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Characterising public transport shifting to active and private modes in South American capitals during the COVID-19 pandemic

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ABSTRACT

During the year 2020, the COVID-19 pandemic affected mobility around the world, significantly reducing the number of trips by public transport. In this paper, we study its impact in five South American capitals (i.e., Bogotá, Buenos Aires, Lima, Quito and Santiago). A decline in public transport patronage could be very bad news for these cities in the long term, particularly if users change to less sustainable modes, such as cars or motorbikes. Notwithstanding, it could be even beneficial if users selected more sustainable modes, such as active transport (e.g., bicycles and walking). To better understand this phenomenon in the short term, we conducted surveys in these five cities looking for the main explanation for changes from public transport to active and private modes in terms of user perceptions, activity patterns and sociodemographic information. To forecast people's mode shifts in each city, we integrated both objective and subjective information collected in this study using a SEM-MIMIC model. We found five latent variables (i.e., *COVID-19 impact*, *Entities response*, *Health risk*, *Life related activities comfort* and *Subjective well-being)*, two COVID-19 related attributes (i.e., *new cases* and *deaths*), two trip attributes (i.e., *cost savings* and *time*), and six socio-demographic attributes (i.e., *age, civil status, household characteristics, income level*, *occupation* and *gender*) influencing the shift from public transport to other modes. Furthermore, both the number of cases and the number of deaths caused by COVID-19 increased the probability of moving from public transport to other modes but, in general, we found a smaller probability of moving to active modes than to private modes. The paper proposes a novel way for understanding geographical and contextual similarities in the pandemic scenario for these metropolises from a transportation perspective.

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1. Introduction and background

COVID-19, considered as a global pandemic by the World Health Organization (WHO) in March 2020, had caused over 1.6 million deaths by December 2020 (WHO, 2021). South America was one of the regions most affected by the virus: according to Johns Hopkins University (2020), by December 2020 seven of the 12 independent nations in the region were among the 30 nations with highest mortality rate per 100,000 inhabitants in the world.

The impact of COVID-19 in travel behaviour has begun to be studied and analysed in various contexts (Abdullah et al., 2020; Neuburger and Egger, 2020; Tirachini and Cats, 2020), but the long-term impacts are still uncertain. Wearing masks is a crucial measure to minimize the spread of the virus (Matuschek et al., 2020; Rab et al., 2020), and allowing a certain amount of social distancing (Milne et al., 2020), keeping bus frequencies (De Vos, 2020) and sustaining hygiene measures inside vehicles and stations, are all relevant measures to combat the general perception that using public transport may be unhealthy (Tirachini and Cats, 2020). However, and although social distancing has been viewed as a threat to public transport use (Beck et al., 2020; De Vos, 2020), it has also been suggested as an opportunity to promote travel by active transport modes (Brooks et al., 2020).

COVID-19 transmission has been reported to increase with factors such as metropolitan area population (Hamidi et al., 2020), air pollution (Zhang et al., 2020), and population density (Rashed et al., 2020). We look at these and other factors in the case of five Spanish-speaking capitals in South America: Bogotá, Buenos Aires, Lima, Quito and Santiago, which were selected to provide a comparable sample in terms of geographical and cultural contexts. Basic information about these cities is provided in Table 1.

In particular, Table 1 shows that by mid-November 2020, Bogotá and Buenos Aires were the most affected cities in terms of mortality rates and also had the highest COVID-19 incidence rates, with around one confirmed case per 20 inhabitants (although antibody test studies suggested that the real rate was much higher, Buenos Aires Ciudad, 2020). On another hand, with the exception of Quito, all capitals had a higher mortality rate than their country average, and even though the global effects of the pandemic were comparable among them, the peak impacts occurred on different dates (WHO, 2021).

Most South American countries undertook several measures to contain or mitigate the spread of COVID-19, such as closing schools, forbidding mass gatherings and implementing lockdowns and/or night curfews. However, their effect was hampered by social inequalities and poor strategies to test and track for the virus (Benítez et al., 2020). Regarding transportation, the main measures adopted to mitigate the transmission of COVID-19 in the cities under study are presented in Table 2. These measures limited the possibility of using public transport and favoured the switch to other modes, particularly during the first months of the pandemic, when various benefits were established for car drivers. As public transport is a mode with a naturally close contact between passengers, it was perceived as riskier than active and private motorised travel (Tirachini and Cats, 2020). The following paragraphs explain the changes from public transport to active modes and private motorised modes.

Table 1
Main information about COVID-19 for the selected cities (data from mid-November 2020).

City / Metropolitan Area[A]	Population	Confirmed cases	Confirmed deaths	Death rate / 100,000	City death rate / Country death rate[B]
Bogotá, Colombia	7.743.955[(1)]	356.711[(6)]	8.113[(6)]	104.80	1.53
Buenos Aires, Argentina	3.075.646[(2)]	153.670[(7)]	5.434[(7)]	176.70	2.22
Lima, Perú	10.804.609[(3)]	428.412[(8)]	16.229[(8)]	150.20	1.37
Quito, Ecuador	3.228.233[(4)]	63.555[(9)]	2.099[(9)]	65.00	0.85
Santiago, Chile	8.125.072[(5)]	301.207[(10)]	10.134[(10)]	124.70	1.58

Data sources:
[1] DANE (2019) Proyecciones de Población Departamental para el Periodo 2018–2050 (in Spanish). https://www.dane.gov.co/index.php/estadisticas-por-tema/demografia-y-poblacion/proyecciones-de-poblacion.
[2] INEC (2019) Proyecciones de Población por Sexo y Grupo de Edad 2010–2040, para cada Provincia (in Spanish). https://www.indec.gob.ar/indec/web/Nivel4-Tema-2–24-85.
[3] INEI (2019) Estimaciones y Proyecciones de Población por Departamento, Provincia y Distrito, 2018–2020 (in Spanish). https://www.inei.gob.pe/media/MenuRecursivo/publicaciones_digitales/Est/Lib1715/libro.pdf.
[4] INEC (2019) Proyección de la Población Ecuatoriana, por años Calendario, según Regiones, Provincias y Sexo, Periodo 2010–2020 (in Spanish). https://www.ecuadorencifras.gob.ec/proyecciones-poblacionales/.
[5] INE (2019) Estimaciones y Proyecciones de la Población de Chile 2002–2035 (in Spanish). https://www.ine.cl/estadisticas/sociales/demografia-y-vitales/proyecciones-de-poblacion.
[6] Observatorio de Salud de Bogotá (2019) Saludata (in Spanish) https://saludata.saludcapital.gov.co/osb/index.php/datos-de-salud/enfermedades-trasmisibles/covid19/.
[7] Gobierno Ciudad de Buenos Aires (2019) Parte Diario de Situación Sanitaria Covid-19 (in Spanish). https://www.buenosaires.gob.ar/coronavirus/noticias/actualizacion-de-los-casos-de-coronavirus-en-la-ciudad-buenos-aires (resident population only).
[8] Sala Situacional COVID-19 Perú (2019) https://covid19.minsa.gob.pe/sala_situacional.asp (in Spanish).
[9] Gobierno de la República de Ecuador (2019) Coronavirusecuador.com (in Spanish) https://www.coronavirusecuador.com/datos-provinciales/ ("deceased" + "probably deceased" included).
[10] Ministerio de Salud (2019) Casos confirmados en Chile COVID-19 (in Spanish). https://www.minsal.cl/nuevo-coronavirus-2019-ncov/casos-confirmados-en-chile-covid-19/.
[A] Data corresponding to: Bogotá – City; Buenos Aires – Inner City; Lima - City of Lima + El Callao Province; Quito - Pichincha Province; Santiago - Metropolitan Region. Data retrieved on November 16th, 2020.
[B] Country death rate/100,000 obtained from Johns Hopkins University (2020).

Table 2
Transport-related measures in the selected cities.

City	Bogotá	Buenos Aires	Lima	Quito	Santiago
Public transport					
Mandatory face masks in public transport	✓	✓	✓	✓	✓
Public transport restricted to essential workers		✓			
Crowding restrictions	% of maximum vehicle capacity	seated only (trains) / up to 10 persons standing (buses)	seated only	% of maximum vehicle capacity	
App-based seat reservation		✓(in trains)			
Other modes					
Temporary lanes for non-motorised transport	✓	✓	✓	✓	✓
Driver's license expiration extension		✓	✓	✓	✓
Temporary lift of on-street parking fares		✓		✓	
Temporary lift of car use restrictions	✓			✓	

COVID-19 significantly affected mobility in these five cities, particularly public transport patronage (Aloi et al., 2020; Jenelius et al., 2020). As an example, Fig. 1 shows the variation in mobility in Buenos Aires, the whole of Colombia and Santiago during 2020.

A sharp drop in mobility is observed in all cases in March 2020, coinciding with the arrival of COVID-19 to South America. Recovery begins in the following months, faster in Colombia and slower in the capitals of Chile and Argentina, where mobility by car recovered faster than walking, contrary to what happened in Colombia. This difference may be due to the lower availability of cars and motorbikes in rural areas. Now, although there are no disaggregate data that allows observing the evolution of public transport ridership in all the cities considered in this study, the available information shows a sharp decline in public transport use during 2020. For example, ridership of the Buenos Aires Metro fell by 76.6 % in 2020 compared to 2019 (Metrovías SA, 2021), in the Santiago Metro the decrease was 62.6% (Santiago Metro, 2021) and in the Bogotá BRT system it was approximately 50% (Transmilenio SA, 2021). The larger decline in public transport use, compared to driving and walking, suggests that some of its former patronage shifted to these other options (i.e., active and private transport).

