Impact of perceptions and attitudes on air travel choices in the post-COVID-19 era: A cross-national analysis of stated preference data

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A B S T R A C T

The COVID-19 pandemic and the consequent travel restrictions have had an unprecedented impact on the air travel market. However, a rigorous analysis of the potential role of safety perceptions and attitudes towards COVID-19 interventions on future air passenger choices has been lacking to date. To investigate this matter, 1469 individuals were interviewed between April and September 2020 in four multi-airport cities (London, New York City, Sao Paulo, Shanghai). The core analysis draws upon data from a set of stated preference (SP) experiments in which respondents were asked to reflect on a hypothetical air travel journey taking place when travel restrictions are lifted but there is still a risk of infection. The hybrid choice model results show that alongside traditional attributes, such as fare, duration and transfer, attitudinal and safety perception factors matter to air passengers when making future air travel choices. The cross-national analysis points towards differences in responses across the cities to stem from culturally-driven attitudes towards interpersonal distance and personal space. We also report the willingness to pay for travel attributes under the expected future conditions and discuss post-pandemic implications for the air travel sector, including video-conferencing as a substitute for air travel.

1. Introduction

The COVID-19 pandemic has had an unprecedented impact on the global air travel market. Whilst it is not yet entirely clear what attributes of SARS-CoV-2 set it apart from the SARS-CoV 2003 outbreak, leading to a global pandemic (Petersen et al., 2020), the high levels of international air travel in recent times have been seen as a contributing factor towards the quick spread of the epidemic (Wilder-Smith, 2021). The exceptional restrictions on air travel have led to a direct impact on the air travel industry that is without precedent, amounting to a 94 % reduction in the revenue passenger kilometres (RPK) flown worldwide, and leading to the loss of revenue by airlines and airports of up to $314bn and $100bn respectively (International Civil Aviation Organization, 2021). In addition to such direct impacts, restrictions on air travel lead to secondary impacts (Iacus et al., 2020): indirect (on the supply chain of the aviation industry), induced (on further sectors that rely on the expenditure of those employed in the aviation sector and its supply chain) and catalytic (in relation to a reduced number of tourists and visitors, affecting multiple sectors of the economy, especially the hospitality industry). Moreover, restrictions on air travel generate negative social impacts, by keeping families apart, inhibiting visits among friends and relatives, and

reducing the options available to meet personal needs, including educational, cultural and spiritual needs (Smyth et al., 2012).

At the time of writing the paper (June 2022), COVID-19 emergency status is still maintained by the WHO, though an increasing number of countries have lifted virtually all epidemic prevention and management measures. In fact, there is a hope to reach a 'new normal' with the help of the extensive use of non-pharmaceutical interventions (NPIs) (Chakraborty and Maity, 2020) and the mass vaccination programme (Zhu and Iboi, 2021), despite obstacles in the production and distribution capacity and the reduced effectiveness of the vaccine on virus mutations (Schlagenhauf et al., 2021, Lopez Bernal et al., 2021). It is therefore fundamental and urgent for the whole air travel sector to better understand air travel behaviour during and post the pandemic. In such conditions, the willingness to travel but also the sensitivity of passengers to air travel itinerary attributes, such as cost, duration and airport access, should be revised to take into consideration the effect of measures to manage the pandemic such as the implementation of suitable NPIs (social distancing or quarantine rules) and the safety perception of travellers. Indeed, the interaction between the conventional set of attributes (price, duration, transfer type, journey purpose), the attitudes towards COVID-19-related measures in the context of air travel, and

cultural and sociodemographic factors (which might vary from country to country) can be very important in the decision-making process of the travellers.

Accordingly, this paper presents an analysis of data collected between April and September 2020 in four multi-airport cities on different continents (Sao Paulo in Brazil, Shanghai in China, London in the UK, New York City in the US). The principal objective is to investigate the drivers of air passenger choice behaviour in the context of the COVID-19 pandemic. The core analysis draws upon data from a stated preference (SP) experiment including a set of hypothetical air travel choice scenarios about a journey taking place when the restrictions will be lifted but there is still a risk of infection. The questionnaire also included several attitudinal statements on frequency of use of video calls before, during and after (anticipated behaviour) the pandemic; safety concerns when travelling (including attitude towards NPIs); and the 'Big Five' personality traits (Rammstedt and Joh,n 2007). Given the nature of available data, we employed the Hybrid Choice Modelling (HCM) approach (Walker, 2001, Vij and Walker, 2014) to model the choices and elicitation of preferences while incorporating psychometric and other unobservable measures alongside directly measured attributes, such as travel cost and duration.

The paper contributes to the state of the art in a number of ways. Firstly, it is the only study in the context of COVID-19 that looks in a detailed manner at the pre- and post-pandemic air travel decision-making at a disaggregated level and follows a cross-national perspective with a unified survey design. To date, disaggregate studies in similar contexts have been confined to single study area contexts (Manca et al., 2021, Jiao and Azimian, 2021) whilst cross-national studies use aggregate data (Chu et al., 2021, Santos et al., 2021). The joint consideration offers ways in which differences in behaviour can be attributed to the specificity of the places under study, resulting from a mix of cultural, geographical and policy factors, the latter including differences in the epidemic management measures employed.

Secondly, to the best of our knowledge, this study uniquely complements the emerging understanding of the role of videoconferencing and online collaboration in shaping post-pandemic air travel decision-making. The domain of interaction between travel and information and communication technologies has been thriving since the 1980s, including consideration of impacts on air travel (Lu and Peeta, 2009, Denstadli et al., 2013). Nonetheless, the unique context of the COVID-19 pandemic that forced an unprecedentedly widespread and rapid adoption of online substitutes for physical activities requires examination, in order to understand the extent and longevity of such substitution.

Thirdly, the present paper quantifies the effects of disrupted attributes of the alternatives (changes in travel time and costs) alongside perceptions of safety and concern, whilst also controlling for personality attributes. This is a first in the context of modelling air travel behaviour. These insights are critical to assessing and tailoring measures and policies to aid the recovery of the air travel sector. In this manner, the study complements the growing body of research looking at similar aspects in the context of urban transport (Aaditya and Rahul, 2021, Chen et al., 2022, Rahimi et al., 2021).

The rest of this paper is structured as follows. Section 2 briefly presents an overview of studies describing the challenges currently faced by the air transport sector and summarises the importance of taking into account the COVID-19 effect in modelling air travel demand. Section 3 presents the data, survey design and modelling methodology adopted in this work. Section 4 presents the substantive model results. Section 5 presents a discussion of the main findings and Section 6 concludes the paper.

2. Literature review

Having been identified as the primary channel through which COVID-19 propagated internationally, air travel was swiftly and unprecedentedly restricted as a means of containing the transmission.

From the point of view of managing the pandemic, restrictions on mobility have been effective at reducing transmission (Linka et al., 2020, Chakraborty and Maity, 2020). Particularly striking examples include those of New Zealand (Baker et al., 2020, Jefferies et al., 2020, Cousins 2020) and Taiwan (Cheng et al., 2020), where early restrictions on international travel and quarantine requirements, combined with the effective internal management of the outbreak, virtually eliminated new cases and rebound.

What is also clear, however, is that the widespread mobility restrictions, including on air travel, come at a substantial economic and societal cost (Chakraborty and Maity, 2020). As the world hopes to see an exit strategy in the form of a combination of post-infection immunity and mass vaccinations against COVID-19 (Gumel et al., 2021, Zhu and Iboi, 2021), therapies (Vegivinti et al., 2021, Deb et al., 2021, Rodriguez-Guerra et al., 2021) and a variety of NPIs (Chakraborty and Maity, 2020), questions naturally emerge regarding air travel behaviour during and post the pandemic. Most, if not all, existing research on air travel decisions of passengers dates back to pre-pandemic conditions (Ashford and Benchemam, 1987, Proussaloglou and Koppelman, 1999, Algers and Beser, 2001, Adler et al., 2005, Warburg et al., 2006, Hess et al., 2007, Parrella, 2013, Garrow, 2016, Acuna-Agost et al., 2021).

It is known, however, that unusual and extreme circumstances affect people's decision processes through the operation of 'visceral factors' such as drive states (hunger, thirst), moods and emotions, and physical pain (Loewenstein, 1996). In particular, we argue that the COVID-19 pandemic presents circumstances that can be a source of visceral factors in the context of air travel decisions, such as a fear of getting infected while travelling, concerns over possible quarantine measures, or anxiety due to the risk of prolonged separation from relatives due to flight cancellations or changes in travel restrictions (Suau-Sanchez et al., 2020, Graham et al., 2020). Understanding air passenger decision-making in this context necessitates primary data collection based on suitably designed surveys carried out in the direct context of the pandemic.

Even assuming the availability and affordability of effective vaccines, their global roll-out is expected to take time due to production and distribution capacity constraints and uncertain effectiveness of the vaccine on virus mutations (variants of concern) (Mills and Salisbury, 2021, Wouters et al., 2021, Schlagenhauf et al., 2021, Lopez Bernal et al., 2021). Moreover, a number of pharmaceutical interventions have been shown to reduce the risk of death (Ledford, 2020a,b), including the first oral antiviral treatment that is claimed to cut the risk of hospitalisation by 50 % in clinical trials (Reed, 2021, Willyard, 2021). Hence in the short- to medium-term, air travel and COVID-19 are very likely to co-exist, and so will NPIs in the context of air travel (Nakamura and Managi, 2020, Wilson and Chen, 2020, Dube et al., 2021). This justifies revisiting our existing understanding of the sensitivity of passengers to air travel itinerary attributes, such as cost, duration and airport access, alongside attributes related to pandemic management through the implementation of suitable NPIs such as social distancing or quarantine rules. The resulting insights can feed into the design of travel-oriented policies that are effective in containing the virus while sustaining the air travel industry (International Civil Aviation Organization, 2021).

This complex interaction between attitudes towards COVID-19-related measures in the context of air travel, cultural and sociodemographic factors, as well as the more conventional set of considerations (price, duration, transfer type, journey purpose), calls for focussed cross-national analysis of data collected in the current context of the pandemic that suitably accounts for the various observable and latent drivers of air travel behaviour. The choice behaviour perspective of this paper complements the wider literature of modelling (Brauner et al., 2021, Liu et al., 2021) and laboratory studies (Barasheed et al., 2016, Christopherson et al., 2020, Chu et al., 2020) that explore the effectiveness of NPI measures in containing the virus, such as HEPA filters installed in the aircraft (Mangili and Gendreau, 2005, International Air Transport Association, 2020, Schultz and Soolaki, 2021). Beyond the immediate

behavioural insights, the outcome of this analysis can also support the design of strategies and mitigation measures for future COVID-19-like scenarios.

In the transport and tourism literature, previous studies have shown the strong influence of latent perceptions on travel behaviours during the pandemic. These studies mostly focus on perceived risk, fear of infection and travel anxiety affecting public transport users (Aaditya and Rahul, 2021, Chen et al., 2022), shared mobility users (Rahimi et al., 2021) and the tourism sector (Sánchez-Cañizares et al., 2021, Zenker et al., 2021, Chua et al., 2021, Rahman et al., 2021). There have not been any studies that specifically quantify the effect of disrupted attributes of alternatives (changes in travel time and costs) and perceived safety on air travel behaviour, using cross-national data.

In this study, a combined stated preference (SP) experiment and attitudinal investigation on individual safety concerns has been employed. The SP survey is an important tool used to elicit preferences and sensitivity by presenting hypothetical choice situations to the respondent (Louviere et al., 2000). It enables the analyst to define the independent effect of attributes characterising each alternative and investigate the trade-offs that characterise the decision-making process of the respondent during the SP experiment (Louviere et al., 2000; Ortúzar and Willumsen, 2011). SP experiments have been employed widely in the context of air travel to investigate the choice of air passengers (Proussaloglou and Koppelman, 1999, Warburg et al., 2006, Hess et al., 2007, Bliemer and Rose, 2011). In this specific study, attribute levels are designed to vary due to the COVID-19 measures adopted by airports and airlines, such as higher travel costs or waiting time at the airport (Manca et al., 2021). The attitudinal analysis specifically focuses on the safety perception statements that are associated with the many drawbacks generated by the pandemic and the use of non-pharmaceutical interventions (fear of contracting the virus, need to quarantine or to wear the mask and so on) within hypothetical choice scenarios.

