, indication the lack of proper information of the disease in the rural regions. It can be observed that the mean awareness increases with an increase in age, except for the age group of (40–56). In accordance with the literature, the mean conformity is observed to decrease with age (Pasupathi, 1999; Walker and Andrade, 1996). The mean perception of strictness is higher for rural dwellers, and is reflected in the subjective wellbeing, which is higher for urban people. This is due to the fact that lockdown has caused a decrease in the general quality of life, decreasing the wellbeing of people. Respondents of Occupation category 1 perceive lower strictness, which is reflected in their higher wellbeing. As the age increases, people become

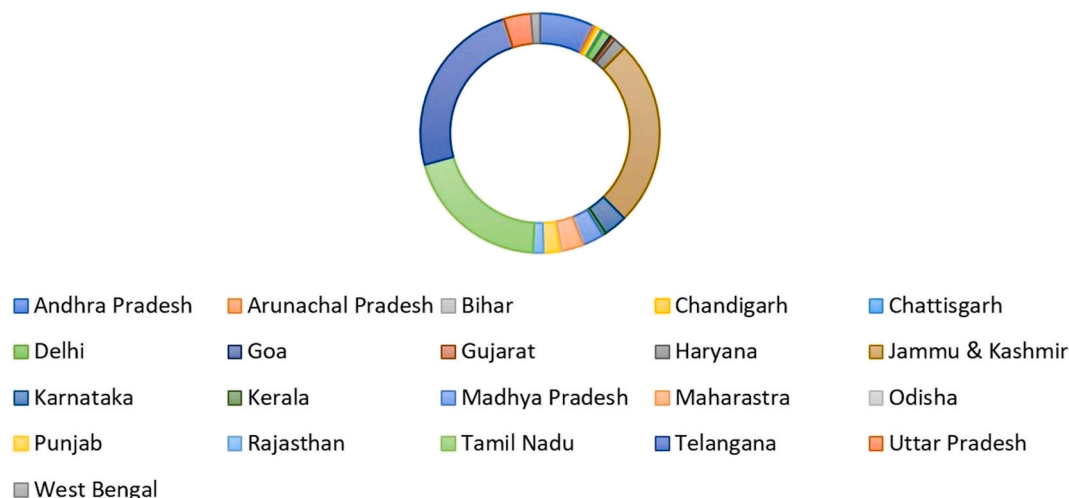


Fig. 2. Geographical spread of respondents across India.

Table 2
Stated Preference experiment.

Scenario	Sanitization	Crowd Management	Social Distancing	Increase in Travel Time (%)	Increase in Travel cost (%)
1	Not done	Not done	Not done	0	0
2	Done	Not done	Not done	20	5
3	Not done	Done	Not done	20	5
4	Not done	Not done	Done	20	5
5	Done	Done	Not done	30	10
6	Done	Not done	Done	30	10
7	Not done	Done	Done	30	10
8	Done	Done	Done	50	15

Table 3
Mean perception ratings for COVID-19 specific indicators.

Variable	Categories	%	Indicator- mean (standard deviation)						Safety	
			Awareness symptoms of COVID 19	Awareness: age groups affected	Awareness: precautionary measures	Conformity: relying upon others	Conformity: reliability for decisions	Strictness perception		Subjective Well Being
Gender	male	60.8	3.84(0.9)	4.46(0.54)	4.06(0.78)	2.84(0.97)	3.14(0.99)	3.02(1.26)	3.02(1.02)	3.48 (1.30)
	female	39.2	3.87(0.92)	4.40(0.61)	4.03(0.85)	3.02(0.75)	3.29(0.92)	3.03(1.07)	2.98(0.97)	3.60 (1.26)
Regionality	urban	83	3.88(0.89)	4.45(0.56)	4.08(0.80)	2.89(0.88)	3.14(0.96)	3.02(1.19)	3.05(1.01)	3.54 (1.28)
	rural	17	3.71(0.99)	4.31(0.58)	3.91(0.82)	3.01(0.95)	3.47(0.92)	3.08(1.16)	2.79(0.99)	3.45 (1.31)
Age	18–24	30	3.82(0.932)	4.46(0.62)	3.93(0.88)	3.03(0.85)	3.29(0.96)	3.04(1.23)	2.89(0.96)	3.45 (1.31)
	24–40	55.9	3.89(0.90)	4.44(0.57)	4.11(0.79)	2.85(0.90)	3.16(0.95)	2.96(1.19)	2.96(1.01)	3.52 (1.26)
	40–56	10.2	3.61(0.93)	4.33(0.52)	4.0(0.73)	2.88(0.88)	3.21(0.95)	3.28(1.13)	3.28(0.99)	3.81 (1.22)
	56–65	3.9	4.3(0.72)	4.53(0.35)	4.23(0.72)	2.86(1.12)	3.2(1.26)	3.46(0.91)	3.86(0.83)	3.43 (1.51)
Education	Post graduate or above	52.2	3.84(0.88)	4.44(0.54)	4.06(0.74)	2.91(0.89)	3.25(0.95)	3.12(1.15)	3.06(1.00)	3.48 (1.27)
	Graduate or below	46.8	3.86(0.95)	4.43(0.59)	4.04(0.88)	2.91(0.89)	3.14(0.97)	2.93(1.22)	2.94(1.01)	3.58 (1.30)
Occupation	Category 1	45.9	3.84(0.91)	4.44(0.54)	4.06(0.80)	2.87(0.91)	3.08(0.98)	2.97(1.16)	3.10(0.94)	3.58 (1.26)
	Category 2	54.1	3.86(0.91)	4.43(0.59)	4.03(0.82)	2.94(0.87)	3.30(0.94)	3.08(1.21)	2.92(1.04)	3.48 (1.31)

