Modelling the COVID-19 Travel Choices in Colombia and India: A Hybrid Multiple Discrete-Continuous Nested Extreme Value Approach

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ABSTRACT

The COVID-19 pandemic has affected many daily activities, primarily due to the perceived contagion risk and the government restrictions to mitigate the spread of the virus. To this end, drastic changes in the trip choices for commuting to work have been reported, and studied, mostly via descriptive analysis. On the other hand, modelling-based research that can understand both changes in mode choice and its frequency simultaneously at an individual level has not been frequently used in existing studies. As such, this study aims to understand the changes, in mode choice preference and the frequency of trips during pre-COVID versus during-COVID scenarios, in two different countries of the Global South - Colombia and India. A hybrid multiple discrete-continuous nested extreme value model was implemented using the data obtained from online surveys in Colombia and India during the early COVID-19 period of March-April 2020. This study found that in both countries, utility related to active modes (more used) and public transportation (less used) changed in the during-COVID-19 period. Besides, this study highlights potential risks about likely unsustainable futures where there may be an increased private vehicle use, like car and motorcycle, in both countries. It was also identified that perception towards government response had a significant impact on the choices in the Colombian case, while it was not the case in India. These results may help decision-makers focus on public policies to encourage sustainable transportation, by avoiding the detrimental long-term behavioural changes resulting from the COVID-19 pandemic.

Keywords: COVID-19; Mode choice; Trip frequency; Commute trips; Colombia; India

INTRODUCTION

COVID-19 was declared a pandemic back in March 2020 (*1*); however, even after more than a year, several nations are still experiencing the subsequent waves of the coronavirus, e.g. Colombia is currently experiencing the third peak, while India is easing out of its second wave. COVID-19 pandemic has affected travel activities worldwide due to the risk of contracting the virus that resulted in restrictive government policies (e.g., lockdowns). The effectiveness of these restrictive policies in modifying the activity and travel behaviour of people and the associated similarities/ dissimilarities has emerged as an important research question. This motivates this study where we mathematically model the heterogeneity associated with trip frequencies and mode choice in two countries of the Global South: Colombia and India.

During the early stages of the pandemic, a general lockdown was declared in Colombia. The national lockdown was generalised for non-essential sectors (e.g., schools, industry, commerce) and began on March 25 and was extended three times until it ended on August 31. After ending this stage, local measures were taken in each Colombian state, given governmental decrees established by the national health ministry. In 2020 some local administrations decided to promote bicycling by providing new bicycle lanes using primarily the existing transport infrastructure for cars (*2*, *3*), and the public transportation systems kept working under some restrictions (*3*, *4*). In early COVID-19, public transport presented crowding restrictions (i.e., reduction of vehicle capacities), and using facemasks were mandatory. Despite the mentioned restrictions, public transit for Colombia was available (*4*). Besides, different organisations also made an effort to promote bicycle use for specific groups of the population (i.e., medical workers) who continued travelling (*3*). Similarly, there was a lockdown announced in India from March 25, initially for 21 days, which was later extended until May 31 (*5*, *6*). The COVID-19 timeline for the two countries is shown below (**Figure 1**). Despite the difference between the dates of the first cases, the lockdown measures were implemented on similar dates.

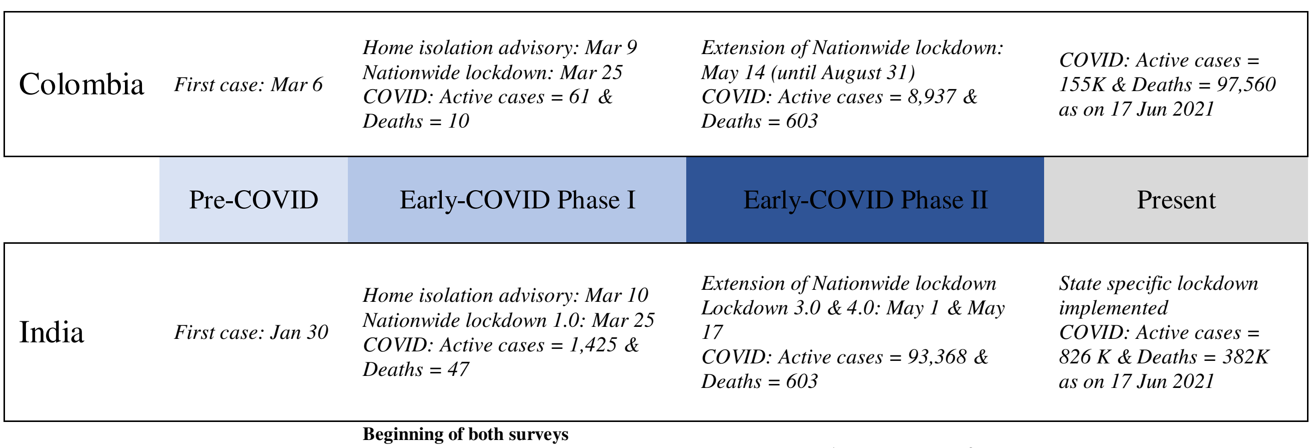


Figure 1 Timeline of COVID-19 related major events in Colombia[1] and India[2]

1 Source: Ministry of Health and social protection, Government of Colombia; National health institute (INS) (https://www.ins.gov.co/Noticias/Paginas/Coronavirus.aspx)

2 Source: Ministry of Health and Family Welfare, Government of India (https://www.mygov.in/covid-19)

In both countries, a decline in the number of trips and a change in the mode choice preferences was observed (*3*–*6*). In the transportation domain, changes in the frequency of trips and mode choice during COVID-19 have usually been explored independently and some without considering peoples' insights (e.g., perceptions). As such, this study aims to explore the combined changes in mode choice and frequency of travel during various stages of COVID-19 using both the characteristics of the alternatives and users' perceptions. The research employed a hybrid multiple discrete-continuous nested extreme value (HMDCNEV) model using data collected from Colombia and India. The two nations have experienced and are experiencing varying intensities of the pandemic resulting in different government actions to mitigate the spread of COVID-19. Understanding the respective population's perception of those actions and their relation with travel choices can provide valuable insights to many middle-income countries worldwide in developing urban transport strategies to minimise the spread of the virus.

The contributions of this study are: (i) the travel choices for commute change comparisons between two different global south contexts; (ii) the first application of the HMDCNEV framework in modelling mode and trip frequencies that explicitly includes the effect of perceptions on the travel choices during COVID-19; (iii) the relationship between the perception towards the Government actions and the shifts in travel choices. It must be noted that during the initiation of the survey exercise, concerned administrative bodies laid down various travel restrictions intending to stop the spread of the pandemic. The current study attempts to empirically test how people perceived such restrictions and subsequently their impact on travel-related choices. Moreover, few recent studies in the context of developing nations have indicated potential spatial heterogeneity during-COVID travel behaviour arising out of residents' perceptions regarding the administrative policies employed in respective countries (*7*, *8*). Although, to the best of the authors' knowledge, none of those attempted to quantify the influence of such perceptions. Besides, the present study also considers the during-COVID contextual (i.e. SP) attributes (e.g., number of infected persons in a household) in the estimation.

The rest of the paper is organised as follows: The following section presents a literature review on commute changes during the pandemic comparing different contexts. This is followed by an explanation of the data collection process and a description of the modelling approach focussing on the HMDCNEV model. The model results for the Colombian and the Indian context are presented and compared in the next two sections. Finally, conclusions are drawn and future research directions are identified in the last section.

REVIEW OF COMMUTE CHANGES DURING COVID-19

The COVID-19 pandemic has impacted mobility in many aspects, primarily minimising interactions between people (*2*, *3*). Governments established different restrictions such as lockdowns, national curfews at night, school closing, among others, in attempts to decrease COVID-19 spread (*9–11*). As a result of those measures daily activity patterns have been substantially altered, resulting in, among others, reduction of commuting trips (*2*, *11*, *12*), changes in modal preferences (*2*, *12*, *13*), and adverse impacts on people's well-being (*2*, *10*, *13*).

In general, it has been reported that a significant difference exists between pre-COVID and during-COVID times in the frequency of trips and mode choice preferences (*5*, *12–16*). Public transport has been one of the most affected modes, which has witnessed frequency reduction resulting from a declining demand (*7*, *11*, *17*, *18*). Notwithstanding the perceived risk when using public transport, the demand decrease has also been influenced by national and local restrictions (*3*, *13*, *19*), with marked inequalities in the ability of individuals and social groups to adapt and respond to those restrictions (*12*) and an increase of working from home (WFH) (*5*, *6*, *20*, *21*). Regarding WFH, it has been quantified in Colombia that overall, 40% of the people were unable to continue their main activities from home, highlighting the relevance of digital connectivity and its role in enabling people to continue performing their main activity during a pandemic (*12*). During the early COVID period, a modal shift from public transportation to non-motorised (*2*, *13*) and private modes was witnessed (*2*, *6*, *13*, *22*). In fact, captive users of active and public transport modes showed a tendency to shift towards the car (*23*). It has also been reported that there was an increase in the use of both private (*2*, *12*, *13*, *17*, *18*, *21*) and active modes (*2*, *12*, *13*, *17*) during the pandemic.

Travellers are especially concerned about travelling on public transportation because of the higher perceived risk of contagion on this mode (*13*, *15*, *17*). For this reason, it has been reported that, during the pandemic, people prefer to choose transport modes that can provide hygienic spaces and the possibility of maintaining social distance (*13*). Public transport operators have been encouraged not to reduce frequency and capacity, to provide a level of service in terms of occupancy that lets people keep safe distances with other passengers, and also considering the decrease in use of public transport (*2*). Besides, the proper use of face masks has also been suggested to significantly reduce the COVID-19 spread probability in closed spaces like those in public transport vehicles. There have also been recommendations to sanitise and implement less-contact ticketing systems to counteract the contagion perception risk of people on other public transport-related spaces/operations (e.g., stations, banknotes) (*11*, *13*, *18*).

Table 1 compiles the main findings of different studies on commuting changes through survey data collection in different cities worldwide.

Table 1 Review of reported commute changes influenced by COVID-19 pandemic

(Author, year)	Data collection period	Sample	Compared countries/cities	Main findings
(Pawar et al., 2020) (*5*)	18th to 28th of March 2020	1542	India (Multiple cities)	This study found 51.3% of the people continued using the same mode they used to use before COVID-19, 41.7% stopped travelling, and 5.3% shifted from public transport to private modes. Besides, safety perceptions were not significant in people's mode choice because of the few available alternatives.
(Moslem et al., 2020) (*17*)	March and April 2020	400	Italy (Palermo and Catania)	This study reported higher walking activity and private car use and decreased public transportation use, explained by considering public transport as a potential risk mode. As a result of increased private car use and reduced public transport share, the study also reported a significant pollution reduction.
(Beck et al., 2020) (*21*)	30th of March to 15th of April 2020 (wave 1) and 23rd of May to 15th of June 2020 (wave 2)	1073 (wave 1) and 1258 (wave 2)	Australia (New South Wales, ACT, Victoria, Queensland, South Australia, Western Australia, Northern Territory, and Tasmania)	This study suggests that WFH is going to be a substitute for commuting behaviour. Besides, the authors suggest that as the Australian government relaxes restrictions, an increase in commuting by car is expected. The results also show resistance towards the use of public transport.
(Labonté-Lemoyne et al., 2020) (*18*)	1st to 10th of May 2020	1968	Canada (Vancouver, Calgary, Toronto, Ottawa, Montréal, Halifax)	This study suggests that commuters prefer to use their cars compared to public transportation after COVID-19 restrictions end because of fear contagion. The study results showed that cleaning strategies for vehicles and mandatory handwashing might counteract the low public transport preference.

(Bhaduri et al., 2020) (*6*)	24th of March to 12th of April 2020	498	India (Multiple cities)	This study suggests a high propensity to continue using the same modes as before, i.e., pre-COVID-19, a high propensity to WFH, and a shift from public transportation to private modes.
(Barbieri et al., 2021) (*15*)	11th to 31st of May 2020	9394	Australia, Brazil, China, Ghana, India, Iran, Italy, Norway, South Africa, and the United States	This study suggests a substantial reduction in the frequency of commuting and non-commuting trips. Besides, this study found that airplanes and buses are the transport modes perceived as riskiest by users, explaining low public transport use across all countries.
(Winslott Hiselius and Amfalk, 2021) (*19*)	Mid-April to beginning May 2020	719	Sweden (Borlänge, Eskilstuna, Östersund, Stockholm, Sundsvall)	This study found a dramatic reduction in commuting trips because of restrictions. Besides, the study found a public transport agencies' proper response to continue offering their service with digital tools support.
(Shibayama et al., 2021) (*20*)	23rd of March to 12th of May 2020	11555	Austria, Brazil, Bulgaria, Czechia, Germany, Hungary, Iran, Italy, Japan, Malaysia, Slovakia, Slovenia, Thailand, and United Kingdom	This study found a relevant amount of people doing WFH (between 40 to 60%) when considering people working. For those with the possibility of WFH, the percentage is from 60 to 80%. Besides, for those people with the required presence in their jobs, the rate of WFH is below 30%. This study also reported the infection risk as a reason to switch from public transport to other modes on those who still commute. Besides, it was also found a reduction in their travel time.
(Balbontin et al., 2021) (*24*)	August to December 2020	4628	Australia, Argentina, Brazil, Chile, Colombia, Ecuador, Peru, and South Africa	This study found a significant increase in the proportion of people working from home, explained by different government restrictions. However, it has also been reported that most people in these countries would like to WFH in the future (even if it is not mandatory). Besides, it has not been reported a no significant change in productivity while WFH.
(Vallejo-Borda et al., 2022) (*4*)	September to November 2020	3803	Argentina, Chile, Colombia, Ecuador, and Peru	This study compares the COVID-19 effects influencing people's choices to shift from public transport to other modes in five capital cities in Latin America. It has been reported cost or time savings for those who switched from public transport to active and private modes. Besides, it has been found five subjective elements represented with latent variables (i.e., COVID-19 impact, entities response, health risk, life-

				related activities comfort, and subjective well-being) that influence the shift from public transport to active and private modes.