Other possible attitudinal characteristics such as the effects of environmental and climate change concerns could also be considered in the analysis of the decision-making process of the individual (Schultz, 2002, Davison et al., 2014, Alcock et al., 2017, Cocolas et al., 2020). However, since this study was specifically designed to investigate the COVID-19 effect on air travel behaviour, only the individual's safety concern related to COVID-19 is considered. The combination of multiple

attitudinal characteristics is an interesting topic that might be the object of future studies.

3. Study context and data collection

The principal objective of this piece of analysis is to investigate the drivers of air passenger choice behaviour in the context of the COVID-19 pandemic, by investigating data from four different multi-airport cities: London (UK), New York (USA), Shanghai (China), Sao Paulo (Brazil).

The data for this analysis was collected via a survey that was administered in two waves (Fig. 1) in each of these cities, with the market research company Panelbase (https://www.panelbase.net) providing the sampling frame. The first wave asked respondents about their most recent air travel journey prior to January 2020, including trip purpose, origin and destination locations and airports, airlines, flight cost and duration, class of travel, transfers, loyalty programmes and companions, amongst others. This information on the actual choice of air travel itinerary, i.e. revealed preference (RP) was used to obtain a statistically efficient design of the SP experiments in the subsequent wave of the survey. In addition, the first wave collected information about the socioeconomic attributes of the respondents.

The second wave included a set of SP experiments, which asked the respondents to consider six hypothetical choice scenarios (based on their individual RP responses) assuming that such a hypothetical air travel journey would take place when travel restrictions are lifted but the risk of infection remains (see the "SP survey design" section for more theoretical background on the SP design). Three possible choice alternatives were presented for each choice scenario: two air travel options (differing in itinerary attributes) and a "prefer not to travel" option. Respondents were also asked to assume that specific measures will be put in place by the airports and airlines that minimise the risk of infection, including enforcement of social distancing at the airport and during the flight, the requirement to wear a facemask, as well as administration of COVID-19 tests before departure and upon arrival. All these measures can, however, impact the travel experience as compared to pre-COVID-19 air travel and the SP experiments were accordingly designed with a range of attribute values characterising the travel alternatives. For instance, the fare might be higher because of the reduced capacity of the aircraft due to social distancing requirements or reduced overall demand. Similarly, travel duration may increase due to longer wait times at check-in,
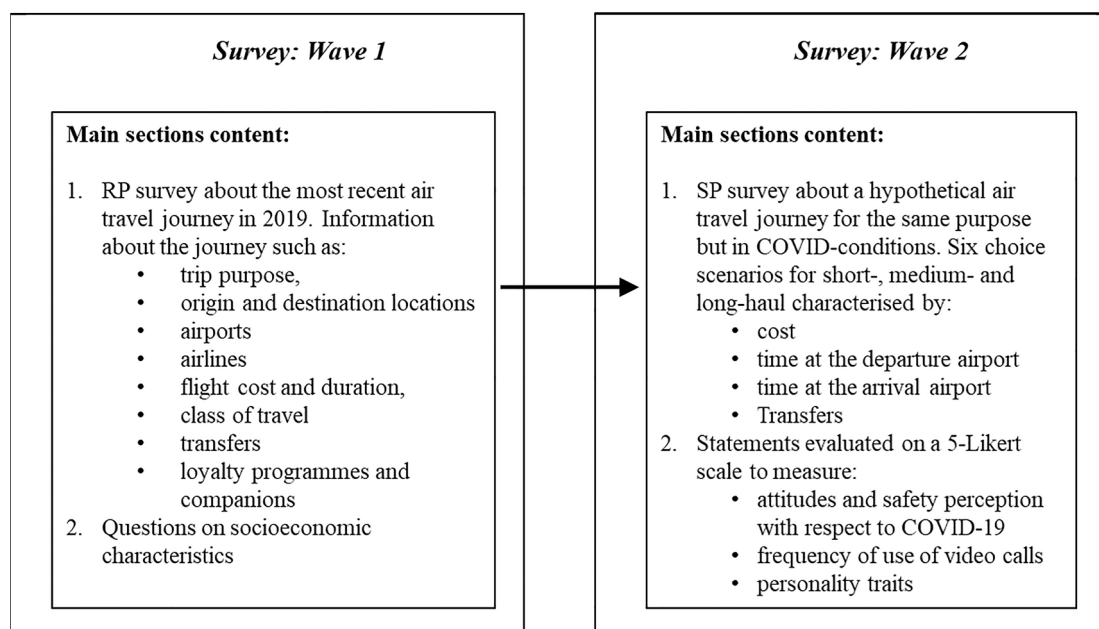

Fig. 1. Survey process.

security and gates or due to COVID-19 testing. For this reason, in the six hypothetical choice scenarios of the SP experiments, the air travel fare, the total time at the departure airport and the arrival airport were increased compared to the pre-pandemic values observed in the RP data. In addition, the choice alternatives were designed to differ in the number of transfers (0 or 1+), in order to reflect the reduced availability of direct routes due to the pandemic. The air travel attributes presented to the respondents were also tailored based on the trip purpose (business vs non-business) as well as flight distance (short-, medium- and long-haul).

Additionally, in the second wave of the survey, respondents were asked about their frequency of use of video calls to connect with family and friends, as well as their frequency of use of online/virtual software in place of travelling for business/work, before, during and after (anticipated behaviour) the COVID-19 pandemic (Greaves et al., 2013, Whitmarsh et al., 2020, Mouratidis and Papagiannakis, 2021). Furthermore, starting from literature analysing safety perceptions when travelling (Reisinger and Mavondo, 2006, Seabra et al., 2013, Abenoza et al., 2018) and adapting the theory to the COVID-19 study context (Manca et al., 2021; Chen et al., 2022), the second wave of the survey included several 5-point Likert scales (i.e. strongly disagree to strongly agree) statements to measure the attitudes and safety perceptions of the respondent with respect to COVID-19 circumstances, which are then analysed using factor analysis methods as described below. Moreover, based on the seminal papers by Barrick et al. (2001) and Rammstedt and John (2007) and some applications in the transport literature (Wu et al., 2019, Manca et al., 2021), ten statements, again evaluated on a 5-Likert scale (from strongly disagree to strongly agree), were included in the survey to investigate the "Big Five" personality traits of the respondent, each trait associated with a positive and a negative connotation: 1) extraversion ("outgoing, sociable" and the opposite "reserved"), 2) agreeableness ("generally trusting" and the opposite "tends to find fault with others"), 3) conscientiousness ("does a thorough job" and the opposite "tends to be lazy"), 4) neuroticism ("relaxed handles stress well" and the opposite "gets nervous easily"), and 5) openness ("active imagination" and the opposite "few artistic interests"). The inclusion of the "Big Five" is motivated by the desire to control for personality effects

in the decision-making process, especially under conditions of uncertainty due to COVID-19.

With respect to the COVID-19 context, the data collection for each of the cities took place at different stages of the pandemic, both with respect to the global conditions as well as local circumstances. As seen in the graphs in Fig. 2 of the daily new confirmed COVID-19 cases, when the survey was administered in London from July 7 to July 18, the UK was just over the first wave of infections. In the US (between August 19 and October 6), cases were dropping and rising again during the survey. China was way over the first wave of infections (between August 14 and August 24). Finally, Brazil (between August 27 and September 3) had just passed the peak of the first wave of COVID-19 infections.

3.1. SP survey design

The statistical SP design employed to create the scenarios is an efficient design generated with the help of the Ngene software (Choice Metrics, 2014). With the efficient design, the standard errors of the parameter estimates are minimised to obtain statistically significant results during the model estimation (Bliemer and Rose, 2011). The attribute levels of Fare (round trip per person), Total time at the departure airport, Total time at the arrival airport, Transfer for each city are illustrated in Table 1. Since the three segments for short-, medium- and long-haul distances had to be investigated, a heterogeneous pivot design with 33 % weight for each segment to calculate the Fisher Information Matrix was performed (Rose et al., 2008). However, differently from a classical pivot design, no fixed reference alternative linked to pre-pandemic levels was considered because it should have been dominant compared to the alternatives affected by the pandemic conditions where an increase in fare and times is assumed. Since no information on model estimates from previous studies was available under the COVID-19 circumstances, the parameters used to develop the efficient design experiment (i.e. the priors) were assumed to be zero. For this reason, once the SP choice situations were generated, the utility balance among the alternatives was also evaluated using a dataset obtained through a Monte Carlo simulation (Sottile et al., 2015, Manca et al., 2019). The utility balance is indeed very important to avoid
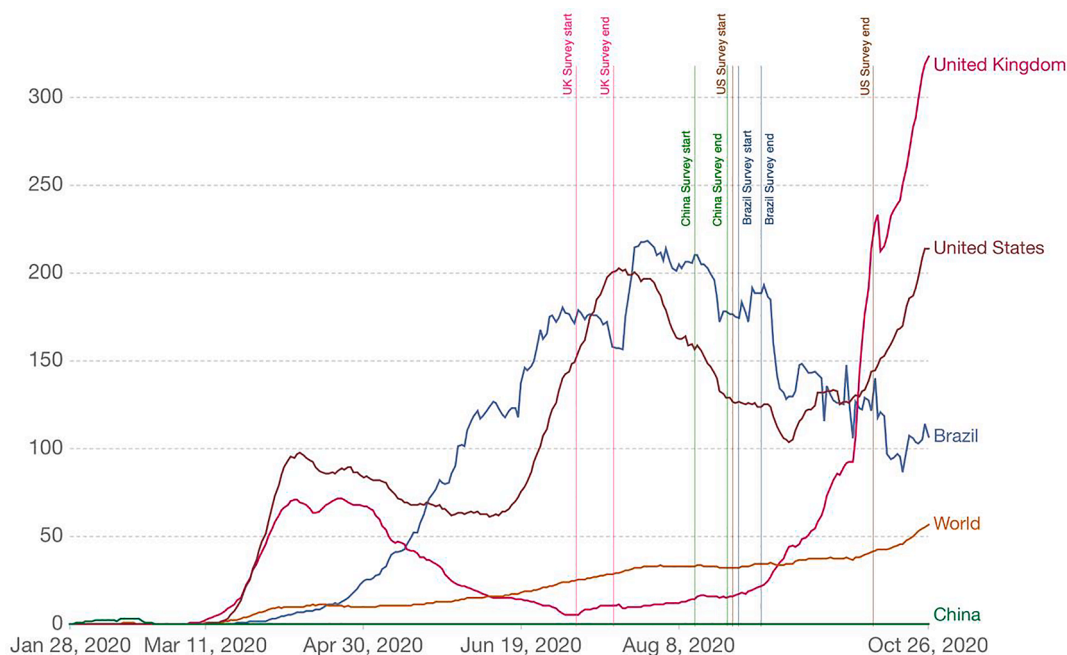
Fig. 2. Daily new confirmed COVID-19 cases per million people by country and COVID-survey administration, start and end (source: Our World in Data (Roser et al., 2020, Dong et al., 2020)).

Table 1
Attribute levels.

