

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

Jose Agustin Vallejo-Borda^{1,2,3} , Eeshan Bhaduri⁴ ,
Hernan Alberto Ortiz-Ramirez⁵ , Julián Arellana⁶ ,
Charisma F. Choudhury⁷ , Alvaro Rodriguez-Valencia⁵ ,
Zia Wadud⁷, and Arkopal K. Goswami⁴ 

Abstract

The COVID-19 pandemic has affected many daily activities, primarily as a result of the perceived contagion risk and 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 through descriptive analysis. On the other hand, modeling-based research that can simultaneously understand both changes in mode choice and its frequency at an individual level has not been much used in existing studies. As such, this study aims to understand the changes in mode-choice preference and the frequency of trips, comparing pre-COVID with 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 and April 2020. This study found that, in both countries, utility related to active modes (more used) and public transportation (less used) changed during the pandemic. In addition, this study highlights potential risks in likely unsustainable futures where there may be increased use of private vehicles such as cars and motorcycles, in both countries. It was also identified that perceptions toward government responses had a significant impact on the choices in Colombia, though this 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 behavioral changes resulting from the COVID-19 pandemic.

Keywords

COVID-19, mode choice, trip frequency, commute trips, Colombia, India

¹Civil Engineering Department, Universidad de Cartagena, Cartagena de Indias, Colombia

²Civil Engineering Department, Universidad de Investigación y Desarrollo, Bucaramanga, Colombia

³Department of Transport Engineering and Logistics, BRT + Centre of Excellence, Pontificia Universidad Católica de Chile, Santiago, Chile

⁴Ranbir and Chitra Gupta School of Infrastructure Design and Management, Indian Institute of Technology Kharagpur, Kharagpur, India

⁵Department of Civil and Environmental Engineering, Universidad de los Andes, Bogotá, Colombia

⁶Department of Civil and Environmental Engineering, Universidad del Norte, Barranquilla, Colombia

⁷Institute for Transport Studies & School of Chemical and Process Engineering, University of Leeds, Leeds, UK

Corresponding Author:

Jose Agustin Vallejo-Borda, jvallejob@unicartagena.edu.co

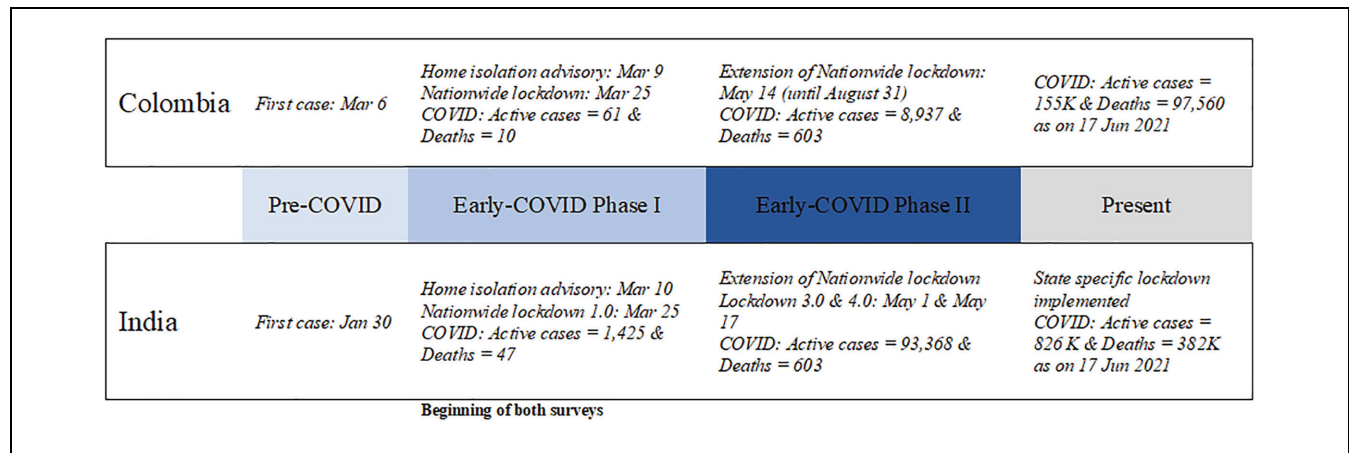


Figure 1. Timeline of COVID-19 related major events in Colombia¹ and India²

Source: ¹Ministry of Health and Social Protection, Government of Colombia; National Health Institute (INS) (<https://www.ins.gov.co/Noticias/Paginas/Coronavirus.aspx>); ²Ministry of Health and Family Welfare, Government of India (<https://www.mygov.in/covid-19>).

COVID-19 was declared a pandemic in March 2020 (1). However, even after more than a year, several nations are still experiencing waves of the virus. For example, Colombia is currently experiencing its third peak, while India is easing out of its second wave. The COVID-19 pandemic has affected travel around the world given the risk of contracting the virus that led to restrictive government policies (e.g., lockdowns). The effectiveness of these restrictive policies in modifying the activity and travel behavior of people and the associated similarities/dissimilarities have emerged as an important research question. This motivates this study in which 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 generalized for non-essential sectors (e.g., schools, industry, commerce). It began on March 25, 2020 and was extended three times until it ended on August 31. After ending this stage, local measures were taken in each Colombian state, on the basis of governmental decrees established by the national health ministry. In 2020 some local administrations decided to promote cycling by providing new bicycle lanes using primarily the existing transport infrastructure for cars (2, 3) while the public transportation systems kept working under some restrictions (3, 4). In the early phase of COVID-19, public transport introduced crowding restrictions (i.e., reductions in vehicle capacities) and made facemasks mandatory. Despite these restrictions, public transit in Colombia remained available (4). In addition, different organizations also made an effort to promote bicycle use for specific groups of the population (e.g., medical workers) who continued traveling (3).

Similarly, there was a lockdown announced in India from March 25, 2020 initially for 21 days, which was later extended until May 31 (5, 6). The COVID-19 timeline for the two countries is shown in Figure 1. Despite the difference between the dates of the first cases, the lockdown measures were implemented on similar dates.