more favourable to public transport, but a sudden dip is found for the age group of 56–65. A similar trend is observed for perception of safety towards public transport as well.

5. Methodology

5.1. Z-test for proportions

To establish a statistical significance of the change in the mode choice in between the pre lockdown and post lockdown scenario, a two-sample Z-test for proportions was undertaken. In the current study context, this test checks whether there is a significant difference in the mode share between a prelockdown and a post lockdown scenario. The null hypothesis of the test assumes that there is no significant difference between the proportions and the alternate hypothesis assumes that there is a significant difference between the proportions

The test statistic ‘Z’ for the test could be expressed as below:

$$Z = \frac{P_{pre} - P_{post}}{\sqrt{P_t^*(1 - P_t) \left(\frac{1}{N_{pre}} + \frac{1}{N_{post}} \right)}} \quad (1)$$

where, P_{pre} is the proportion of respondents who chose a specific mode before lockdown, P_{post} is the proportion of people who intended to choose the same mode after lockdown, P_t is the proportion of the people choosing the mode in the total sample, N_{pre} = size of sample for the before lockdown scenario, N_{post} = size of sample for the after-lockdown scenario.

5.2. Integrated choice and latent variable (ICLV) framework

Integrated choice and latent variable framework is an extension of the conventional discrete choice set-up to include psycho-attitudinal variables that enhance the explanatory power. Formulation of an ICLV model involves two inter-connected components: the discrete choice model and the latent variable model. The latent variable model can be further described by two components: a structural equation and a measurement equation. Fig. 3 depicts the framework of a typical ICLV model.

In an ICLV model, the utility of a choice is described by both observed and latent variables. Further, the latent variables, which are measured using a set of indicator variables, are expressed through their structural part.

Mathematically, the framework in Fig. 3 can be described by the following three equations that respectively describes the discrete choice model, structural model and measurement model.

$$U_n = AX_{n1} + BX_n^* + E X_{n2} + \varepsilon_n \quad (2)$$

$$X_n^* = C_0 + FX_{n3} + CX_{n2} + \nu_n \quad (3)$$

$$i_n^* = D_0 + DX_n^* + \eta_n \quad (4)$$

In equation (2), U_n represents the $(J \times 1)$ vector of utilities of J

alternatives for the individual n . X_n^* is the $(M \times 1)$ vector representing the latent variables. i_n^* is the $(R \times 1)$ vector of latent variables defining the ordered measurement indicators. A is the $(J \times K)$ matrix, representing the parameters for the observed variables x_{n1} , entering only the utility equation. B is the $(J \times M)$ matrix, representing the parameters for the latent variables X_n^* . E is the $(J \times L)$ matrix, representing the parameters for the observed variables X_{n2} entering both the utility equation and the structural equation. X_{n1} is the $(K \times 1)$ vector representing the observed variables entering only the utility equation. X_{n2} is the $(L \times 1)$ vector representing the observed variables entering both the utility equation and the structural equation. X_{n3} is the $(P \times 1)$ vector representing the observed variables entering only the structural equation. ε_n is the $(J \times 1)$ vector, representing the gumbel distributed error specification in the utility of a multinomial logit model. C is the $(M \times K)$ matrix of parameters defining the variables X_{n2} in the structural model. F is the $(M \times H)$ matrix of parameters for the $(H \times 1)$ variable vector X_{n3} that represents the observed variables that enter only the structural model. ν_n is the $(M \times 1)$ vector of normally distributed stochastic terms with a mean vector of zero and a diagonal covariance matrix θ . D is the $(R \times M)$ matrix of parameters representing the relationship between the latent variables and their respective indicators. η_n is the $(R \times 1)$ vector of the normally distributed stochastic components in the measurement equation, with a mean of vector of zero and covariance matrix λ , which is an identity matrix. C_0 and D_0 represent the vector of intercepts entering the measurement and structural equations respectively.