	London		New York		Shanghai		Sao Paulo	
	Alt 1	Alt 2	Alt 1	Alt 2	Alt 1	Alt 2	Alt 1	Alt 2
	Short-haul		*Short-haul*		*Short-haul*		*Short-haul*	
Fare (round trip per person)	£ 80 / 160 / 240		$ 90 / 190 / 290		RMB 680 / 1360 / 2040		R$ 520 / 1040 / 1560	
Total time at the departure airport	h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6	
Total time at the arrival airport	h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6	
Transfer	Yes / No		Yes / No		Yes / No		Yes / No	
	Medium-haul		*Medium-haul*		*Medium-haul*		*Medium-haul*	
Fare (round trip per person)	£ 250 / 450 / 650		$ 300 / 540 / 780		RMB 2120 / 3820 / 5520		R$ 1620 / 2920 / 4220	
Total time at the departure airport	h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6	
Total time at the arrival airport	h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6	
Transfer	Yes / No		Yes / No		Yes / No		Yes / No	
	Long-haul		*Long-haul*		*Long-haul*		*Long-haul*	
Fare (round trip per person)	£ 500 / 800 / 1100		$ 600 / 960 / 1320		RMB 4250 / 6800 / 9350		R$ 3250 / 5200 /7150	
Total time at the departure airport	h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6	
Total time at the arrival airport	h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6		h 2 / 4 / 6	
Transfer	Yes / No		Yes / No		Yes / No		Yes / No	

dominant alternatives which are clearly better than the other alternatives and are likely to be chosen without trade-off (Sottile et al., 2015). The final experimental design included 18 choice scenarios which were divided into 3 blocks. The blocks were randomly and uniformly distributed among the respondents. A total of 8802 choice observations from 1469 individuals were collected.

3.2. Descriptive data analyses

The final dataset collected included 388 respondents in London, 228 in New York, 414 in Shanghai and 439 in Sao Paulo with a wide coverage of socioeconomic characteristics (gender, age, education, employment, number of households members, income) and trips by purpose (see Table 2). Indeed, it provides a reasonably representative sample of typical air travel passengers in pre-pandemic conditions based on the distribution of income, gender, age, and purpose of travel (business or personal) in London, New York, Shanghai and Sao Paulo.

First, according to the Civil Aviation Authority (CAA) (Civil Aviation Authority, 2018), in London in 2018, the share of flights for business and personal reasons was respectively 23 % and 77 % and the data shows, in Table 2, 19 % and 81 %. International vs domestic flight passengers were 94 % and 6 % respectively, while in our sample these are 92 % and 8 %. Looking at the passenger age, for the age group "35–44" our sample is 14 % higher than the CAA figures. However, the CAA reports 6 % of travellers in the age group below 18 years who could not be interviewed during our survey and are part of the reason for the different figures. The income groups are well represented although the income category "50,000–99,999" is slightly higher (sample: 36 % and CAA: 28 %) and for the income category "£100,000 or more" is slightly lower (sample: 9 % and CAA: 16 %).

Second, according to the Port Authority of New York and New Jersey (Port Authority of New York and New Jersey, 2020), in New York in 2019, the share of flights for business and personal reasons was respectively 18 % and 82 % and, in our sample, 14 % and 86 %. International vs domestic flight passengers were 68 % and 32 % respectively while in the sample these are 61 % and 39 %. Moreover, at first glance the number of females and males sampled might appear slightly unbalanced, 62 % and 38 % respectively. However, this is not so far from the proportion of females and males that travel from New York airports, 55 % and 45 % respectively. Regarding the age distribution, 45 to 75-year-old individuals are slightly over-represented as they form 59 % of the sample and only 40 % of the actual passengers according to the Port Authority. On the other hand, the age group from 18 to 34 is slightly under-represented. No information on income is provided by the Port Authority of New York and New Jersey.

As regards the Shanghai airports, no official disaggregated information about the sociodemographics of the passengers was found. Therefore, the representativeness of the sample for Shanghai is assessed against (non-official) national figures reported in the references (Xinhua News (新华社) 2016, TravelDaily (环球旅讯) - 国双科技 2019). First, the share of the Chinese passengers travelling for business vs personal reasons in 2018 was 25 % and 75 % respectively while in the sample it is 28 % and 72 %. Female and male passengers in China were 32 % and 68 % respectively while in the sample they are 48 % and 52 %. The age distribution of travellers in the country was very similar to the age distribution in the sample. The main difference is that, in the national figures, the age group "18–24" was 15 % higher than the sample figures while the age group "25–34" was 15 % lower. Many of these differences could be attributed to the differences between Shanghai (where our survey data was collected) and the rest of China. Finally, according to the Departamento de Controle do Espaço Aéreo (DCEA) and Secretaria de Aviação Civil (SAC) (Secretaria de Aviação Civil, 2013, Departamento de Controle do Espaço Aéreo - Ministério da Defesa, 2020), in Sao Paulo, the share of the passengers on domestic vs international flights in 2019 was 86 % and 14 % respectively while in the sample this was 62 % and 38 %. Other statistics are provided on a regional basis. For instance, considering the Sao Paulo region (the south-east region), a marked difference can be observed between the Secretaria de Aviação Civil data and our sample for the share of passengers flying for business and personal reasons (SAC: 47 % and 53 % respectively vs sample: 20 % and 80 %). Female and male passengers were 44 % and 56 % respectively while in the sample 49 % and 51 % and, also, the distributions of age and income in the sample and the statistics for the south-east region are very similar.

Moreover, looking at the sample statistics in Table 2, it is important to notice that 55 % of the respondents from London, 44 % from New York, 66 % from Shanghai and 56 % from Sao Paulo were also travelling for tourism, which was, therefore, the main purpose of travel. Most of the Shanghai respondents are relatively young (i.e. 87 % is between 25 and 44 years old), have a Bachelor's or Master's degree (93 %) and are almost all full-time employed (97 %). For the other cities, the different categories of these variables are more uniformly distributed. Nonetheless, the distribution of income in New York seems slightly unbalanced with respect to the other cities as 38 % of the respondents belong to Level 5, with an annual household income greater than $100 k.

Looking further at the composition of the sample, Fig. 3 reveals that the respondents' last air travel trip in 2019 was mostly for personal purposes, ranging from 70 to 80 %. There was a similar share of international and domestic flights for both purposes. Indeed, between 8 % and 17 % of the domestic flights and between 5 % and 11 % of the international flights were made for business whereas between 35 and 52 % of the domestic flights and between 31 and 45 % of the international flights were made for business. When the respondents were presented with the hypothetical choice situations, a large percentage of them, almost 40 %, preferred the non-travelling option in London, New York, and Sao Paulo. Whereas, in Shanghai, 80 % of the respondents were

Table 2
Frequency analysis.

Variable	Categories	London (n = 388)	New York (n = 228)	Shanghai (n = 414)	Sao Pau lo (n = 439)
		Percentage	Percentage	Percentage	Percentage
Travel purpose (multiple choice were allowed)	Business	19 %	14 %	28 %	21 %
	Charity and volunteering	3 %	1 %	2 %	1 %
	Events	6 %	5 %	5 %	7 %
	Health	3 %	1 %	3 %	0 %
	Personal and social	40 %	53 %	20 %	33 %
	Religious and reflective	3 %	1 %	0 %	1 %
	Tourism	55 %	44 %	66 %	56 %
Gender	Male	51 %	38 %	52 %	51 %
	Female	49 %	62 %	48 %	49 %
Age	18–24	6 %	4 %	5 %	7 %
	25–34	21 %	18 %	50 %	31 %
	35–44	31 %	20 %	37 %	23 %
	45–59	27 %	30 %	7 %	27 %
	60–74	15 %	29 %	0 %	11 %
	75+	1 %	0 %	0 %	1 %
	No information	0 %	0 %	0 %	0 %
Education	No schooling	0 %	0 %	0 %	0 %
	Elementary school	0 %	0 %	0 %	0 %
	Secondary school	11 %	1 %	0 %	0 %
	High school	10 %	7 %	0 %	8 %
	Vocational, technical school or equivalent	12 %	13 %	6 %	6 %
	Bachelors degree	40 %	46 %	77 %	67 %
	Masters degree	22 %	26 %	16 %	12 %
	Doctorate	4 %	5 %	0 %	1 %
	Other or no information	0 %	1 %	0 %	6 %
Employment	Working: Full-time employee	62 %	61 %	97 %	55 %
	Working: Part-time employee	11 %	9 %	0 %	5 %
	Working: Self-employed	10 %	6 %	1 %	22 %
	Working: Domestic worker	0 %	0 %	0 %	0 %
	Not working: Retired	10 %	2 %	1 %	2 %
	Not working: Student	2 %	15 %	0 %	8 %
	Not working: Unemployed	3 %	6 %	0 %	5 %
	Other or no information	1 %	1 %	0 %	2 %
Number of household members	1	31 %	41 %	9 %	38 %
	2	21 %	25 %	37 %	25 %
	3	23 %	19 %	34 %	17 %
	4	17 %	9 %	11 %	13 %
	5	5 %	2 %	6 %	3 %
	6 or more	2 %	1 %	2 %	2 %
	No information	2 %	2 %	0 %	3 %
Annual household income level	Level 1[a]	3 %	3 %	3 %	2 %
	Level 2[b]	11 %	3 %	43 %	27 %
	Level 3[c]	33 %	14 %	36 %	29 %
	Level 4[d]	36 %	42 %	15 %	25 %
	Level 5[e]	8 %	38 %	3 %	5 %
	Prefer not to answer	9 %	0 %	0 %	12 %
[a]	*London:* <£10 GBP	*New York:* <10 k USD	*Shanghai:* <100 k RMB	*Sao Paulo:* <12 k BRL
[b]	£10 k-25 k GBP	10 k-25 k USD	100 k-300 k RMB	12 k-60 BRL
[c]	£25 k-50 k GBP	25 k-50 k USD	300 k-500 k RMB	60 k-120 k BRL
[d]	£50-100 k GBP	50–100 k USD	500 k-1 M RMB	120 k-300 BRL
[e]	>£100 k GBP	>100 k USD	>1M RMB	>300 k BRL

willing to travel (Fig. 3). This marked difference in Shanghai may be due to the fact that they were at a different stage of the pandemic (recall Fig. 2). During the administration of the survey in Shanghai, the number of reported cases in China was well below the peak experienced in January, and stable. Moreover, as seen in Table 1, the sample in Shanghai is on average composed of a younger age group, who may have

been less concerned about the pandemic effects during air travel, and a larger business travel segment.