1.1. Shifting to active and private motorised modes

An increase in bicycle use worldwide had been observed prior to the coronavirus outbreak, but data indicates that the mode share of bicycles and other forms of non-motorised transport have grown more strongly during the pandemic in many cities throughout the world (Aloi et al., 2020; Bucsky, 2020; Meena, 2020). The advantages of cycling were, of course, known before the pandemic. Indeed, there is a wide range of literature promoting cycling and walking to foster benefits in health, the environment and energy (Aldred et al., 2017; Arellana et al., 2020a, 2020b; Deenihan and Caulfield, 2014; Götschi et al., 2016; Oja et al., 2011).

Projects undertaken during the COVID-19 pandemic in London (United Kingdom), Melbourne (Australia) and Rome (Italy), but also in Bogotá and other cities in Latin America, are also proof that the expansion of cycling infrastructure has been recurrent almost everywhere. As shown in Table 2, all the capital cities built temporary and/or permanent bike lanes during the pandemic. In Bogotá, in particular, 76 km of temporary bicycle lanes were quickly created on the main streets, and added to 550 km of permanent bicycle lanes.

Notwithstanding, although the pandemic has been taken as an opportunity to promote the use of sustainable transport in the medium and long term, many users have shifted also from public transport to car. Beck et al. (2020) observed a rapid recovery in car travel during a phase when restrictions were relaxed in Australia, which could be explained by reasons of hygiene and perceived risk associated with the use of public transport. Given that various cities in South America adopted measures to reducing the cost of travelling by car, there may also be an economic incentive (hopefully unintended) towards greater use of private motorised transport in the region. Short-term spatial transformations, in immediate response to virus mitigation, have been recognised as an opportunity for initiating long-term radical transformation in cities, modifying not only the transport system but also land use planning (Honey-Roses et al., 2020). In this sense, it is relevant to know what types of users may be prone to modify their travel behaviour during a pandemic. To understand the users' decision process when both tangible and intangible (e.g., perceptions) elements enter into play, the use of latent variable models is recommended (Ortúzar and Willumsen, 2011).

Studies performed in different countries have found a decline in daily trips as a result of COVID-19, which affected particularly public transport (Aloi et al., 2020; Balbontin et al., 2021; Beck and Hensher, 2020; Bucsky, 2020). Indeed, for the five cities considered in our study, the most frequent shift corresponded to users who stopped travelling by public transport, as shown in Fig. 2 and Table 3 below[1]. The largest falls in public transport use were observed in Bogotá, Buenos Aires and Santiago. In the latter case, there was a

[1] The Sankey diagrams were built using data from the surveys presented in section 2.2 and the R package "networkD3" (Allaire et al., 2017; R Core Team, 2020). The data were corrected with the R package "survey" (Lumley, 2020; R Core Team, 2020), using age and gender information from each city.

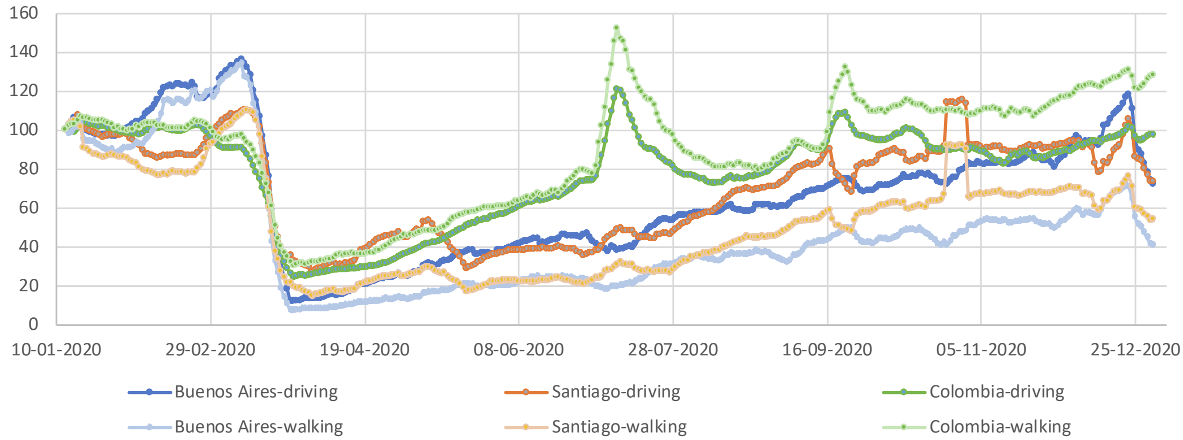

Fig. 1. Mobility trends in certain cities during 2020. Data source: Apple Mobility Trends, 2021 (https://covid19.apple.com/mobility) 7-day moving average was applied to the original data.

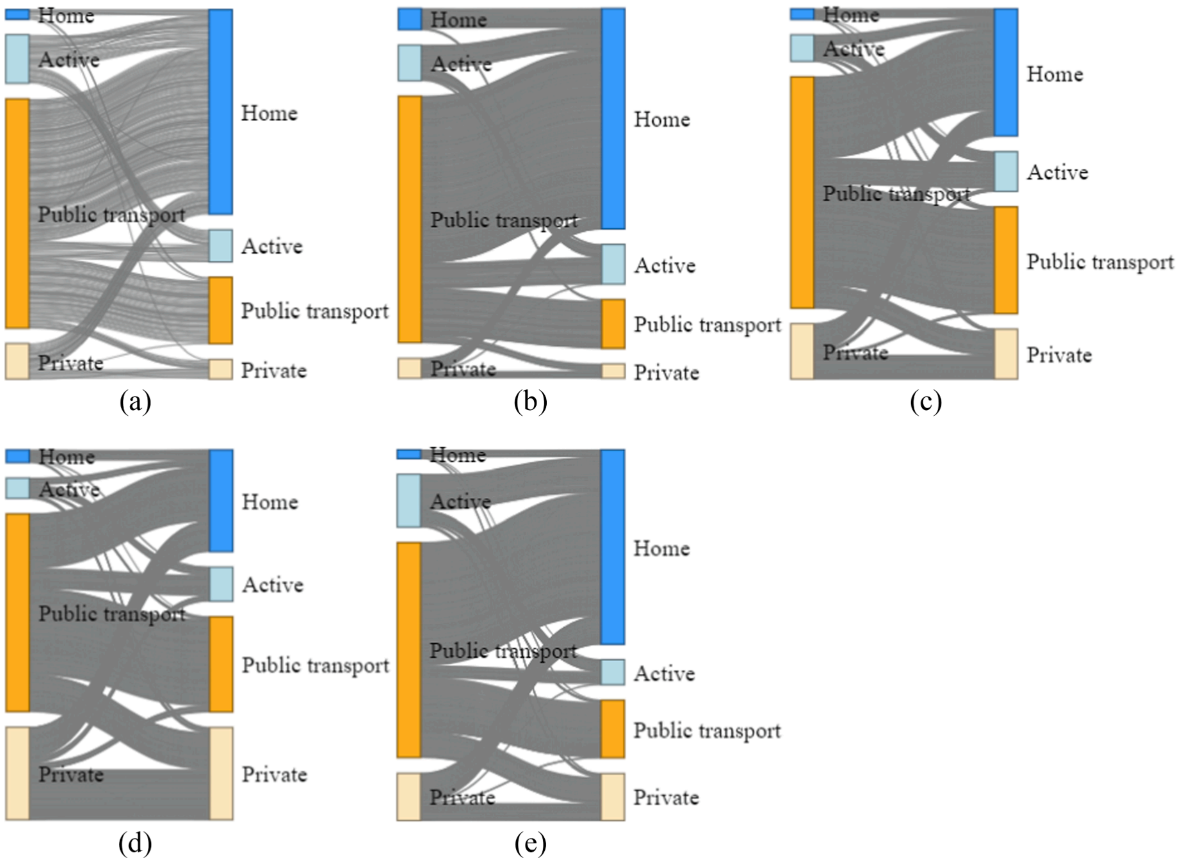

Fig. 2. Modal shifting for (a) Bogotá, (b) Buenos Aires, (c) Lima, (d) Quito, and (e) Santiago.

formal restriction on public transport use (see Table 2). These three cities also recorded the highest growth in *working from home* (i.e., Home in the diagrams).

We are interested in understanding the short-term mobility impacts of the coronavirus outbreak in a Latin American context. Specifically, the travel behaviour motivations that produce shifts from public transport to active modes and private motorised vehicles. In this quest, we estimated a Structural Equation - Multiple Indicator Multiple Cause (SEM-MIMIC) model to identify which kinds of users had a propensity to change from public transport to other modes. This could be useful to design public policies aimed at sustainable urban mobility. The paper focus on revising the short-term impacts of COVID-19, but we are also planning a second wave of

Table 3
Modal shifting values for this study's sample.

		Bogotá [%]	Buenos Aires [%]	Lima [%]	Quito [%]	Santiago [%]
Before COVID-19	Work from home	2.95	6.59	3.27	3.94	2.73
	Active	15.08	10.96	8.14	6.28	16.31
	Public transport	70.96	76.30	71.51	61.15	66.38
	Private	11.01	6.15	17.08	28.64	14.58
Wave 1	Work from home	63.33	68.22	39.30	31.47	60.00
	Active	9.94	12.23	12.31	10.54	7.69
	Public transport	20.61	15.11	33.01	29.45	17.81
	Private	6.12	4.45	15.38	28.53	14.50

surveys to study longer term effects.