Literature reported relevant changes in the number of trips and modal preferences because of COVID-19 (*4*, *5*, *11*, *13*, *15*, *17*, *18*). Besides, it has also been reported that government policies result in a reduction in the number of trips (*3*, *4*, *13*, *19*), but it was not clear if people's perceptions of those policies could influence their mode choice. Mode choice and frequency of trips have been mostly studied separately, and there is a lack of studies using people's perceptions to explain the previously mentioned changes. Besides, it has been recommended that further research in mode choice considers impacts at the individual level (*3*), focusing on making the public transport mode safer (*2*, *11*) by considering the different phases of the pandemic (*11*).

Understanding and comparing the effects of the pandemic on people's travel preferences within two countries from the Global South (i.e., Colombia and India) is relevant to travel modelling within these contexts further. As shown in **Table 1**, dramatic changes in mobility have been common for all the countries, and travel reduction seems to be a viable option in the post-COVID era. However, there is a substantial difference between the transportation system in the primarily developed countries and those from the Global South, especially due to differences in informal working and transport arrangements. In addition, there haven't been many studies that have modelled the travel changes during COVID-19 in developing and emerging nations, which may not only be different from developed economies but may also have substantial differences among themselves. Hence, approaching the similarities and differences between countries within the Global South context can enhance the understanding of the factors that affect decisions on whether to travel or not (in which mode and how many times).

DATA AND METHODOLOGICAL APPROACH

Data source and survey design

The data was collected using an online questionnaire administered in Bogotá, Colombia (2 April - 1 May 2020) and India (24 March - 12 April 2020). In the case of India, the data constitutes urban respondents with 60%-40% distribution from big cities (population > 1 million) and small cities (population < 1 million), respectively. Understandably megacities like Kolkata, Bengaluru, and New Delhi are prominent in terms of the number of responses. The questionnaire was composed of four sections, including questions about (i) true/false questions related to COVID-19 general knowledge (not used for this study), (ii) commute patterns (including WFH) in four situations (i.e., Pre-COVID-19 commute behaviour (January 2020), early COVID-19 commute behaviour (March – April 2020), and commute behaviour under two hypothetical scenarios), (iii) respondents' detailed socio-demographic characteristics, and (iv) subjective perceptions about government and societal response to the pandemics, measured on a semantic scale. Questions in sections i and ii are presented in Appendix A for India (instrument applied originally in English), and the full questionnaire can be downloaded from https://tinyurl.com/pi0oj3sj (DOI: 10.13140/RG.2.2.24070.70727). The Colombian instrument was presented in Spanish, and the available modes changed. The responses were collected from people who commuted before the COVID-19 pandemic or worked/studied from home in the mentioned period. **Table 2** presents the socio-demographic characteristics (section iii) and questions to capture people's perceptions about the government response to affront COVID-19 collected in this study (section iv).

Table 2 List of collected socio-demographic and perceptions

Variable	Colombia	India
	Socio-demographic information	
Educational level	Elementary school; secondary school; technician; graduate; postgraduate	SSC or below (i.e. 10^{th} grade or below); HSC (i.e. 12^{th} grade); graduate; postgraduate
Household income	<\$828,116; \$828,116 – \$1,500,000; \$1,500,001 – \$2,000,000; \$2,000,001 – \$2,500,000; \$2,500,001 – \$3,500,000; \$3,500,001 – \$4,900,000; \$4,900,001 – \$6,800,000; \$6,800,001 – \$9,000,000; >\$9,000,000 [Colombian Peso]	<10,000; 10,000 – 25,000; 25,001 – 50,000; 50,001 – 75,000; 75,001 – 100,000; >100,000 [Indian Rupee]
Gender	Female; male	
Occupation	Student; employee; self-employed; homemaker	
Vehicle ownership	[number] of cars; motorcycles; bicycles	
Age	18 – 25; 25 – 40; 40 – 60; older than 60	
	Perception questions about the government response to affront COVID-19	
Government reaction	The government reaction to confront COVID-19 is (very extreme/insufficient, somewhat extreme/insufficient, appropriate)	
Government honesty	The government has been (very untruthful, somewhat untruthful, neither untruthful nor truthful, somewhat truthful, very truthful) about the COVID-19	
Trust in government	I (strongly distrust, somewhat distrust, neither distrust nor trust, somewhat trust, strongly trust) in government to take care of its citizens	

Given the responses related to the four situations, there were three to four observations per respondent: two revealed preference (RP) responses associated with reported commute patterns and one to two stated preferences (SP) responses related to the stated commute patterns under hypothetical scenarios. The hypothetical scenarios were different between the two countries given their total populations, COVID-19 situations (i.e., number of cases, number of deaths, number of cases in the household), and administrative restrictions (i.e., extent of lockdown). A D-optimal design was used to select the scenarios in the Ngene software (*25*). Overall, 12 scenarios were developed for India, of which two dominant scenarios were identified and removed subsequently. For Colombia, there were two scenarios. The SP attributes and the number of levels are presented in **Table 3**. We have also added Appendix A which depicts the sample of SP survey used for India.

Table 3 SP levels used in the data collection process

Attribute	Levels in India	Levels in Colombia
Number of cases in the country	750, 2000, 10000*	2000 (scenario 1), 10000 (scenario 2)
Number of cases in the city	5%, 10%, 15% (of the number of cases in the country)	800 (scenario 1), 5000 (scenario 2)
Number of deaths in the city	1%, 2%, 5% (of the number affected in the city)	40 (scenario 1), 250 (scenario 2)
Number of affected household members	0,1,2	2 (scenario 1), 0 (scenario 2)
Type of Government restriction	No lockdown[1], Semi lockdown[2], Relaxed lockdown[3], Full lockdown[4]	No lockdown (scenario 1), Full lockdown (scenario 2)

* Replaced by 3000, 10000, 25000 on the last week as the actual number of affected people soared more than initially expected

[1]Social distancing (No lockdown) - Institutions closed / WFH encouraged/ Mass gatherings discouraged

[2]Semi-lockdown - Office+Schools closed/ Night curfew imposed/ Limited movement allowed other than essential ones

[3]Relaxed lockdown - Limited public transport services operate as well as essential services like food, medicine, the bank is allowed for a restricted duration (say 12 hrs/ day)

[4]Full-lockdown- ONLY essential services like food, medicine, bank are allowed, and that too for a highly restricted duration (say 6 hrs/ day)

In each choice situation (i.e., RP and SP), the respondent was asked to identify whether they travelled or stayed in-home. If they travelled, the mode and the frequency of each reported/declared mode were asked. These modes varied between the two countries, some were common in both contexts, and others were not (see **Table 4**). The commute pattern was asked on a weekly rather than on a daily scale. The daily scales can hence be affected by engagement in occasional activities, reducing the ability to identify patterns in discretionary activity engagement (*26*). We merged private taxi and ride-hailing services into one category along with private cars because of the low number of observations for these modes and their similarities for the Colombian case. It must be noted that in the survey questionnaire respondents were asked to report both the travel alternative and the number of trips they make using respective alternatives. The study also included WFH as a virtual travel alternative where respondents were expected to report 1 if they would engage in WFH in a day. However, the frequency of WFH is not directly comparable with other modes and its reported frequency depends on the perception of the respondent to some extent. Hence, in the estimation process, WFH has been treated as the outside good.

Table 4 List of commuting options in Colombia and India during pre-COVID time

Commute mode	Colombia	India
In-person		
Active (walking and cycling)	✓	-
Non-motorised transport (NMT) (walking, cycling, and pedalled rickshaw)	-	✓
Private car	✓	✓
Motorcycle	✓	✓
Office shuttle	✓	-
Public transport (bus and subway)	✓	✓
Public transport (suburban rail)	-	✓
Auto Rickshaw (CNG powered 3-wheeler taxis)	-	✓
Private taxi	✓	✓
Ride-hailing service (car)	✓	✓
Remote Options		
WFH	✓	✓

Given the situation and restrictions associated with the pandemic (i.e., nationwide lockdowns), the study used google forms software to make the questionnaire accessible online through a link in each country. Participation of respondents was randomly solicited on social media platforms including Facebook, LinkedIn, Twitter, WhatsApp, Instagram, and on research circles such as the Transport Research Group of India and the Academic Network on Mobility in Colombia. In addition, paid publicity was employed through Facebook in both countries to increase participation and reach people who are out of the professional circles of the survey administrators. In Colombia, we asked Facebook to show the survey publicity to women and men older than 18 years old and living in Bogotá with a radius of 40 kilometres. Similarly, in India, the virtual survey questionnaire was disseminated in major metropolitan cities with a radius of 40-50 kilometres from the city centre and applied only to adult individuals. Finally, the number of respondents in Facebook, Instagram, LinkedIn and Twitter are 334, 23, 50, and 29 respectively. Moreover, we were also able to obtain 175 responses through unpaid channels. In total, responses from 611 individuals were collected out of which 557 were used for final estimation after data cleaning.

The present study makes an effort to avoid quick-and-dirty approaches while also being cautious about non-probability sampling (i.e., snowball effect) to reduce potential biases. That is why it has primarily employed paid publicity campaigns through Facebook in both countries instead of opting for free chain-referral (i.e., respondent-driven) sampling. This study also attempts to minimize sample biasedness by weighting the observations utilizing key socio-demographic characteristics (e.g., age, gender).

This research also identified people who are unlikely to provide proper responses (i.e., speeders) to run quality models, where the time each respondent took to provide their responses can be used to identify them. The literature suggests establishing a duration cut-off between 46% to 63% of the average duration to complete the instrument to identify "speeders" (responses collected in less time than the established cut-off) (27). For this reason, timer ads were included in google forms to obtain the time each respondent took to fill out the form for Colombia, and basic descriptive statistics were obtained to understand the time distribution (min = 4'23"; Q1 = 6'10"; Q2 = 7'32" mean = 8'3"; Q3

= 9’18” and max = 16’6”). In the case of India, the timer ads were not included, and it was not possible to obtain how much time the respondents took to fill out the instrument. Following the literature recommendation, the responses from persons who completed the survey in less than four minutes (approximately 50% of the average duration) were dropped from the Colombian dataset to enhance the dataset quality.

Sample characteristics

After data cleaning, we obtained responses from 267 individuals from Colombia and 557 individuals from India. Based on the collected socio-demographic data, **Table 5** shows individual and household characteristics for both countries. Also, the equivalent census information is presented.

Table 5 Sample characteristics of socio-demographic variables

Independent variables: *categorical variables*	Sub-categories	Colombia		India	
		Sample distribution (%)	Census distribution* (%)	Sample distribution (%)	Census distribution# (%)
Gender	Male	31.23	45.74	63.74	51.5
	Female	68.77	54.26	36.26	48.5
Age (years)	Young millennial (18-25)	9.29	18.87	31.05	15.5
	Old millennial (25-40)	40.52	29.75	46.31	22.8
	Middle age (40-60)	44.98	31.36	16.51	17.5
	Old age (> 60)	5.20	20.02	5.38	7.1
Monthly household income (USD)	Low income HH (0-333)	39.41	49.66	22.61	NA
	Middle income HH (>333-666)	17.84	22.34	28.0	NA
	High-income HH (more than 666)	42.75	27.99	49.36	NA
Occupation	Salaried worker	87.34	73.98	53.68	39.8
	Non-salaried worker	12.66	26.02	46.32	60.2
Household vehicle ownership	Car ownership – 0	62.83	63.83	60.50	NA
	Car ownership – 1	33.83	29.09	35.55	NA
	Car ownership – more than 1	3.35	7.08	3.95	NA
	Motorbike ownership – 0	89.59	83.39	52.42	NA
	Motorbike ownership – 1	10.04	14.44	40.75	NA
	Motorbike ownership – more than 1	0.37	2.17	6.82	NA
	Bicycle ownership – 0	56.88	47.77	64.81	NA
	Bicycle ownership – 1	35.69	25.51	33.21	NA
	Bicycle ownership - more than 1	7.43	26.73	1.97	NA

* source: 2019 Home travel survey (*28*)
# source: Census Data India, 2011

Given the differences in the sociodemographic characteristics in the surveyed sample and the census information, the samples were weighted to match the census shares before the model estimation to increase the representativeness for both cases. The weights were obtained with information about gender, age, income, occupation, and vehicle ownership in Colombia and about gender, age, vehicle ownership, and occupation in India using the R package "survey". For Colombia, all the weighting variables were obtained from the 2019 Home travel survey (*28*). In the case of India, the population distribution regarding occupation was obtained from Census data whereas the vehicle ownership information was extracted from Bansal et al. (*29*). The different weights were calculated to converge the sample proportions into the census proportions through an iterative proportional fitting process (*30*, *31*).

Indians appear to have better perception levels towards their government than Colombians. The mean value for the perception of government honesty was 3.63 in India and 2.62 in Colombia. The perception about the government response to the disease was also higher for India (i.e., 2.41, compared with 2.30 in Colombia). Finally, the trust in the government showed a mean value of 3.80 for India and 2.51 for Colombia. All the differences between means were tested and proved to be significant at the 95% level. These indicators' values were used in further modelling steps as indicators of a latent variable that included the government perception within the modelling framework. **Figure 2** shows the response distribution for both countries.