Upon analysing the attitudinal statements (Fig. 4), we observe a common pattern across the cities in the use of tele-/video-conferencing in place of flying. In all the cities, there was a large (greater than 50 %) share of people before the pandemic who either did not use tele- and
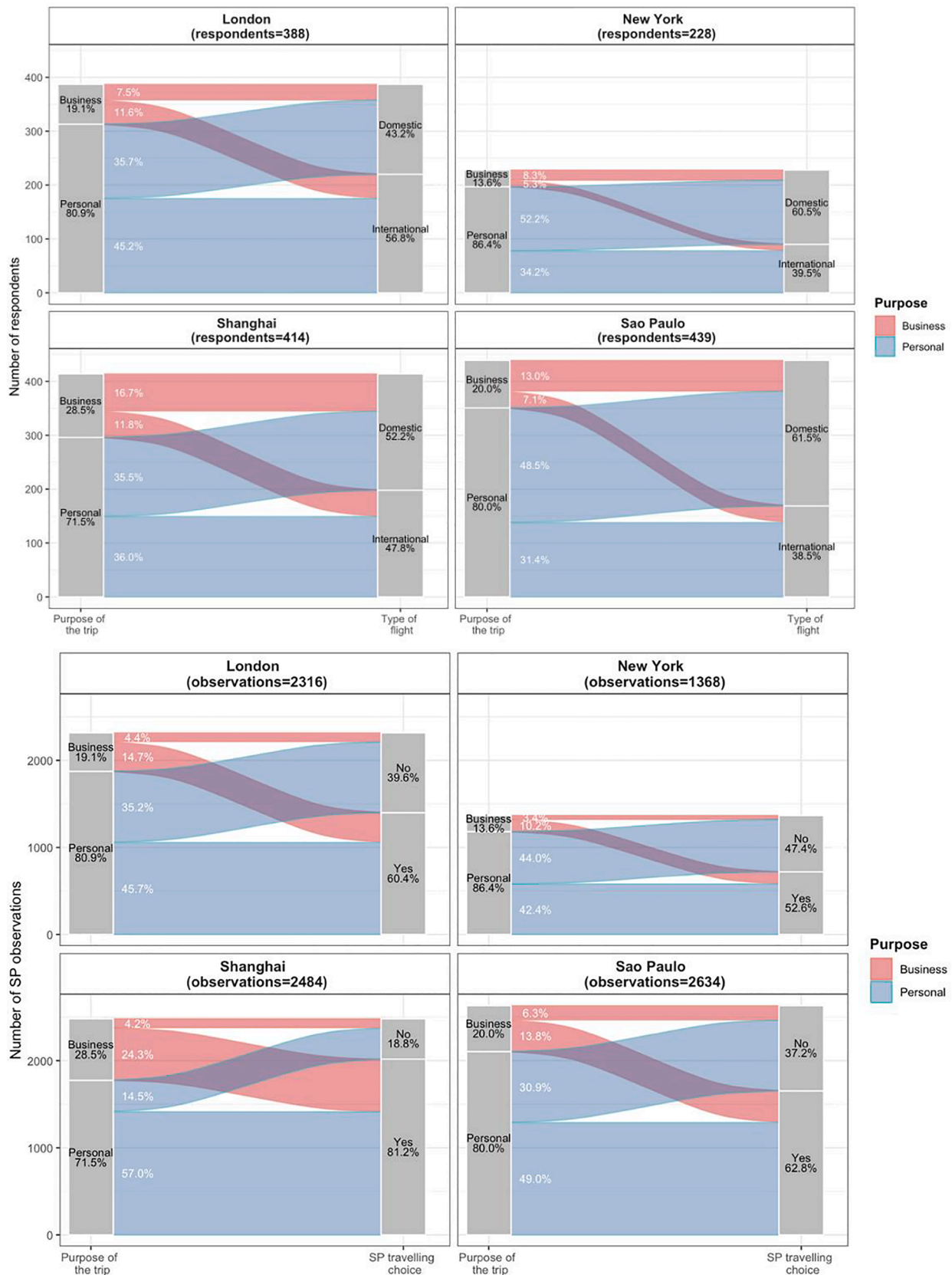
Fig. 3. a) Air Travel Purpose of respondents with respect to International vs Domestic (most recent travel prior to January 2019) and b) SP choices after the COVID-19 pandemic: to travel or not? [Note that the UK domestic flight passengers include individuals flying to a UK destination (i.e. 8.5%) and individuals flying to a country in the EU (i.e. 33.8%)].
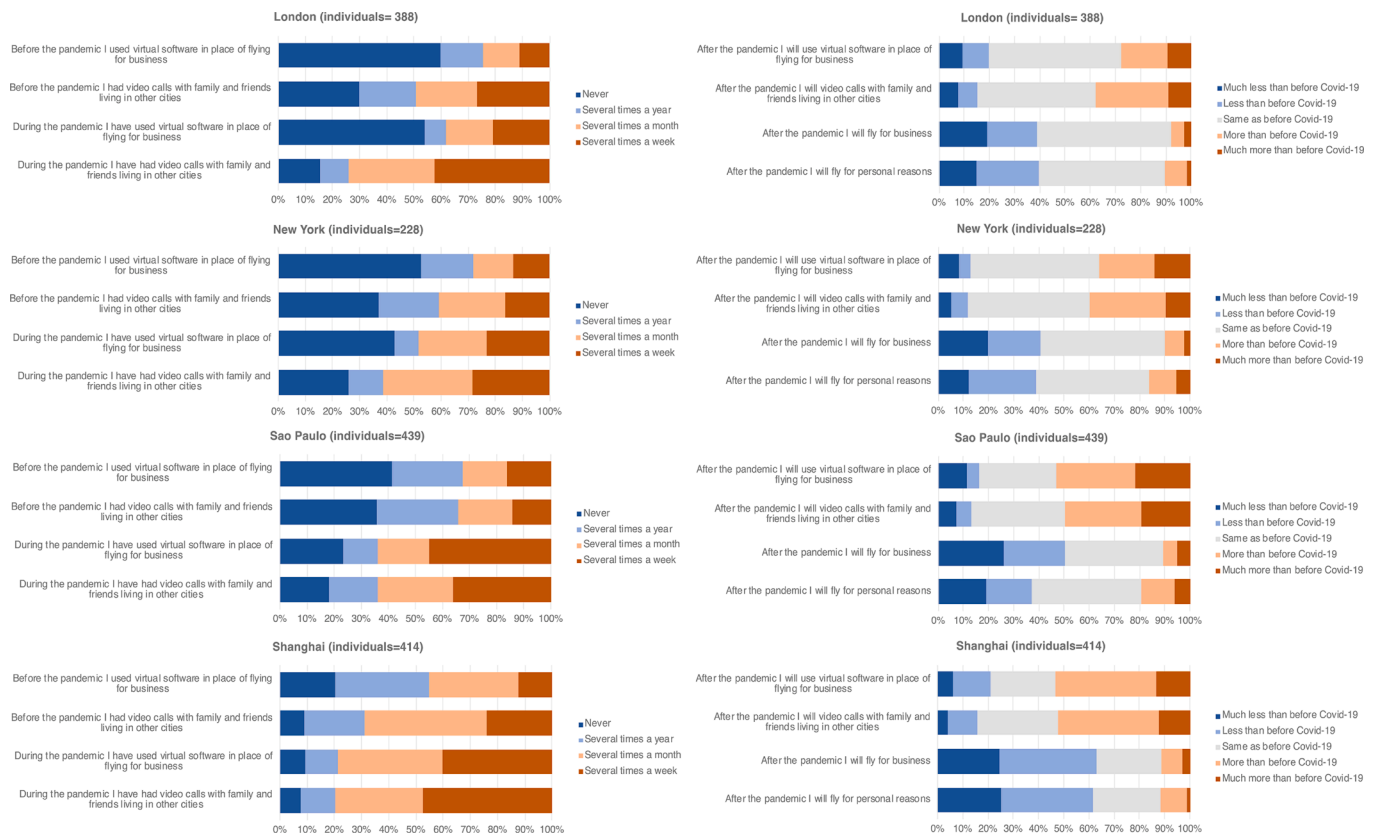
Fig. 4. Use of virtual means in place of flying, before and during COVID-19 and potential use of virtual means in place of flying, post-COVID-19.

video-conferencing or did only several times a year. During the pandemic, on the other hand, the trend was reversed, as expected, with some cultural and regional differences in the extent of the impact on business and social meetings. We also observe that the highest frequency category of 'Several times a week' increased the most, which suggests that physical interaction has been replaced by high-frequency virtual interaction. When asked about the potential use of virtual meetings in place of flying in the post-pandemic future (Fig. 4), most of the respondents in London and New York indicated an expectation that they would go back to the pre-pandemic levels of flying to in-person meetings vs virtual meetings. In Shanghai and Sao Paulo, on the other hand, we observe a more prevalent sentiment that video calls will be used much more than before. Moreover, among the respondents of all the cities, there is a strong expectation, shared by ca. 40 % of the respondents, that they will fly less or much less than before regardless of the reasons.

4. Modelling methodology

The methodology used for this research was developed to explore air passenger choice behaviour and, simultaneously, take into consideration measures of safety perceptions and attitudes towards COVID-19 in multiple cities. In order to gain insights into the role of attitudinal factors on air travel decision-making, we firstly performed exploratory factor analysis of the psychometric statements and then employed the Hybrid Choice Modelling (HCM) technique to model the individual's choices.

4.1. Exploratory factor analysis

The latent factors included in the model were defined with Exploratory factor analysis (EFA performed over the 14 statements concerning the perceptions of safety. Initially, the internal consistency and the sampling adequacy were evaluated, indicating good performance for

each city. First, the KMO was always greater than or equal to 0.83, showing very good sampling adequacy (Kaiser, 1974). Second, the determinants of the Spearman correlation matrix are all greater than 0.00001, between 0.0004 and 0.0054, showing no evidence of multi-collinearity (Prato et al., 2005) while Bartlett's test of sphericity with all the p-values smaller than 0.001 shows that the null hypothesis of having an identity matrix can be rejected (Bartlett, 1951). Finally, the Cronbach's α for all the factors in every city vary between 0.80 and 0.88, showing high reliability in the indicators and denoting that the respondents had a very good perception of the scale over the different statements which led to consistent responses (Gliem and Gliem, 2003). EFA was performed through a maximum likelihood factor analysis with varimax rotation to produce the factor loadings (Table 3) by employing the R package 'GPArotation' (Bernaards et al., 2015).

Table 3 shows the factor loadings, interpretable as measures of correlation, greater than 0.60. This cut-off is large enough to retain the important items and avoid overlapping of the same items on different factors (Comrey and Lee, 1992, Tabachnick et al., 2007). Through a semantic exploration of the psychometric statements listed in Table 3, three latent factors reflecting specific behavioural patterns were identified in each city: Afraid of catching COVID-19, *Afr* (afraid of catching/ passing the virus), Trust in safety measures, *Saf* (feeling safe wearing a mask, empty seat), and Dislike of quarantine, *Qrt* (not travel in case of quarantine). These three latent factors are fairly consistent across the cities and characterised by similar combinations of statements. In particular, the "Afraid of catching COVID-19" factor is defined by the following attitudes: being afraid of catching the virus due to health implications for oneself or family and friends, prefer not to travel to avoid catching COVID-19, belief in the ease of catching the virus at the airport or on the airplane, and worry about meeting careless travellers during the flight. The "Trust in safety measures" factor is characterised by: feeling safer wearing a facemask at the airport and during the flight, and preference for social distancing in the form of empty seats in

Table 3

Exploratory factor analysis, factor loadings [values < 0.6 suppressed].

Item	Statement	London			New York			Shanghai			Sao Paulo		
		Afr	*Saf*	*Qrt*	*Afr*	*Saf*	*Qrt*	*Afr*	*Saf*	*Qrt*	*Afr*	*Saf*	*Qrt*
1	I am afraid of catching COVID-19 for my health	0.68			0.66			0.62			0.72		
2	I am afraid of passing COVID-19 to my family and friends				0.66			0.63			0.62		
3	I would prefer not to travel to avoid catching COVID-19	0.75			0.65						0.79		
4	I would prefer not to travel to avoid quarantining			0.68									
5	I think it would be easy to catch the virus at the airport	0.73			0.74			0.74			0.73		
6	I think it would be easy to catch the virus on the airplane	0.74			0.80			0.70			0.75		
7	I will be safer wearing a mask at the airport		0.83			0.85			0.82			0.89	
8	I will be safer wearing a mask during my flight		0.89			0.91			0.81			0.87	
9	I will be safer having an empty seat between me and the next traveller		0.61			0.66							
10	I will not travel if I have to quarantine upon arrival			0.88			0.82			0.74			0.78
11	I will not travel if I have to quarantine upon my return			0.75			0.93			0.78			0.87
12	I would not mind being tested at the airport												
13	I am worried about meeting careless travellers during my flight	0.64											
14	I would prefer for travellers to be prevented from carrying luggage in the cabin, in order to avoid contact with other passengers												

between travellers. And the "Dislike of quarantine" factor is characterised by the preference not to travel if required to quarantine upon arrival or return.

4.2. Hybrid choice model

The different variables affecting the decision-making process of the individual were included in a hybrid choice model (HCM). The HCM is an integrated discrete choice and latent variable model that enables us to account for psychometric and other unobservable measures within a mixed model formulation (Vij and Walker, 2014) by incorporating structural relationships between observable and latent variables and correcting for measurement errors to reduce the variance of the estimates (Vij and Walker, 2016). As with simpler discrete choice models, the HCM is based on the random utility maximisation (RUM) framework (Domencich and McFadden, 1975, McFadden, 1981), however, its formulation has three different components (Walker, 2001, Ben-Akiva et al., 2002). The choice model component (CMC) represents the utility of the individual i, U_{jit}, associated with the alternative j in the choice task $t = [1, \cdots, T]$ (Manca et al., 2021):

$$U_{jit} = ASC_j + \beta_{jX}X_{jit} + \beta_{jS}S_i + \beta_{jA}A_i + \eta_{ji} + \varepsilon_{jit} \quad (1)$$

in which X_{jit} is the vector of alternative attributes, S_i is the vector of the socioeconomic characteristics of the individuals, A_i includes the possible latent variables, β_{jX}, β_{jS} and β_{jA} are the parameters to be estimated, ASC_j is the alternative-specific constant, ε_{jit} is the error term assumed to be identically and independently distributed extreme value type 1 (EV1), η_{ji} is the error component assumed normally distributed with mean 0 and standard deviation σ_η, $N(0, \sigma_\eta)$ to account for heteroskedastic utilities.

