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Mobility perceptions regarding the COVID-19 pandemic from around the world

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ABSTRACT

The COVID-19 pandemic has entailed profound societal changes at many levels and, in particular, the mobility patterns of communities worldwide. There has been a profound modification in collective travel behaviour, mainly because of the restrictions enforced by governing authorities to reduce the likelihood of infection transmission. Perceptions regarding the severity of the disease and mitigation measures to restrict its spread may have an effect on travel behaviour. This research explores the impact of these perceptions on individuals' travel behaviour by utilising a structural equation modelling approach for different travel modes regarding free-time and leisure mobility. The investigation considers data derived from a global survey performed in nine countries during May 2020, during the first wave of the pandemic. The countries included were Australia, Brazil, China, Ghana, India, Italy, Norway, South Africa, and the United States of America. Results indicate that inhabitants of these countries have various perceptions regarding the effectiveness of travel restrictions for different transport modes. The disease contraction probability is perceived as higher for public transport modes; accordingly, people tend to travel significantly less by train and bus. For some countries, even if the disease restriction policies are considered effective for both private and public transport, survey participants travel less frequently across all travel modes. Active travel or travelling alone is not influenced significantly by an individual's perceptions of the disease. This study examines the correlations between disease perception and travel behaviour for policymaking to revive sustainable travel transports and active travel, which is essential for improving physical and mental health during the pandemic.

1. Introduction

COVID-19 is the seventh discovered coronavirus that can be transferred to humans, and it is the cause of severe acute respiratory syndrome coronavirus 2 (SARS-COV-2) (Andersen et al., 2020). The first cases of this highly infectious disease were reported in mainland China prior to being identified in other countries, with an exponential increase in positive cases. The World Health Organization (WHO) soon classified this world health emergency as a pandemic on 11 March 2020 (Maier and Brockmann, 2020; WHO Director-General's opening remarks at the media briefing on COVID-19 - 27 July 2020, n.d.). The COVID-19 pandemic has transformed how society functions and the mobility of communities worldwide. People have changed their travel behaviour collectively as a consequence of the restrictions imposed by governing authorities to reduce the likelihood of infection. Global transport activity declined by 50% during March 2020 as compared to the 2019 average, and freight activity also reduced by 75% during mid-April 2020 as compared to the average of 2019 (IEA, 2020). Nouvellet et al. (2021) recent comprehensive study presents results concerning the relationship between mobility and COVID-19 transmission across 52 countries. COVID-19 transmission significantly decreased due to social distancing measures to restrict the virus in 73% of the countries analysed, highlighting the importance of limiting mobility in a pandemic scenario. Several other recent studies support these findings. For example, Badr

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et al. (2020) correlate the case numbers in the United States of America with mobile phone mobility data to show a time delay of 3 weeks in realising the benefits of travel restrictions. A case study from Italy reveals the exponential growth in case numbers due to delays in social distancing restrictions (Cartenì, Di Francesco, & Martino, 2020). Linka, Goriely, and Kuhl (2021) conducted a mobility analysis of ten European countries and suggested that tracking travel patterns in real-time allow for more dynamic management of local pandemic conditions.

Due to travel restrictions, there have been significant effects on the utilisation and performance of transport systems. Zhang et al. (2021) indicated a decrease in travel volume of 52.3% within the MTR system in Hong Kong due to COVID-19. The GPS tracking panel data analysis of 1439 Swiss residents presented a 60% reduction in daily travel distance with a 90% decline in public transport use (Molloy et al., 2021). Traffic volume analysis in Florida revealed a 47.5% fall in traffic in 2020 compared with 2019 (Parr, Wolshon, Renne, Murray-Tuite, & Kim, 2020). These empirical studies present a significant shift in travel patterns as a result of COVID-19. Research has also revealed that travellers' decisions are influenced by the perception of the severity and susceptibility of disease (Barbieri et al., 2021; Cahyanto et al., 2016; Lee et al., 2012). Risk perception and its impact on travel decisions have been studied regarding the COVID-19 outbreak for tourism purposes (Bae and Chang, 2021; Li et al., 2020; Neuburger and Egger, 2021). These studies reveal the significant influence of perceived risk and perceptions about the COVID- 19 on the intention and decision to travel for tourism purposes.

There is a plethora of research concerning the correlation between mobility and the spread of COVID-19 documenting that globally communities' have restricted travel as a mitigation strategy to limit the infection. However, there is a certain paucity of investigations concerning the latent factors which affect public perceptions of the spread of COVID-19 in the context of travel restrictions. Furthermore, given the travel restrictions imposed and the severity of disease, the impact of perceptions towards different modes of transport in the context of a pandemic and its influence on the travel behaviour of the system users have not been studied in detail yet. This study provides insight into these research questions by applying Structural Equation Modelling (SEM) (Bentler, 1988). A comprehensive questionnaire survey data set gathered online responses from respondents across nine countries (Australia, Brazil, China, Ghana, India, Italy, Norway, South Africa and the United States of America) and details about its collection can be found in Barbieri et al., (2020). Each country is analysed separately to determine the latent factors that affect the perceptions towards travel modes in the context of the COVID-19 pandemic.