In both countries, a decline in the number of trips and a change in mode-choice preferences were observed (3–6). In the area of transportation, changes in the frequency of trips and mode choice during COVID-19 have usually been explored independently and, in some cases, without considering people's perceptions. To address this, 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 populations' perceptions of those actions and their relationship with travel choices can provide valuable insights for middle-income countries worldwide in developing urban transport strategies to minimize the spread of the virus.

The contributions of this study are: (i) a comparison of the travel choices for changes in commuting in two different Global South contexts; (ii) the first application of the HMDCNEV framework in modeling mode and trip frequencies that explicitly includes the effect of perceptions on the travel choices during COVID-19; and (iii) exploration of the relationship between perceptions of government actions and the shifts in travel choices. It

must be noted that during the initiation of the survey, concerned administrative bodies introduced various travel restrictions intending to stop the spread of the pandemic. The current study attempts to empirically test how people perceived such restrictions and their subsequent impact on travel-related choices. Moreover, few recent studies in the context of developing nations have indicated potential spatial heterogeneity in during-COVID travel behavior arising from people's perceptions with regard to 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. Moreover, the present study also considers the during-COVID contextual (i.e., stated preferences [SP]) attributes (e.g., number of infected persons in a household) in the estimation.

The rest of the paper is organized as follows: the next 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 modeling approach focusing on the HMDCNEV model. The model results for the Colombian and the Indian contexts are then presented and compared. Finally, conclusions are drawn and future research directions are identified.

Review of Commute Changes During Covid-19

The COVID-19 pandemic has affected mobility in many ways, in particular by minimizing interactions between people (2, 3). Governments established different restrictions such as lockdowns, national night-time curfews, school closures, among others, in attempts to decrease the spread of COVID-19 (9–11). As a result of those measures, daily activity patterns were substantially altered, resulting in, among others, a 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 there is a significant difference in the frequency of trips and mode-choice preferences before and during the pandemic (5, 12–16). Public transport has been one of the most affected modes, witnessing frequency reductions resulting from 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 in working from home (WFH) (5, 6, 20, 21). With regard to WFH, it has been quantified in Colombia that, overall, 40% of 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-motorized (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 toward 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.

Travelers are especially concerned about traveling 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 preferred to choose transport modes that could provide hygienic spaces and the possibility of maintaining social distance (13). Public transport operators have been encouraged, despite the decrease in use of public transport, not to reduce frequency or capacity, but to provide a level of service and occupancy that lets people maintain safe distances from other passengers, and also considering (2). Moreover, it has been established that the proper use of face masks can significantly reduce the spread of COVID-19 in closed spaces such as public transport vehicles. There have also been recommendations to sanitize 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.

Literature reported relevant changes in the number of trips and modal preferences because of COVID-19 (4, 5, 11, 13, 15, 17, 18). 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 mostly been studied separately, and there is a lack of studies using people's perceptions to explain the previously mentioned changes. It has also been recommended that further research into mode choice consider 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 (Colombia and India) is relevant to travel modeling within these contexts. As shown in Table 1, dramatic changes in mobility have been common in all countries, and travel reduction seems to be a viable option in the post-COVID era. However, there is a substantial difference between the transportation systems in

Table 1. Review of Reported Commute Changes Influenced by the COVID-19 Pandemic

Author	Data collection period	Sample	Compared countries/cities	Main findings
Pawar et al. (5)	March 18 to 28, 2020	1,542	India (Multiple cities)	This study found 51.3% of the people continued using the same mode they had used before COVID-19, 41.7% stopped traveling, and 5.3% shifted from public transport to private modes. Moreover, safety perceptions were not significant in people's mode choice because of the few available alternatives.
Moslem et al. (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 and Hensher (21)	March 30 to April 15, 2020 (wave 1) and May 23 to June 15, 2020 (wave 2)	1,073 (wave 1) and 1,258 (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 behavior. In addition, the authors suggest that as the Australian government relaxes restrictions, an increase in commuting by car is expected. The results also show resistance to the use of public transport.
Labonté-Lemoyne et al. (18)	May 1 to 10, 2020	1968	Canada (Vancouver, Calgary, Toronto, Ottawa, Montreal, Halifax)	This study suggests that commuters prefer to use their cars compared with public transportation after COVID-19 restrictions end because of fear of contagion. The study results showed that cleaning strategies for vehicles and mandatory handwashing might counteract the low public transport preference.
Bhaduri et al. (6)	March 24 to April 12, 2020	498	India (multiple cities)	This study suggests a high propensity to continue using the same modes as before COVID-19, a high propensity to WFH, and a shift from public transportation to private modes.
Barbieri et al. (15)	May 11 to 31, 2020	9,394	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. This study also found that airplanes and buses are the transport modes perceived as riskiest by users, explaining low public transport use across all countries.

(continued)

Table 1. (continued)

Author	Data collection period	Sample	Compared countries/cities	Main findings
Hiselius and Amfalk (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. The study also found a proper response by public transport agencies who continued to offer their service with digital tools support.
Shibayama et al. (20)	March 23 to May 12, 2020	11,555	Austria, Brazil, Bulgaria, Czech Republic, Germany, Hungary, Iran, Italy, Japan, Malaysia, Slovakia, Slovenia, Thailand, and United Kingdom	This study found a significant proportion of people (between 40% and 60%) of the working population. For those able to 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. A reduction in travel time was also reported.
Albontin et al. (24)	August to December 2020	4,628	Australia, Argentina, Brazil, Chile, Colombia, Ecuador, Peru, and South Africa	This study found a significant increase in the proportion of people WFH, 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). Moreover, no significant change in productivity has been reported while WFH. This study compares the COVID-19 effects influencing people's choices to shift from public transport to other modes with five capital cities in Latin America. Cost or time savings were reported for those who switched from public transport to active and private modes. In addition, the study identified 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.
Vallejo-Borda et al. (4)	September to November 2020	3,803	Argentina, Chile, Colombia, Ecuador, and Peru	

Note: WFH = working from home.