The structural model component (SMC) makes it possible to relate the latent variable A_i to the socioeconomic characteristics S'_i of the individual i:

$$A_i = c + \delta S'_i + \gamma_i \quad (2)$$

in which c and δ are respectively the intercept and the coefficients (to be estimated) associated with the characteristics of the individual i, and γ_i is the disturbance assumed normally distributed $N(0, \sigma_\gamma)$.

The measurement model component (MMC) includes the indicators I_{fi}, for each individual i manifesting the latent variables:

$$I_{fi} = d_f + \theta_f A_i + \mu_{fi}, \quad \text{with } f = 1, \cdots, F \quad (3)$$

where d_f and θ_f are respectively the intercept and the coefficient of the latent variable to be estimated, and μ_{fi} is the disturbance assumed normally distributed $N(0, \sigma_\mu)$. For identification reasons, the first indicator, d_f was normalised to 0 while θ_f was normalised to 1 following the

normalisation of Ben-Akiva et al. (2002).

The joint probability of observing the choice and the indicators is given by the integral over the distribution of η_i and γ_i:

$$P_{j'i}(\eta_{ji}, \gamma_i) = \int_{\eta, \gamma} \prod_t P_{jit}(\eta_{ji}, \gamma_i) g_A(\gamma_i) \prod_f g_{I_f}(I_{fi}|A_i(\gamma_i)) g(\eta) g(\gamma) d\eta d\gamma \quad (4)$$

where $P_{jit}(\eta_{ji}, \gamma_i)$ is the conditional probability of choosing j during task t, $g_A(\gamma_i)$ is the distribution of the latent variable and $g_{I_f}(I_{fi}|A_i(\gamma_i))$ is the distribution of the indicators. The model estimations were implemented through simulated maximum likelihood using PythonBiogeme software (Bierlaire and Fetiarison, 2009).

Nonetheless, a joint estimation across the cities was performed. First, the estimations initially included the scale parameters to test and consider the potential difference in the variance of the errors associated with each dataset across the cities (Louviere et al., 2000, Ortùzar and Willumsen, 2011). Since they were never significantly different from 1 (i.e. no significant difference in the unobserved variance) and also dramatically increased the computational burden and the running time, the scale parameters were not considered for further model estimations. Second, the monetary measures included in the model (such as the travel cost in Table 1) were all converted to US dollars. The conversion was implemented using the 2019 Purchasing Power Parities (PPP) conversion factor for the gross domestic product (GDP) provided by the World Bank and Eurostat-OECD PPP Programme (The World Bank, 2020). The PPP conversion factor in local currency unit per $ is 4.1759 [*RMB/USD*] for China, 2.3996 [*BRL/USD*] for Brazil and 0.7755 [*GBP/USD*] for the UK.

Trade-off analysis is also performed by calculating the willingness-to-pay (WTP) for saving the time spent at the departure and arrival airports and for non-stop flights across the various sample segments considered during the estimation. In general, the WTP is an indicator of the maximum price at which an individual is willing to buy a unit of a certain product (Varian and Varian, 1992). Thus, in the present case, WTP corresponds to an improvement of the characteristics of the trip. For instance, the WTP for saving time, also called value-of-time, is calculated as the marginal rate of substitution between perceived time t_i and cost C_i characterising the alternative i in its constant utility V_i (Gaudry et al., 1989, Ortùzar and Willumsen 2011):

$$WTP = -\frac{dC_i}{dt_i}\bigg|_v = \frac{\partial V_i/\partial t_i}{\partial V_i/\partial C_i} \quad (5)$$

5. Model results

The HCM framework estimates the sensitivity of individual preferences for the attributes characterising the choice alternatives (attributes

such as fares, trip duration, transfers), and the difference in these sensitivities across individuals as explained by observable characteristics (such as individual socioeconomic characteristics) as well as latent unobservable characteristics inferred through the psychometric statements. The HCM enables this by combining a choice model component (CMC), a structural model component (SMC) and a measurement model component (MMC). The CMC incorporates the utility functions associated with the alternatives, including the observed attributes. The SMC relates the characteristics of the individual and the latent variables. The MMC, on the other hand, relates the indicators and the manifested latent variables, which were identified during the EFA, and effectively acts as the confirmatory factor analysis (Vij and Walker, 2016). The parameters of the HCM were estimated on the full dataset, segmenting by city, haul distance (i.e., short-, medium-, and long-haul) and purpose of the trip (i. e., business, and personal). Only statistically significant (at 95 % confidence level) segmentation parameters were retained, otherwise, a generic parameter across segments was employed. Models were tested and compared using likelihood ratio tests for nested model specifications, and ρ^2 and the *adjusted* ρ^2 indexes for non-nested specifications (Ortùzar and Willumsen, 2011). The full model results are included in Appendix, Table 1.

The final model specification was driven by a combination of literature-based a priori hypotheses and exploratory search for novel drivers of behaviour. In the former group, we incorporated conventional attributes characterising travel alternatives, such as costs, time at the airports, number of transfers or purpose of travel. Such factors, alongside passenger sociodemographic characteristics, have been shown to affect air travel decision-making (as per studies cited earlier in the paper). As for the latter group, we chose to explore the role of COVID-19 attitudes and the use of digital alternatives, which, due to the unprecedented nature of the pandemic, are not clearly established in the literature, at least in the context of air travel. Last but not least, due to the limited size of the data relative to the model specifications, we also had to take into account the need for model parsimony to ensure statistical robustness.

Due to the size of the model, only parameters that are statistically significant at the 95 % confidence level are presented to facilitate readability and analysis. Fig. 5 presents a comparison of the parameters associated with the fare, number of transfers and time spent at the airport on departure and upon arrival. The results are segmented by city and flight type: *SH, MH, LH, SMH, LMH,* and *All* respectively indicate *Short-haul, Medium-haul, Long-haul, Short- and Medium-haul, Medium- and Long-haul,* and *All* distances. Nonetheless, since the MMC technically performs a confirmatory factor analysis which showed that the latent variables considered in the model are correctly "manifested" by the statements that were identified during the EFA (i.e. they were all statistically significant), we do not present, for a matter of conciseness, these results separately from the EFA. These results can be found in Appendix, Table 1.

5.1. HCM: Choice model component

All fares were converted to US$ to allow cross-national comparisons. In all the cities, the sensitivity to travel cost for personal travel purposes is higher than that for business travel and decreases with increasing haul-distance (Fig. 5). This is intuitive and has been observed in other studies (Proussaloglou and Koppelman, 1999, Adler et al., 2005, Hess and Polak, 2005, Zhou et al., 2019). When compared across cities, respondents from London and New York are clearly the most sensitive to cost, especially for personal trips, followed by respondents from Sao Paulo, with the respondents from Shanghai being the least sensitive to travel cost. At the same time, Shanghai respondents are the most sensitive to the number of transfers for all but long- and medium-haul business trips. In addition, Shanghai is the only city where the dis-preference for transfers is higher for short-haul flights than for medium- or long-haul flights. In London, we do not observe a significant difference in sensitivity to transfers across haul distances, and so we use a generic ('All distances') parameter. This sensitivity to the number of transfers for London-based travellers is much lower (less negative) than for the other cities. In New York, on the other hand, we did not observe any difference in sensitivity to transfers across journey purposes. Regarding the time spent at the airport, we observe that the sensitivity
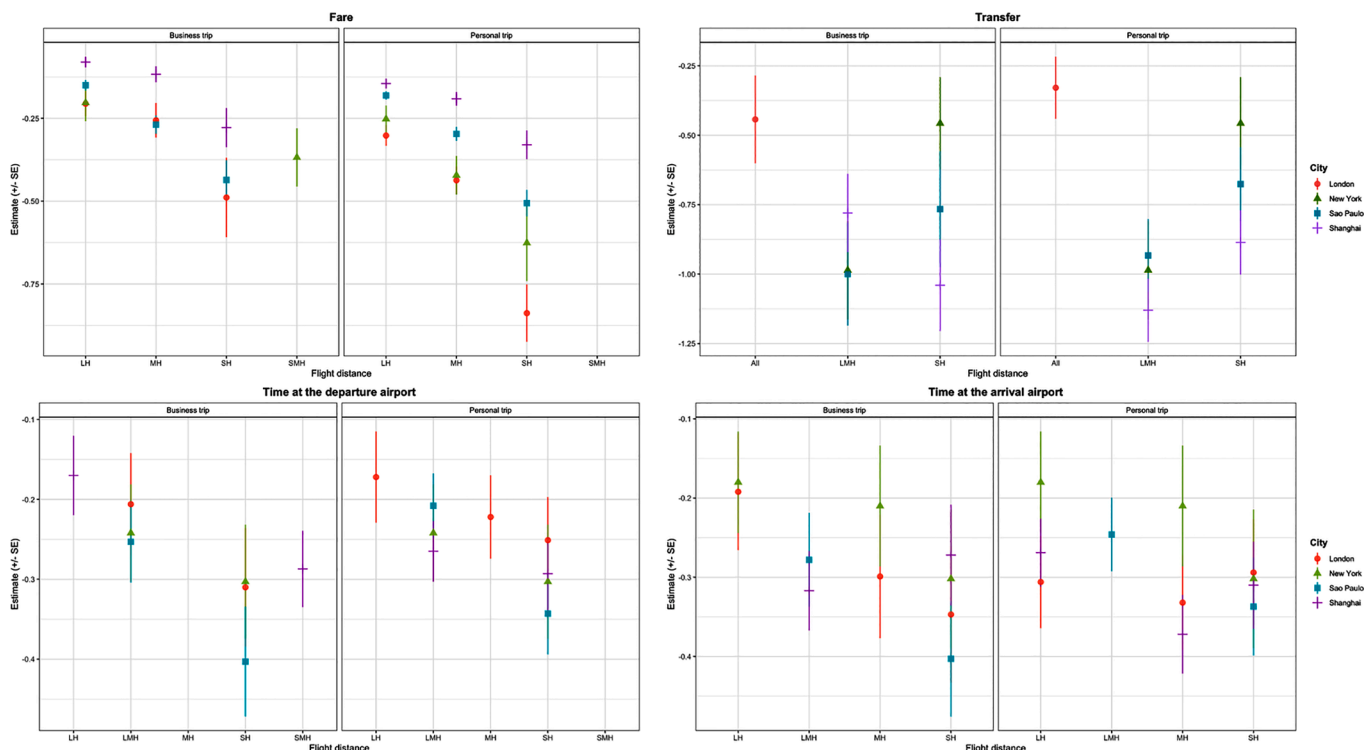

Fig. 5. Sensitivity analysis of cost, number of transfers, time at the departure airport and time at the arrival airport.

increases when the flight distance decreases for both business and personal reasons. In other words, the shorter the flight the higher the dispreference for long wait times at the airports due to COVID-19-related procedures. This observation applies to both times spent at the departure airport and at the arrival airport, though the effect is less pronounced for the time at arrival airports during personal flights for London and Shanghai travellers. On the other hand, Sao Paulo travellers are less sensitive to the time spent at the airport for personal trips compared to business trips, especially for short-haul flights. Whereas, New York travellers are more sensitive to the time spent at the departure airport than the time spent at the arrival airport. Again, for the New York sample, we do not observe segmentation by purpose, similar to the transfers.

In addition to the travel attributes, we tested for socioeconomic variables to investigate their role in shaping air travel preferences (Fig. 6). For London, the three variables were found to be statistically significant: "household annual income of £100 k (or $128 k) or more",

"occupation, full-time employed" and "age above 45 years". The negative sign on the income and age variables show that these two segments have a lower willingness to travel whereas full-time employed respondents have a higher willingness to travel, ceteris paribus. The parameter of the variable "age above 45 years" for New York is also negative and significant, like London. No socioeconomic variable was found to be statistically significant when included in the choice model component of the Sao Paulo and Shanghai utility functions.