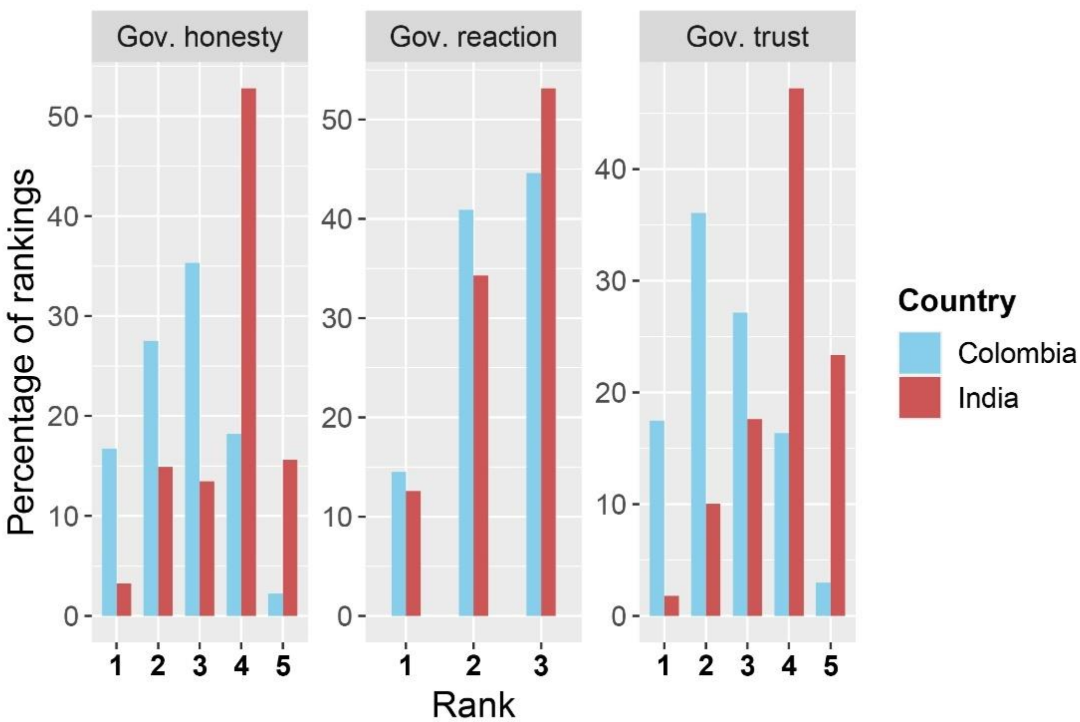


Figure 2 Response distribution to LV indicators

Commute pattern

The collected data included the weekly commuting patterns for each individual during the pre-COVID-19 and early COVID-19 situations. Some similarities and differences emerged between the two countries (see Appendix B for more details).

In the pre-COVID-19 (January 2020) situation, a similar percentage of respondents reported engaging in WFH for both countries. In the case of Colombia (**Figure 3 (a)**), about 20% of the sample is engaging with WFH. Similarly, for India, **Figure 3 (b)** reveals that before the COVID-19 outbreak, nearly one-fourth (i.e., 25% of total respondents) did engage in WFH. However, while 12.5% opted for five times or more in a week in the Indian case, just 5.5% worked from home with a similar frequency in the Colombian case.

In contrast, in the case of in-person travelling, some differences emerge. Colombia respondents prefer public transportation with a third of the trips (with 6.4% using it more than five times a week), followed by private car (26%) and active transportation (20%). On the other hand, in the

Indian context, before the outbreak, non-motorised (NMT) modes were the most frequently used, closely followed by public transport and private vehicles (car and motorbike). Approximately 22% of the respondents used NMT modes, with about 9.5% using it more than five times a week. At the same time, the share of the respondents who selected public transit, private car, and motorbike are found to be 16.5%, 18.5%, and 15.5%, respectively. Remarkably, the percentage of motorbike trips in India is about three times higher than in Colombia (5.5%).

When considering trends during the COVID-19 period (**Figure 3**), WFH, as expected, is more dominant. The WFH patterns are similar for the two cases, and most importantly, overall physical travel diminished. In both countries, the share of non-travelling respondents increased to almost 40%. Among them, 19.6% WFH five or more days in Colombia, while the share was17.5% for the Indian respondents. Among the respondents who opted to travel, it was found that the share of active/NMT modes and public transit decreased in the two countries. In the case of Colombia, these modes' share decreased by 1% and 24%, respectively, while in India, they declined by 3% and 4%, respectively. As expected, the share of transit trips declines in both contexts given the WFH increase and the limited space in public transport vehicles, making it difficult to maintain social distancing. Hence, crowded vehicles are abandoned by users. The relevant reduction for Colombia is also intuitive considering that the percentage of occupancy allowed on buses was restricted (*3*). Also, many low-income people in Colombia, who are primarily captive to public transport, stopped performing their main activity because of the pandemic (*12*). Private modes' shares, on the other hand, show different behaviour in both contexts. In Colombia, private car trips decreased by 11%, whereas a slight increase can be observed in India (1%). Likewise, motorbike trips decreased in India by 3%, while motorbike trips increased almost 1% in Colombia.

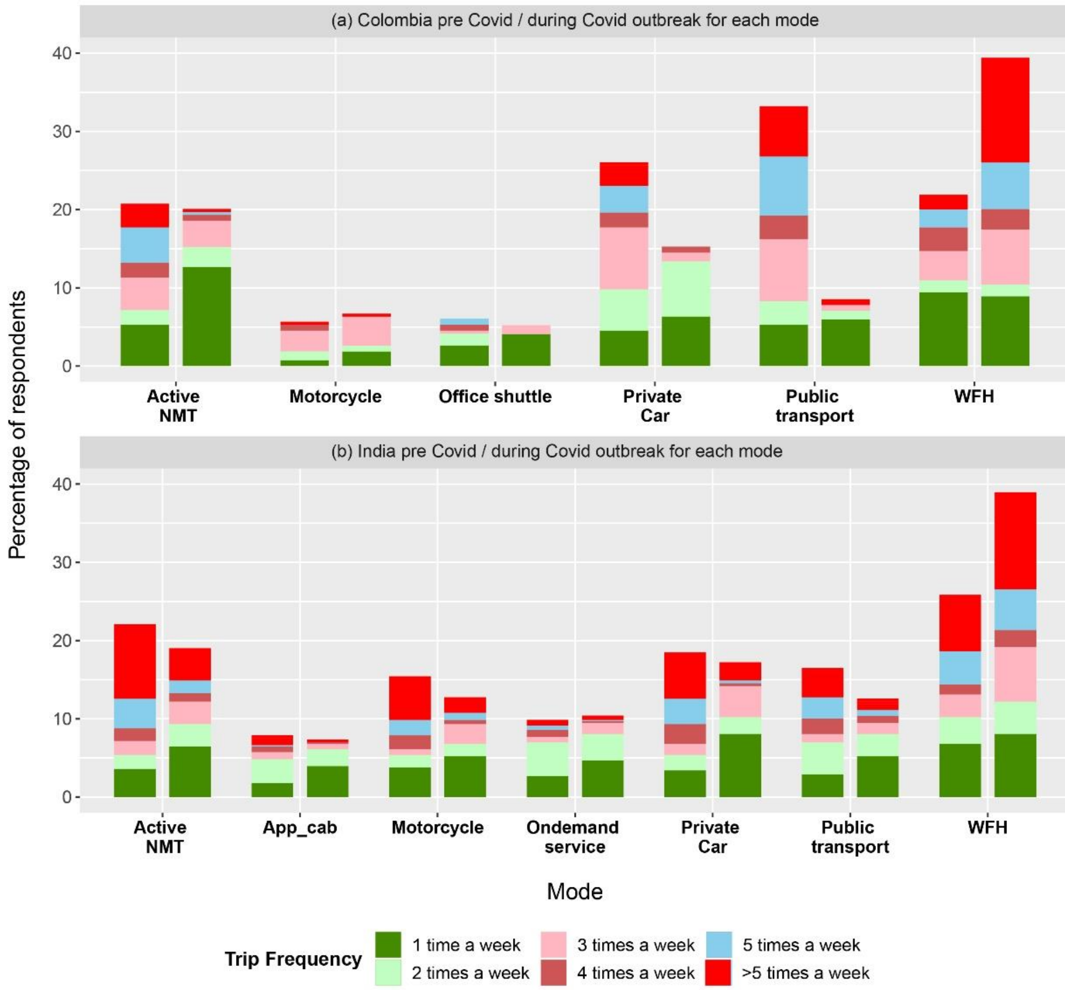


Figure 3 Mode used for commute trips pre and during the COVID-19 outbreak for (a) Colombia and (b) India

Further investigations were carried out regarding the occupation of the WFH users, who comprise a significant section of commuters in both countries, especially in the pre-COVID period, as shown in **Figure 4**. In the case of Colombia, self-employed and private company employees were the groups that mostly worked from home. Self-employed persons account for more than 70% of the people who WFH two times a week, more than 40% for three times, and more than 60% for four times. A higher proportion of employees from a private company, on the other hand, worked from home either five days a week (i.e., half of the people who WFH), or more than five days (i.e., 40%. same percentage as the self-employed persons). For India, intuitively, the self-employed respondents have worked from home more frequently (nearly 45% of self-employed individuals opted for WFH more than 5 times a week) as compared to other occupations. Besides, we could observe a fair share of students that selected study from home (approximately 35% of students selected study from home more than 5 times a week).