The contributions of this study are: (i) a comparison of the COVID-19 effects in five capital cities in South America, showing the diversity of contexts in the region; these cities are comparable in geography and language and were strongly impacted by the pandemic; (ii) a discussion of the factors that influence subjective preferences towards mode shifts (i.e., public transport to active modes, and public transport to private motorised modes) in a South American context.

The rest of the paper is organised as follows. Section 2 discusses the methodology, explaining the model formulation and data collection process. Section 3 presents and discuss the estimated model, which seeks to explain the shifting decision from public transport to active and private modes. Section 4 presents the limitations and possible extensions of this study. Finally, section 6 summarises our main conclusions.

2. Methodology

A classic approach to explaining the shift from public transport to active and private motorised modes would consider objective attributes of the alternatives, such as travel times and cost, and user characteristics, such as gender, age and income. However, attitudes and perceptions have been recently incorporated to identify latent variables representing intangible elements (e.g., well-being) that can be used to improve our understanding of the cognitive process and the effects of objective information (e.g., sociodemographic attributes) in shaping individual choices (Bahamonde-Birke et al., 2017; Vij and Walker, 2016).

The COVID-19 outbreak has obviously impacted life and subjective well-being (Blasco-Belled et al., 2020; Möhring et al., 2020). Studies about subjective well-being have gained attention to explain travel behaviour and the impacts of using active transport in the last years (Dolan and White, 2007; Kahneman and Krueger, 2006). The measurement of well-being in transportation has been mainly explored through satisfaction with travel scales (Bergstad et al., 2011); however, more recent studies have shown that positive subjective well-being is also related to several other dimensions. For instance, active travel is associated with improvements in physical and mental health (Humphreys et al., 2013; Martin et al., 2014), happiness (Kroesen and De Vos, 2020), overall hedonic well-being (Singleton, 2019), satisfaction compared to travel by car or public transport (Ettema et al., 2011; Olsson et al., 2013), and even sociability (Wang and He, 2015).

Peoplés responses to the COVID-19 outbreak are influenced by different elements, where trust in institutions and governments plays a key role (Bavel et al., 2020). Public entities have taken action by limiting people's movements to face the virus, impacting their ability to perform activities, such as shopping and working (Güner et al., 2020). Besides, Benítez et al. (2020) have argued for the need to explore how the pandemic management, in terms of communication and coordination at different governmental or private levels and of diverse agents, has influenced not only the health system capacity and the contagion rate, but also travel behaviour and mode choice.

Community participation has also been crucial during the coronavirus pandemic (Marston et al., 2020), and collective responses to restrictions, lockdowns and measures have proved helpful in previous epidemics (Güner et al., 2020). Community, geographic location and epidemiological criteria must act together (Bispo Júnior and Brito Morais, 2020).

The intangible elements to explain shifting choice have to incorporate the elements mentioned above. To capture this information, we need to collect information that captures people's perceptions. In this case, we are interested in peoplés perceptions about the impacts of COVID-19 on health, life and subjective well-being, and the general activities (e.g., leisure, shopping, work); we are also interested in peoples' perceptions about the entities and community response against COVID-19.

2.1. Data collection

An online survey was applied in Bogotá, Buenos Aires, Lima, Quito and Santiago. The questionnaire was based on one developed by Beck and Hensher (2020) and Beck et al. (2020). The design process included an initial translation of the original instrument to Spanish and a contextualization for each city (although everybody speaks Spanish, each country has different idioms and word usages). Before launching the survey, a pilot was applied in each city. The questionnaire included: (i) an initial section about travel activity and mode choice in a typical week both before and during the COVID-19 outbreak; (ii) employment information, including the ability to work from home and the respondent's role at work; (iii) potential impacts of COVID-19 in respondents' lives, including questions related to ordinary activity changes (e.g., go shopping); (iv) respondents working from home were asked about that experience; (v) attitudinal questions and perceptions about government, businesses, and people in general, related to facing the COVID-19 outbreak, and (vi) socio-demographic information.

We used the platform *SurveyMonkey* to make the questionnaire accessible online using a web link for each city. Participation was solicited on social media platforms including *Facebook*, *Instagram*, *LinkedIn* and *Twitter*. Paid publicity was also hired in all the cities to increase participation through *Facebook* and *Instagram*, showing the survey advertising to people over 18 living within 40 km from each city centre. To avoid multiple responses from the same respondent, we used cookies especially provided by *SurveyMonkey*.

We seek to explain the mode chosen before and during the COVID-19 outbreak through attitudinal questions, sociodemographic information, data on new cases and deaths, and time and cost savings indicators. Table 4 presents the different questions used to capture people's perceptions about the COVID-19 impact on respondents' health, life and subjective well-being, the entities and community response against COVID-19, and the comfort associated with doing general activities.

Table 5 presents the objectively measured information collected in the surveys. Three secondary variables were calculated based on the objectively measured attributes shown: *corrected equivalent income, time* and *cost savings*. The first was calculated following the guidelines of Departamento de Operaciones División de Focalización (2019), as the ratio of the reported *household income* and a *needs index* related with household size and the presence of children at home[2].

Using this information, the level *low income* was as assigned to those with a corrected equivalent income lower than 80% of the minimum wage for each country, *middle income* to those with a corrected equivalent income between 0.8 and 4 minimum wages, and *high income* to those with a corrected equivalent income higher than 4 minimum wages for each country. On the other hand, *time saving* was taken as the difference between the trip duration prior to COVID-19 and during COVID-19. *Cost saving* was calculated similarly and corrected afterwards, by dividing it into the corrected equivalent income. Finally, we also included data about the new cases and deaths reported the day before the respondents answered the questionnaire[3].

Table 6 shows the socio-demographic data of the sample for each city survey, as well as gender, age and income proportions for the population of each city. After data cleaning and validation, we obtained 282 valid responses for the study in Bogota, 779 in Buenos Aires, 924 in Lima, 896 in Quito and 922 in Santiago. The responses from people who completed the survey in less than two minutes were dropped from the dataset to enhance the dataset quality (Barrero et al., 2021). The surveys were conducted in September 2020 (except for Quito, where part of it was also taken in October and November); completion time took 12–14 min on average, and the completion rate varied from 45% in Bogotá to 56% in Santiago.

2.2. Modelling approach

We initially conducted an exploratory factor analysis (EFA) using the indicators in Table 5, and a PROMAX oblique rotation method to allow correlations between the latent variables (Hair et al., 2014). The EFA results helped us identifying several latent variables, based on the groupings presented in Table 4 and confirmed using a screen test, but kept only those with eigenvalues greater than one. Then, we specified a SEM-MIMIC model to test the direct effects of the latent variables over the dependent variables, keeping only those effects with 90% or higher significance. If the direct effects were not significant, we tested the indirect effects of the latent variables over the dependent variables through other latent variables with statistically significant direct effects (Vallejo-Borda et al., 2020). Finally, the dependent variables and the latent variables with a significant relation over them were explained by objectively measured attributes (see Table 5), keeping only those significant over the 90% level.

We aimed to explain mode shifts from public transport modes (e.g., BRT) to active (e.g., walk, bicycle) and private modes (e.g., car, motorcycle), using people's perceptions and sociodemographic information. We compared the respondent's mode choices for a typical week both prior and during the COVID-19 outbreak to obtain each dependent variable. If the respondents' mode choice was public transport in the typical week prior to the COVID-19 outbreak and active or private transport during the outbreak, we assigned a value of 1 for the corresponding model; if there was no change, we assigned a value of 0. To forecast people's shifts from public transport to active and private modes in each city, we integrated the objective and subjective information using the SEM-MIMIC model, the generic structure of which is shown in Fig. 3.

SEM-MIMIC models have latent variables ($\boldsymbol{\eta}$), indicators ($\mathbf{y}$), and objectively measured attributes ($\mathbf{x}$). As shown in Fig. 3, the SEM-MIMIC structure can be divided into a *measurement model*, given by equation (1), and a *structural model*, given by equation (2):

$$\boldsymbol{y} = \boldsymbol{\Lambda}_y \boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{1}$$

$$\boldsymbol{\eta} = \Gamma \boldsymbol{x} + \boldsymbol{\zeta} \tag{2}$$

where $\boldsymbol{y}$ represents the vector of indicators used to identify each latent variable (i.e., the subjective information presented in Table 4); Λ_y is a vector of coefficients weighing the change in the value of the indicators if there is a one-unit change in the latent variable; $\boldsymbol{\eta}$ is the vector of latent variables; $\boldsymbol{\varepsilon}$ is an error vector associated with each indicator; Γ is a row vector of structural parameters, indicating the change in the value of the latent variable if there is a one-unit change in the objectively measured attributes; $\boldsymbol{x}$ is the column vector of objectively measured attributes, and $\boldsymbol{\zeta}$ is an error vector associated with each latent variable. We assumed that the error terms ($\boldsymbol{\varepsilon}$ and $\boldsymbol{\zeta}$)

[2] Needs index = $N^{0.7}$ + 0.4 (Ch between 0 and 4) + 0.29 (Ch between 5 and 8) + 0.29 (Ch between 8 and 12) + 0.11 (Ch between 12 and 18) + 0.34 (Ch older than 18), where N is household size and Ch the number of children in the home.

[3] This information was obtained from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (https://github.com/CSSEGISandData/COVID-19).