As for the variables regarding the "Use of Virtual Software" before, during and after COVID-19, we observe their importance for business trips (Fig. 6). We notice that in New York, and London to a lesser extent when the norm was to use virtual software in place of flying several times a month or more before and during the pandemic, the respondents are more willing to travel by air again when feasible. Interestingly, only in London do we observe the belief, that virtual software will be used more after the pandemic than before the pandemic, to be associated with a lower probability of air travel. And in Shanghai, when the norm was
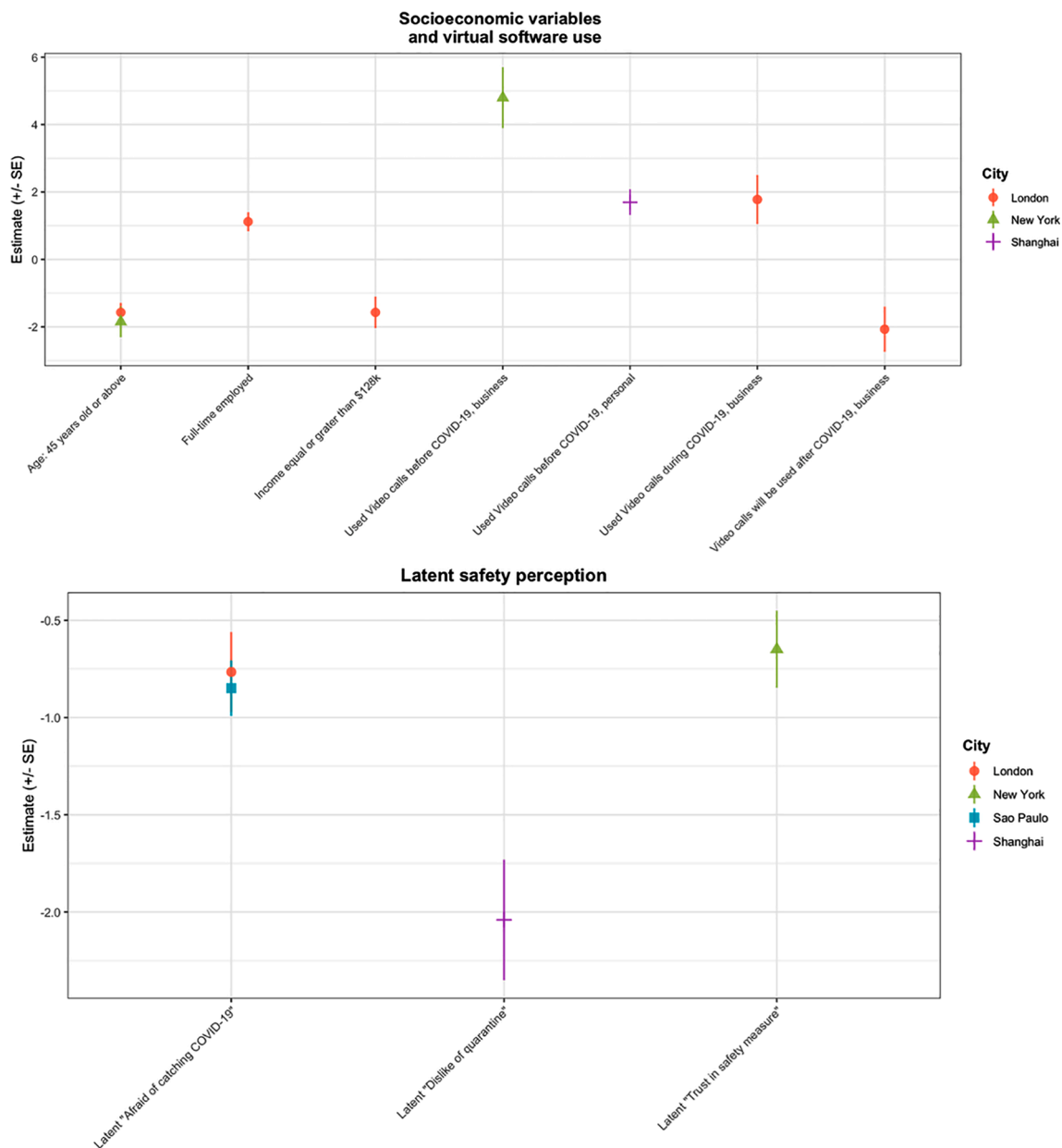

Fig. 6. a) Sensitivity analysis of socioeconomics and virtual software use variables and b) Latent safety perception effects [Note: for Sao Paulo, no statistically significant socio-economic variables were found when included in the CMC].

the frequent "Use of video calls with family and friends" before the COVID-19 pandemic, we observe the intention to travel again when possible after the pandemic.

As for the latent variables identified through the exploratory factor analysis, we find that only one variable for each city is a statistically significant determinant in the choice behaviour (Fig. 6). In London and Sao Paulo, respondents are less likely to travel when they are "afraid of catching COVID-19" at the airports or on-board the airplane, or meeting careless travellers (London only, cf. Table 3), or passing the virus to family and friends (Sao Paulo only, cf. Table 3). In New York, respondents are also less likely to travel when they have indicated a preference for mask-wearing compliance at airports and in the airplane and a preference for an empty seat between passengers (i.e. the "Trust in safety measure" latent variable). This behaviour appears to have its source in the cross-national differences in perceptions of crowding. As for the concern of passing the virus to family and friends observed among respondents from Sao Paulo, this can relate to Hofstede's cultural dimension theory and the associated notions of individualism and collectivism (Hofstede and Hofstede, 1984). In particular, past studies (Beekun et al., 2003, Clearly Cultural, 2005) have shown that Brazilian society leans towards collectivism, i.e. a high degree of integration in cohesive groups such as extended family. However, such an explanation would also require a similar effect to being observed among respondents from Shanghai, given that China is perceived as an even more collectivistic society than Brazil (Tu et al., 2011, Clearly Cultural, 2005). Here we propose two potential explanations. On the one hand, results in Table 1 indicate that the respondents from Shanghai were younger than those in Brazil, which could point towards a higher degree of individualism that has been observed among younger individuals in China (Chen 2015). On the other hand, past research has shown substantial variations in cultural dimensions across Chinese regions (Huo and Randall, 1991, Li et al., 2013). Studies have shown Shanghai to differ from other regions, due to its level of economic development and pace of

life, prompting more individualistic lifestyles (Sun and Wang, 2010). Moreover, at ca. 40 %, Shanghai has one of the highest proportions of migrants in its population (Liao and Wong, 2015). Inevitably, this translates into more distant (in a physical sense) relationships to family and arguably a reduced risk of transmission, due to less frequent interaction. Thus, it appears that in their concern about transmission of the virus to family and friends stemming from social collectivism, respondents from Shanghai may more resemble those from New York and London than those from Sao Paulo and, possibly though not verifiable using the current data, other regions of China.

Moving on to the "Dislike of quarantine" factor, the potential need to quarantine upon arrival or return decreases the probability of air travel for Shanghai travellers. This observation may be interpreted in the context of differences in the quarantine regimes across the cities and countries (Haug et al., 2020). In particular, at the time of data collection, China already had in place a hotel-based quarantine regime that required travellers to isolate themselves in designated hotels for 14 days at their own expense. This contrasts with the other cities where, at the time of data collection, the quarantine regime relied on home-based and self-monitored self-isolation. Clearly, the difference in the expected monetary and psychological burden associated with quarantine aligns with the results observed in our model.

Lastly, we observe that having controlled for all the factors discussed above, the respondents still have an inherent preference towards air travel. This is manifested in the positive value of the alternative specific constant (ASC) parameters in Appendix, Table 1.

5.2. HCM: Structural model component

Fig. 7 maps the latent variables established as being statistically significant in the choice model component onto individual characteristics i.e. identifying the type of person expressing the specific latent attitudes in terms of their socioeconomic characteristics and personality
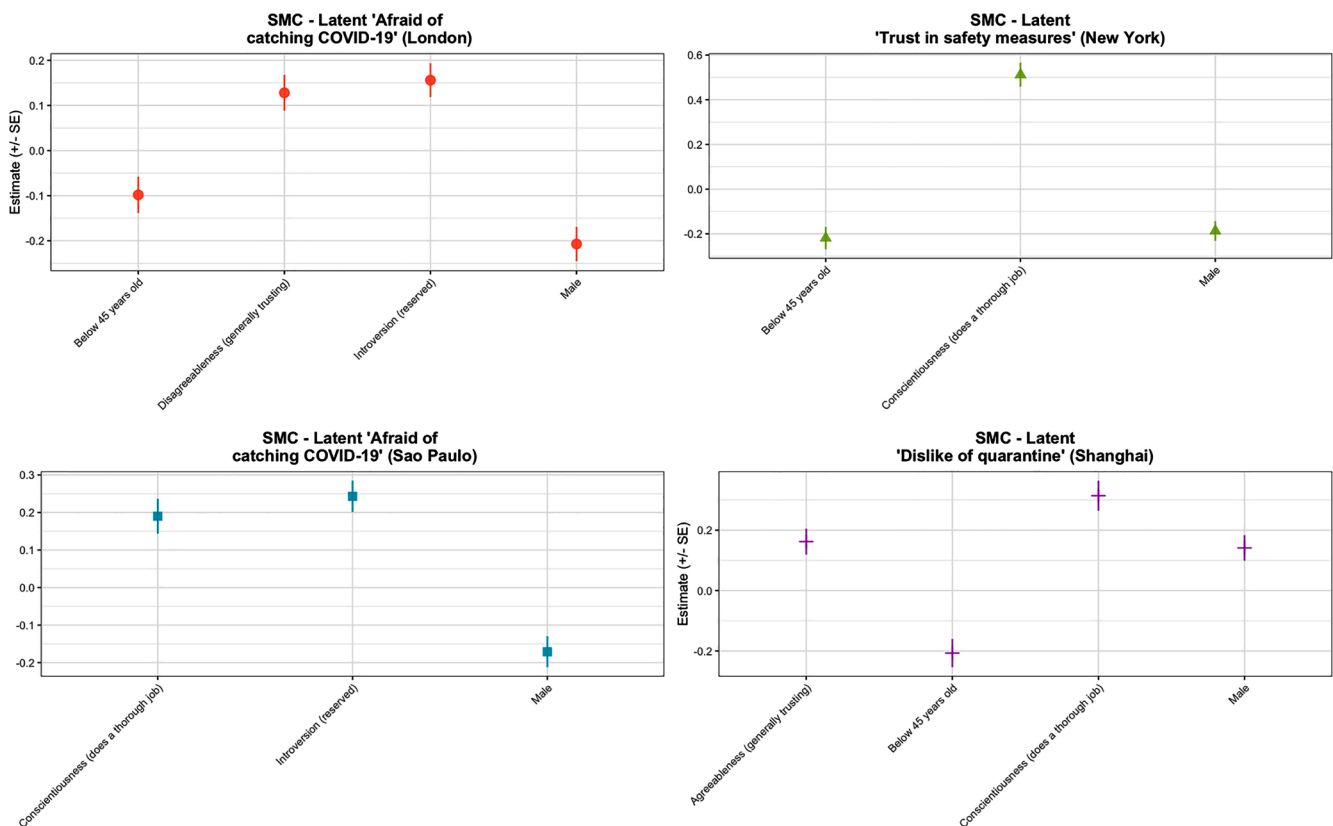

Fig. 7. Individual characteristics correlated with the latent variables.

traits.