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 in confronting 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) government to take care of its citizens	

Note: SSC = senior school certificate; HSC = high school certificate.

developed countries and those in the Global South, especially given differences in informal working and transport arrangements. In addition, there have not been many studies that have modeled travel changes during COVID-19 in developing and emerging nations, which may differ from developed economies and may also have substantial differences among themselves. Therefore, 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 (April 2 to May 1, 2020) and India (March 24 to April 12, 2020). In the case of India, the data constitutes urban respondents with 60% to 40% distribution from big cities (population >1 million) and small cities (population <1 million), respectively. Understandably, megacities such as Kolkata, Bengaluru, and New Delhi are prominent in 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 behavior [January 2020], early COVID-19 commute behavior [March and April 2020], and commute behavior under two hypothetical scenarios); (iii) respondents' detailed socio-demographic characteristics; and (iv) subjective perceptions about government and societal response to the pandemic, 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 or studied from home in the mentioned period. Table 2 presents the socio-demographic characteristics (section iii) and questions to capture people's perceptions of the government response to COVID-19 collected in this study (section iv).

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 or two stated preference (SP) responses related to the stated commute patterns in hypothetical scenarios. The hypothetical scenarios were different between the two countries given their total populations, COVID-19 situations (i.e.,

Table 3. Stated Preference Levels Used in the Data Collection Process

Attribute	Levels in India	Levels in Colombia
Number of cases in the country	750, 2000, 10,000*	2000 (scenario 1), 10,000 (scenario 2)
Number of cases in the city	5%, 10%, 15% (of the number of cases in the country)	800 (scenario 1), 5,000 (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 3,000, 10,000, 25,000 on the last week as the actual number of affected people soared more than initially expected.

¹Social distancing (no lockdown): Institutions closed/working from home encouraged/Mass gatherings discouraged.

²Semi-lockdown: Office + Schools closed/Night curfew imposed/Limited movement allowed other than the essential.

³Relaxed lockdown: Limited public transport services operate as well as essential services such as food, medicine, the bank is allowed for a restricted duration (e.g., 12 h a day).

⁴Full-lockdown: Only essential services such as food, medicine, banks are allowed, and that only for a highly restricted duration (say 6 h a day).

number of cases, number of deaths, number of cases per 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 subsequently removed. 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.

In each choice situation (RP and SP), the respondent was asked to identify whether they traveled or stayed at home. If they traveled, questions were asked to establish the mode and the frequency of each reported/declared mode. These modes varied between the two countries, some were common in both contexts, and others were not (see Table 4). Questions asked about the commute pattern on a weekly rather than on a daily basis. The daily scales can therefore 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 in 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 made using respective alternatives. The study also included WFH as a virtual travel alternative where respondents were expected to report 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. Therefore, in the estimation process, WFH has been treated as the outside good.

Table 4. List of Commuting Options in Colombia and India Before the COVID-19 Pandemic

Commute mode	Colombia	India
In-person		
Active (walking and cycling)	✓	x
Non-motorized transport (walking, cycling, and pedaled rickshaw)	x	✓
Private car	✓	✓
Motorcycle	✓	✓
Office shuttle	✓	x
Public transport (bus and subway)	✓	✓
Public transport (suburban rail)	x	✓
Auto rickshaw (CNG powered 3-wheeler taxis)	x	✓
Private taxi	✓	✓
Ride-hailing service (car)	✓	✓
Remote options		
Working from home	✓	✓

Note: CNG = compressed natural gas.

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. The 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 deployed through Facebook in both countries to increase participation and reach people who are not in the same professional circles as the survey administrators. In Colombia, we asked Facebook to show the survey publicity to women and men older than

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, I	33.83	29.09	35.55	NA
	Car ownership, more than I	3.35	7.08	3.95	NA
	Motorbike ownership, 0	89.59	83.39	52.42	NA
	Motorbike ownership, I	10.04	14.44	40.75	NA
	Motorbike ownership, more than I	0.37	2.17	6.82	NA
	Bicycle ownership, 0	56.88	47.77	64.81	NA
	Bicycle ownership, I	35.69	25.51	33.21	NA
	Bicycle ownership, more than I	7.43	26.73	1.97	NA

Note: HH = household; NA = not available.

Source: *2019 Home Travel Survey (28); #Census Data India, 2011.

18 years old and living in Bogotá with a radius of 40 km. Similarly, in India, the virtual survey questionnaire was disseminated in major metropolitan cities with a radius of 40 to 50 km from the city center and applied only to adult individuals. Finally, the numbers of respondents on Facebook, Instagram, LinkedIn, and Twitter were 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, of which 557 were used for final estimation after data cleaning.

As the present study was carried out with the intention of capturing potential changes in the travel behavior during the early stages of a rare event (i.e., COVID-19), traditional means of data collection were not possible. However, all efforts were made to maintain scientific integrity. Caution was also shown with non-probability sampling (i.e., the snowball effect) to reduce potential biases. That is why it mainly used 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 bias by weighting the observations using 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% and 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 min 23 s; Q1 = 6 min 10 s; Q2 = 7 min 32 s; mean = 8 min 3 s; Q3 = 9 min 18 s; and max. = 16 min 6 s). In the case of India, the timer ads were not included, and it was not possible to ascertain how much time the respondents took to fill out the survey. Following the literature recommendation, the responses from persons who completed the survey in less than 4 min (approximately 50% of the average duration) were dropped from the Colombian data set to enhance the data set 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.

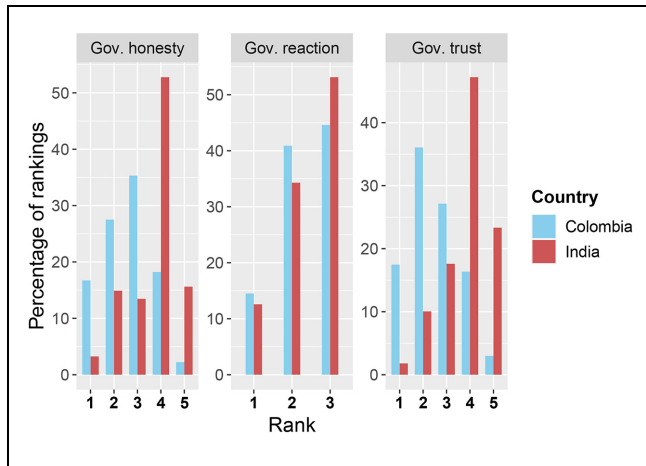


Figure 2. Response distribution to latent variable (LV) indicators.