Table 4
List of indicators and corresponding questions.

Indicator	Question (response labels)
Leisure and shopping comfort	
Going to pubs	How comfortable would you feel about completing these activities at the moment? (very uncomfortable, uncomfortable, neither, comfortable, very comfortable)
Going to the movies	
Eating in restaurants	
Watching live entertainment	
Working out in the gym	
Going to school	
Shopping	
Doctor's appointments	
Playing sports	
Entities response	
The national government response is appropriate	How much you agree or disagree with the following statements (totally disagree, disagree, neither disagree nor agree, agree, totally agree)
The Government COVID-19 strategy was adequate	
I trust the nation to confront COVID-19	
The municipal government response is appropriate	
Health risk	
For myself	On a scale of 1 (extremely low risk) to 5 (extremely high risk), how much of a threat do you think COVID-19 is to the following?
For people I know	
For other people	
Preoccupation about public transport's hygiene	What is your level of concern about hygiene on public transport today? (not at all concerned, slightly concerned, somewhat concerned, moderately concerned, extremely concerned)
Community actions	
Adequate social distance	People have been keeping appropriate social distancing as a measure to combat COVID-19 (totally disagree, disagree, neither disagree nor agree, agree, totally agree)
Adequate self-isolation	People have been appropriately self-isolating as a measure to combat COVID-19 (totally disagree, disagree, neither disagree nor agree, agree, totally agree)
Appropriate community response	The response of the wider community to COVID-19 has been appropriate (totally disagree, disagree, neither disagree nor agree, agree, totally agree)
Comfort with life related activities	
Meeting with friends	How comfortable do you feel about completing these activities at the moment? (very uncomfortable, uncomfortable, neither, comfortable, very comfortable)
Meeting with relatives	
Attending work functions	
COVID-19 impact	
COVID-19 is a serious public health concern	How much do you agree or disagree with the following statements (totally disagree, disagree, neither disagree nor agree, agree, totally agree)
COVID-19 requires drastic measures	
COVID-19 will affect travel	
Subjective well-being	
Life is worth it	To what extent do you feel that the things you do are worthwhile? (not at all worth it, not worth it, indifferent, worth it, completely worth it)
Happiness	How happy did you feel yesterday? (completely unhappy, unhappy, neither unhappy nor happy, happy, completely happy)
Life satisfaction	How satisfied are you with your life nowadays? (totally dissatisfied, dissatisfied, neither dissatisfied nor satisfied, satisfied, totally satisfied)

Table 5
Objectively measured attributes.

Variable	Options/unit
Gender identity	Female, male*
Age	[years]
Occupation	Unemployed*, employer, employee, self-employed, student
Marital status	Single*, living together (married, domestic partnership), union dissolved (divorced, separated)
Household income level	Different ranges for each country depending on the minimum wage
Household size	[number]
Number of children at home	[number]
Travel duration prior to COVID-19	[min]
Travel duration during COVID-19	
Travel cost prior COVID-19	[in each country's currency]
Travel cost during COVID-19	

* Used as the base in the models presented in Section 3.

Table 6
Basic socio-demographic data of sample and population.

Indicator	Bogota	Buenos Aires*	Lima	Quito	Santiago	Total
Gender						
Female	42.14% (53%)	63.58% (51%)	49.78% (51%)	54.11% (51%)	65.65% (51%)	56.89%
Male*	57.86% (47%)	36.42% (49%)	50.22% (49%)	45.89% (49%)	34.35% (49%)	43.11%
Age						
18 – 25*	19.50% (19%)	5.26% (19%)	19.59% (20%)	9.71% (15%)	8.46% (17%)	11.62%
26–40	60.28% (29%)	64.06% (31%)	58.77% (33%)	71.09% (39%)	76.46% (31%)	67.16%
41–60	19.86% (31%)	24.90% (30%)	18.72% (31%)	18.42% (32%)	13.88% (33%)	18.83%
Older than 60	0.35% (21%)	5.78% (20%)	2.92% (16%)	0.78% (14%)	1.19% (19%)	2.39%
Income						
Low income*	57.09% (67%)	23.36% (47%)	50.65% (63%)	61.50% (66%)	26.90% (33%)	42.33%
Middle income	36.88% (31%)	62.64% (51%)	40.69% (36%)	35.83% (33%)	53.15% (62%)	46.78%
High income	6.03% (2%)	13.99% (2%)	8.66% (1%)	2.68% (1%)	19.96% (5%)	10.89%
Occupation						
Unemployed*	23.13%	10.29%	9.34%	19.95%	8.15%	12.76%
Employer	2.24%	1.67%	3.71%	2.95%	1.25%	2.41%
Employee	55.60%	72.6%	56.81%	51.24%	77.01%	63.51%
Self-employed	13.81%	12.38%	19.35%	18.65%	9.29%	14.92%
Student	5.22%	3.06%	10.80%	7.20%	4.30%	6.41%
Marital status						
Single*	55.76%	52.23%	61.88%	54.34%	65.83%	58.64%
Living together	40.65%	38.22%	34.06%	39.46%	29.68%	35.61%
Union dissolved	3.60%	9.55%	4.05%	6.20%	4.49%	5.75%

Note: The population proportions are presented in parenthesis without decimals for readability and were obtained from each city's last census, except for Bogotá, where it was obtained from the last OD survey.
* Used as the base in the models presented in Section 3.

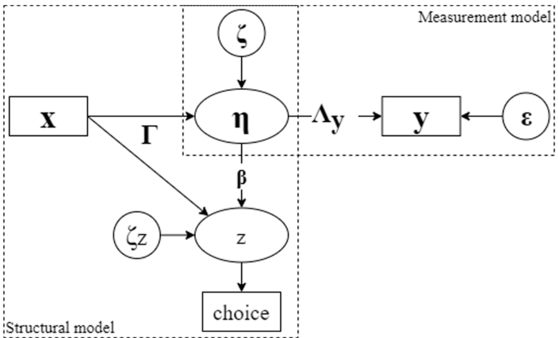

Fig. 3. Generic SEM-MIMIC model.

distribute Normal with an expected value of 0 and unit variance.

The complete model was estimated using the function "sem" of the R package "lavaan" (R Core Team, 2020; Rosseel, 2012). Choice was defined as a binary variable, and we used a diagonally weighted least squares algorithm to estimate the model parameters. To forecast choices, we need to calculate an unobserved variable $\boldsymbol{z}$ using equation (3):

$$z = \boldsymbol{\beta}\boldsymbol{\eta} + \Gamma\boldsymbol{x} + \zeta_z \tag{3}$$

where $\boldsymbol{\beta}$ is a vector of parameters indicating the change in the value of $\boldsymbol{z}$ if there is a one-unit change in the latent variables $\boldsymbol{\eta}$, and ζ_z is the error associated with z, which is also assumed to distribute Normal with an expected value of 0 and unit variance. Then, to categorize the obtained value of **z**, it has to be compared with a threshold (μ) that is estimated jointly with the other model parameters. If z is lower or equal to μ the choice is considered as no shift from public transport to the other modes, and if z is higher than μ, the choice is a shift from public transport to either private or active modes, depending on the evaluation.

As the parameters related to the objectively measured attributes reflect these attributes' metrics, they cannot be directly compared. To make them comparable, we also calculated their standardized coefficients indicating the expected increase of the dependent variable in standard deviation units. Relationships with standardized coefficients close to 0.1 are usually considered *weak*, those with values close to 0.3 are usually considered *medium* effects, and those higher than 0.5 are considered *large* effects (Gana and Broc, 2019). Here, we assumed that standardized coefficients below 0.1 were weak effects, those between 0.1 and 0.5 were medium effects and those higher than 0.5 were considered large effects.

All the assumed relationships are considered simultaneously in the SEM-MIMIC model, and goodness-of-fit is evaluated using the indicators described in Appendix 1, which have been classified as *absolute*, *incremental* and *parsimonious*. We used three absolute indicators, normed χ^2, goodness-of-fit index (GFI) and standardized root mean residual (SRMR); two incremental indicators, Tucker Lewis index (TLI) and comparative fit index (CFI), and one parsimonious indicator, root mean square error of approximation (RMSEA). Note that the latter can also be found in the literature as an absolute indicator (Gana and Broc, 2019).

3. Results and discussion

From seven potential latent variables, only five were finally considered: (i) *Subjective well-being*, *Entities response* and *Life-related activities comfort,* which represent "positive" constructs; (ii) *Health risk,* which represents a "negative" construct, given the indicators used to identify them, and (iii) *COVID-19 impact*, which may represent either a positive or a negative construct, as the indicators used to identify its impact may be perceived positively or negatively depending on the respondent's perspective. Fig. 4 shows the graphic representation of the estimated SEM-MIMIC model; the relationships with positive coefficients are represented in green, and those with negative coefficients in red. The model appears to fit the data well and we did not conduct *post-hoc* modifications given its good fit[4]. We will analyse each component of this figure in turn.

3.1. Measurement model results

The *measurement model* component of our SEM-MIMIC model considers five latent variables explained by 17 indicators (measured through the online surveys in each city). The coefficients and *t*-test associated with the relationship between latent variables and indicators in this model are presented in Table 7. As can be seen all effects are highly significant, and can be considered either medium or strong.

3.2. Structural model results

Table 8 shows the estimated coefficients of the structural model depicted in Fig. 4, where the medium and high effects are shown in bold. Note that this strength is not always associated with a higher significance of the estimated coefficient.