Further, if ‘ i_n^* ’ represents $(R \times 1)$ vector of chosen indicator levels corresponding to ‘ i_n^* ’ and y_{nj} denotes the specific choice in the discrete choice model such that:

$$y_{nj} = 1 \text{ if } U_{nj} > U_{nj'} \text{ for } j' \in \{1, 2, \dots, J\} \text{ and } j \neq j' \quad (5)$$

= 0 otherwise

Then the joint probability density function in terms of the choice and the measurement indicators that can be used for formulation of the maximum likelihood estimator could be written as:

$$f_{y,i} \left(y_n, i_n | x_n; A, B, C, \theta, D, \lambda \right) = \int f_y \left(y_n | x_{n1}, x_{n2}, x_n^*; A, B, E \right) f_i \left(i_n | x_n^*; D_0, D, \lambda \right) f_x \left(x_n^* | x_{n3}, x_{n2}; C_0, C, F, \theta \right) dx_n^* \quad (6)$$

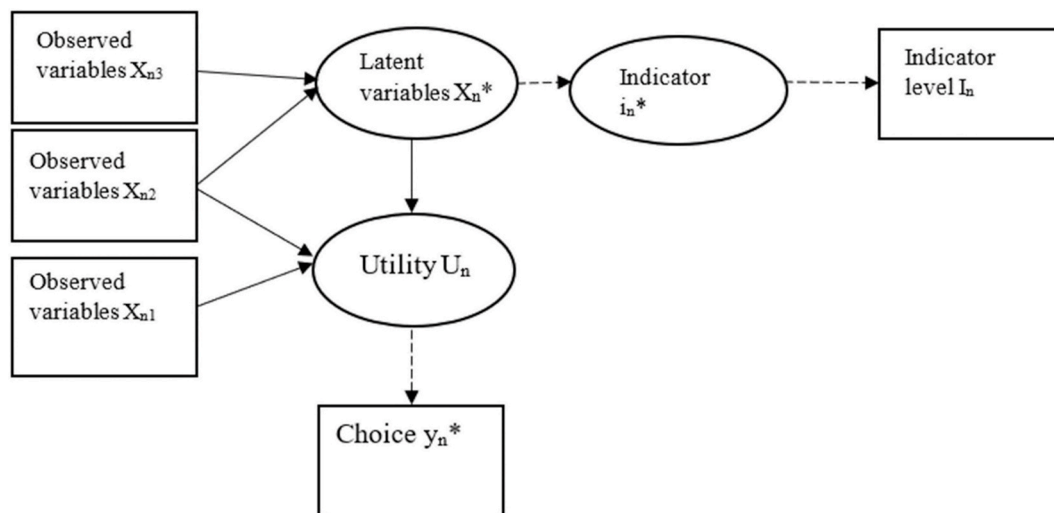


Fig. 3. Framework of ICLV model(modified and adapted from Ben-Akiva et al. (2002)).

5.2.1. Variables used

Three different ICLV models were used in the study for analysing the impact of different latent variables upon mode choice. The first model determined the impact of the latent variables including the awareness regarding the disease, societal conformity of the people and the perception of strictness of the lockdown, on the mode shift between pre and post lockdown scenario for work trips. The second model assessed the impact of awareness regarding the disease and societal conformity on the shift of mode between the pre and post lockdown scenario, for recreational trips. The third model determined the impact of perception of safety of people and their attitude towards public transportation, on the mode choice of public transport in the post lockdown scenario.

5.2.2. Mode shift

Awareness regarding the disease, conformity and strictness are the opted latent variables, which influence the mode shift in work and recreational trips. In the three indicators available for awareness regarding the disease, one of the indicators was set to be identified, to address the identity issue of HCM models. Similarly, one of the two indicators available for conformity and the only indicator of strictness were set to be identified.