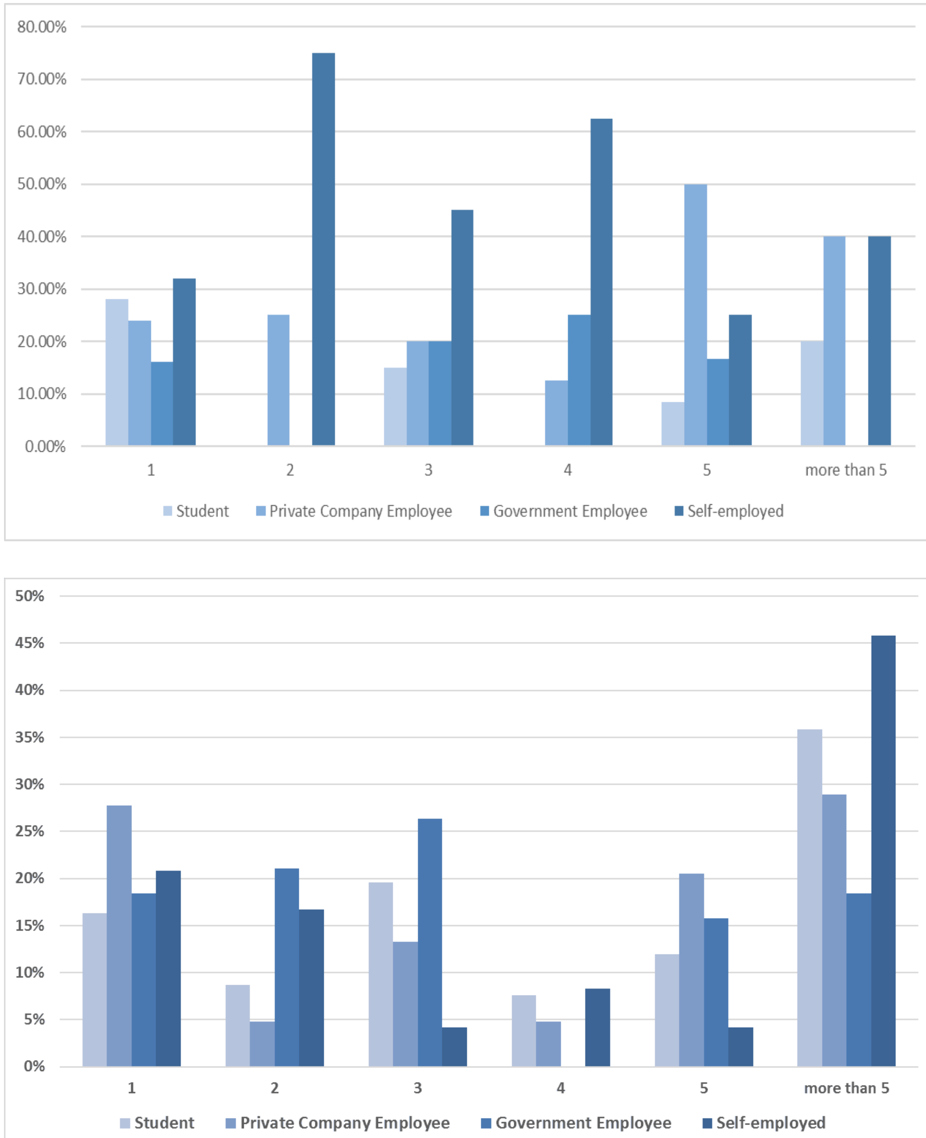


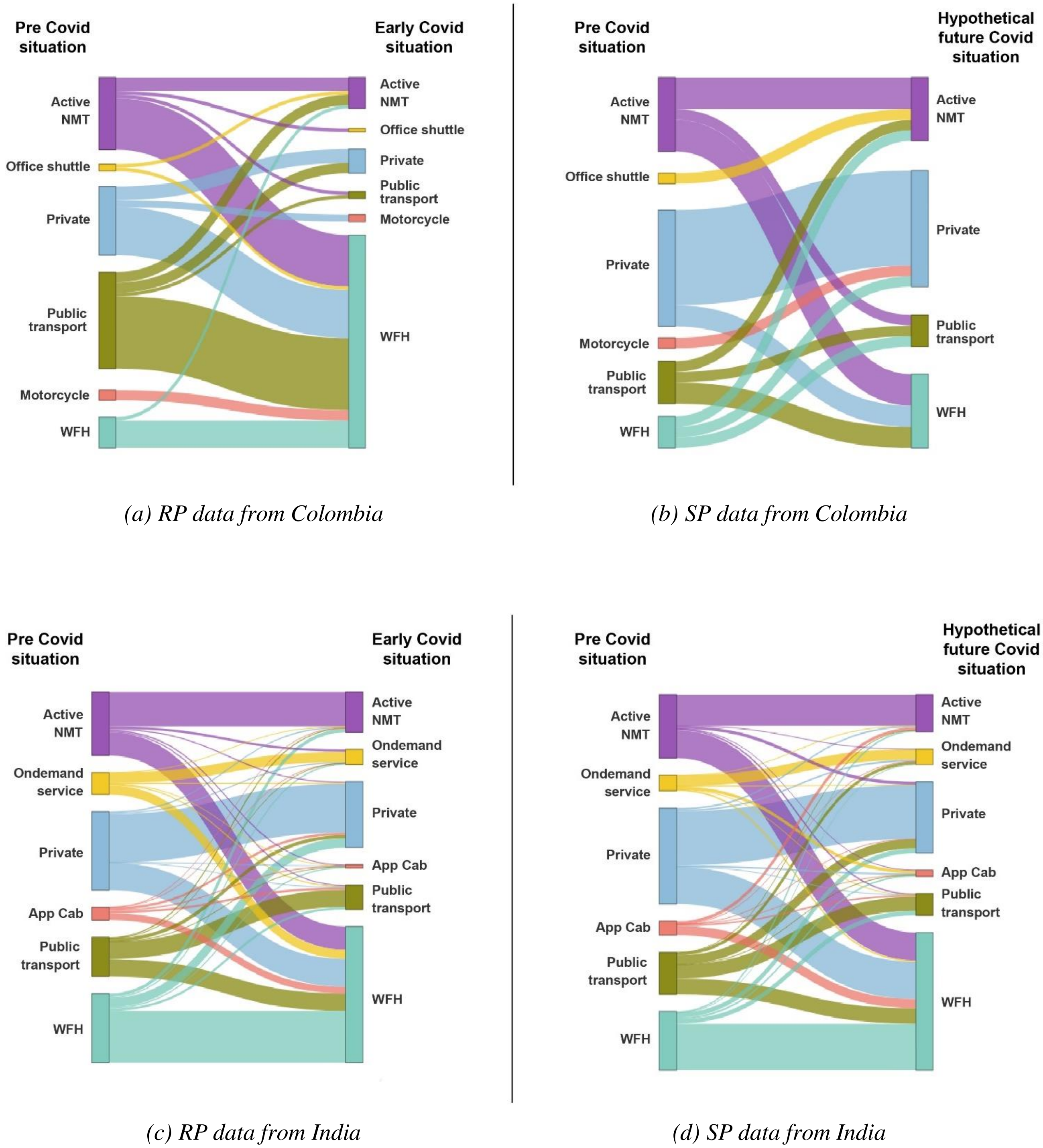
Figure 4 Occupation of WFH users in pre-COVID days in (top) Colombia and (bottom) India

The data collected was examined separately for RP (pre-COVID to early-COVID period) and SP data (pre-COVID to future-COVID period) with the help of sankey diagrams. In a sankey diagram, the rectangular nodes represent the modal share of travel alternatives whereas the direction and thickness of connections (also known as links) depict the switching inclination and its proportion respectively. For example, RP data from India (**Figure 5 (c)**) reveals that approximately 37% of NMT users shifted to WFH whereas nearly 55% continued using their pre-COVID mode, i.e., NMT. RP variation graph contrasts pre-COVID-19 and early COVID-19 situations, (**Figure 5 (a-c)**), while SP variation graph contrasts pre-COVID-19 with hypothetical future situations, (**Figure 5 (b-d)**).

In both cases, similarities emerge in terms of WFH considering the RP behaviour. In both contexts, WFH significantly increases during the early COVID-19 phase. Remarkably, all the modes show at least a small share change towards WFH in the two countries. The RP data also indicates that physical travelling decreased for every mode, which supports an increase in WFH and a substitution of travelling in Colombia and India. Furthermore, in the RP graph **Figure 5 (a)** and **Figure 5 (c)**, it is shown that in all the modes, at least some portion of respondents continued using the pre-COVID-19 mode during the early-COVID-19 phase. In the India case, non-travelling showed the highest stickiness, since 75% of the pre-COVID home-based workers continued WFH in the early days of COVID, likewise happens in the Colombia case (i.e., 88.89%). Of those who travelled, the highest percentage of people who kept using the same mode was the people who travelled by private car in both India and Colombia (61.76% and 20.00% respectively). The ones with the lowest stickiness travelled using ride-hailing in India (9.09%). In contrast, those who travelled using an office shuttle/school bus or motorcycle in Colombia did not travel at all on the same modes during the early COVID period.

However, in the SP graph, differences are more evident than in the RP case. In Colombia (**Figure 5 (b)**), the share of WFH in SP data is not as high as that in the RP case. Conversely, India data shows that in both cases (i.e., RP and SP), WFH indicates almost the same share (**Figure 5 (d)**).

Regardless of the scenario, Indian respondents are more inclined to WFH. While in India WFH is the alternative chosen with a higher share in the hypothetical scenario, in Colombia private car takes the higher percentage of trips. Preference to have less physical contact to avoid contracting COVID-19 can explain both findings. For Colombia respondents, to prevent contracting COVID-19, the strategy seems to be travelling on private modes. For Indian respondents, the strategy seems to keep WFH (i.e., not travelling at all). This strategy can also be explained by internet access, which is not so high in low-income areas in Colombia. Besides, most respondents in Colombia (approximately 60%) belong to middle and high-income groups, characterised by having access to a car. These have been reported to increase the use of private modes during the pandemic (*12*).



(a) RP data from Colombia

(b) SP data from Colombia

(c) RP data from India

(d) SP data from India

Figure 5 Inertia (measured in primary mode switching) of different modes

It may be noted that given the RP and the SP scenarios presented different contexts, the inertia values cannot be directly compared. However, this exploratory analysis provides us with insights about the data that is useful for interpreting the models. Besides these charts merely provide an indication about the inertia levels which have been further tested empirically.

Modelling approach

The dependent variable in the model is the weekly frequency of choosing each mode reported separately by the respondents. The alternatives include eight modes for both contexts: WFH, active/NMT, office shuttle/school bus, on-demand service, ride-hailing service, public transport, motorcycle, and car. 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. The 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 ten 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 alternatives and the trip maker (e.g., travel time, income, age, car availability); (b) travel behaviour potential changes (termed as inertia); and (c) subjective indicators indicating the perception towards government's response to affront COVID-19, presented as a latent variable. Travel time in each period (i.e., before and during COVID-19) was obtained using the reported travel distance from each dataset and information reported in secondary data regarding the average speed considering each mode in each period. In the Colombian case, the average speed was gathered from the bit carrier data repository of the Bogota transport authority (*32*). Similarly, in India, it was obtained from various secondary sources (*33–35*).

In typical mode choice models, discrete choice models based on random utility maximisation (RUM) principles, which are used to quantify how each of the influencing factors affects the mode choice. The multiple discrete-continuous nature of choices presented, the interdependence among alternatives (i.e., travel and no travel), and the need to incorporate the people's perception of government to control COVID-19 (i.e., the hybrid component in choice models), prompted us to estimate a Hybrid Multiple Discrete-Continuous Nested Extreme Value (HMDCNEV) model. **Figure 6** presented a graphical representation of the model used for this study in each of the periods. To test both periods it was interacted the COVID-19 periods (i.e., before and during) and the different characteristics of the alternatives and travellers used to estimate the modes utilities.

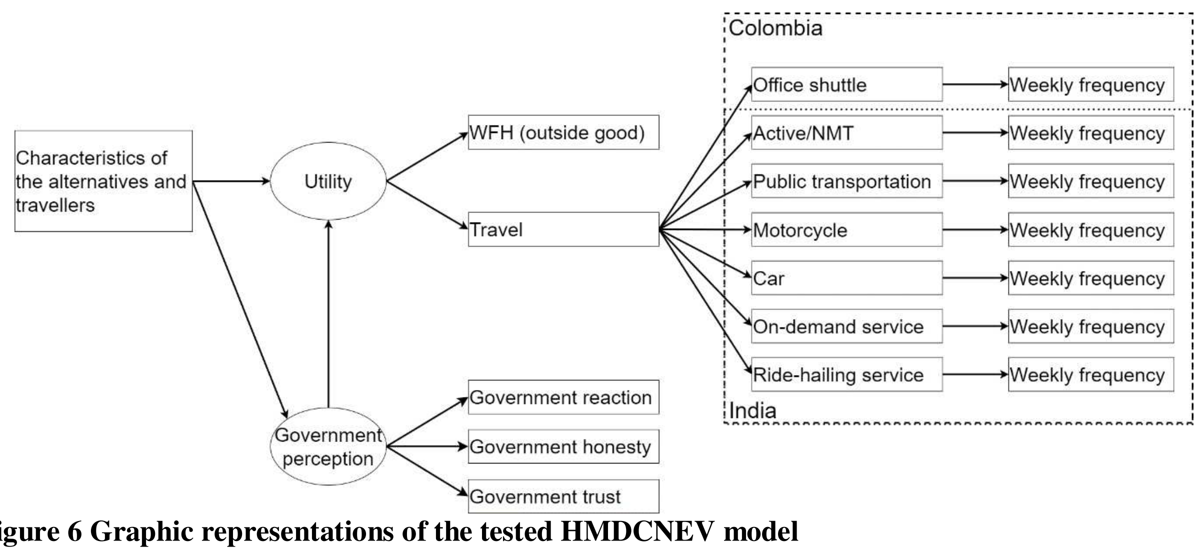


Figure 6 Graphic representations of the tested HMDCNEV model

The latent variable (i.e., government perception) was initially identified from three ordinal indicators (i.e., government reaction, government honesty, and trust in the government) previously introduced in **Table 2**. The measurement model used to identify the latent variable is shown in equation (1) (*36*).

$$y_0{}^* = \tilde{\delta} + \tilde{d}z^* + \tilde{\xi} \tag{1}$$

where $y_0{}^*$ represents the indicator vector identifying the latent variable (i.e., Government perception); $\tilde{\delta}$ is the constant terms vector; $\tilde{d}$ is the latent variable loading matrix; z^* is the latent variable (see equation (2)); and $\tilde{\xi}$ is the indicators errors vector, assumed normally distributed with an expected value of 0. The structural model is shown in equation (2) (*36*).

$$z^* = \omega\rho + \eta \tag{2}$$

where ω is the observed covariates matrix to explain the latent variable; ρ is the observed covariates vector, and η is the latent variable errors vector, assumed normally distributed with an expected value of 0.

Bhat (*37*) formulated the utility functional form as presented in equation (3) (*38*).

$$U(t) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \psi_k \left\{ \left(\frac{t_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} \tag{3}$$

where $U(t)$ is the total utility of consuming non-negative amounts of the K available alternatives; t is the vector of consumption quantity assuming $t_k \geq 0$ for all k; γ_k and α_k are the satiation parameters; and ψ_k is the baseline marginal utility (i.e. marginal utility at the point of zero consumption), represented in equation (4).

$$\psi_k = exp(\beta' z_k + \lambda z^* + \varepsilon_k) \tag{4}$$

Where β' is a coefficients vector associated with z_k, z_k is the set of attributes characterising the individual and the alternative k; λ is the coefficient matrix associated with the latent variable, and ε_k are the unobserved attributes that impact the baseline utility of alternative k assumed to have an extreme value distribution, independent of z_k and independently distributed across alternatives.

The budget (i.e., number of trips) was assumed as 14, considering a displacement of two times per day during seven days a week. In an extension to this, we assume the outside good as those not travelling (i.e., WFH). It is worth mentioning that the total weekly trips for a significant majority (97.16%) of the respondents fall within 14 trips, which also equates to a maximum of two trips per day for all seven days in a week. This makes sense in the Indian context as Bansal et al. (*29*) observed 8.75 weekly trips (4.37 round trips) for commute purposes. However, their study suggested non-reporting of short trips and forgetting trips as a caveat to explain is a stark difference with 26.53 weekly trips for a US citizen (*39*). Hence, we assumed 1.5 times of the reported trips as the budget, which comes as 13.12 (14 trips after rounding off) weekly trips. Furthermore, increasing the budget would mean higher consumption of outside goods, i.e., work from home, which might lead to erroneous estimation of respondents' preference towards it. In the case of Colombia, it was found in the Home travel survey from 2019 that the respondents travel 1.96 times a day, on average, for commute purposes (*28*). This number of daily trips aligns with the value presented before (i.e., two trips per day and 14 trips a week). Hence, the total weekly trips (13.73) was rounded to 14 which corresponds to the maximum value of the travel budget. As the objective of this study is to investigate the change in mode choice behaviour from pre-COVID days to the early-COVID period, no price variations among alternatives have been considered. Besides, in both cases, we estimated the model parameters (i.e., nesting, alternative specific constants, utility parameters) to understand travel choices in pre-COVID and during-COVID situations. The satiation parameters have been constrained, which corresponds to fixing α and γ values of all alternatives equal to 1. Essentially, the role of gamma parameters is to ensure zero consumption of a particular good (travel alternative in the present study) where a higher gamma value indicates a stronger preference for the respective good (*37*). At the same time, alpha parameters work solely as a satiation parameter which reduces the marginal utility with increasing consumption of a good (*37*). In the current context, constraining both the parameters to 1 stems out of assuming the absence of satiation effects in mode choice decisions which are expected to be majorly driven by trip-related attributes and availability of alternatives.