First, the latent variable "Afraid of catching COVID-19", which was found to be statistically significant in the London sample, is negatively correlated with males and people younger than 45 years of age, and positively correlated with two personality traits: "disagreeableness" (i.e. the propensity to see oneself as someone who tends to find fault with others) and "introversion" (i.e. the propensity to see oneself as a reserved person). In other words, females above 44 years who see themselves as reserved people tending to find fault with others are more likely to be afraid of catching COVID-19, and therefore affected by these concerns in their air travel choice behaviour. The same latent variable "Afraid of catching COVID-19" was also found significant in Sao Paulo. The variable is again negatively correlated with being male and positively correlated with "introversion" (i.e. the propensity to see oneself as a reserved person). The third characteristic that is positively correlated to the latent is "conscientiousness" (i.e. the propensity to do a thorough job"). Therefore, in this case, there is a lower inherent preference towards travelling among females that see themselves as reserved and conscientious. For New York, the model estimation suggests that the latent variable "Trust in safety measures" is negatively correlated with being younger than 45 years of age and male. It is also positively correlated with being "conscientiousness" (i.e. the propensity to do a thorough job"). Travellers in New York who have trust in safety measures are, therefore, female, 45 years old or older, who see themselves as conscientious and diligent. Finally, the latent variable "Dislike quarantine" which was found significant in Shanghai is negatively correlated with being under the age of 45 and positively correlated with being male, "agreeable" (i.e. the propensity to see oneself as a person who trusts others) and "conscientious" (i.e. the propensity to do a thorough job"). Travellers in Shanghai who dislike quarantine are, therefore, male, 45 years old or older, who see themselves as trusting and diligent.

In general, the fact that being younger than 45 years of age is negatively correlated with being afraid of catching the virus and trust in safety measures suggests that people who are 45 years old or older have a lower inherent preference towards air travel after the pandemic, possibly because this age group is at a higher risk of facing severe consequences from COVID-19 (Jordan et al., 2020). Nonetheless, males are usually much more willing to take risks (Halek and Eisenhauer, 2001) and this explains the negative sign when interacted with these two variables.

5.3. Trade-off analysis

The fundamental concept of trade-off analysis is to estimate the respondent's willingness-to-pay (WTP) for improved travel conditions, for example, the WTP to save one hour of wait time at the departure or arrival airports, or the WTP to go from a one-transfer air travel itinerary to a direct (no transfers) flight. In this section, we present the trade-off analysis based on our survey data and the models estimated on the data, in order to determine the passengers' willingness to pay under the expected future conditions.

The results (Table 4) are broadly consistent with the model results discussed so far. In general, the WTP in Shanghai and Sao Paulo is higher than in London and New York. Shanghai travellers are particularly keen to pay much more than respondents from the other cities for saving time and for direct flights.

Nonetheless, for all cities, the WTP of people travelling for business purposes is higher than the WTP of people travelling for personal purposes and, for both purposes the WTP increases as the haul distance increases; these results are coherent with the results of previous studies in the air travel literature (Proussaloglou and Koppelman, 1999, Warburg et al., 2006, Hess et al., 2007).

Looking at the average WTP for reducing one hour of time at the departure airport (also, sometimes, referred to as the value-of-time (Ortúzar and Willumsen, 2011)), we observe that in London, Shanghai and Sao Paulo it is slightly lower than the WTP for saving one hour at the

Table 4
A trade-off analysis.

	Willingness-to-pay			
	London	New York	Shanghai	Sao Paulo
Time at the airport:	WTP for −1h [$/h]			
Before flying out				
Long-haul, personal	57	96	183	115
Medium-haul, personal	51	57	139	70
Short-haul, personal	30	48	89	68
Long-haul, business	100	119	212	169
Medium-haul, business	80	66	245	94
Short-haul, business	63	82	103	92
After landing				
Long-haul, personal	101	71	186	136
Medium-haul, personal	76	50	195	83
Short-haul, personal	35	48	94	67
Long-haul, business	93	89	395	185
Medium-haul, business	117	57	271	103
Short-haul, business	71	82	98	80
Transfer	WTP for direct flight versus 1 + transfers [$]			
Long-haul, personal	109	391	779	515
Medium-haul, personal	75	234	592	314
Short-haul, personal	39	73	205	134
Long-haul, business	215	486	973	667
Medium-haul, business	173	268	667	372
Short-haul, business	91	124	374	176

arrival airport. Interestingly, the situation is reversed in New York, where the respondents are willing to pay more to reduce time spent at the departure airport than the arrival airport, perhaps because most trips made by New York respondents are domestic i.e. the arrival airport is within the country, no border controls are required and, therefore, there is less uncertainty after landing.

The WTP for nonstop flights is much higher than that reported in the pre-pandemic studies. This is likely to be a manifestation of people's willingness to avoid transfers and the associated social contact and arguably increased risk of infection. For instance, comparing our WTP figures for New York against those of Warburg et al. (2006) and Hess et al. (2007) for US air trips, we can see that, on average, for non-stop business flights, air travellers are willing to pay an additional amount that has increased from around $50 before the pandemic to $290. And for non-stop personal flights, air travellers from New York are willing to pay an additional amount that has increased from $40 pre-pandemic to $230 under the expected future conditions.

6. Discussion

The analyses in this study highlight the importance of COVID-19-related safety perceptions on passengers' decision to travel by air, along with traditional attributes characterising air travel alternatives (such as travel time and cost). The results with respect to the conventional determinants of air travel decision-making, such as fare, number of transfers or purpose of travel, are in line with the literature. Consistent with our expectations, we also find that safety perceptions matter in the context of air travel under post-pandemic circumstances. We also observe that safety perceptions differ in terms of the sources of fear (from getting infected to infecting family) as well as the characteristics of the person who experiences the fear. Our modelling approach allows us to characterise the typical passengers who are driven by such concerns. For instance, in London, we observe that individuals who are "Afraid of catching COVID-19" tend to be females above 44 who see themselves as reserved and tend to find fault with others. In New York, individuals who have "Trust in safety measures" are female, 45 years old or older, who see themselves as conscientious and diligent. In Sao Paulo, individuals who are "Afraid of catching COVID-19" tend to be females

that see themselves as reserved and diligent. In Shanghai individuals who "Dislike quarantine" are male, 45 years old or older, who see themselves as trusting and diligent. These outcomes are useful to define actions and campaigns targeting the segment of the population that is more concerned and help recapture the lost air travel demand. More generally, a better and more consistent clarification, and its diffusion, of how airports and airlines try to minimize the risk of infections and guarantee the safety of passengers is needed (Manca et al., 2021).

Nonetheless, looking at the differences across the cities (in different countries) in our study, we argue that the dissimilarities may also stem from deeper, culturally-driven attitudes towards interpersonal distance and personal space (the notion of contact versus non-contact communities) and differences in Hofstede's cultural dimension of individualism and collectivism (Hall, 1966, Hofstede and Hofstede, 1984). In particular, back in the 1960s, Hall (1966) concluded that residents of 'contact cultures', including Latin, Asian, and Arab, accept closer interpersonal distances in comparison to those from noncontact cultures, such as Northern Europe or North America. Such results were subsequently verified in the context of crowding tolerance (Evans et al., 2000). This helps to better understand the differences in the attitudes towards COVID-19-related measures, such as the concern of passing the virus to family and friends, across different countries.

Whilst the recovery in air travel demand appears to be ongoing (International Air Transport Association, 2021), the pandemic has strained the budgets of the air industry and governments. In this landscape, insights helping to prioritise investments and adapt models of operation are crucial. Our trade-off analysis provides evidence that the WTP for travel time reduction is higher during the pandemic conditions as compared to the pre-pandemic levels (along the same line looking at other transport industries, a higher post-pandemic travel time valuation was also observed for the London Underground in a study by Bansal et al. (2022)). It is uncertain if this increase is permanent but certainly offers an insight to the air industry with respect to running operations during the ongoing pandemic, even despite the hopeful outlook provided by the ongoing vaccine rollout and research into therapies. For example, our evidence shows that longer waiting time at the airports, such as for testing, appears to be more acceptable (lower WTP) upon arrival for people from New York and before departure for travellers based in London, Sao Paulo and Shanghai. Similarly, our analysis indicates a much higher WTP for direct flights among business travellers on all hauls, especially for London-based travellers. Such insights can aid the airlines in adapting their routing and pricing strategies.

Another finding relates to the role of virtual substitutes in place of air travel. The use of information and communication technologies (ICT) in place of travel has been acknowledged as a possibility since the late 1970s (Pawlak et al., 2020). ICT-based alternatives have also begun to be incorporated alongside traditional models of travel in transport modelling (Pawlak et al., 2015), such as in the context of telecommuting (Nurul Habib et al., 2012, Singh et al., 2013) or online shopping (Suel and Polak, 2017, 2018). A more comparable context, however, is arguably the 2010 eruption of Eyjafjallajökull volcano in Iceland, which led to the closure of European airspace and prompted increased use, but also discussion about the role, of videoconferencing as a substitute to air travel (Denstadli et al., 2012). The permanent substitution of air travel with videoconferences did not materialise at that point, given the sharp recovery and subsequent increase in demand for air travel (NBC News, 2011). At the same time, the 2010 circumstances were not similar in scale to the COVID-19 pandemic, with respect to the scale of restrictions and their duration. Thus arguably, past events offer relatively limited indication with respect to what role videoconferencing will play in the post-COVID world. Based on the stated intentions of the survey respondents, our findings point towards a continuing intention to travel. In fact, we observe that in the case of business trips, it is the frequent users of virtual software that expressed willingness to travel as soon as possible after the pandemic. However, our results also indicate that expectations, with respect to the use of videoconferencing post-

pandemic, vary cross-nationally. A consistent finding across the cities is the existence of a substantial segment of individuals who foresee increased use of videoconferencing in place of flying for both business and personal reasons. This is arguably an artefact of the captive increased use or initial adoption of such solutions to maintain the sense of 'togetherness' (Hacker et al., 2020). It does remain to be seen, however, whether this form of communication will remain a substitute or a complement to air travel.

It must be noted, however, that this is a cross-sectional study which aims to shed light on the different factors affecting the decision-making process. This is a dynamic research field, and it is important to evaluate the potential evolution of attitudes and choices as the pandemic evolves over time in order to generate a clearer picture of long-term COVID-19 impacts on air travel demand. Future studies could also try to simultaneously investigate multiple types of attitudinal factors such as environmental and climate change concerns, alongside the pandemic-related safety concerns, as these are considered very important for the air travel sector. For instance, aviation features prominently in the European Commission's legislative proposals for achieving net-zero carbon emissions by 2021 (European Commission, 2021) and eco-anxiety trends have continued through the pandemic, showing that a growing proportion of society is concerned as well, and for some this even leads to mental health issues (Panu, 2020).

7. Conclusions

The COVID-19 pandemic has exceptionally affected air travel globally, including knock-on effects on the supply chain of the air industry but also society as a whole. Although necessary NPI-based measures, such as keeping social distance, imposing the use of masks at all times and providing test centres at the airports, have been taken in order to minimise the risk of infection, the role of visceral factors and safety perception on future air travel behaviour is not much understood.

In this study, we provide evidence, based on survey data collected from four multi-airport cities around the world during the pandemic, that such visceral perceptual and attitudinal factors are likely to play a role in air passenger decision-making in future air travel choices, at least in the short and probably also in the medium run. We also note that these effects vary across the cities, which we attribute to the societal differences in the acceptance of interpersonal distance and in the cultural dimension of social individualism vs collectivism. What this implies is that efforts, including NPI strategies, business operations and marketing campaigns associated with air travel must be tailored to the specificities of local societies in order to be effective. The current research provides strong evidence for the need to adopt this localisation approach also for the variety of innovative measures devised in the air travel industry to mitigate the negative impacts of the COVID-19 pandemic (Amankwah-Amoah, 2021). For example, social distancing measures may work more effectively among noncontact societies (in our study this refers to London and New York). Such markets may be more receptive to offers oriented at effectively realising in-flight social distancing via upgrades to seating class with empty middle seats or more distanced seating by design. As for segments and communities concerned with transmitting the virus to extended family members and friends, for example Sao Paulo in our research, the air travel sector should focus on measures oriented more specifically at reducing such risks. This could involve access to cheap and reliable testing, raising awareness of personal hygiene and disinfection practices or clearly advertising (and implementing) 'deep cleaning' procedures. The case of Shanghai is clearly-one that may require further research as the observed effects may be related to either or both of the younger sample profile and Shanghai city's specific context within China, which may not be representative of the overall Chinese context. On the one hand, the concern associated with quarantine could mean a shift towards domestic air travel, for which evidence started to emerge already in 2020 (Li et al., 2022). This could suggest the need for airlines to re-orient themselves

towards the domestic market. However, strict adherence to the 'zero COVID' policy in China (at the time of writing) has started posing challenges even to internal travel, due to risks of rapid and pro-longed lockdowns. Such an uncertain environment should encourage policies looking at maximising flexibility for passengers, including refunds and free modifications to travel plans as well as the provision of suitable insurance policies.