The choice modelled in the framework is a binary choice with a logit kernel. Since the study had information on both the pre and post COVID-19 mode choices of the respondents, the binary choice was formulated to reflect the change in the mode choice.

The observed variables used in the study can be categorized into 3 types:

1. Variables which strictly entered the utility equation only X_{n1}
2. Variables which strictly entered the structural equation only X_{n3}
3. Variables which entered both utility and structural equations X_{n2}

Mode shift model of work trips: X_{n1} for the work trips model consist of the variables gender and educ. X_{n3} for the work trips, which enter the structural equation only, consist of age, income, urban and occupation category 1. Age and income enter the structural equation of awareness. Similarly, urban and age for conformity and occupation category 1 and urban determine the strictness, along with respective intercepts for each structural equation.

Mode shift model of recreational trips: The vector X_{n1} for the recreational trips model consists of gender variable only. The vector X_{n2} which includes the variables entering both utility and structural equations, consists of the variable age. As only awareness and conformity are the latent variables opted for recreational trips, the vector X_{n3} for the recreational trips, which enter the structural equation only, consist of age, income and urban. Similar to work trips, age and income enter the structural equation of awareness, and urban and age determine conformity.

5.2.3. Model for public transport willingness

The willingness of using public transport is hypothesised to be affected by the perception of safety, the respondents have, towards each of the eight hypothetical scenarios adapted in the public transport, and the attitude of the respondents towards public transport, along with the change in travel time and travel cost of each scenario and other observed variables.

X_{n1} for the SP experiment consists of the hypothesised difference in travel time and travel cost between each scenario, along with zoneR. X_{n3} consists of the variables education and occupation category 1 entering the structural equation of attitude towards public transportation and the dummy variables of sanitization, crowd management, social distancing, along with age and gender determining the perception of safety. To address the identity issue, one of the indicators of attitude towards public transport and the only indicator of perception of safety are set to be identified.

A binary choice model with a logit kernel was adapted for choice

modelling.

5.2.4. Model for willingness of NMT

A binary logit choice model was considered for modelling the willingness of respondents to use non-motorised transport in the post lockdown scenario, as the latent variables which would impact the use of NMT have a single indicator each. For this purpose, the indicators of the latent variables-subjective well-being, attitude towards using NMT and attitude towards the infrastructure built for NMT, were incorporated directly into the utility function of NMT, along with gender and occupation category 1 (occu1).

6. Results and discussion

The significance of mode shift in the pre and post lockdown period, tested by the Z-test for proportions, is presented in Table 4. These results are presented for Public transport (PT), personal vehicles (PV), cab/auto rickshaw (CorA) and non-motorised transport (NMT). Public transport in our analysis includes buses, metro trains and local trains, whereas NMT includes walking and cycling as well. Individual proportions of the vehicles in the total sample for the pre lockdown and post lockdown periods were tested for the Z-statistic. From the table, it could be observed that there is a significant difference in the mode share of public transportation and personal vehicles for work trips. To be specific, there is a reduction in the number of people using public transport, and there is an increase in the number of people using personal vehicle. This might be an indication of preference for personal vehicles, which give a perception of safety from virus spread, among respondents for their work trips. Similar to work trips there was a decline in public transport usage for recreational trips. This decline in the ridership of public transport is reflected in the rise in the prices of crude oil and ownership of personal vehicles (Thanks to COVID-19, personal car ownership isn't going anywhere; Global crude oil prices rise on buoyant China, U.S. economic data). However, for NMT, a significant increase in the usage is observed, which can be observed in the two-fold rise of bicycle ownership (How Covid-19 is boosting non-motorised transport in cities). This

Table 4
Z test for proportions.

Shift of mode in WORK trips at 5% level of significance				
	Public Transport	Personal Vehicles	Cab or Auto (ride hailing services)	Non-Motorised Transport
Before	156	176	28	50
After	86	250	28	46
Z-value	5.46	-5.26	0	0.44
Z - critical	1.96	-1.96	1.96	1.96
Significance of results	significant	significant	not significant	not significant
Shift of mode in ESSENTIAL trips at 5% level of significance				
	Public Transport	Personal Vehicles	Cab or Auto (ride hailing services)	Non-Motorised Transport
Before	57	236	10	107
After	41	246	12	111
Z-value	1.42	0.88	0.45	0.33
Z-critical	1.96	1.96	1.96	1.96
Significance of results	not significant	not significant	not significant	not significant
Shift of mode in RECREATIONAL trips at 5% level of significance				
	Public Transport	Personal Vehicles	Cab or Auto (ride hailing services)	Non-Motorised Transport
Before	86	264	38	22
After	49	289	28	44
Z-value	3.55	1.875	1.269	3.01
Z-critical	1.96	1.96	1.96	1.96
Significance of results	significant	not significant	not significant	significant

Table 5
ICLV parameter estimates for work trips.