Regarding the availability of travel alternatives, it has been observed in both countries that the share of instances where respondents belonging to households who don't own a vehicle but still have a positive (non-zero) usage of personal vehicles (car and motorbike) are 12.45% and 3.39%, for Colombia, and 3.82% and 1.85% for India, respectively. We decided not to ignore such data points as those potentially indicate vehicle-pooling options. Finally, we set personal vehicles as unavailable alternatives for respondents belonging from no-vehicle owning households and having zero usage. Besides, in one specific SP scenario (refer to **Table 3**), i.e., Full lockdown, it has not been considered public transport as an available alternative. Although public transport was always available, it has been deemed unavailable to those reporting long active mode trips and unavailability of private vehicles assuming public transit was not an option. All the other travel modes have been set as available for all the respondents.

The scale parameters and the other model coefficients are estimated jointly using the Maximum Likelihood Estimation (MLE) technique within Apollo's software (*40*). A panel effect term was used to account for the correlation of multiple responses by the same individual. It may be noted that MDCEV and MDCNEV models have been applied in different empirical contexts, both in transport and beyond. Examples include applications to the choice of vehicle type and mileage (*41*) time-use (*36*, *38*, *42–45*); multi-buy alcohol promotions (*46*), patterns of social interaction between people and their social contacts (*47*), and more recently in modelling the choice of mode and frequency (*6*). However, the effect of attitudes and perceptions has been ignored in Bhaduri, et al. (*6*). Then, to the best of our knowledge, this is the first application of the HMDCNEV framework in modelling mode and trip frequencies that explicitly includes perceptions on the travel choices during COVID-19.

RESULTS AND DISCUSSION

Three sets of variables have been used to understand the change of commuting behaviour during-COVID times as compared to the pre-COVID situation: (i) socio-demographic variables, (ii) pre-COVID travel behaviour (termed as inertia), and (iii) the latent variable related to the perception of government response towards pandemic. In the subsequent paragraphs, we will be discussing the estimation results for each variable set. The results for the Colombian model are in **Table 6**, where initially general information about the model is shown; then the alternative specific constants for each mode are depicted; followed by the coefficients related to the characteristics of the alternatives and travellers influencing the utilities; and finally, the hybrid part through the latent variable inclusion.

Table 6 Estimated results for commute activities in Colombia.

Number of individuals	269			
RP observations	531[a]			
SP observations	537[a]			
LL (0)	-10649.26			
LL (final, whole model)	-7569.74			
AIC	15255.48			
BIC	15576.40			
Model Parameters				
	Pre-COVID days		**During-COVID days**	
	Estimate	Robust *t*-stat	Estimate	Robust *t*-stat
Alternative specific constants				
Outside good (base)	0 (fixed)		0 (fixed)	
Active	-1.30	-5.37 (***)	-2.18	-7.96 (***)
Office shuttle/school bus	-2.05	-14.64 (***)	-2.37	-11.77 (***)
Public transport	-1.05	-8.85 (***)	-2.29	-15.52 (***)
Motorcycle	-2.85	-8.36 (***)	-2.46	-14.44 (***)
Car	-0.88	-7.59 (***)	-1.87	-11.32 (***)
Attribute of the alternatives				
Travel time	-0.17	-3.08 (**)	0.06	1.31
Covariates				
Gender				
Female dummy for active	-0.13	-1.80 (.)	-0.21	-2.58 (**)
Household income				
High income dummy for active	0.04	2.77 (**)	0.02	0.96
High income dummy for Office shuttle/school bus	0.07	4.07 (***)	-0.03	-1.10
Household vehicle ownership				
Households with no own cars: active modes	0.17	2.13 (*)	0.23	2.50 (*)
Households with no own cars: Motorcycle	0.73	3.31 (***)	0.07	0.56
Households with no own cars: Car	-0.40	-6.37 (***)	-0.26	-2.71 (**)
Households who own motorcycles: Motorcycle	1.09	6.88 (***)	0.28	2.12 (*)
Individual working as technician: Car	-0.28	-3.55 (***)	-0.48	-3.15 (**)
Individual working as professional: Active	-0.10	-1.48	0.15	1.99 (*)
Individual working as student: Office shuttle /school bus	0.51	4.73 (***)	0.15	1.00
Individual working as student: Motorcycle	0.67	3.90 (***)	-0.01	-0.04
Government perception latent variable				
Active			-0.12	-2.59 (**)
Public transport			-0.08	-1.72 (.)
Motorcycle			-0.11	-1.84 (.)
Structural model				
Owning bicycle			0.23	2.31 (*)
Owning car			-0.41	-1.68 (.)
More than 60 years			1.51	4.39 (***)
Graduate degree			0.27	2.58 (**)
Student			-0.44	-2.59 (**)
Measurement model				
Government reaction			1 (fixed)	
Government honesty			4.11	4.16 (***)
Government trust			2.89	6.63 (***)
Satiation parameters				
Alpha base	1 (fixed)			
Gamma base	1 (fixed)			

Scale parameters	Estimate	Robust *t*-stat
No Travel	1 (fixed)	
Travel	0.27	19.45 (***)
mu_RP	1 (fixed)	
mu_SP	0.91	0.97
Inertia		
RP	0.26	3.44 (***)
SP	0.12	0.97

[a] *There were eight non-valid or unanswered observations (i.e., SP = 1, RP = 7)*
Significance level above 90.0% (.), 95.0% (*), 99.0% (**) and 99.9% (***) for two tail test

Travel time was considered as the alternative's characteristic, used to explain people's sensitivity to this attribute in the number of trips made using each mode. As expected, in pre-COVID, a negative relationship was found between the travel time and the number of trips made in each mode. In other words, people carried out more trips using those modes with a lower travel time. However, a non-significant relationship was found for the during-COVID period, which at first sight suggests a counterintuitive result for the Colombian case. This finding is linked to a significantly increased propensity (refer to Table 6) to work from home (WFH) (considered as an outside good), which does not involve any physical travel. This result is in line with other studies that reported a substantial increase in WFH since new infection fear heavily influenced mode-choice decisions that altered perceptions regarding conventional attributes (e.g., travel time) (*3*, *7*, *8*, *21*, *48*).

Regarding socio-demographics in Colombia, the model suggests a declining propensity for choosing active modes among female respondents in both pre-COVID and during-COVID days. This negative propensity can be explained by the suggestion of Sagaris & Tiznado-Aitken (*49*), who identified barriers (e.g., safety) limiting the active mobility of women in the Latin American context. The significant relationship in the during-COVID scenario suggests that the COVID-19 situation will reinforce the barriers for female individuals to select active modes for their commute trips.

It was also found that there is an increase in the propensity of making more trips for those with higher income by using office shuttles/school bus and active modes in the pre-COVID situation but not during-COVID. The loss of significance for commuting in active modes during-COVID for those with higher income can be explained by their car availability (*2*), reported as a motivator for using private vehicles during-COVID (*22*).

Furthermore, professionals in the pre-COVID situation had a lower affinity towards active modes, which may be related to the perceived low social status of using these modes (*50*). However, during-COVID, professionals are more likely to choose an active mode (and WFH) which may modify the social stigma with active modes. Model results also show that students are more likely to use motorcycles and school buses in pre-COVID than during-COVID situations. These changes are expected considering the different restrictions, reducing trips and activities, established to reduce the spread of COVID-19 (*51*).

Vehicle ownership also plays a role in the use of the different modes during commute trips. In both the pre-COVID and during-COVID situation, households with no cars intuitively had a lower likelihood of using it for commute purposes; however, such households have a higher likelihood of using active modes in both periods and motorcycle only in the pre-COVID. A similar situation was found for those having motorcycle(s) in households where it was found a higher likelihood of using the motorcycle in both periods.

Regarding subjectivity and the different governments' restrictions to affront COVID-19 (*51*), it is expected the perception about the government response to affront COVID-19 influence in the transport mode used for commute. In Colombia, we found a significant relationship between people's perception of government actions and a reduction in the use of active modes, public transport, and motorcycle. In other words, people with a positive perception of government response's effectiveness had a reduced propensity to use these modes. Results also show that households with bicycle(s), individuals older than 60 years, or those with a graduate degree are the ones that have a positive perception about the government response during the early COVID-19 outbreak. Bicyclist perception about government response may be influenced by the actions taken by the government to promote bicycle use in Colombia (*3*, *12*). Alternately, students and those owning a car appear to have a poor perception of the government reaction during-COVID scenario.

Finally, the alternative specific constants (ASC) suggest that all else being equal, the preference for WFH (termed as outside good) is higher relative to all other modes, followed by car in pre-COVID and by active modes during-COVID days. In the case of pre-COVID days, the ASC is smallest for motorcycle (-2.85), closely followed by office shuttle/scholar bus (-2.05) and active modes (-1.30). Whereas, during-COVID days, ASC is smallest for motorcycle (-2.46), followed by office shuttle/scholar bus (-2.37) and public transport (-2.29).

Like Colombia, for India, the same three sets of variables have been used to understand the change of commute behaviour during-COVID times compared to the pre-COVID situation. The model results for India are in **Table 7** which is similarly organized compared to the Colombian one.

Table 7 Estimated results for commute activities in India.

Number of individuals	557			
RP observations	1114			
SP observations	664 [a]			
LL(0)	-11623.60			
LL(final, whole model)	-9656.12			
AIC	37263.63			
BIC	37656.96			
	Model Parameters			
	Pre-COVID days		**During- COVID days**	
	Estimate	**Robust *t*-stat**	**Estimate**	**Robust *t*-stat**
	Alternative specific constants			
Work from home[#] (base)	0 (fixed)			
NMT	-2.14	-9.25 (***)	-2.56	-12.90 (***)
On-demand service	-2.28	-10.48 (***)	-2.93	-12.58 (***)
Ride-hailing service	-2.41	-10.21 (***)	-3.14	-12.04 (***)
Public transport	-2.04	-11.78 (***)	-2.64	-15.41 (***)
Motorcycle	-1.72	-17.32 (***)	-2.18	-17.83 (***)
Car	-2.01	-13.10 (***)	-2.32	-15.43 (***)
	Attribute of the alternatives			
Travel time	-0.23	-4.64 (***)	0.06	1.35
	Covariates			
Gender				
Female dummy for NMT	-0.35	-2.23 (*)	-0.34	-1.93 (.)
Female dummy for Ride-hailing service	-0.52	-2.26 (*)	-0.12	-0.75
Female dummy for Public transport	-0.15	-0.90	-0.24	-1.68 (.)
Age				
Young Millennial Dummy[##] for NMT	-0.12	-0.87	-0.31	-2.13 (*)
Young Millennial Dummy[##] for Car	-0.29	-1.76 (.)	-0.10	-0.70
Household income				
High income dummy[$] for Car	0.27	1.80 (.)	0.37	2.70 (**)
High income dummy[$] for On-demand service	0.17	0.99	0.38	2.39 (*)
High income dummy[$] for Ride-hailing service	0.36	1.93 (.)	0.38	2.19 (*)
Household vehicle ownership				
Households with no own cars: NMT	0.73	4.55 (***)	0.43	3.32 (***)

Households with no own cars: On-demand service	0.22	1.21	0.50	3.16 (**)
Households with no own cars: Ride-hailing service	0.26	1.32	0.66	3.81 (***)
Households with no own cars: Public transport	0.56	3.47 (***)	0.52	3.64 (***)
Households with no own motorcycles: NMT	0.67	4.55 (***)	0.54	3.91 (***)
Households owning more than one motorcycle: Motorcycle	0.47	1.48	0.48	2.50 (*)
Households owning more than one bicycle: NMT	0.51	2.28 (*)	0.34	1.19
Government perception latent variable				
NMT			-0.07	-0.58
Motorcycle			0.06	0.45
Public transport			0.07	0.91
Structural model				
Female			-0.29	-2.51 (*)
Measurement model				
Government reaction			1 (fixed)	
Government honesty			1.87	5.65 (***)
Government trust			2.09	4.97 (***)
Satiation parameters				
Alpha base	1 (fixed)			
Gamma base	1 (fixed)			
Scale parameters	**Estimate**	**Robust *t*-stat**		
No travel	1 (fixed)			
Travel	0.51	15.38 (***)		
mu_RP	1 (fixed)			
mu_SP	1.02	10.78 (***)		
Inertia				
RP	0.93	8.73 (***)		
SP	0.94	7.65 (***)		

[a] In an earlier stage of the survey, each respondent was asked about one SP scenario, whereas later it was increased to two SP scenarios

** Significance level above 90.0% (.), 95.0% (*), 99.0% (**) and 99.9% (***) for two-tail test*

 # Work from home has been considered as outside good for the model estimation purpose

The young millennials include individuals in the age group 18–25 years

$ The high income individuals belong from households with monthly income of more than 75,000 INR

Intuitively, the travel time coefficient for the Indian case is negative in the pre-COVID period, which corresponds to the fact that respondents prefer quicker travel alternatives to reach their commute destinations. Similar to the Colombian case, the travel time turns out to be insignificant for travel-related decision-making in the during-COVID period, which probably indicates the disruptive influence of travel restrictions.

The first set of variables is related to the socio-demographic attributes of respondents and their households. The results indicate an increased affinity towards ride-hailing service during during-COVID days for female commuters as compared to the pre-COVID period whereas they expectedly avoid public transport.