3.2.1. Analysis of the latent variables' effects

As mentioned in the introduction, the COVID-19 pandemic has brought drastic changes in daily life patterns, including reductions in the number of trips and changes in mode choice (De Vos, 2020; Guzman et al., 2021; Tirachini and Cats, 2020). Our results partially support this information by suggesting that although the perceived *COVID-19 impact* influences the decision to shift from public transport to private modes, it does not influence the change to more sustainable active transport modes. Besides, our findings indicate that the perceived *COVID-19 impact* also acts as a mediator to include the effect of other subjective attributes (i.e., *Subjective well-being*, *Entities response*, *Life-related activities comfort* and *Health risk*) in the decision to shift to private modes.

Considering *Subjective well-being*, it is interesting to note that the literature reports improvements in several well-being dimensions when using active modes (Ettema et al., 2011; Humphreys et al., 2013; Kroesen and De Vos, 2020; Martin et al., 2014; Olsson et al., 2013; Singleton, 2019; Wang and He, 2015), whilst our model suggests the opposite relation. In particular, people who reported higher *Subjective well-being* appear more likely to shift to private modes and less likely to shift to active modes. This finding could be related to the social stigma associated with bicycles (i.e., being mainly used by poor people) in certain countries of the region (Gómez et al., 2005; Rosas-Satizábal and Rodriguez-Valencia, 2019). Notwithstanding, our results also indicate a relevant role for *Subjective well-being* as a mediator to explain the shifting decision to active modes, and indirectly to private modes for the perceived *Entities response* and *Life-related activities comfort*. Also, given that *Subjective well-being* is explained by three indicators, among which *Life satisfaction* is the most relevant in terms of weight, and that the average income of individuals switching to private modes is significantly higher than for the rest, we could posit that the higher *Subjective well-being* reported by new car or motorcycle users is possibly explained by wealth rather than by their choice of mode.

The management of the COVID-19 outbreak by the government may also influence travel behaviour (Benítez et al., 2020), suggesting an interest in understanding how people's perception of the *Entities response* may influence their modal shift decisions. Our results establish an indirect relationship between the perceived government *Entities response* and modal shift with a similar effect to *Subjective well-being* in the shifting decision; in other words, people who reported higher perceived *Entities response* were more likely to shift to private modes and less likely to shift to active modes. This relationship can be explained by the positive influence of the

[4] The normed χ^2 is 2.992; GFI is 0.987; SRMR is 0.042; TLI is 0.997; CFI is 0.991; and RMSEA is 0.023.

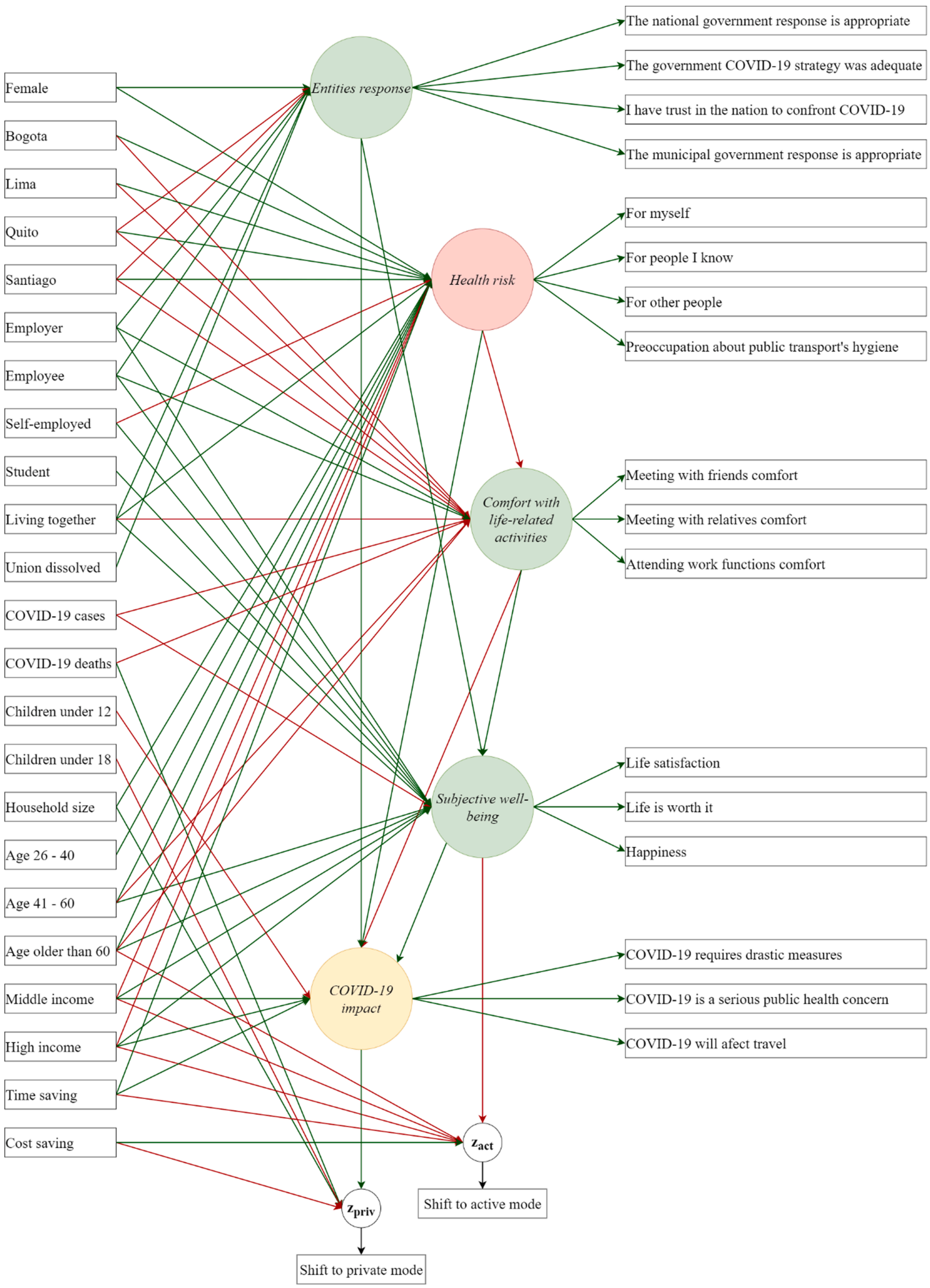

Fig. 4. SEM-MIMIC model of shifting from public transport to private and active modes.

Table 7
Parameters of the measurement model.

Latent variable	Indicator	Coefficient (*t*-test)	Standardized coefficient
COVID-19 impact	COVID-19 requires drastic measures	1.000 (fixed)	–
	COVID-19 is a serious public health concern	0.985 (32.12)	0.827
	COVID-19 will affect travel	0.483 (19.85)	0.412
Subjective well-being	Life satisfaction	1.000 (fixed)	–
	Life is worth it	0.666 (20.01)	0.663
	Happiness	0.662 (19.68)	0.659
Entities response	Appropriate national government response	1.000 (fixed)	–
	The Government COVID-19 strategy was adequate	0.965 (146.36)	0.900
	I trust the nation to confront COVID-19	0.912 (132.60)	0.854
	Appropriate municipal government response	0.623 (54.15)	0.596
Health risk	For myself	1.000 (fixed)	–
	For people I know	0.980 (81.58)	0.867
	For other people	0.940 (77.79)	0.837
	Preoccupation about public transport's hygiene	0.597 (30.80)	0.554
Life-related activities comfort	Meeting with friends	1.000 (fixed)	–
	Meeting with relatives	0.887 (40.73)	0.832
	Attending work functions	0.508 (29.18)	0.484

perceived *Entities response* on the people's perceived *Subjective well-being* suggested by our model.

Blasco-Belled et al. (2020) reported that changes in daily life activities impact people's lives. Similarly, our model suggests that perceived *Life-related activities comfort* influences the shifting decision from public transport to private and active modes in a similar way. In other words, we found a decrease in the probability of shifting from public transport to the other modes for people who feel higher *Life-related activities comfort*. This finding can be explained by the positive relationship found between the perceived *Life-related activities comfort* and *Subjective well*-being, and the negative relationship between the perceived *Life-related activities comfort* and the perceived *COVID-19 impact* reported in our model. A higher number of COVID-19 cases also affected negatively the level of comfort with daily activities in Australia (Beck and Hensher, 2021).

Perceived health risks associated with COVID-19 have also been reported as motivators to reduce interactions between people, discourage commuting trips, and alter cities' usual daily activity patterns (De Vos, 2020; Guzman et al., 2021; Tirachini and Cats, 2020). Our results suggest that a higher perceived *Health risk* is associated with an increase in the probability to shift from public transport to other modes. This finding is consistent with reports stating that public transport is perceived as a risky mode in terms of contagion (Abdullah et al., 2020; Barbieri et al., 2021; Moslem et al., 2020). Higher levels of perceived *Health risk* increased the perceived *COVID-19 impact*, which is associated with an increase in the propensity to shift from public transport to private modes. In other words, higher levels of perceived *Health risk* may, as reported in previous studies, discourage public transport use (Beck and Hensher, 2021) and also encourage the use of private modes (Beck et al., 2020). Besides, the perceived *Health risk* also negatively influences the latent variable *Life-related activities comfort*, increasing it the propensity to shift from public transport to other modes.