Name	Value	Robust. p-value
<i>Structural model</i>		
Awareness		
Age	5.2	0
Income	2.87	0
Conformity		
Age	-0.558	0.18
Urban	-0.29	0.32
Strictness		
Occupation category 1	-0.174	0.01
Urban	-0.147	0.12
Intercept	0.266	0.02
<i>Measurement model</i>		
Awareness		
Age groups affected by COVID-19(i ₁₁)	0.507	0
Precautions to be taken against COVID-19(i ₁₂)	0.875	0
Intercept_awareness2	5.19	0.
Intercept_awareness3	1.8	0
Conformity		
Basically, my friends/family are the ones who decide what we do together(i ₂₁)	0.386	0
Intercept_conformity2	0.608	0.001
<i>Utility model</i>		
ASC	0.571	0.19
Awareness (X ₁ [*])	0.047	0.13
Conformity (X ₂ [*])	0.028	0.71
Education	0.57	0.02
Gender	0.26	0.33
Strictness (X ₃ [*])	-5	0.05

Table 6
ICLV parameter estimates for recreational trips.

Name	Value	Rob. p-value
<i>Structural model</i>		
Awareness		
Age	2.35	0.01
Income	1.7	0.02
Conformity		
Age	-0.142	0.31
Urban	-0.225	0
Strictness		
Occupation category 1	-0.109	0.10
Urban	0.088	0.17
Intercept	0.163	0.06
<i>Measurement model</i>		
Awareness		
Age groups affected by COVID-19(i ₁₁)	0.476	0
Precautions to be taken against COVID-19(i ₁₂)	0.88	0
Intercept_awareness2	4.09	0
Intercept_awareness3	0.987	0.01
Conformity		
Basically, my friends/family are the ones who decide what we do together(i ₂₁)	2.05	0
Intercept_conformity2	0.498	0
<i>Utility model</i>		
ASC	1.64	0
Awareness (X ₁ [*])	0.123	0.04
Conformity (X ₂ [*])	-0.78	0.14
Gender	-0.13	0.65
Strictness (X ₃ [*])	-5	0.13
Age	1.06	0.15

increase may be a result of change in the recreational activity of the people, even though, in the questionnaire this was not explicitly elicited. Further, there was no significant changes in the mode share for non-work essential trips.

The estimates of parameters of the ICLV models estimated for the

Table 7
Parameter estimates of willingness to choose model for public transport.

Name	Value	Rob. p-value
<i>Structural model</i>		
Safety		
Crowd Management	2.5	0
Social Distancing	3.8	0.
Age	-3.68	0
Gender	0.819	0
Sanitization	2.69	0
Attitude		
Education	0.273	0.32
Occupation category 1	1.61	0
Intercept	-5.89	0
<i>Measurement model</i>		
Attitude		
I believe using motorised modes are a sign of prosperity compared to public transport(i ₁₁)	0.205	0.01
Intercept	1.2	0
<i>Utility model</i>		
ASC	-0.407	0.38
Attitude (X ₁ [*])	-0.003	0.87
Safety (X ₂ [*])	0.734	0
Travel cost difference	-0.178	0.52
Travel Time difference	0.005	0.75
Zone Red	0.193	0.23

Table 8
Parameter estimates for willingness to choose model for non-motorised transport.

Name	Value	Rob. p-value
ASC	1.13	0.02
Subjective Well Being(i ₁₁)	-0.012	0.90
Attitude towards NMT (i ₂₁)	0.285	0.002
Attitude towards NMT infrastructure (i ₃₁)	-0.174	0.08
Gender	-0.278	0.19
Occupation category 1	-0.425	0.04

Table 9
Non-nested hypothesis test for base MNL and predictive models.

	Work	Recreational	Public transport willingness
Predictive rho square	0.174	0.345	0.288
base rho square	0.129	0.325	0.282
LL (0)	-257.15	-262.7	-2273.523
K _L	3	2	4
K _H	10	9	8
significance	0	0	0

work trips, and recreational trips are presented in Table 5 and Table 6. Table 7 and Table 8 respectively presents the results of models estimated for determining the willingness to choose public transport and NMT.