Given the differences in the socio-demographic 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 with regard to 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 perceptions of 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 modeling steps as indicators of a latent variable that included the government perception within the modeling framework. Figure 2 shows the response distribution for both countries.

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 in both countries reported engaging in WFH. In the case of Colombia (Figure 3a), about 20% of the sample engaged with WFH. Similarly, for India, Figure 3b reveals that before the COVID-19 outbreak, nearly 25% of total respondents engaged 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 Colombia.

In contrast, in the case of personal preferences for traveling, some differences emerge. Colombia respondents prefer public transportation for a third of 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-motorized (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 them more than five times a week. At the same time, the share of the respondents who selected public transit, private car, and motorbike were 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-traveling respondents increased to almost 40%. Among them, 19.6% WFH five or more days in Colombia, while the share was 17.5% 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 declined in both contexts given the WFH increase and the limited space in public transport vehicles, making it difficult to maintain social distancing. Therefore, 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). The private mode share, on the other hand, showed different behavior in both contexts. In Colombia, private car trips decreased by 11%, whereas a slight increase can be observed in India (1%). Likewise,

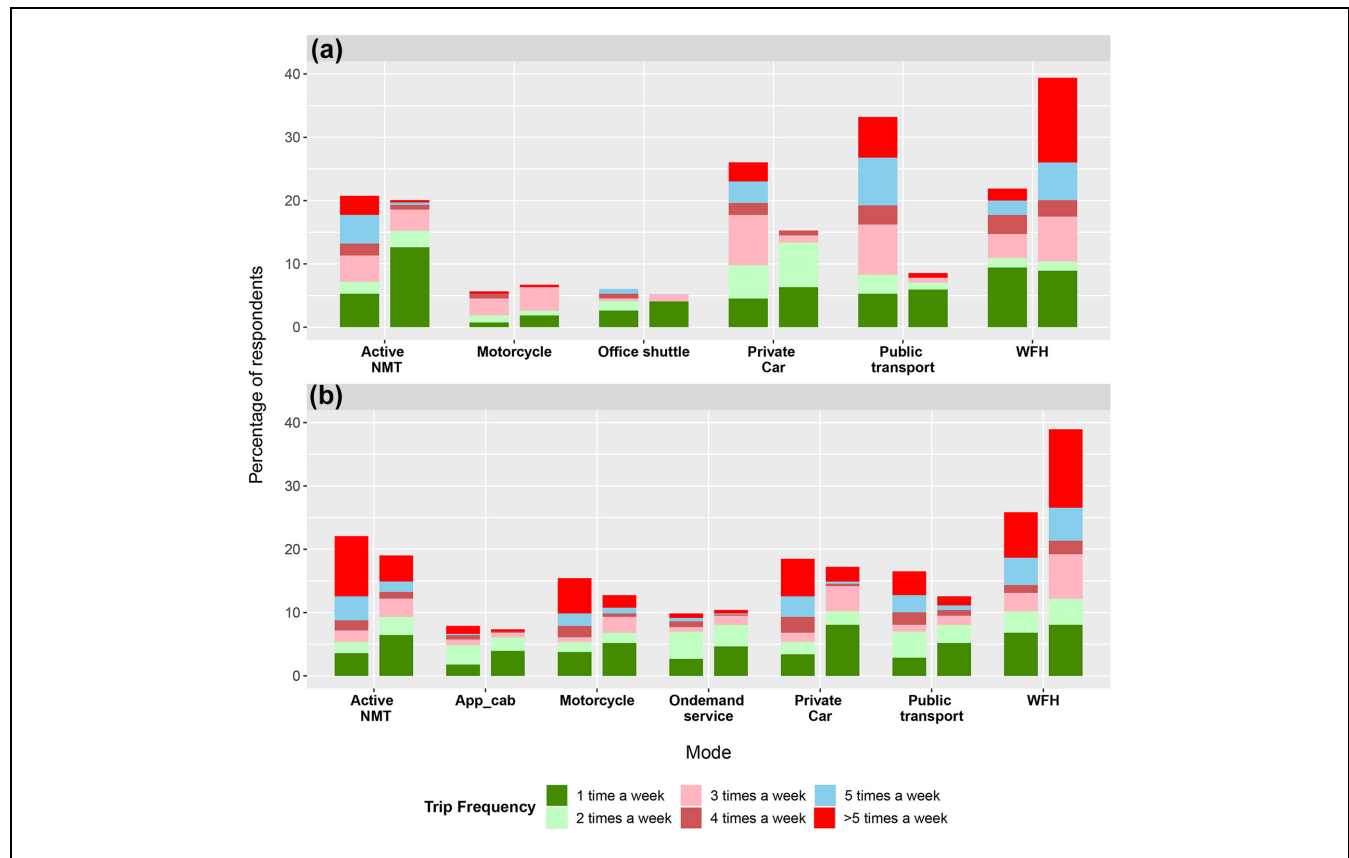


Figure 3. Mode used for commute trips before and during the COVID-19 outbreak for: (a) Colombia; and (b) India.

Note: WFH = working from home.

motorbike trips decreased in India by 3%, while motorbike trips increased almost 1% in Colombia.

Further investigations were carried out with regard to 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% three times, and more than 60% 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%, the 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 five times a week) as compared with other occupations. In addition, we could observe a fair share of students that selected study from home (approximately 35% of students selected study from home more than five times a week).

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 5c) reveals that approximately 37% of NMT users shifted to WFH whereas nearly 55% continued using their pre-COVID mode, that is, NMT. The RP variation graph contrasts pre-COVID-19 and early COVID-19 situations, (Figure 5, a to c), while the SP variation graph contrasts pre-COVID-19 with hypothetical future situations, (Figure 5, b to d).