The objectively measured attributes presented in Table 5 also influence the decision to shift from public transport to private and active modes, both directly and indirectly through the latent variables. Household information, COVID-19 numbers (in terms of new cases and deaths), and time and cost savings, directly influence the decision to shift to private modes. On the other hand, the age, income level, and time and cost savings, directly affect the decision to shift to active modes. Besides, the latent variable *COVID-19 impact* is identified as a mediator to include the influence of household information, income level, and time and cost savings. *Subjective well-being* is identified as a mediator of the effect that occupation, civil status, age, income level and COVID-19 numbers have in the shift to private and active modes. Also, *Life-related activities comfort* mediates the effect of occupation, civil status, age and COVID-19 numbers into the shifting decisions. Further, the perceived *Health risk* is also identified as a mediator of all categories of objectively measured attributes, except for the COVID-19 numbers. *Entities response* mediates the effect of gender, occupation and civil status in the decision to shift to private and active modes. Finally, we also found differences in the decision to shift to private and active modes in each city through the latent variables *Life-related activities comfort*, *Health risk* and *Entities response*.

3.3. Total effects

Table 8 referred to the different impact of the various independent variables (i.e., latent variables and objectively measured attributes) in the shift to private and active modes, as direct and indirect effects. However, we are also interested in quantifying the total influence (i.e., total effect) of the different independent variables on the shifting decision. These are presented in Table 9. A total effect is represented by the addition of each independent variable's direct and indirect effects. A direct effect is measured by the coefficient of the variable considered (Gana and Broc, 2019); the indirect effect is represented by the sum of all possible path coefficient chains products from one variable to another (Hoyle, 2014). For example, the *total effect* of being older than 60 in the shift to active modes (−0.910) in Table 9, is calculated as follows: first, the direct effect (−0.851) comes from Table 8; then, in Fig. 4 we can observe three different paths from being older than 60 to the shift to active modes decision: (i) *Age older than 60 - Health risk – Comfort with life-related activities – Subjective well-being* - z_{act}; (ii) *Age older than 60 - Comfort with life-related activities – Subjective well-being* - z_{act}; and (iii) *Age older than 60 - Subjective well-being* - z_{act}. Thus, from the coefficients in Table 8 the product of coefficients in each path is as follows: (i)

Table 8
Parameters of the structural model explaining the shift from public transport to private and active modes.

Attribute	Unstandardized effect		Standardized effect
	Estimate	*t*-test	
Shift to private mode			
$\mu_{private}$	3.025		
COVID-19 deaths*	0.504	1.506	**0.260**
Children under 18	−0.347	−2.159	**−0.158**
Household size	0.066	2.557	0.100
Cost savings	−0.105	−7.675	**−0.191**
COVID-19 impact	0.169	3.677	**0.137**
Shift to active mode			
μ_{active}	0.755		
Age older than 60*	−0.851	−1.630	**−0.123**
Middle income*	−0.139	−1.562	−0.066
High income*	−0.227	−1.422	−0.067
Time savings	−0.009	−7.473	**−0.271**
Cost savings	0.039	2.769	0.072
Subjective well-being	−0.130	−3.449	**−0.127**
COVID-19 impact			
Children under 12	−0.114	−1.678	−0.061
Middle income	0.065	1.771	0.038
High income	0.115	1.916	0.042
Time savings	0.002	3.136	0.061
Entities response	0.088	4.850	0.100
Health risk	0.523	27.756	**0.583**
Comfort with life-related activities	−0.067	−3.892	−0.075
Subjective well-being	0.076	4.215	0.091
Subjective well-being			
Employer	0.564	4.741	0.082
Employee	0.517	10.313	**0.246**
Self-employed	0.464	7.187	**0.157**
Student	0.398	4.264	0.092
Living together	0.136	3.303	0.063
COVID-19 cases*	−0.905	−1.644	**−0.209**
Age 41 – 60	0.288	3.881	**0.110**
Age older than 60	0.484	3.473	0.072
Middle income*	0.375	8.640	**0.182**
High income*	0.641	8.918	**0.194**
*Entities response**	0.260	14.774	**0.247**
Comfort with life-related activities *	0.055	2.642	0.052
Comfort with life-related activities			
Bogota	−0.669	−3.336	**−0.182**
Lima	−0.912	−4.501	**−0.407**
Quito	−0.726	−2.796	**−0.320**
Santiago	−0.731	−2.938	**−0.326**
Employer	0.229	1.911	0.036
Employee	0.136	2.669	0.069
Living together	−0.078	−2.063	−0.039
COVID-19 cases*	−0.974	−1.986	**−0.240**
COVID-19 deaths*	−0.267	−1.708	**−0.152**
Age 41 – 60	−0.135	−1.956	−0.055
Age older than 60	−0.418	−3.368	−0.066
*Health risk**	−0.400	−21.285	**−0.398**
Health risk			
Female	0.191	5.775	0.099
Bogota	0.654	3.036	**0.179**
Lima	0.784	3.576	**0.352**
Quito	1.071	3.870	**0.475**
Santiago	0.911	3.411	**0.408**
Self-employed	−0.128	−2.174	−0.047
Living together	0.071	1.919	0.036
Household size	0.028	2.367	0.047
Age 26 – 40*	0.112	2.009	0.055
Age 41 – 60*	0.170	2.517	0.070
Age older than 60*	0.192	1.493	0.031
Middle income*	−0.083	−2.190	−0.043
High income*	−0.234	−3.877	−0.076
Time savings	0.002	2.935	0.053
Entities response			
Female	0.081	2.405	0.041

(*continued on next page*)

Table 8 (*continued*)

Attribute	Unstandardized effect		Standardized effect
	Estimate	*t*-test	
Quito	−0.685	−2.447	**−0.298**
Santiago	−0.509	−1.897	**−0.223**
Employer	0.201	1.886	0.031
Employee	0.149	3.142	0.075
Living together	0.095	2.501	0.046
Union dissolved	0.176	2.332	0.042

Note: medium and high effects are presented in bold.
* Relation significant at the 90% level considering a one-tailed test as the sign of the relationship is known (i.e., *t*-test higher than 1.282).

Table 9
Total effects on the decision to shift from public transport to private and active modes.

Attribute	Unstandardized effect		Standardized effect	
	Shift to private	Shift to active	Shift to private	Shift to active
COVID-19 impact	0.169 (3.677)	0	**0.137**	0
Subjective well-being	0.013 (2.775)	−0.130 (−3.449)	0.013	**−0.127**
Comfort with life-related activities	−0.011 (−2.579)	−0.007 (−2.093)	−0.010	−0.007
*Health risk**	0.093 (3.662)	0.003 (2.096)	0.084	0.003
Entities response	0.018 (3.224)	−0.034 (−3.353)	0.017	−0.031
Female	0.019 (3.113)	−0.002 (−1.648)	0.009	−0.001
Bogota	0.068 (2.519)	0.007 (1.892)	0.017	0.002
Lima	0.083 (2.748)	0.009 (1.966)	0.033	0.004
Quito	0.095 (2.520)	0.031 (2.323)	0.038	0.013
Santiago	0.083 (2.384)	0.025 (2.092)	0.034	0.010
Employer	0.009 (2.175)	−0.082 (−2.893)	0.001	−0.012
Employee	0.008 (2.676)	−0.073 (−3.318)	0.004	−0.034
Self-employed	−0.006 (−0.978)	−0.061 (−3.132)	−0.002	−0.020
Student	0.005 (2.322)	−0.052 (−2.700)	0.001	−0.012
Living together	0.011 (2.326)	−0.020 (−2.519)	0.005	−0.009
Union dissolved	0.003 (1.893)	−0.006 (−1.897)	0.001	−0.001
COVID-19 cases*	−0.001 (−0.136)	0.124 (1.551)	-3.04×10^{-4}	0.028
COVID-19 deaths*	0.507 (1.514)	0.002 (1.313)	**0.262**	0.001
Children under 12	−0.019 (−1.526)	0	−0.008	0
Children under 18	−0.347 (−2.159)	0	**−0.158**	0
Household size	0.068 (2.650)	7.92×10^{-5} (1.587)	**0.104**	1.22×10^{-4}
Age 26 – 40*	0.010 (1.761)	3.21×10^{-4} (1.444)	0.005	1.43×10^{-4}
Age 41 – 60*	0.021 (2.453)	−0.036 (−2.542)	0.008	−0.013
Age older than 60*	0.029 (1.963)	−0.910 (−1.746)	0.004	**−0.132**
Middle income*	0.008 (1.155)	−0.188 (−2.146)	0.004	−0.089
High income*	0.006 (0.532)	−0.311 (−1.980)	0.002	−0.092
Time savings	4.25×10^{-4} (2.847)	−0.009 (−7.470)	0.013	**−0.270**
Cost savings	−0.105 (-7.675)	0.039 (2.769)	**−0.191**	0.072

Note: medium and high effects are presented in bold.
* Relation significant at the 90% level considering a one-tailed test as the sign of the relationship is known (i.e., *t*-test higher than 1.282).

$(0.192)\cdot(-0.400)\cdot(0.055)\cdot(-0.130) = 5.49 \times 10^{-4}$; (ii) $(-0.418)\cdot(0.055)\cdot(-0.130) = 2.99 \times 10^{-3}$; and (iii) $(0.484)\cdot(-0.130) = -0.063$. From these, the indirect effect of being older than 60 in the shift to active modes decision is simply the sum of the coefficient products for each path: $5.49 \times 10^{-4} + 2.99 \times 10^{-3} + (-0.063) = -0.059$. Finally, the total effect is the sum of the direct and indirect effects: $-0.851 + (-0.059) = -0.910$. These findings are commented in the subsections below.