Furthermore, the model estimates suggest a declining propensity towards NMT modes among younger respondents, whereas a reverse trend (increasing propensity) can be observed for the car. In general, the preferences of young millennials in pre-COVID days agree with previous findings (*52*). Intuitively, the changes in the during-COVID situation are expected considering the shutdown of educational institutions, the government's encouragement for online classes, and their preference for personal vehicles (PVs), where higher social distance can be maintained. In the pre-COVID situation, respondents from affluent households are more likely to use PVs (especially cars), which is in line with existing mode choice literature in India (*53*, *54*). During-COVID estimates indicate that this preference has increased, which could be attributed to the greater affordability of such households and the perceived usefulness of PVs in avoiding crowding of shared modes.

It was observed that household income plays a relevant role in travel-related decisions. Respondents from the high-income group show an increased propensity for car, on-demand services, and ride-hailing services during-COVID days, which could be attributed to avoidance of crowded travel modes because of contagious COVID-19. This might be linked to the opportunity provided by ride-hailing services where they can avail personal vehicle-like exclusive rides which prove to be a somewhat safe option to low-income households which are expectedly low on vehicle ownership. Similar observation related to the vehicle ownership variable reinforces the above-mentioned hypothesis.

The effect of different types of vehicle ownership (car, motorcycle, and bicycle) at household levels have also been explored. Each ownership level (i.e., zero, one and more than one) has been tested separately to capture the possible non-linearity of various ownership levels and mode choices. In harmony with present literature, the results indicate that households that do not own PVs (car and motorcycle) have a high affinity towards NMT modes followed by public transport, on-demand services and ride-hailing service, respectively (*5*). It is worth mentioning that their preference for low social distancing modes (generally overcrowded ones like public transport and NMT modes) diminishes during-COVID days. Conversely, the reverse inclination can be found in ride-hailing services and on-demand services that provide comparatively higher social distancing and lower risk of contracting COVID from unknown co-passengers. Furthermore, households owning more than one motorcycle show a slightly higher propensity to use the same mode in the during-COVID situation compared to pre-COVID days. Intuitively, households with more than one bicycle have shown a greater preference towards NMT modes in pre-COVID days, but it dwindles during-COVID times. This result may be driven by the overall propensity to opt for WFH and avoidance of bicycle (slowest and without protection cover), which may be perceived as a mode that allows greater exposure to COVID-19 in the dense Indian urban traffic scenario.

No significant relationship could be observed between the latent variable related to the government perception towards pandemic and modal preference in India. This result might be attributed to the fact that citizens of India developed self-protective behavioural changes learning from the countries in the west, as observed by some of the recent literature (*6*, *8*). This may have led to a comparatively lesser 'jolt' on regular travel behaviour, allowing the government to transcend effectively into newer travel norms. Also, the effect of inertia needs to be considered which has been highlighted in both RP and SP scenarios. Besides, a significant association between the latent variable and socio-demographic variables, i.e., gender, could be identified when considering the latent variable. It can be observed that women perceive government measures worse than their male counterparts which might result from an inherent bias towards the former on various social fronts. Duflo and Topalova (*55*) suggested that in Indian society, women are less favourably judged than men for reasons unrelated to evaluation parameters and extend to the gender-skewed workforce (*56*). Besides, our finding about females having lower trust in government response is in line with an opinion poll in India where data showed that 'Men are more likely than women to give Indian democracy a thumbs-up' (*57*). This information also syncs with findings from other parts of the world. For example, it is reported that ' Younger people and women tend to have lower trust in government ' (*58*).

At the same time, the contextual attributes (i.e., SP attributes) were tested during the estimation process in the initial models. It is worth mentioning that two attributes - (1) number of household members with COVID-like symptoms, and (2) Government advisory were found to be statistically significant with an intuitively inverse relationship with physical mode usage. Although, when other alternative specific attributes and demographics were included as explanatory variables, SP attributes lost their statistical significance (at 90% significance level) and were subsequently dropped from the final model.

Finally, for India, the ASC values suggest that all else being equal, the preference for WFH (treated as outside good) is higher relative to all other modes followed by motorcycle in both pre-COVID and during-COVID days. Furthermore, this preference increases during-COVID as compared to pre-COVID times. In the case of pre-COVID days, the ASC is lowest for ride-hailing service (-3.14), closely followed by on-demand service (-2.28) and NMT modes (-2.14). During-COVID days, ASC is the smallest for ride-hailing service (-2.73), followed by on-demand service (-2.93) and public transportation (-2.64).

COMPARISON BETWEEN CONTEXTS

The results suggest that WFH could be preferred to commuting using any mode in any period (i.e., pre or during-COVID) in both contexts from an ASC perspective. It may be noted that ASCs merely indicate the part of the utility unexplained by the covariates; they do not reflect the absolute preferences. For both contexts and almost every mode (except NMT on the India case), a decrease in the utility of travelling was shown since every ASC shows a lower coefficient for the utility for the during-COVID days than the ASC's coefficients from the pre-COVID days. When considering only mode preferences to commute, changes have been found during the COVID-19 outbreak, as the literature suggested (*2*, *13*), and different alternative and travellers' attributes appeared to influence choices in both contexts differently.

Travel time has negative coefficients in the pre-COVID period (as expected) and non-significant coefficients in during-COVID times in both contexts. Abdullah et al., (*13*) found that during COVID-19, fewer people are giving high importance to travel time. Meanwhile, other attributes (i.e., infection risk, safety, social distance, and hygiene) have been reported as a priority in the COVID-19 scenario, which can explain the results found in both contexts (*13*). This result is in line with other studies done in the sub-continent (*3*, *7*, *8*) and global context, as suggested by studies done in Australia (*21*) and the USA (*48*). Those pointed out a substantial increase in WFH since infection fear heavily influenced mode-choice decisions, which has altered perceptions regarding conventional attributes (e.g., travel time, distance to work). Albeit such a strong effect might be short-lived, this indicates how the post-pandemic travel behaviour is shaping up with the emergence of virtual commute (for example, voluntary WFH replacing enforced WFH).

Our results reinforce the previous finding regarding the socio-demographic effect on mode changes during COVID-19 (e.g., gender, occupation) (*13*). Regarding gender, the models suggest a decrease in the active modes' utility for women that are significant in both the pre and during-COVID contexts. The negative propensity for during-COVID days could be explained by the fact that males travelled more in this period (*13*, *59*). When considering age, it was found for the Indian case that for young people, the use of NMT modes during pandemic reduces their utility, while the significant utility reduction when using cars before COVID-19 is not significant during the pandemic. These results have to be considered carefully considering that, in general, there is reported a migration from public transport to active/NMT modes and private modes during COVID-19 (*2*, *6*, *13*, *22*). In the case of Colombia, a significant relationship with age could not be found. We hypothesize that in Colombia the large changes towards WFH can incorporate the effects related to age. Hence, such variable did not significantly affect the change to private modes during COVID-19.

Employment status and educational level variables appear significant to explain frequency and choice only for the Colombian case. Professionals saw their utility reduced when using active modes before the pandemic; however, during COVID-19 it is found a significant utility increase, suggesting a potential increase in the use of active modes, as is also reflected in literature (*2*, *13*, *17*). For students in Colombia, it has been found that before COVID-19, their utility was increased when using school buses and motorcycles, coefficients that were not significant during the COVID-19 period. In line with the young people in India, the previously mentioned finding poses the young student population as a key stakeholder of habit changes. In India, an increase in the utility of cars was observed for those with a high income, which is expected from the literature too (*2*, *6*).

Vehicle ownership has also been reported to influence mode choice and frequency during the pandemic (*2*, *13*, *22*). Some studies suggest a propensity to continue using pre-COVID modes, during the COVID-19 period, mainly in India (*5*, *6*). According to the results, this behaviour was observed and reinforced for those owning motorcycles in both countries, considering that the utility, when using the motorcycle has been found positive and significant during the COVID-19 period. Besides, the non-availability of private modes poses no changes on the utility for active, on-demand service, ride-hailing service, and public transportation, suggesting no differences between COVID-19 periods.

Government decisions have influenced mode choices and trip frequencies (*3*, *13*, *19*). This influence in terms of frequencies has been previously observed in Colombia (*3*) and India (*5*, *6*). However, when analysing both mode choice and frequencies, the results suggest that a good perception of government response to combat COVID-19 leads to a decrease in active modes, public transportation and motorcycle utilities in Colombia, but not in India. This inconsistency can be explained in the light of disparities in reactions from administrative ends as well as the temporal difference of pandemic spreading across two countries.

LIMITATIONS AND FURTHER RESEARCH

Online-based surveys are a preferred way to collect responses from people worldwide during COVID-19, to avoid contagious risks. However, the approach has known limitations, such as internet access, that may generate a lack of representativeness and coverage bias (*60*). While our sample is not free from coverage biases, the distribution of sample size collected from each social media channel is presented to avoid any ambiguities and added words of caution while interpreting the results. The data collection method was the most feasible considering the situation and restrictions associated with the pandemic (i.e., nationwide lockdowns).

Besides, the speeders identification is a recommended practice, and this study implemented it to enhance the dataset quality. The selected duration cut-off (i.e., responses collected in less than 50% of the average duration to complete the instrument) may remain a lower threshold compared with the highest value suggested by the literature (i.e., 63% of the average time to complete the instrument). However, an increase in the mentioned threshold did not result in relevant changes to the presented results for the Colombian dataset. This practice could not be followed for India, and the duration cut-off cannot be implemented.

Some limitations regarding the survey instrument were found after reviewing our results. The internet conditions (e.g., quality or access) for the work-related activities and the conditions to develop remote work was not asked in our survey, which might generate a lack of understanding of the relationships between home-based working, technology, and commuting. Furthermore, the study did not ask for the specific job types (which relate to the WFH's susceptibility). This was not included due to the uncommon conditions of the pandemic, and under the assumption that most of the population in countries across the world was forced to home-based work. The sample considered different groups of people as per gender, age, income, occupation, and vehicle ownership to reduce coverage bias.

Another limitation of this study is that for the case of Colombia the different information regarding the SP was not able to be gathered adequately from the online survey. This occurred because there was a coding error in the survey and the SP scenarios did not vary among respondents. This situation meant that the SP situations could not be compared between contexts, which diminished the scope of the study. However, with the available data, the model was developed finding that the SP attributes were not significant for Colombia, which, in any case, would have rendered a non-comparable model when considering the results from India.

This study mainly considered people who commute (i.e., study or work) or worked or studied from home before COVID-19. However, considering a wider population for further research may help understand how the travel patterns were modified by COVID-19. Moreover, a panel dataset instead of a cross-sectional one (as used in the present study) with attitudes measured at multiple time intervals for the same individual would also facilitate dealing with behavioural changes as a function of the temporal evolution of attitudes. Besides, it might be interesting to test this approach for non-commute trips considering their relevance during the pandemic. It is also advisable to explore other relevant subjective variables (e.g., lifestyle, social norms) for better insights into change in travel patterns.

CONCLUSIONS

This study explains the commute changes during different stages of COVID-19 through simultaneous estimation of choice preference and mode use frequency. Furthermore, it incorporates both objective and subjective elements at an individual level in the same model. The major contributions of the present research are many-folds – *firstly*, it develops and extends the use of the MDCEV modelling framework into a hybrid-MDCEV (HMDCEV) one by including latent (subjective) variables which aid in investigating the role of attitudes. This helped us to get further insights that have additional policy implications. For example, citizens' perception of government responses to combat pandemic influences usage of travel alternatives in Colombia but not in India. *Secondly*, the virtual mode (i.e., WFH) and physical modes were analysed in separate nests (nested-HMDCEV or HMDCNEV) which better resembles the real-life scenario. *Thirdly*, incorporation of panel data within HMDCNEV model structure, i.e., simultaneously using revealed preference and stated preference data points along with estimating a scale parameter to acknowledge the temporal difference. Moreover, the new structure also affected the magnitude and statistical significance of some of the model coefficients. For example, the role of inertia towards the RP and SP modes was separately estimated in the current framework, which shows almost similar values for India, whereas, in Colombia, RP inertia is relatively greater. *Finally*, it provides a comparison of changes in commute patterns between two Global-South economies i.e. Colombia and India. This allows to check the transferability of travel behaviour in the pandemic situation and subsequently derive generic policy insights.

The post-pandemic mobility in the global south will come with new challenges that can be exemplified and assessed from the results of this study. *First*, the model showed that the enhancement of modelling techniques is crucial to better understand travel behaviour in developing nations. Within this perspective, two factors draw attention. The inclusion of subjective variables on choice models appears to provide insight into travelling decisions and political perceptions. In addition to typical trip-related and sociodemographics-related variables, the way people perceive their contexts and their governments' responses towards, for instance, global warming and the climate crisis, will affect how they choose to behave. These kinds of decision-making influences need to be assessed while describing and modelling urban transportation in global south cities.

Secondly, WFH proved once again its significance with transportation in cities, and the results showed that indeed a nested structure can be incorporated into transport modelling. This new mobility is going to be, at least in a small portion, organized towards some home-based working activities and hence nesting a first "choice" (whether to WFH or not), before choosing a transportation mode will be needed to take into account when developing the assignment part of the four-step model. This trend undoubtedly has come to stay and transportation systems need to be rearranged to incorporate it to increase transport models' accuracy.