In both cases, similarities emerge for WFH considering the RP behavior. In both contexts, WFH significantly increases during the early COVID-19 phase. Remarkably, all the modes show at least a small share change toward WFH in the two countries. The RP data also indicate that physical traveling decreased for every mode, which supports an increase in WFH and a substitution of traveling in Colombia and India. Furthermore,

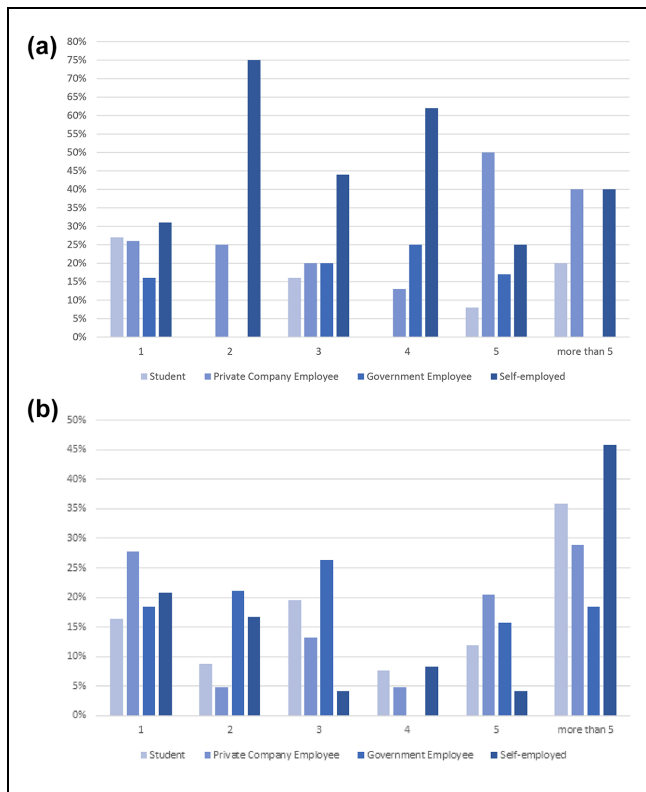


Figure 4. Occupation of those working before the pandemic in: (a) Colombia; and (b) India.

in the RP graph Figure 5, *a* and *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-traveling showed the highest stickiness, since 75% of the pre-COVID home-based workers continued WFH in the early days of COVID, likewise in Colombia (i.e., 88.89%). Of those who traveled, the highest percentage of people who kept using the same mode was the people who traveled by private car in both India and Colombia (61.76% and 20.00%, respectively). The ones with the lowest stickiness traveled using ride-hailing in India (9.09%). In contrast, those who traveled 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 show 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. A preference for less physical contact to avoid contracting COVID-19 can explain both

findings. For Colombian respondents, to prevent contracting COVID-19, the strategy seems to be traveling by private modes. For Indian respondents, the strategy seems to keep WFH (i.e., not traveling 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, characterized by having access to a car. These have been reported to increase the use of private modes during the pandemic (12).

It may be noted that, since 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 are useful for interpreting the models. Besides these charts merely provide an indication of the inertia levels which have been further tested empirically.

Modeling 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 10 modes (1 to 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 therefore a multiple discrete-continuous (MDC) variable with two components: (1) discrete mode choice (i.e., individual-level choice of the 10 modes); and (2) continuous mode-specific weekly trip frequencies.

The mode choices of travelers 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 behavior potential changes (termed as inertia); and (c) subjective indicators indicating the perception of the government’s response to 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 data set and information reported in secondary data with regard to 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 Bogotá 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 maximization (RUM)