3.3.1. Effect of COVID-19 new cases and deaths

The numbers of COVID-19 new cases and deaths appear to have influenced the shifting decisions. In particular, the number of deaths per hundred thousand population has a medium effect in the shift from public transport to private modes. The values shown in Table 9 suggest that, *ceteris paribus*, a growth in the number of deaths per hundred thousand population may indeed had increase the shift from public transport to private modes (Fig. 5). This increase has a much higher a slope when the deaths are over 4.6 per hundred thousand population, revealing a threat not only to health but also to sustainable transport development. The number of reported deaths was also found to negatively impact the *Life-related activities comfort*, which, according to our results, may increase the propensity to shift from public transport to other modes.

The new cases of COVID-19 were also found to significantly explain the shifting decision from public transport to active modes through the perceived *Comfort with life-related activities* and *Subjective well-being*. The data in Table 9 suggest that, *ceteris paribus*, a growth in the number of cases per thousand population may increase the shift from public transport to active modes (Fig. 6). This

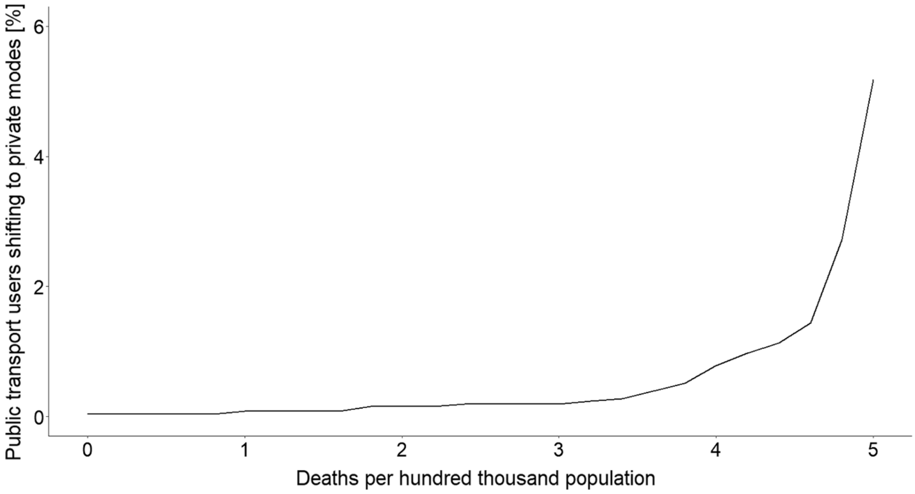

Fig. 5. COVID-19 deaths influence on the shifting from public transport to private modes.

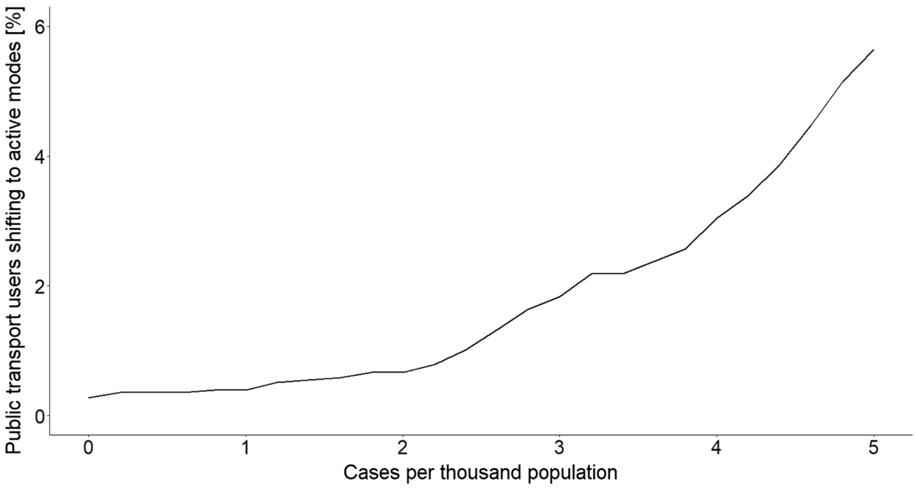

Fig. 6. COVID-19 cases influence in the shifting from public transport to active modes.

increase has a higher slope when the cases per thousand population are over 2.

The slope of the curve in Fig. 6 is smoother than the one representing the shift to private modes (Fig. 5). For this reason, reducing the number of cases and deaths caused by COVID-19 seems to be a goal, not only for health reasons, but also to support the different plans to make cities sustainable from a transport planning perspective, reducing the public transport user's probability of shifting to other modes.

3.3.2. Travel-time and costs savings

A significant increase in travel costs was reported for those who switched from public transport to private modes, which was partially balanced by savings in travel time. In contrast, results from Sydney, Australia (Hensher et al., 2021) indicated a lower average monetary cost per km travelled for car commuters, which may be explained by higher public transport fares. On the contrary, a significant increase in travel times was observed (and also balanced by significant savings in travel costs) for those switching from public transport to active modes. Thus, trade-offs between time and cost savings are very evident in our data.

Time savings had a medium effect over the shift from public transport to active modes (and it is the attribute with more influence on this decision) and a weak effect over the change to private modes (see Table 9). The data in Table 9 suggests that public transport users may tolerate an increase of 20% in travel time before starting the process of shifting to active modes (see Fig. 7). Besides, when time increases are higher than 60%, the slope of the curve increases. However, time increases on public transport trips represent a decrease in level-of-service (Lunke et al., 2021; Tiznado-Aitken et al., 2021), which is not a sustainable transportation goal.

On the other hand, corrected cost savings had a medium effect over the shift from public transport to private modes and a weak effect over the change to active modes (Table 9). In other words, a reduction in the corrected cost savings used for transportation may

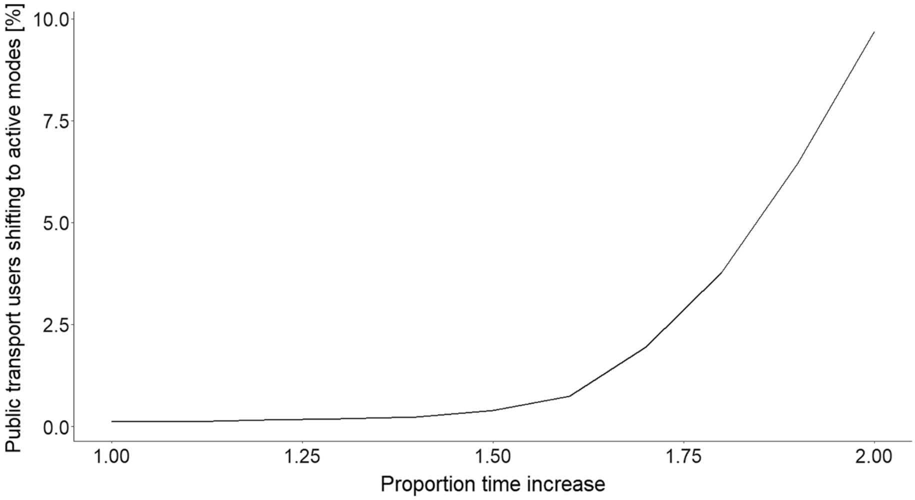

Fig. 7. Time increase influence on shifting from public transport to active modes.

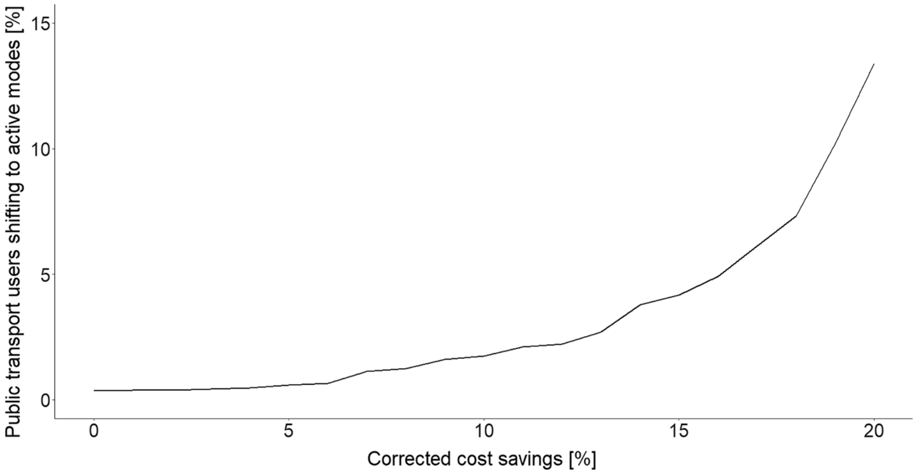

Fig. 8. Corrected cost savings influence on shifting from public transport to active modes.

influence shifting from public transport to active modes. People can obtain such a reduction directly, from using active modes, and also from any incentives to using active modes by the public entities (e.g., tax reductions). The total effects in Table 9, suggest that public transport users may start moving to active modes when savings up to 7% of their corrected equivalent income are offered. Also, an increase in the rate of public transport users shifting to active modes can be observed from savings over 18% of their corrected equivalent income (see Fig. 8).

Note that following the surge of COVID-19 contagions and deaths, travel times and costs are likely to become less relevant to explain mode choice. According to Abdullah et al. (2020), the proportion of respondents who give high importance to savings in travel time fell from 38% to 29%, while in the case of travel cost, this proportion decreased from 25% to 19%. Meanwhile, the risk of infection, safety, social distance and hygiene appeared as the highest priority factors. Although that research dealt mainly with respondents from Asia, it is likely that South Americans may have a comparable change in perceptions.