The results also showed that sustainable development could be at stake in the post-COVID-19 era. As was observed, aligned with the literature, increasingly, people have begun to commute using private vehicles for different reasons, including fear about the disease. This poses a threat to sustainability since these transportation modes are the least efficient and contribute to increasing negative externalities of transportation in urban contexts. However, as the results also show, non-motorised alternatives also appear to be a somewhat preferred mode after the pandemic. This can provide a long-term solution to the mentioned issue. However, for non-motorised alternatives to be an acceptable mode, changes to the urban form are necessary. Among these changes, decision-makers should grant an accessible city (For example, oriented by the 15-minute city concept) that allows the people to reach a vast and diverse offer of urban services within walking / bicycling distances.

In the context of both countries, it was found that travel time became less relevant to explain choice during the during-COVID situation which may be related to the use of active modes to commute. It was also found that during COVID-19, the choice and use of personal motorised modes is likely to increase when compared to the pre-COVID period. Besides, there is a negative impact on the public transportation choice and use during the COVID-19 period in both countries. This finding suggests that re-attracting people use public transport needs actions in terms of restricting virus spread, as proposed by the literature, accompanied by programs that incentivize people to use public transportation.

The model results suggest that sociodemographic attributes significantly influence the joint preference of mode choice and its frequency. For example, different age groups and households with vehicle availability show varied propensity towards their mode usage. The study finds the young millennial group in India to be of specific interest as their inclination towards using NMT modes reduces and likely use of car mode increases during-COVID times, as opposed to the pre-COVID period. This is likely to create an unsustainable situation for urban transit, which needs to be addressed.

In general, these concerns will impact post-COVID mobility in the Global South and should be addressed. In terms of governmental commitment, response, and perception, the model indicates significant effects for Colombia albeit no such effect could be observed for India.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Vallejo-Borda, Bhaduri, Ortiz-Ramirez, Arellana, Rodriguez-Valencia, Wadud, Choudhury, Goswami; data collection: Vallejo-Borda, Bhaduri; analysis and interpretation of results: Vallejo-Borda, Bhaduri, Ortiz-Ramirez, Arellana, Rodriguez-Valencia, Wadud, Choudhury, Goswami; draft manuscript preparation: Vallejo-Borda, Bhaduri, Ortiz-Ramirez. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. World Health Organization. WHO Coronavirus Disease (COVID-19) Dashboard. https://covid19.who.int/. Accessed Dec. 13, 2020.

2. De Vos, J. The Effect of COVID-19 and Subsequent Social Distancing on Travel Behavior. *Transportation Research Interdisciplinary Perspectives*, Vol. 5, 2020, p. 100121. https://doi.org/10.1016/j.trip.2020.100121.

3. Arellana, J., L. Márquez, and V. Cantillo. COVID-19 Outbreak in Colombia: An Analysis of Its Impacts on Transport Systems. *Journal of Advanced Transportation*, Vol. 2020, 2020, p. 1DUMMMY. https://doi.org/10.1155/2020/8867316.

4. Vallejo-Borda, J. A., R. Giesen, P. Basnak, J. P. Reyes, B. Mella Lira, M. J. Beck, D. A. Hensher, and J. de D. Ortúzar. Characterising Public Transport Shifting to Active and Private Modes in South American Capitals during the COVID-19 Pandemic. *Transportation Research Part A: Policy and Practice*, Vol. 164, 2022, pp. 186–205. https://doi.org/10.1016/j.tra.2022.08.010.

5. Pawar, D. S., A. K. Yadav, N. Akolekar, and N. R. Velaga. Impact of Physical Distancing Due to Novel Coronavirus (SARS-CoV-2) on Daily Travel for Work during Transition to Lockdown. *Transportation Research Interdisciplinary Perspectives*, Vol. 7, 2020, p. 100203. https://doi.org/10.1016/j.trip.2020.100203.

6. Bhaduri, E., B. S. Manoj, Z. Wadud, A. K. Goswami, and C. F. Choudhury. Modelling the Effects of COVID-19 on Travel Mode Choice Behaviour in

India. *Transportation Research Interdisciplinary Perspectives*, Vol. 8, No. December, 2020, p. 100273. https://doi.org/10.1016/j.trip.2020.100273.

7. Das, S., A. Boruah, A. Banerjee, R. Raoniar, S. Nama, and A. K. Maurya. Impact of COVID-19: A Radical Modal Shift from Public to Private Transport Mode. *Transport Policy*, Vol. 109, 2021, pp. 1–11. https://doi.org/10.1016/j.tranpol.2021.05.005.

8. Zannat, K. E., E. Bhaduri, A. K. Goswami, and C. F. Choudhury. The Tale of Two Countries: Modeling the Effects of COVID-19 on Shopping Behavior in Bangladesh and India. *Transportation Letters*, 2021, pp. 1–13. https://doi.org/10.1080/19427867.2021.1892939.

9. Benítez, M. A., C. Velasco, A. R. Sequeira, J. Henríquez, F. M. Menezes, and F. Paolucci. Responses to COVID-19 in Five Latin American Countries. *Health Policy and Technology*, Vol. 9, No. 4, 2020, pp. 525–559. https://doi.org/10.1016/j.hlpt.2020.08.014.

10. Neuburger, L., and R. Egger. Travel Risk Perception and Travel Behaviour during the COVID-19 Pandemic 2020: A Case Study of the DACH Region. *Current Issues in Tourism*, Vol. 24, No. 7, 2021, pp. 1003–1016. https://doi.org/10.1080/13683500.2020.1803807.

11. Tirachini, A., and O. Cats. COVID-19 and Public Transportation: Current Assessment, Prospects, and Research Needs. *Journal of Public Transportation*, Vol. 22, No. 1, 2020, pp. 1–34. https://doi.org/10.5038/2375-0901.22.1.1.

12. Guzman, L. A., J. Arellana, D. Oviedo, and C. A. Moncada Aristizábal. COVID-19, Activity and Mobility Patterns in Bogotá. Are We Ready for a '15-Minute City'? *Travel Behaviour and Society*, Vol. 24, No. August 2020, 2021, pp. 245–256. https://doi.org/10.1016/j.tbs.2021.04.008.

13. Abdullah, M., C. Dias, D. Muley, and M. Shahin. Exploring the Impacts of COVID-19 on Travel Behavior and Mode Preferences. *Transportation Research Interdisciplinary Perspectives*, Vol. 8, No. October, 2020, p. 100255. https://doi.org/10.1016/j.trip.2020.100255.

14. Aloi, A., B. Alonso, J. Benavente, R. Cordera, E. Echániz, F. González, C. Ladisa, R. Lezama-Romanelli, Á. López-Parra, V. Mazzei, L. Perrucci, D. Prieto-Quintana, A. Rodríguez, and R. Sañudo. Effects of the COVID-19 Lockdown on Urban Mobility: Empirical Evidence from the City of Santander (Spain). *Sustainability*, Vol. 12, No. 9, 2020, p. 3870. https://doi.org/10.3390/su12093870.

15. Barbieri, D. M., B. Lou, M. Passavanti, C. Hui, I. Hoff, D. A. Lessa, G. Sikka, K. Chang, A. Gupta, K. Fang, A. Banerjee, B. Maharaj, L. Lam, N. Ghasemi, B. Naik, F. Wang, A. F. Mirhosseini, S. Naseri, Z. Liu, Y. Qiao, A. Tucker, K. Wijayaratna, P. Peprah, S. Adomako, L. Yu, S. Goswami, H. Chen, B. Shu, A. Hessami, M. Abbas, N. Agarwal, and T. H. Rashidi. Impact of COVID-19 Pandemic on Mobility in Ten Countries and Associated Perceived Risk for All Transport Modes. *PLoS ONE*, Vol. 16, No. 2 February, 2021, pp. 1–18. https://doi.org/10.1371/journal.pone.0245886.

16. Bucsky, P. Modal Share Changes Due to COVID-19: The Case of Budapest. *Transportation Research Interdisciplinary Perspectives*, Vol. 8, 2020, p. 100141. https://doi.org/10.1016/j.trip.2020.100141.

17. Moslem, S., T. Campisi, A. Szmelter-Jarosz, S. Duleba, K. M. Nahiduzzaman, and G. Tesoriere. Best-Worst Method for Modelling Mobility Choice after COVID-19: Evidence from Italy. *Sustainability (Switzerland)*, Vol. 12, No. 17, 2020, pp. 1–19. https://doi.org/10.3390/SU12176824.

18. Labonté-Lemoyne, É., S. L. Chen, C. K. Coursaris, S. Sénécal, and P. M. Léger. The Unintended Consequences of Covid-19 Mitigation Measures on Mass Transit and Car Use. *Sustainability (Switzerland)*, Vol. 12, No. 23, 2020, pp. 1–13. https://doi.org/10.3390/su12239892.

19. Hiselius, L. W., and P. Arnfalk. When the Impossible Becomes Possible: COVID-19's Impact on Work and Travel Patterns in Swedish Public Agencies. *European Transport Research Review*, Vol. 13, No. 1, 2021. https://doi.org/10.1186/s12544-021-00471-9.

20. Shibayama, T., F. Sandholzer, B. Laa, and T. Brezina. Impact of Covid-19 Lockdown on Commuting: A Multi-Country Perspective. *European Journal of Transport and Infrastructure Research*, Vol. 21, No. 1, 2021, pp. 70–93. https://doi.org/10.18757/ejtir.2021.21.1.5135.

21. Beck, M. J., and D. A. Hensher. Insights into the Impact of COVID-19 on Household Travel and Activities in Australia – The Early Days under

Restrictions. *Transport Policy*, Vol. 96, No. July, 2020, pp. 76–93. https://doi.org/10.1016/j.tranpol.2020.07.001.

22. Beck, M. J., D. A. Hensher, and E. Wei. Slowly Coming out of COVID-19 Restrictions in Australia: Implications for Working from Home and Commuting Trips by Car and Public Transport. *Journal of Transport Geography*, Vol. 88, 2020, p. 102846. https://doi.org/10.1016/j.jtrangeo.2020.102846.

23. Thombre, A., and A. Agarwal. A Paradigm Shift in Urban Mobility: Policy Insights from Travel before and after COVID-19 to Seize the Opportunity. *Transport Policy*, Vol. 110, 2021, pp. 335–353. https://doi.org/10.1016/j.tranpol.2021.06.010.

24. Balbontin, C., D. A. Hensher, M. J. Beck, R. Giesen, P. Basnak, J. A. Vallejo-Borda, and C. Venter. Impact of COVID-19 on the Number of Days Working from Home and Commuting Travel: A Cross-Cultural Comparison between Australia, South America and South Africa. *Journal of Transport Geography*, Vol. 96, 2021, p. 103188. https://doi.org/10.1016/j.jtrangeo.2021.103188.

25. ChoiceMetrics. Ngene 1.1.1 User Manual & Reference Guide.

26. Spissu, E., A. R. Pinjari, C. R. Bhat, R. M. Pendyala, and K. W. Axhausen. An Analysis of Weekly Out-of-Home Discretionary Activity Participation and Time-Use Behavior. *Transportation*, Vol. 36, No. 5, 2009, pp. 483–510. https://doi.org/10.1007/s11116-009-9200-5.

27. Barrero, J. M., N. Bloom, and S. Davis. *Why Working from Home Will Stick*. Cambridge, MA, 2021.

28. Alcaldía Mayor de Bogotá. *Resultados de La Encuesta de Movilidad de Bogotá y Municipios Vecinos 2019*. Bogotá, 2019.

29. Bansal, P., K. M. Kockelman, W. Schievelbein, and S. Schauer-West. Indian Vehicle Ownership and Travel Behavior: A Case Study of Bengaluru, Delhi and Kolkata. *Research in Transportation Economics*, Vol. 71, 2018, pp. 2–8. https://doi.org/10.1016/J.RETREC.2018.07.025.

30. R Core Team. R: A Language and Environment for Statistical Computing.

31. Lumley, T. Survey: Analysis of Complex Survey Samples.

32. Secretaría Distrital de Movilidad. Datos Abiertos Secretaría Distrital de Movilidad. *Bit carrier speeds*. https://datos.movilidadbogota.gov.co/search?groupIds=71ef3e63c60749cbb89028c76558a304.

33. Chandra, S., and A. K. Bharti. Speed Distribution Curves for Pedestrians During Walking and Crossing. *Procedia - Social and Behavioral Sciences*, Vol. 104, 2013, pp. 660–667. https://doi.org/10.1016/J.SBSPRO.2013.11.160.

34. Majumdar, B. B., and S. Mitra. Analysis of Bicycle Route-Related Improvement Strategies for Two Indian Cities Using a Stated Preference Survey. *Transport Policy*, Vol. 63, 2018, pp. 176–188. https://doi.org/10.1016/J.TRANPOL.2017.12.016.

35. Fatima, E., B. T. Rajendra, D. Soni, and R. Kumar. Travel Time Reliability Analysis of Three Wheelers: An Indian City Case Study. *International Journal of Traffic and Transportation Engineering*, Vol. 4, No. 4, 2015, pp. 107–114. https://doi.org/10.5923/J.IJTTE.20150404.02.

36. Enam, A., K. C. Konduri, A. R. Pinjari, and N. Eluru. An Integrated Choice and Latent Variable Model for Multiple Discrete Continuous Choice Kernels: Application Exploring the Association between Day Level Moods and Discretionary Activity Engagement Choices. *Journal of Choice Modelling*, Vol. 26, No. July 2017, 2018, pp. 80–100. https://doi.org/10.1016/j.jocm.2017.07.003.

37. Bhat, C. R. The Multiple Discrete-Continuous Extreme Value (MDCEV) Model : Role of Utility Function Parameters , Identification Considerations , and Model Extensions. *Transportation Research Part B*, Vol. 42, 2008, pp. 274–303. https://doi.org/10.1016/j.trb.2007.06.002.