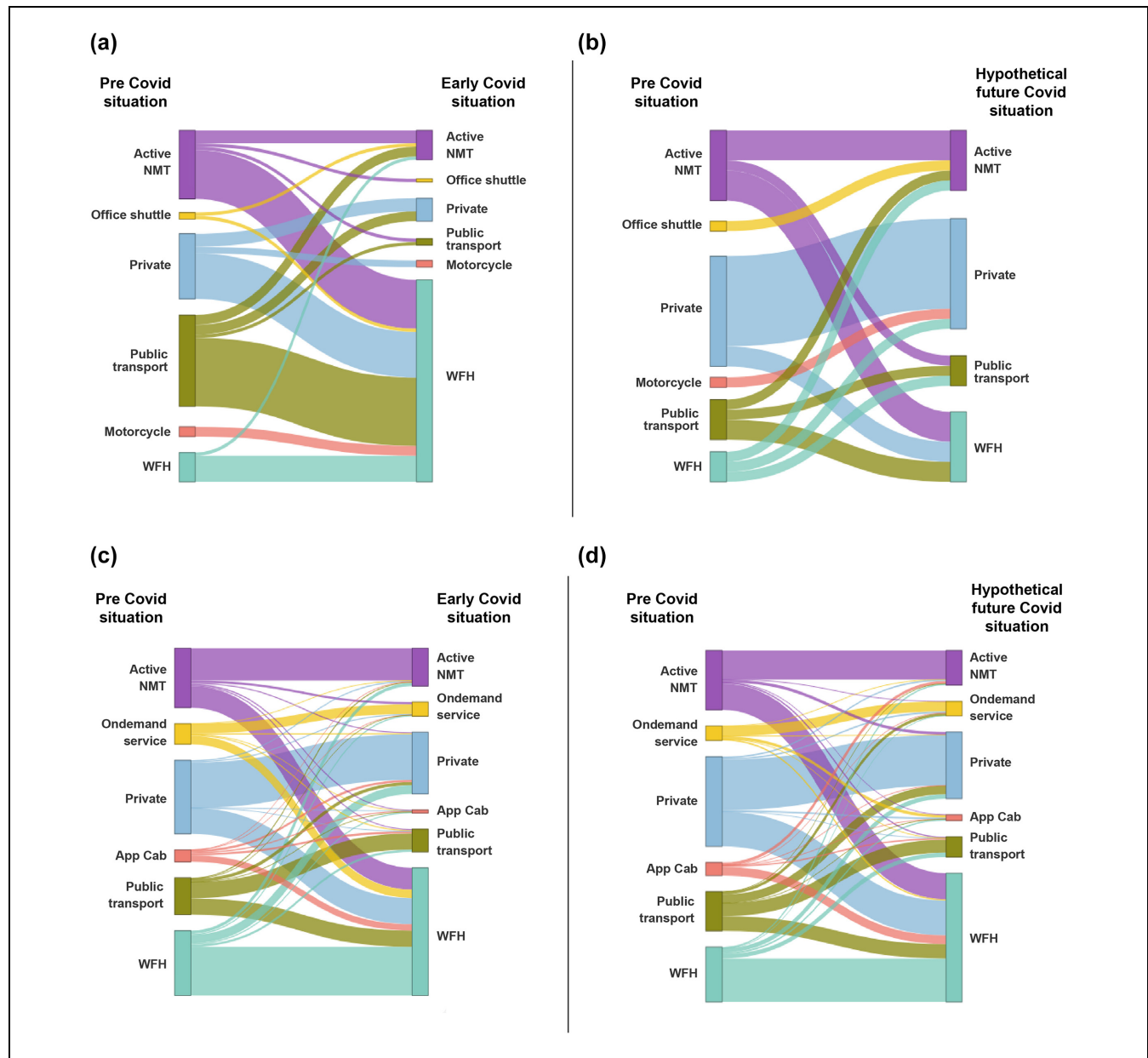


Figure 5. Inertia (measured in primary mode switching) of different modes: (a) RP data from Colombia, (b) SP data from Colombia, (c) RP data from India, and (d) SP data from India.

Note: RP = revealed preference; SP = stated preference.

principles, which are used to quantify how each of the influencing factors affects the mode-choice. The MDC nature of the choices presented, the interdependence among alternatives (i.e., travel and no travel), and the need to incorporate the people's perceptions of government efforts 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 estimate the different travel modes' utility, both periods (i.e., before and during COVID-19) were tested, considering the varying characteristics of both the alternatives and the travelers.

The latent variable (i.e., perception of government) 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).

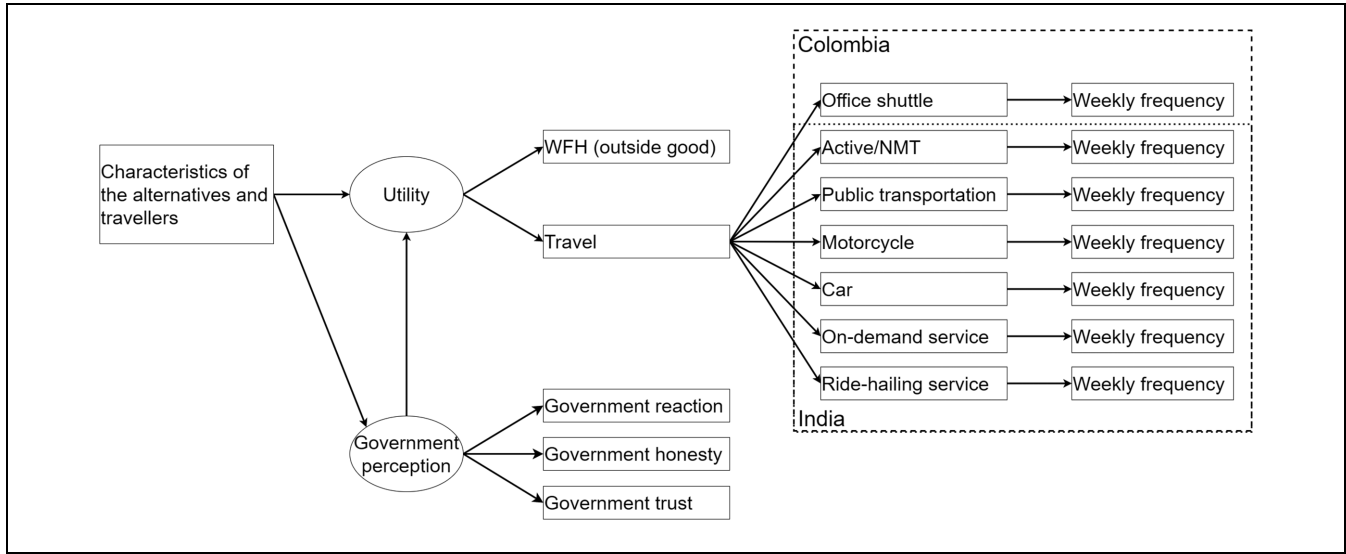


Figure 6. Graphic representations of the tested HMDCNEV model.

Note: HMDCNEV = hybrid multiple discrete-continuous nested extreme value.

$$y_0^* = \tilde{\delta} + \tilde{d}z^* + \tilde{\xi} \quad (1)$$

where

y_0^* represents the indicator vector identifying the latent variable (i.e., perception of government),

$\tilde{\delta}$ 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).

$$z^* = \omega\rho + \eta \quad (2)$$

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).

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

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.

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

where

β' is a coefficients vector associated with z_k ,

z_k is the set of attributes characterizing the individual and the alternative k ,

λ is the coefficient matrix associated with the latent variable, and

ε_k are the unobserved attributes that affect 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 to be 14, considering a displacement of two times a day for seven days a week. In an extension to this, we assume the outside good as those not traveling (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 a 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 commuting 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 U.S. citizen (39). Therefore, we assumed 1.5 times of the reported trips as the budget, which works out as 13.12 (14 trips after rounding off) weekly trips. Furthermore, increasing the

budget would mean higher consumption of outside goods, that is, WFH which might lead to erroneous estimation of respondents' preferences toward it. In the case of Colombia, the Home Travel Survey found that in 2019 the respondents traveled 1.96 times a day, on average, for commuting purposes (28). This number of daily trips aligns with the value presented before (i.e., two trips per day and 14 trips a week). Therefore, the total for 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 behavior from before COVID to the early COVID period, no price variations among alternatives have been considered. Moreover, 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 from an assumption that the absence of satiation effects in mode-choice decisions which are expected to be largely driven by trip-related attributes and the availability of alternatives.

With regard to 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 to no-vehicle owning households and having zero usage. In addition, in one specific SP scenario (Table 3), that is, full lockdown, public transport was not considered 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 modeling 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 modeling mode and trip frequencies that explicitly includes perceptions of the travel choices during COVID-19.

Results and Discussion

Three sets of variables have been used to understand the change of commuting behavior during COVID as compared with the pre-COVID situation: (i) socio-demographic variables; (ii) pre-COVID travel behavior (termed as inertia); and (iii) the latent variable related to the perceptions of government responses to the 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; the alternative specific constants for each mode are then depicted, followed by the coefficients related to the characteristics of the alternatives and travelers influencing the utilities. Finally, the hybrid part through the latent variable inclusion is given.