3.3.3. Socio-demographic characteristics

We found that women show a positive tendency to move to private modes and a negative tendency to shift to active modes. A potential explanation for this is that the latent variable *Entities response* is rated higher by women. This is a similar finding to Australia, where women tend to have more positive views on the state government response to COVID-19 (Beck and Hensher, 2020). Besides, the shift of women from public transport to private modes, is indirectly associated with *Health risk*. Both women and low-income individuals perceive a higher *Health risk* threat, contrary to Australia (Beck and Hensher, 2020), where no differences in terms of gender or income were observed.

Recent literature (Aldred et al., 2016; 2017; Lam, 2018) has explored the factors that contribute to increasing the use of bicycle by women. On the other hand, Sagaris and Tiznado-Aitken (2020) identified many barriers (e.g., safety) that limit the use of bicycles for women in a Latin American context. According to our model, the pandemic seems to be a new barrier for women to use active modes. In this sense, the existence of cycling lanes (and cycling infrastructure in general) are key to developing sustainable trends, especially considering the travel needs of women that tend to be different than for men (Sagaris and Tiznado-Aitken, 2020).

Regarding age, we found that the older the respondent, the higher the propensity to shift from public transport to private modes, and the lower the propensity to move to active modes. Physical effort is obviously a barrier for active mode use by older people, and this may explain the lower rate of older transport users shifting to active modes (Fernández-Heredia et al., 2014; Grudgings et al., 2021). Besides, the increase in the propensity to shift from public transport to private modes, is related to the higher perceived *Health risk* for older respondents, which is in line with reports regarding higher risks related to COVID-19 in older people (Beck and Hensher, 2020; Nimgaonkar et al., 2021; Sasson, 2021).

According to our model, employers, employees and students are more likely to shift to private motorised transport and less likely to change to active modes. On the other hand, self-employed are less likely to change mode when compared with the unemployed. Similarly, middle and high-income people are also more likely to shift to private modes and less likely to change to active modes. Given that car ownership increases with household income (de Jong et al., 2004) and that formal workers have higher average income than informal workers, it is expected that employees should have greater availability of private transport and therefore a greater probability of switching from public transport to car or motorcycle. Besides, the smaller propensity to change to active modes for middle and high-income people, can also be related to the aforementioned *bicycle use stigma* that associates bicycle use mostly with poor people (Rosas-Satizábal and Rodriguez-Valencia, 2019).

Regarding differences between the five cities studied, we found that Bogotá, Lima, Quito and Santiago showed a higher propensity to change from public transport to other modes compared with Buenos Aires. It is worthwhile noting that the sharpest reduction in public transport trips was observed precisely in Buenos Aires, the only city that imposed a formal limitation on public transport use to essential workers (see Table 2 and Fig. 2). The fact that people from Buenos Aires reported the lowest *Health risk* and the highest *Life-related activities comfort*, suggests that at least part of the shift from public transport is explained by compliance to regulations rather than by risk perceptions. Unfortunately, our model does not allow to distinguish to what extent the mode shifting decision is influenced by health-related policy measures.

4. Limitations and further research

Different trade-offs need to be considered, in further research, to improve the understanding of the COVID-19 influences on transportation in South America. Applying online-based surveys is the fastest way to collect responses from people around the world (Dillman et al., 2014) and is the preferred option to collect information considering the pandemic nature. However, there are many limitations regarding this data collection method. Internet access is one of the most recognized limitations as it may generate a *coverage bias* by not reaching a, perhaps, not insignificant proportion of the population (Dillman et al., 2014). We sought to collect a comparative sample in terms of gender, age, income, occupation, and marital status among the different cities, through diverse social networks, as explained in section 2.1. Partly for this reason, the final sample in most cities overrepresents younger and high-income people, as shown in Table 6. However, we do not consider this a serious problem given the study's objectives and the modelling approach. The final model reaches the requirements of goodness-of-fit indices, and the sample size (i.e., 3803) is enough to achieve a power higher than 0.8 reducing potential biases (Gana and Broc, 2019; MacCallum et al., 1996). On the other hand, as our survey was open to any visitor, obtaining multiple responses from the same person was a risk. To mitigate it, we used SurveyMonkey's cookies option to avoid having the same browser completing more than one survey.

Behaviours and attitudes during COVID-19 may change from day to day, considering the pandemic's natural state of flux and evolution. However, we need to develop research about sustainable transport in the future to understand how people's perceptions may influence changes in public transport use. In our case, the subjective information was collected for five capital cities of South America. It would enlarge the scope if we were able to bring together similar experiences around the world, as we have done in Australia. Both the research results and an updated version of the data collected would also benefit from other data collection waves, considering the changes in the development of the pandemic, as well as the governments and people's responses prior to the vaccination and decline of the contagions. The team leading this paper has already started preparing further data collection waves for the coming years in an effort to comprehend better the short-, medium- and long-term effects of COVID-19 in transportation. A follow-up study should allow comparing the first period of the pandemic and the transitions after the lockdown scenarios in similar contexts.

Besides, as the main objective of this study was to explain the modal shifts from public transport to other modes based on people's perception, no information about the level of service of the various modes was collected. A more detailed analysis could be carried out in the future incorporating certain peculiarities of each city and its transport modes, which can certainly affect users' perceptions. Finally, future surveys should give a more detailed insight into which part of the mode choice change is driven by regulations and which one is driving by individual perceptions, such as health risk.

5. Conclusions

We adapted and collected information about travel patterns and telecommuting during the COVID-19 pandemic in five South American capitals, based on previous surveys performed in Australia by Beck and Hensher (2020) and Beck et al. (2020). The study collected information in Bogotá, Buenos Aires, Lima, Quito and Santiago through a survey carried out between August and November 2020. The approach has allowed us to improve our understanding of geographical and contextual similarities in the pandemic scenario.

Since the pandemic's beginning, these five cities showed a decline in public transport use, which meant similar and significant challenges to keep public transport service standards.

The study proposed a model for understanding the profile of users that shifted from public transport to other modes during the COVID-19 outbreak. Having to perform face-to-face activities, public transport users tended to shift to other transport options (such as private and active modes). In contrast, users working at home shifted to immobility in their main productive activities. In general terms, our model implies a smaller probability of moving from public transport to active modes, than to private modes, suggesting difficulties in terms of encouraging active mode use as an alternative for public transport during the COVID-19 pandemic. This challenge can be added to the other barriers reported in the literature on the use of active modes in terms of safety (Manaugh et al., 2017; Sagaris and Tiznado-Aitken, 2020; Vallejo-Borda et al., 2020), security (Sagaris and Tiznado-Aitken, 2020; Vallejo-Borda et al., 2020) and even social stigma (Rosas-Satizábal and Rodriguez-Valencia, 2019). Confidence in the actions undertaken by both national and local authorities was essential to explain changes in commuting patterns. According to our findings, those who stopped travelling by public transport during the pandemic and switched to active modes, generally had less trust in public entities than those who changed to private modes. Besides, our findings also suggest that sustainable transport goals can be threatened by an increase in the number of deaths caused by COVID-19, giving the positive influence of this variable in the probability to shifting to private modes.

CRediT authorship contribution statement

Jose Agustin Vallejo-Borda: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Ricardo Giesen:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Paul Basnak:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **José P. Reyes:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition. **Beatriz Mella Lira:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Matthew J. Beck:** Conceptualization. **David A. Hensher:** Conceptualization, Writing – review & editing. **Juan de Dios Ortúzar:** Validation, Formal analysis, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1. Goodness of fit indicators for the SEM-MIMIC model

Indicator	Accepted threshold	Explanation
Normed $\chi^2 = \frac{\chi^2_{model}}{df_{model}}$	< 3.0 (Bollen, 2014; Hair et al., 2014)	These indicators are based on the standardised comparison of the observed and reproduced variance–covariance matrices
$GFI = 1 - \frac{\chi^2_{model}}{\chi^2_{null}}$	> 0.95 (Hair et al., 2014; Hoyle, 2012; Schumacker and Lomax, 2016)	
$SRMR = \sqrt[2]{\left(\frac{1}{k}\right)(e'W_s e)}$	< 0.05 (Schumacker and Lomax, 2016)	
$TLI = \frac{\frac{\chi^2_{null}}{df_{null}} - \frac{\chi^2_{model}}{df_{model}}}{\frac{\chi^2_{null}}{df_{null}} - 1}$	> 0.95 (Gana and Broc, 2019; Hoyle, 2012)	These indicators are based on the comparison of the baseline and proposed models

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(*continued*)

Indicator	Accepted threshold	Explanation
$CFI = 1 - \frac{\chi^2_{model} - df_{model}}{\chi^2_{null} - df_{null}}$		
$RMSEA = \sqrt[2]{\frac{\chi^2_{model} - df_{model}}{(N-1)df_{model}}}$	< 0.05 (Gana and Broc, 2019; Schumacker and Lomax, 2016)	This indicator serves to estimate the parsimony of the model

Note: χ^2 = chi-square test statistic; df = degrees of freedom; k = number of unique distinct values in the observed variance–covariance matrix; e = vector of residuals from the observed and model-implied variance–covariance matrices; W_s = diagonal weight matrix to standardize the elements of the observed variance–covariance matrix; N = sample size (Hoyle, 2012; Schumacker and Lomax, 2016).

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