38. Pinjari, A. R., and C. Bhat. A Multiple Discrete-Continuous Nested Extreme Value (MDCNEV) Model: Formulation and Application to Non-Worker Activity Time-Use and Timing Behavior on Weekdays. *Transportation Research Part B: Methodological*, Vol. 44, No. 4, 2010, pp. 562–583. https://doi.org/10.1016/j.trb.2009.08.001.

39. Department of transportation, U. S. *Federal Highway Administration, 2009 National Household Travel Survey*. 2009.

40. Hess, S., and D. Palma. Apollo : A Flexible , Powerful and Customisable Freeware Package for Choice Model Estimation and Application User Manual. No. January, 2021.

41. Bhat, C. R., and S. Sen. Household Vehicle Type Holdings and Usage: An Application of the Multiple Discrete-Continuous Extreme Value (MDCEV) Model. *Transportation Research Part B: Methodological*, Vol. 40, No. 1, 2006, pp. 35–53. https://doi.org/10.1016/j.trb.2005.01.003.

42. Bhat, C. R. A Multiple Discrete – Continuous Extreme Value Model : Formulation and Application to Discretionary Time-Use Decisions. Vol. 39, 2005, pp. 679–707. https://doi.org/10.1016/j.trb.2004.08.003.

43. Calastri, C., S. Hess, A. R. Pinjari, and A. Daly. Accommodating Correlation across Days in Multiple Discrete-Continuous Models for Time Use. *Transportmetrica B: Transport Dynamics*, Vol. 8, No. 1, 2020, pp. 108–128. https://doi.org/10.1080/21680566.2020.1721379.

44. Pendyala, R. M., and C. R. Bhat. An Exploration of the Relationship between Timing and Duration of Maintenance Activities. *Transportation*, Vol. 31, No. 4, 2004, pp. 429–456. https://doi.org/10.1023/B:PORT.0000037060.42921.35.

45. Srinivasan, S., and C. R. Bhat. Modeling Household Interactions in Daily In-Home and out-of-Home Maintenance Activity Participation. *Transportation*, Vol. 32, No. 5, 2005, pp. 523–544. https://doi.org/10.1007/s11116-005-5329-z.

46. Lu, H., S. Hess, A. Daly, and C. Rohr. Measuring the Impact of Alcohol Multi-Buy Promotions on Consumers' Purchase Behaviour. *Journal of Choice Modelling*, Vol. 24, 2017, pp. 75–95. https://doi.org/10.1016/j.jocm.2016.05.001.

47. Calastri, C., S. Hess, A. Daly, M. Maness, M. Kowald, and K. Axhausen. Modelling Contact Mode and Frequency of Interactions with Social Network Members Using the Multiple Discrete – Continuous Extreme Value Model q. *Transportation Research Part C*, Vol. 76, 2017, pp. 16–34. https://doi.org/10.1016/j.trc.2016.12.012.

48. Shamshiripour, A., E. Rahimi, R. Shabanpour, and A. (Kouros) Mohammadian. How Is COVID-19 Reshaping Activity-Travel Behavior? Evidence from a Comprehensive Survey in Chicago. *Transportation Research Interdisciplinary Perspectives*, Vol. 7, 2020, p. 100216. https://doi.org/10.1016/J.TRIP.2020.100216.

49. Sagaris, L., and I. Tiznado-Aitken. Sustainable Transport and Gender Equity: Insights from Santiago, Chile. In *Transport and Sustainability*, Emerald Group Holdings Ltd., pp. 103–134.

50. Rosas-Satizábal, D., and A. Rodriguez-Valencia. Factors and Policies Explaining the Emergence of the Bicycle Commuter in Bogotá. *Case Studies on Transport Policy*, Vol. 7, No. 1, 2019, pp. 138–149. https://doi.org/10.1016/j.cstp.2018.12.007.

51. Güner, R., İ. Hasanoğlu, and F. Aktaş. Covid-19: Prevention and Control Measures in Community. *Turkish Journal of Medical Sciences*, Vol. 50, No. 3, 2020, pp. 571–577. https://doi.org/10.3906/sag-2004-146.

52. Verma, M., M. Manoj, and A. Verma. Analysis of the Influences of Attitudinal Factors on Car Ownership Decisions among Urban Young Adults in a Developing Country like India. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 42, 2016, pp. 90–103. https://doi.org/10.1016/j.trf.2016.06.024.

53. Ashalatha, R., V. S. Manju, and A. B. Zacharia. Mode Choice Behavior of Commuters in Thiruvananthapuram City. *Journal of Transportation Engineering*, Vol. 139, No. 5, 2013, pp. 494–502. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000533.

54. Devaraj, A., G. Ambi Ramakrishnan, G. S. Nair, K. K. Srinivasan, C. R. Bhat, A. R. Pinjari, G. Ramadurai, and R. M. Pendyala. Joint Model of Application-Based Ride Hailing Adoption, Intensity of Use, and Intermediate Public Transport Consideration among Workers in Chennai City. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2674, No. 4, 2020, pp. 152–164. https://doi.org/10.1177/0361198120912237.

55. Duflo, E., and P. Topalova. Unappreciated Service: Performance, Perceptions, and Women Leaders in India. *Framed Field Experiments*, Vol. 65, No. 4, 2004, pp. 741–766. https://doi.org/10.1086/692114.

56. Ministry of Home Affairs Govt. of India. *Census of India 2011*. 2011.

57. How Indians Feel About Political, Economic and Social Issues | Pew Research Center. https://www.pewresearch.org/global/2019/03/25/a-sampling-of-public-opinion-in-india/. Accessed Nov. 2, 2022.

58. Executive Summary | Building Trust to Reinforce Democracy : Main Findings from the 2021 OECD Survey on Drivers of Trust in Public Institutions | OECD ILibrary. https://www.oecd-ilibrary.org/sites/b407f99c-en/index.html?itemId=/content/publication/b407f99c-en. Accessed Nov. 2, 2022.

59. Molloy, J., C. Tchervenkov, B. Hintermann, and K. W. Axhausen. Tracing the Sars-CoV-2 Impact: The First Month in Switzerland. *Findings*, 2020, pp. 1–8. https://doi.org/10.32866/001c.12903.

60. Dillman, D. A., J. D. Smyth, and L. M. Christian. *Internet, Phone, Mail, and Mixed-Mode Surveys*. Wiley & Sons, New Jersey, 2014.

Appendix A: Sample survey questionnaire

Section i - true/false questions related to COVID-19 general knowledge

What are the features of Corona Virus Disease 2019 (COVID-19)

True // False

1. COVID-19 is not a threat in countries with hot and humid climates
2. Maintaining 'social distancing' (e.g. avoiding mass-gatherings, hand shakes, etc.) can prevent spread of COVID-19
3. Regularly washing our hands with soaps/sanitizer will prevent getting infected with COVID-19
4. Face mask is essential to prevent spreading of COVID-19
5. People infected with COVID-19 might not necessarily show symptoms immediately

Section ii – commute patterns

In the CURRENT scenario, please state for the LAST WEEK (early COVID-19)

6. Did you WORK/STUDY (at-office/school and/or at-home) LAST WEEK?
   - Yes
   - No
   - Not applicable to me (e.g. Homemaker, retired persons)
7. How many times have you used different travel modes for OFFICE/SCHOOL/COLLEGE during the LAST WEEK? For example, if you went from home to office in a bus and returned by Uber, that counts as 1 trip in bus, 1 trip in Uber; if you had used Uber both ways, that count as 2 trips by Uber. If you HAVE NOT used a particular mode (e.g. private car) last week, leave the row BLANK (for private car).

   Only once last week // 2 times last week // 3 times last week // 4 times last week // 5 times last week // > 5 times last week
   - Worked/studied from home
   - Walked/ Cycled or used Rickshaw
   - Used CNG
   - Used private Car
   - Used shared office car/microbus
   - Used own Motorcycle
   - Used Humanhauler/Maxi/Tempo
   - Used App-based taxi (Uber/Pathao Car)
   - Used App-based Motorcycle (UberMoto/PathaoBike)
   - Used Bus

If you have used any option more than 5 times then please specify which mode and how many times?

8. What is the distance you had travelled for the longest of these trips?
   - I did not travel
   - 0 – 3 km
   - >3 – 5 km
   - >5 – 10 km
   - >10 – 15 km
   - >15 km
   - I do not know

Now we would like to ask you about your travel pattern BEFORE Coronavirus outbreak in the world - think January 2020

9. Did you USUALLY WORK/STUDY (at-office/school and/or at-home)?
   - Yes
   - No
   - Not applicable to me (e.g. Homemaker, retired persons)
10. What was the distance you travelled for your regular trip to WORK/STUDY?
    - No travel
    - 0 – 3 km
    - >3 – 5 km
    - >5 – 10 km
    - >10 – 15 km
    - >15 km
    - I do not know
11. How many times did YOU USUALLY USE different modes for OFFICE/SCHOOL/COLLEGE in a TYPICAL week in JANUARY 2020? For example, if you went from home to office in a bus and returned by Uber, that count as 1 trip in bus, 1 trip in Uber; if you had used Uber both ways, that count as 2 trips by Uber. If you HAVE NOT used a particular mode (e.g. private car) last week, leave the row (for private car) BLANK.

    1 time/week // 2 time/week // 3 times/week // 4 times/week // 5 times/week // More than 5 times/week
    - Work/study from home
    - Walk/ Cycle or use Rickshaw
    - Use CNG/Auto-Rickshaw
    - Use my personal Car
    - Use shared office Car/Microbus

- Use my own Motorcycle
- Used Humanhauler/Maxi/Tempo
- Used App-based taxi (Uber/Pathao-car)
- Used App-based motorcycle (UberMoto/PathaoMotorbike)
- Used Bus

If you use any option more than 5 times then please specify which mode and how many times?

We would now like to present you with two future probable scenarios of the COVID-19 outbreak. Please think carefully and let us know what will be your shopping choices in these scenarios.

FUTURE SCENARIO A:

IMAGINE A FUTURE SITUATION:

Number of cases in the country: 10,000

Number of confirmed active cases in your city: 1500

Number of deaths in your city in the past week: 15

Number of your household members with COVID like symptoms (dry cough, fever): 1

Government advisory: Social distancing (Schools closed, Working from home encouraged, Mass gatherings discouraged)

1. WILL you either TRAVEL to OFFICE/SCHOOL/COLLEGE or work from home? (Example: If you are taking leave choose options NO)
    - No
    - Yes
    - Maybe
    - NA
2. How many times WILL YOU USE different options for OFFICE/SCHOOL/COLLEGE in COMING WEEKS? (for example, if you plan to travel 5 times a week from home to office in a bus tick "5 times in a week" for "I will use bus" and return home in a taxi select "5 times in a week" for "I will use taxi") AND If you have not used a particular mode (e.g. Bus) last week, leave the row for Bus blank.

    1 time in a week // 2 times in a week // 3 times in a week // 4 times in a week // 5 times in a week // more than 5 times in a week // option is not available

    - I will work/study from home
    - I will Walk/ Cycle or use Cycle-Rickshaw

- I will use Auto-Rickshaw / Toto
- I will use my Car
- I will use my Motorbike
- I will use an App-based taxi (Ola Micro-Mini /Uber Go/Meru)
- I will use a Shared- App-based taxi (Ola Share/Uber Pool/Meru)
- I will use Bus
- I will use Rail transit (Metro rail, Suburban train)

If you use any option more than 5 times then please specify which mode and how many times?

3. How much maximum distance do you travel for WORK/ STUDY?
    - No travel
    - 0 – 3 km
    - >3 – 5 km
    - > 5 – 10 km
    - >10 – 15 km
    - >15 km
    - I do not know

Appendix B: Travel modes usage in India and Colombia in pre-COVID and during-COVID periods

Table 8. Weekly frequency of choosing different travel modes before and during COVID outbreak

		India				*Colombia*			
Mode	*Category*	*Users (%)*		*Mean fraction#*		*Users (%)*		*Mean fraction#*	
		pre-COVID	*during-COVID*	*pre-COVID*	*during-COVID*	*pre-COVID*	*during-COVID*	*pre-COVID*	*during-COVID*
Active	*Non-motorized transport (NMT)*	124 (22.26)	161 (13.18)	4.30	3.05	55 (19.50)	54 (21.09)	3.36	1.74
Auto-rickshaw	*On-demand service (ODS)*	44 (7.89)	62 (5.07)	2.09	1.64	NA	NA	NA	NA
Taxi	*On-demand service (ODS)*	25 (4.48)	38 (3.11)	1.83	1.62	NA	NA	NA	NA
Ride-hailing	*App based cab service*	36 (6.46)	51 (4.17)	2.25	1.32	NA	NA	NA	NA
Ride-sharing	*App based cab service*	23 (4.13)	25 (2.04)	2.18	1.50	NA	NA	NA	NA
Car	*Personal vehicle (PV)*	104 (18.67)	168 (13.75)	3.97	2.46	69 (24.47)	41 (16.02)	3.17	1.76
Motorbike	*Personal vehicle (PV)*	87 (15.62)	117 (9.58)	3.86	2.82	15 (5.32)	18 (7.03)	2.87	2.50
Bus	*Public transport (PuT)*	62 (11.13)	64 (5.24)	2.70	2.28	88 (31.21)	23 (8.98)	3.72	1.74
Railway	*Public transport (PuT)*	61 (10.95)	72 (5.89)	3.1	2.05	NA	NA	NA	NA
Route	*Office Shuttle*	NA	NA	NA	NA	16 (5.67)	14 (5.47)	2.25	1.43
Work from home	*Virtual*	145 (26.03)	361 (29.56)	3.55	3.89	58 (20.57)	106 (41.41)	2.67	3.90

 # 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)