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 during the pandemic, which at first sight suggests a counter-intuitive result for the Colombian case. This finding is linked to a significantly increased propensity (see Table 6) to 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 of conventional attributes (e.g., travel time) (3, 7, 8, 21, 48).

With regard to socio-demographics in Colombia, the model suggests a declining propensity to choose active modes among female respondents both before and during the pandemic. This negative propensity can be explained by the suggestion of Sagaris and Tiznado-Aitken (49),

Table 6. Estimated Results for Commute Activities in Colombia

Model parameters	Pre-COVID		During COVID	
	Estimate	Robust t-stat	Estimate	Robust t-stat
Alternative specific constants				
Outside good (base)	0 (fixed)	na	0 (fixed)	na
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	na	na	−0.12	−2.59 (**)
Public transport	na	na	−0.08	−1.72 (.)
Motorcycle	na	na	−0.11	−1.84 (.)
Structural model				
Owning bicycle	na	na	0.23	2.31 (*)
Owning car	na	na	−0.41	−1.68 (.)
More than 60 years	na	na	1.51	4.39 (***)
Graduate degree	na	na	0.27	2.58 (**)
Student	na	na	−0.44	−2.59 (**)
Measurement model				
Government reaction	na	na	1 (fixed)	na
Government honesty	na	na	4.11	4.16 (***)
Government trust	na	na	2.89	6.63 (***)
Satiation parameters				
Alpha base		1 (fixed)		
Gamma base		1 (fixed)		
Scale parameters	Estimate			Robust t-stat
No travel	1 (fixed)			na
Travel	0.27			19.45 (***)
mu_RP	1 (fixed)			na
mu_SP	0.91			0.97
Inertia				
RP	0.26			3.44 (***)
SP	0.12			0.97
Model information				
Number of individuals		269		
RP observations		531 ^a		
SP observations		537 ^a		
LL (0)		−10,649.26		
LL (final, whole model)		−7,569.74		
AIC		15,255.48		
BIC		15,576.40		

Note: WFH = working from home; RP = revealed preference; SP = stated preference; LL = log-likelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; na = not applicable.

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

^aThere were eight non-valid or unanswered observations (i.e., SP = 1, RP = 7).

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 commuting trips.

It was also found that there is an increase in the propensity of making more trips for those with higher incomes by using office shuttles/school buses 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 incomes 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 toward 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 in 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 situations, 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 that there was a higher likelihood of using the motorcycle in both periods.

With regard to subjectivity and the different government restrictions in response to COVID-19 (51), it is expected that the perception of the government response to COVID-19 will influence the transport mode used for commuting. In Colombia, we found a significant relationship between people's perceptions of government actions and a reduction in the use of active modes, public transport, and motorcycles. In other words, people with a positive perception of the effectiveness of government responses 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 were the ones that has a positive perception of the government response during the early COVID-19 outbreak. Cyclists' perceptions of government responses 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's reaction during the pandemic.

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. In the case of the pre-COVID period, 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, the 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 commuting behavior during COVID compared with the pre-COVID situation. The model results for India are in Table 7 which is organized in a similar way to the Colombian results.

Intuitively, the travel time coefficient for the Indian case is negative in the pre-COVID period, which corresponds to respondents preferring 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 during the pandemic, 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 for ride-hailing services during COVID for female commuters as compared with the pre-COVID period, whereas they avoid public transport as expected.

Furthermore, the model estimates suggest a declining propensity toward NMT modes among younger respondents, whereas a reverse trend (increasing propensity) can be observed for the car. In general, the preferences of young millennials before COVID agree with previous findings (52). Intuitively, the changes during the pandemic 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 for such households and the perceived usefulness of PVs in avoiding the crowding on 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

Table 7. Estimated Results for Commute Activities in India

Model parameters	Pre-COVID		During COVID	
	Estimate	Robust t-stat	Estimate	Robust t-stat
Alternative specific constants				
Work from home [#] (base)	0 (fixed)	na	0 (fixed)	na
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	na	na	-0.07	-0.58
Motorcycle	na	na	0.06	0.45
Public transport	na	na	0.07	0.91
Structural model	na	na		
Female	na	na	-0.29	-2.51 (*)
Measurement model				
Government reaction	na	na	1 (fixed)	na
Government honesty	na	na	1.87	5.65 (***)
Government trust	na	na	2.09	4.97 (***)
Satiation parameters				
Alpha base			1 (fixed)	
Gamma base			1 (fixed)	
Scale parameters	Estimate			Robust t-stat
No travel	1 (fixed)			na
Travel	0.51			15.38 (***)
mu_RP	1 (fixed)			na
mu_SP	1.02			10.78 (***)
Inertia				
RP	0.93			8.73 (***)
SP	0.94			7.65 (***)
Model information				
Number of individuals		557		
RP observations		1,114		
SP observations		664 ^a		
LL(0)		-11623.60		
LL(final, whole model)		-9656.12		
AIC		37,263.63		
BIC		37,656.96		

Note: WFH = working from home; RP = revealed preference; SP = stated preference; LL = log-likelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; NMT = non-motorized transport; na = not applicable.

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

^aIn an earlier stage of the survey, each respondent was asked about one SP scenario, whereas later it was increased to two SP scenarios.

[#]Work from home has been considered as an 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.