Table 9 provides the estimates of the test for the goodness of fit of the ICLV models when compared to conventional multinomial logit model using non nested hypothesis testing (Koppelman and Bhat, 2006). The test is performed using a reduced form of the ICLV model that does not consider the measurement part. This reduced form is compared to a base multinomial logit model that omits the latent variables in its utility function. The significance level is given by the equation:

$$\text{Significance level} = \phi \left[- \left(-2(\rho_H^2 - \rho_L^2) * LL(0) + (K_H - K_L) \right)^{\frac{1}{2}} \right]$$

where ρ_H^2 and ρ_L^2 are adjusted likelihood ratio indices for model with higher and lower values respectively, K_H and K_L are the number of parameters in higher and lower likelihood models respectively, ϕ is the standard normal cumulative distributive function, and $LL(0)$ is the

likelihood for the zero coefficients model.

Validation of the mode was performed based upon the simulated market share of the dominating choice (in percentage) in the binary choice scenario using the model specification and the actual choices as given by the respondents. A random sub-sample consisting of 25% of the respondents was considered from the sample for validating the model specification. In Work trips and recreational trips, major proportion of the respondents intend to shift to personal vehicles, whereas a high proportion of respondents are not willing to choose public transportation according to the SP experiment. The proportion of respondents choosing to shift to personal vehicles/cab/auto from public transportation/Non-Motorised transport or the ones who retained personal vehicles in post lockdown scenario are taken for validation of work and recreational trips. Respondents who chose not to use public transportation were considered for the validation of SP experiment and respondents who chose Non Motorised Transport were considered for validation of the mode choice model for Non-Motorised transport. It was observed that the difference in market shares of actual data and the simulated market shares of the models differ by less than 2%, suggesting the robustness of the models.

These models for work trips and recreational trips are estimated to determine the impact of latent variables on the reduction of trips as was observed in the Z-test in the previous step. For the work trips, this reduction was quite evident in the public transport and NMT modes, and for recreational trips this drop was observed in the public transport mode. Aply, in the utility model for work trips, the first choice consisted respondents who chose to shift from public transport/non-motorised transport to personal vehicles/cab/auto rickshaw, after lockdown, and respondents who have retained their choice of personal vehicles/cab/auto rickshaw. The second choice is the base mode which included the respondents who had retained the public transport or non-motorised transport in the post lockdown scenario, and respondents who had shifted from personal vehicles/cab/auto rickshaw to the public transport/non-motorised transport. In the case of recreational trips, the first choice considered the respondents who had retained their choice of public transport or cab/auto rickshaw in the post COVID-19 scenario, and the people who have shifted from personal vehicles/non-motorised transport to public transport/cab/auto, and is the base mode. The second choice consisted of respondents who retained their choice of using personal vehicles/non-motorised transport, and the people who have intended to shift from public transport/auto/cab to personal vehicles/non-motorised transport. Further, both alternatives were fixed available for work and non-work recreational trips.

6.1. ICLV model for work trips and recreational trips

6.1.1. Structural and measurement models

In the structural model for work trips, an increase in age increased the awareness. This could be expected as older people were at greater risk of contracting serious health issues because of the COVID-19 (Older people and COVID 19), and hence would be more aware regarding the symptoms and effects of the disease. Further, age had a negative impact on the social conformity. This was in accordance with the results from the studies of (Walker and Andrade, 1996) and (Costanzo and Shaw, 1966), in which an increase in age reduced the social conformity among people.

Increase in the income had a positive impact upon awareness regarding the disease, and It reflected an increased awareness among the higher income group, compared to the lower income groups. Government and private sector full-time employees perceived the level of strictness to be less in their area when compared with students, free lancers and business people.

Being in an urban area decreased the sense of conformity among people and further, the perception regarding the strictness of lockdown. A reduced conformity in urban areas may be attributed to the comparatively liberal nature of the household environment existing in cities

compared with the rural areas where in the decisions depend on the household head most of the times (Hesse, 2017).

Consistent with the work trips, the estimate of the structural part of recreational trips show a positive impact for age upon awareness, and a negative impact upon the conformity. Income of the respondents has a positive impact upon awareness, and further, the respondent being an urban dweller had a significant negative impact upon conformity.

The measurement model in the current study ensured its identity (Vij and Walker, 2014) by fixing the intercept and parameter (defining the impact of latent variable on indicator) of any one of the measurement equations associated with a latent variable respectively to zero and one respectively. As expected, the remaining parameter values representing the impact of latent variables on indicators had a positive value (Tables 5 and 6). An increase in awareness regarding the disease increased an individual's knowledge regarding the age groups affected by the disease and precautions that had to be taken to prevent spread of corona virus. Further, an increase in social conformity increased the chances that family members or friends would have a greater say on the decisions of a person.