Nevertheless, we can confidently state that a 'one-size-fits-all' to managing air travel operations may not prove as effective as an approach tailored to the local socio-cultural contexts. Thus global-level recommendations, such as ICAO guidance (International Civil Aviation Organization, 2021), need to explicitly recognise the need to adapt the mitigation measures and business strategies to the local contexts in order to remain most effective. This finding aligns with past research in management studies that clearly demonstrate higher effectiveness of marketing campaigns (Han and Shavitt, 1994, Chen et al., 2011, Guerreiro and Loureiro, 2020) or profitability of business models (Lim et al., 2004, Kongsompong et al., 2009, Chen, 2013) when tailored to local cultural contexts.

A related aspect observed in our study concerned the role of strict quarantine regimes. In particular, the observations from Shanghai indicate a clearly detrimental role on the international travel demand of a hotel-based quarantine upon arrival, which is an intuitive behavioural response. At the same time, the restriction on international air travel would be expected to lead to increased demand for domestic air travel. Indeed, we observe this to be the case as domestic air travel demand has seen 20 % higher demand compared to the pre-pandemic level (Lei, 2021). Similar trends are observed in the comparable context (low level of community transmission and strict international quarantine regime) of Australia and New Zealand (Anthony, 2021, Cusmano, 2021, Curran, 2021).

Our findings lead us to the conclusion that combating the crisis in the air travel sector will require a departure from the 'one-size-fits-all' approach to more explicitly considering differences in perceptions and inhibitors to travel. Furthermore, we report on how much monetary value people attach to the ability to fly directly or spend less time at the airport, for example due to testing protocols. We suggest that such

willingness to pay metrics may be of use to the air travel industry, in making investment decisions, considering the budget austerity faced by the industry and governments. We also observe consistently across the cities that a substantial segment of individuals believes that the use of videoconferencing as a substitute for air travel will increase post-pandemic. However, the use of videoconferencing in place of flying before and during the pandemic increases the likelihood of flying when this will be possible after the pandemic. At the same time, air travel demand recovery appears to be also facing another set of risks, including geopolitical tensions, volatile energy prices combined with macroeconomic uncertainty (inflation, stalling economic growth, supply chain disruptions) as well as growing environmental concerns with respect to carbon emissions associated with air travel. Therefore, the extent to which this means of communication will continue to be a substitute after the pandemic remains to be seen.

CRediT authorship contribution statement

Francesco Manca: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Jacek Pawlak:** Conceptualization, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Aruna Sivakumar:** Conceptualization, Writing – original draft, Writing – review & editing, Supervision, Project administration.

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

Appendix, Table 1
Complete model estimation

Model estimation

Model part	Name	London			New York			Sao Paulo			Shanghai		
		Value	t-test		Value	t-test		Value	t-test		Value	t-test	
Choice model component (CMC)	ASC	7.39	6.85	**	7.9	6.45	**	9.03	11.33	**	14.7	10.2	**
	Fare [100 $]												
	Long-haul, personal	−0.302	−9.65	**	−0.252	−6.22	**	−0.181	−14.59	**	−0.145	−10.24	**
	Medium-haul, personal	−0.437	−10.53	**	−0.422	−7.22	**	−0.297	−14.07	**	−0.191	−9.19	**
	Short-haul, personal	−0.838	−9.66	**	−0.626	−5.47	**	−0.506	−12.72	**	−0.33	−7.6	**
	Long-haul, business	−0.206	−5.48	**	−0.203	−3.65	**	−0.15	−9.66	**	−0.08	−4.89	**
	Medium-haul, business	−0.256	−4.89	**				−0.269	−9.92	**	−0.117	−4.87	**
	Short- and Medium-haul, business				−0.368	−4.19	**						
	Short-haul, business	−0.489	−4.08	**				−0.436	−7.37	**	−0.278	−4.7	**
	Time at the airport [h] - Before flying out												
	Long-haul, personal	−0.172	−3.02	**									
	Long- and Medium-haul, personal							−0.208	−5.13	**	−0.265	−6.98	**
	Medium-haul, personal	−0.222	−4.24	**									
	Short-haul, personal	−0.251	−4.65	**				−0.343	−6.73	**	−0.293	−6.4	**
	Long-haul, business										−0.17	−3.42	**
	Long- and Medium-haul, business	−0.206	−3.21	**				−0.253	−4.96	**			
	Short- and Medium-haul, business										−0.287	−6	**
	Short-haul, business	−0.31	−4.17	**				−0.403	−5.85	**			
	Long- and Medium-haul, both purposes				−0.242	−3.98	**						

Appendix, Table 1 (*continued*)

Model estimation

Model part	Name	London Value	t-test		New York Value	t-test		Sao Paulo Value	t-test		Shanghai Value	t-test	
	Short-haul, both purposes				−0.303	−4.24	**						
	Time at the airport [h] - After landing												
	Long-haul, personal	−0.306	−5.25	**							−0.269	−6.25	**
	Long- and Medium-haul, personal							−0.246	−5.31	**			
	Medium-haul, personal	−0.332	−5.55	**							−0.372	−7.49	**
	Short-haul, personal	−0.294	−4.38	**				−0.337	−5.46	**	−0.31	−5.63	**
	Long-haul, business	−0.192	−2.6	**									
	Long- and Medium-haul, business							−0.278	−4.69	**	−0.317	−6.33	**
	Medium-haul, business	−0.299	−3.83	**									
	Short-haul, business	−0.347	−4.03	**				−0.403	−5.53	**	−0.272	−4.26	**
	Long-haul, both purposes				−0.18	−2.8	**						
	Medium-haul, both purposes				−0.21	−2.75	**						
	Short-haul, both purposes				−0.302	−3.44	**						
	Transfer												
	Any distance, personal	−0.329	−2.94	**									
	Long- and Medium-haul, personal							−0.933	−7.12	**	−1.13	−9.91	**
	Short-haul, personal							−0.676	−5.08	**	−0.886	−7.63	**
	Any distance, business	−0.443	−2.81	**									
	Long- and Medium-haul, business							−1	−5.42	**	−0.78	−5.53	**
	Short-haul, business							−0.766	−3.66	**	−1.04	−6.31	**
	Long- and Medium-haul, both purposes				−0.986	−5.58	**						
	Short-haul, both purposes				−0.457	−2.74	**						
	Video calls & virtual activities												
	Used before COVID-19 outbreak, personal										1.7	4.45	**
	Used before COVID-19 outbreak, business				4.8	5.3	**						
	Used during COVID-19 outbreak, business	1.78	2.44	**									
	Will be used after COVID-19 outbreak, business	−2.07	−3.09	**									
	Sociodemographic												
	Income: £100 k ($128 k) p.a. or above	−1.57	−3.36	**									
	Full-time employment	1.12	3.91	**									
	Age: 45 years old or above	−1.57	−5.49	**	−1.85	−4.08	**						
	Error component η	2.75	15.47	**	3.85	10.35	**	3.07	15.96	**	3.57	12.48	**
Latent variable (in the CMC)	'Afraid of catching COVID-19'	−0.766	−3.72	**				−0.849	−5.93	**			
Structural model component (SMC)	LV Constant	3.81	79.26	**				3.58	65.9	**			
	'Big 5': Disagreeableness (sceptical)	0.128	3.21	**									
	'Big 5': Introversion (reserved)	0.156	4.16	**				0.243	5.82	**			
	'Big 5': Conscientiousness (does a thorough job)							0.19	4.11	**			
	Below 45 years old	−0.098	−2.44	**									
	Male	−0.207	−5.44	**				−0.171	−4.16	**			
	LV γ	−0.246	−6.33	**				−0.146	−4.21	**			
Measurement model component (MMC)	Intercept indicator 2a (Item 2)							0.668	4.65	**			
	Intercept indicator 2b (Item 3)	−0.487	−2.54	**				−0.015	−0.09				
	Intercept indicator 3 (Item 5)	−0.596	−3.09	**				0.075	0.45				
	Intercept indicator 4 (Item 6)	−0.678	−3.4	**				0.106	0.61				
	Intercept indicator 5 (Item 13)	1.2	7.74	**									
	Coefficient indicator 2a (Item 2)							0.879	23.93	**			
	Coefficient indicator 2b (Item 3)	1.14	23.26	**				1.02	24.81	**			
	Coefficient indicator 3 (Item 5)	1.11	22.41	**				0.935	21.61	**			
	Coefficient indicator 4 (Item 6)	1.17	22.93	**				0.971	21.7	**			
	Coefficient indicator 5 (Item 13)	0.794	19.97	**									
	Standard deviation indicator 1 (Item 1)	−0.22	−10.16	**				−0.316	−12.34	**			
	Standard deviation indicator 2a (Item 2)							−0.259	−11.41	**			
	Standard deviation indicator 2b (Item 3)	−0.266	−11.35	**				−0.259	−11.24	**			
	Standard deviation indicator 3 (Item 5)	−0.412	−16.54	**				−0.338	−13.64	**			

Appendix, Table 1 (*continued*)

Model estimation

Model part	Name	London			New York			Sao Paulo			Shanghai		
		Value	t-test		Value	t-test		Value	t-test		Value	t-test	
	Standard deviation indicator 4 (Item 6)	−0.426	−16.4	**				−0.32	−12.69	**			
	Standard deviation indicator 5 (Item 13)	−0.33	−16.09	**									
Latent variable (in the CMC)	'Trust in safety measures'				−0.649	−3.28	**						
Structural model component (SMC)	LV Constant				3.83	54.42	**						
	Below 45 years old				−0.219	−4.37	**						
	Male				−0.187	−4.22	**						
	'Big 5': Conscientiousness (does a thorough job)				0.512	9.51	**						
	LV γ				−0.108	−4.15	**						
Measurement model component (MMC)	Intercept indicator 2 (Item 8)				−0.246	−2.2	*						
	Intercept indicator 3 (Item 9)				1.25	10.3	**						
	Coefficient indicator 2 (Item 8)				1.06	39.43	**						
	Coefficient indicator 3 (Item 9)				0.717	24.67	**						
	Standard deviation indicator 1 (Item 7)				−0.647	−23.33	**						
	Standard deviation indicator 2 (Item 8)				−0.725	−23.02	**						
	Standard deviation indicator 3 (Item 9)				−0.354	−17.13	**						
Latent variable (in the CMC)	'Dislike of quarantine'										−2.04	−6.58	**
Structural model component (SMC)	LV Constant										3.73	57.63	**
	Below 45 years old										−0.207	−4.45	**
	Male										0.141	3.33	**
	'Big 5': Conscientiousness (does a thorough job)										0.314	6.32	**
	'Big 5': Agreeableness (generally trusting)										0.162	3.78	**
	LV γ										−0.267	−6.68	**
Measurement model component (MMC)	Intercept indicator 2 (Item 11)										−0.56	−2.89	**
	Coefficient indicator 2 (Item 12)										1.1	23.06	**
	Standard deviation indicator 1 (Item 10)										−0.318	−11.72	**
	Standard deviation indicator 2 (Item 11)										−0.274	−9.44	**

Number of draws:	500
Number of estimated parameters:	147
Number of individuals:	1469
Sample size (total number of observations):	8802
Init log-likelihood:	−75135
Final log-likelihood:	−34840
ρ^2	0.536
Adjusted ρ^2:	0.534

** p-value ≤ 0.01.

* 0.01 < p-value ≤ 0.05.

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