cars, on-demand services, and ride-hailing services during COVID, which could be attributed to avoidance of crowded travel modes given the contagious nature of 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 for low-income households which are expectedly low on vehicle ownership. A 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 the present literature, the results indicate that households that do not own PVs (cars and motorcycles) have a high affinity for NMT modes followed by public transport, on-demand services, and ride-hailing services (5). It is worth mentioning that their preference for low social distancing modes (generally overcrowded ones such as public transport and NMT modes) diminishes during COVID. 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 during COVID compared with before the pandemic. Intuitively, households with more than one bicycle have shown a greater preference for NMT modes before COVID, but this dwindles during the pandemic. This result may be driven by the overall propensity to opt for WFH and to avoid cycling (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 of the pandemic and modal preference in India. This result might be attributed to people in India developing self-protective behavioral 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 lower “jolt” to regular travel behavior, allowing the government to transcend effectively into newer travel norms. Also, the effect of inertia needs to be considered. This has been highlighted in both RP and SP scenarios. In addition, a significant association between the latent variable and socio-demographic variables, that is, gender, could be identified when considering the latent variable. It can be observed that women have a worse perception of government measures than their male counterparts which

might result from an inherent bias among the former on various social fronts. Duflo and Topalova (55) suggested that, in Indian society, women are less favorably 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 the government response is in line with an opinion poll in India which showed that “men are more likely than women to give Indian democracy a thumbs-up” (57). This information also coincides 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—the number of household members with COVID-like symptoms and government advisory (see government restrictions in Table 3)—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 an outside good) is higher relative to all other modes followed by motorcycle both before and during the pandemic. Furthermore, this preference increases during COVID as compared with pre-COVID times. In the case of the pre-COVID period, the ASC is lowest for ride-hailing services (−3.14), closely followed by on-demand services (−2.28), and NMT modes (−2.14). During COVID, ASC is the smallest for ride-hailing services (−2.73), followed by on-demand services (−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 in the India case), a decrease in the utility of traveling was shown since every ASC showed a lower coefficient for the utility during COVID than the ASC's coefficients from the pre-COVID period. When considering only mode preferences to commuting, changes have been found during the COVID-19 outbreak, as the literature suggested (2, 13), and different alternative and traveler 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 during COVID in both contexts. Abdullah et al. (13) found that during the pandemic, fewer people gave 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 the global context, as suggested by studies done in Australia (21) and the U.S.A. (48). Those pointed to a substantial increase in WFH since infection fear heavily influenced mode-choice decisions, which has altered perceptions of 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 behavior is shaping up with the emergence of virtual commute (for example, voluntary WFH replacing enforced WFH).

Our results reinforce the previous finding on the socio-demographic effect on mode changes during COVID-19 (e.g., gender, occupation) (13). On gender, the models suggest a decrease in the active modes' utility for women that are significant in both before and during the pandemic. The negative propensity during COVID could be explained by males traveling 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 the pandemic reduced 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 to be 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 toward WFH can incorporate the effects related to age. Therefore, such variables 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 in the Colombian case. Professionals saw their utility reduced when using active modes before the pandemic; however, during COVID-19 a significant utility increase was seen, suggesting a potential increase in the use of active modes. This is also reflected in the 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 pandemic. In line with the young people in India, the previously mentioned finding suggests that the young student population is a key stakeholder in 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 (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 behavior was observed and reinforced for those owning motorcycles in both countries, considering that the utility, when using the motorcycle has been found to be positive and significant during the COVID-19 period. Moreover, the non-availability of private modes results in no change in the utility for active, on-demand services, ride-hailing services, 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 frequencies has been previously observed in Colombia (3) and India (5, 6). However, when analyzing both mode choices and frequencies, the results suggest that a good perception of government responses to 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 during COVID-19, to avoid contagious risks. However, the approach has 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).

In addition, identifying speeders is a recommended practice, and this study implemented it to enhance the data set's 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 data set. This practice could not be followed for India, and the duration cut-off cannot be implemented.

Some limitations in 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 were not questioned 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 given 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 according to 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 with regard to 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 to understand how the travel patterns were modified by COVID-19. Moreover, a panel data set 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 behavioral 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 commuting 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: firstly, it develops and extends the use of the MDCEV modeling 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, people's perceptions of government responses to the pandemic influence usage of travel alternatives in Colombia but not in India. Secondly, the virtual mode (i.e., WFH) and physical modes were analyzed in separate nests (nested-HMDCEV or HMDCNEV) which better resemble the real-life scenarios. Thirdly, panel data within HMDCNEV model structure was incorporated, 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 in the RP and SP modes was estimated separately 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 commuting patterns between two Global South economies, Colombia and India. This allows us to check the transferability of travel behavior 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 modeling techniques is crucial to better understand travel behavior in developing nations. Within this perspective, two factors draw attention. The inclusion of subjective variables on choice models appears to provide insight into traveling decisions and political perceptions. In addition to typical trip-related and socio-demographics-related variables, the way people perceive their contexts and their governments' responses to, 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 when describing and modeling urban transportation in Global South cities.

Secondly, WFH proved once again its significance with transportation in cities, and the results showed that a nested structure can indeed be incorporated into transport modeling. This new mobility is going to be, at least in a small portion, organized toward some home-based working activities and therefore nesting a first "choice" (whether to WFH or not), before choosing a transportation mode will be need to be taken into account when developing the assignment part of the four-step model. This trend is undoubtedly here 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 and shown in the literature, people have increasingly 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-motorized alternatives also appear to be a somewhat preferred mode after the pandemic. This can provide a long-term solution to this issue. However, for non-motorized alternatives to be an acceptable mode, changes to the urban form are necessary. Among these changes, decision makers should grant an accessible city (e.g., oriented by the 15-min city concept) that allows the people to reach a vast and diverse offer of urban services within walking/cycling distances.

In the context of both countries, it was found that travel time became less relevant to explaining choices during the pandemic 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 motorized modes was likely to increase when compared with the pre-COVID period. Besides, there was 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 to use public transport needs actions that restrict virus spread, as proposed by the literature, accompanied by programs that incentivize people to use public transportation.

The model results suggest that socio-demographic 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 toward their mode usage. The study finds the young millennial group in India to be of specific interest as their inclination to using NMT modes reduces and likely use of car mode increased during the pandemic, as opposed to before. This is likely to create an unsustainable situation for urban transit, which needs to be addressed.

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

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.

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ORCID iDs

Jose Agustin Vallejo-Borda  <https://orcid.org/0000-0001-6873-1086>

Eeshan Bhaduri  <https://orcid.org/0000-0002-7020-0986>

Hernan Alberto Ortiz-Ramirez  <https://orcid.org/0000-0001-8807-2460>

Julián Arellana  <https://orcid.org/0000-0001-7834-5541>

Charisma F. Choudhury  <https://orcid.org/0000-0002-8886-8976>

Alvaro Rodriguez-Valencia  <https://orcid.org/0000-0002-4818-2195>

Arkopal K. Goswami  <https://orcid.org/0000-0003-1369-215X>

Supplemental Material

Supplemental material for this article is available online.

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