6.1.2. Choice models

Awareness regarding the disease had a positive impact on the mode shift choice for both work and recreational trips. In the case of work trips, this implied that people having higher awareness regarding the disease are ready to shift their mode from public transport to personal vehicles, or retain their choice of personal vehicle, rather than choosing public transport for their daily commute. This choice set was constructed in accordance with the results of the Z-test for proportions presented in Table 4, which showed a decline in the public transport users and an increase in the personal vehicle users for the work trips. For the recreational trips, this result reflected a reduction in the public transport share with increase in the awareness.

Perception of strictness had a positive influence on the public transport and NMT usage. This meant that a person who strongly believed that the lockdown was strictly executed would prefer choosing public transport/NMT after lockdown This might be a result of the belief that the health standards with respect to prevention of COVID-19 would be strictly enforced for safe adoption of public transport and NMT.

An increase in age reduced the chances that an individual would use a public transport for recreational trips. Further, in accordance with the prior hypothesis, an increase in awareness regarding the disease is associated with reduction in the usage of public transport.

6.2. ICLV model for willingness to choose public transport

6.2.1. Structural and measurement model

An individual's perception of safety, which decides his willingness to choose a public transport, is greatly influenced by the crowd management, sanitization, and social distancing measures adopted by the public transport agency at bus-stops and stations. A better implementation of crowd management and social distancing measures, and frequent sanitization increased the safety perception among people. In addition, age and gender also influenced the safety perception. older people were less likely to consider the public transport as a safe mode for travel. Further, males felt safer to travel in public transport compared with females, in accordance with the risk taking attitude of men compared to women (Harris and Jenkins, 2006). Attitude towards public transport is significantly affected by the variable defining the type of occupation. Individuals in category 1 which include government, private and contractual jobs had a positive attitude towards the public transport compared to students and business people.

6.2.2. Choice model

The utility model of the SP experiment suggests a significant positive impact for safety perception on the willingness to choose public transport. All other variables including the attitude towards public transport

are highly insignificant. This might be suggesting a dominance of safety perception compared with other variables including the changes in travel cost and travel time corresponding to the safety practices adopted.

6.3. Binary choice model for willingness to use NMT

The estimates of the binary logit model of NMT mode choice reveals that perception of subjective well-being associated with lockdown does not have significant effect on the usage of NMT that include walking and cycling. It was the perception regarding the infrastructure provided which was affecting the NMT usage. People who felt that the infrastructure for non-motorised transport is insufficient, are less likely to choose NMT. This negative influence of absence of infrastructure on NMT usage has been elicited in previous studies also (Jain and Tiwari, 2016; Makarewicz, 2018; Rahul and Manoj, 2020; Rahul and Verma, 2013; Verma, 2016). Further, respondents of occupation category 1 have a lesser utility from NMT when compared to students and free lancers.

7. Policy implications

The current study observes some major changes in the mode choices of people due to the lockdown, associated with COVID-19, that might lead to an instability in the efficient management of public transportation systems. From this study, the following policy implications are derived, which might help prevent the decrease in the usage of public transport in a post lockdown scenario:

As evident from the stated preference experiment, social distancing is one of the most important factor, which is influencing people's perception of safety. Stringent social distancing measures have a need to be implemented in the public transportation systems, to restore and maintain the belief and goodwill of public transportation systems. Research is already being done to optimise the space available in the buses, to accommodate social distancing measures (*Guidelines for Public Transport and Feeder Modes considering Social Distancing Norms Commuting in Urban Area during Covid - 19 Pandemic*). Fleet management and demand optimization is a need of hour, to tackle the perceived high mode share of personal vehicles. The fleet of buses should be scheduled and managed to accommodate the new demand of low occupancy, to prevent crowding of passengers. Similar measures need to be followed in local trains and metro rails as well. Further, the scope of contact among individuals while travelling in shared modes of transportation can be reduced by using contactless payment techniques for collecting fares of travel. Due to the recommended 1–2 m of social distancing, there is a 60–90% reduction in the capacity of vehicles (Gkiotsalitis and Cats, 2020). This reduced capacity needs to be compensated with a careful planning of the frequency of the vehicles, to cater to the demand of public.

Crowd management should be done to organize the entry and exit of passengers at bus stops, bus stands, metro stations and local train stations as well. Work force need to be utilized to avoid crowding of people and to ensure a queue system. City buses should maintain utmost care while carrying passengers. Further, crowd management can also be useful to ensure the usage of personal protection equipment (masks, face shields and gloves), so as to prevent the transmission of disease while in the public transport. Every public transport vehicle can also setup a signalling system, notifying the prospective passengers about the occupancy of the vehicle, aiding them to understand the risk involved in using the mode.

Sanitization of public transport before and after every trip should be ensured, to prevent the transmission of virus through physical contact of surfaces. Further, sanitization chambers need to be set up at the entry and exit points of public transport, which, with the combined efforts of crowd management and social distancing, ensures a safe travel in the public transport. Apart from advertising and fare cutting measures such as discounts, the operators can notify the passengers about the number

of times the vehicle is sanitized before the trip, instilling a confidence in the passengers.

As evident from the insignificance of difference in travel time and travel cost in the mode choice of public transportation, people might be willing to pay more and spend more time to ensure their personal safety. Hence the increase in cost and time are to be optimized in a way to increase the utility of public transport, having safety as the highest priority. The long-term effects of the pandemic on choosing the public transportation may be far reaching due to unprecedented future waves of the pandemic. The risk perception of the individuals being greatly altered, a proper scheme of action needs to be implemented on an ad-hoc basis, to regain the trust of public upon public transportation. This might be achieved by proper penetration of information about the risk preventive measures the public transportation systems go through, before initiation of travel. Further, air circulation strategies inside the vehicle need to be improved with respect to the natural air ventilation, so that the virus spread is prevented due to recirculation of air.

Apart from personal vehicles, usage of non-motorised transport is expected to increase in the post lockdown period for recreational trips. Safe usage of non-motorised modes is to be ensured by using public sanitization chambers in each and every locality, to reduce the risk of transmission. As active mode of travel is regaining a boost-up, short distance travels by non-motorised transport can be encouraged using bicycle rental services, providing infrastructure for cycling such as lanes and parking, which prove very important for enhancing the usage of NMT (Rahul et al., 2021). Walking and jogging should also be encouraged by providing pedestrian lanes and planting decorative plants to create a serene atmosphere.

Further, ride hailing services such as cab or auto rickshaw have been observed to have an insignificant change in their mode share. Hence, private transportation under organizations, should be ensured of their safety standards in cabs and autos. New rules must be framed for the organizations controlling shared modes such as private car pooling and auto rickshaws, to ensure sanitization and personal protection equipment for the passengers and the drivers as well.

8. Conclusions

The lockdown has posed many psychological challenges for the people to tackle with. Cases of increasing anxiety and depression have been reported all over the world (Cao, 2020; Goyal, 2020; Kumar and Nayar, 2020; Rehman, 2020). It is quite natural to expect the influence of these psychological impacts on the travel behaviour of people. The current study in this context explores whether there is a significant change in the mode preference of people after the lockdown, and further, what are the possible psychological factors that could induce this change in the mode preference. A Z-test was used to check whether there is a significant change in the mode share, and hybrid choice framework (ICLV model) was employed to determine the impact of these psychological factors on the mode shift. The authors were unable to find any studies in the previous literature that had used an ICLV framework for eliciting the psychological impacts, because of a pandemic, on the travel behaviour. This could be considered a contribution of the current research.

Using the ICLV framework, the study could identify and analyse the impact of pandemic specific psychological constructs such as awareness and perception of strictness, on the change in mode preference among the people after the lockdown. As was evident from the analysis, for work trips, the intended personal vehicle usage increase significantly after the lockdown at the expense of public transport. This was attributed to the increased awareness regarding the pandemic and the subsequent reduction in the public transport safety perception. However, as evident from the results, people were willing to use public transport, if the disease preventive measures such as social distancing, sanitization and crowd management were well executed.

The organizations controlling the public transportation have a

colossal task of maintaining the standards of travel, along with the restoration of goodwill among people for choosing public transportation. This is to be done in the most systematic and robust way, to ensure that the transportation sector is unaffected for the future waves of pandemic. As people are learning their ways to live with the virus through social distancing, and sanitization, public transportation systems should strictly maintain the norms to ensure feeling of safe commute.

The present study is constrained by the limitations of the online data collection techniques, attracting a tech savvy group of participants based on a convenience sampling technique. As the impact of the pandemic is long reaching, analysis of travel behaviour based on secondary psychological effects of the pandemic such as depression, anxiety etc can be considered as a future scope for the study.

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