In addition, recent literature also shows consternation about the decreasing use of public transport due to fear of contracting the disease and restrictive government policies (Gutiérrez et al., 2020). Moreover, due to less travel activity, there are also concerns about the decline in active travel such as walking and cycling (De Vos, 2020; Laverty et al., 2020). Therefore, it is essential to investigate travel behaviour for these two modes in the context of pandemic dynamics to discourage unsustainable travel options. In this sense, the trends and relationships observed in this study can be useful for adopting post-pandemic strategies to revitalise public and active transport utilisation. The study is structured as follows. Section 2 provides background research related to travel behaviour considering COVID-19. Section 3 discusses the methodology and model formulation. This is followed by Section 4, where the results and related insights on the mobility policies in the context of a pandemic and post-pandemic scenario are interpreted.

2. Literature review

As a measure of combating COVID-19 spread, governments and authorities have implemented stringent policies across the world. The guidelines include stay at home orders, cancellation of public gatherings, limiting capacity on public transport, closure of workplaces/ implementing work from home policies and strict social distancing measures. This resulted in the mass reduction of out-of-home activities, mobility patterns and travelling options (Abu-Rayash and Dincer, 2020; De Vos, 2020).

As mentioned above, a series of studies have investigated mobility trends during the pandemic using a variety of data collection techniques. Of note, one investigation presented various methods to evaluate the time-series of human mobility patterns on a large dataset collected through the incognito shared positions of smartphone users (Pepe et al., 2020); this paper revealed a notable reduction in travel of individuals. Many empirical studies of different geographical areas have demonstrated that diminished human mobility strongly correlates to decreased virus infection cases. Policies introduced by governments have played the most important role in travel reduction for any travel mode, especially regarding public ones (Gössling et al., 2021; Jinjarak et al., 2020). Many studies have found a significant relationship between mobility patterns and the spread of COVID-19. For example, one of the studies analysed the relationships between the social distancing measure and the growth rate of COVID-19 in the USA (Badr et al., 2020). Results indicated a significant relationship between the decreased rates of COVID-19 infections and mobility patterns which reduced to more than half the rate compared to the days before the implementation of social distancing. Similar results were also obtained in Italy, where one study found a significant positive correlation between an average number of trips and the number of daily cases of COVID-19 (Cartenì et al., 2020). The paper also revealed a direct relationship between the number of new patients of COVID-19 and several trips performed three weeks before the first case appeared. Another study collected de-identified and aggregated data from Facebook users in Britain, France and Italy. This research simulated the spatial distribution of mobility patterns after lockdown implementation due to COVID-19 by considering the nations' structural diversity (Galeazzi et al., 2020). The analysis indicated that the mobility rates strongly depend on the structural variety of networks of a particular area. In Poland, it was found that there is a strong and significant relationship between the government's policies and the decline in mobility patterns (Michał Wielechowski et al., 2020). It was found that the mobility patterns were more affected by the stringent travel restriction policies of the government as compared to case numbers and the presence of the virus, suggesting that communities require government intervention to contain the spread of the pandemic.

All the studies mentioned above document the unprecedented changes in mobility and travel patterns during the pandemic. Although, as mentioned above, most of the studies suggest that government policies strongly influenced travel behaviors at the time of the pandemic, however, there is another school of thought suggesting that mobility patterns are also influenced by the perceived risk associated with the severity and susceptibility of a disease. As defined in previous studies, the term 'risk' refers to the *potential threat, hazard, or probability of an adverse event to occur in the future timeline* (Slovic and Weber, 2002). This definition suggests that risk can be evaluated in a subjective form. The consequent actions of society derive from the severity of the perceived risk of the situation (Moreira, 2008; Sjöberg et al., 2004). Media and personal experiences are two significant factors that play a major part in formulating risk perception about any adverse situation which affects individuals' travel decisions (Hackett, 2008; Kone and Mullet, 1994; Wahlberg and Sjoberg, 2000). In a pandemic outbreak, individuals' risk perception about contracting the disease plays a vital role in engaging in disease prevention measures such as abstaining from travel (Brewer et al., 2007; Glanz et al., 2008).

Individuals' behaviour and intentions to engage in preventive measures for reducing disease severity have been investigated in the past through health belief models and protection motivation theory (Floyd et al., 2000). These papers have found a significant and positive relationship between the perceived threat of the situation and consequent engagement in protection measures (Rittichainuwat and Chakraborty, 2009; Yanni et al., 2010). Many empirical studies analysed the perceived susceptibility of health crises and their influence on travel behaviour. For example, one study assessed the susceptibility to being infected by the Ebola virus and its correlation with the frequency of domestic travel (Cahyanto et al., 2016). This study found the significant role of perceived risk and severity related to the Ebola virus in domestic travel avoidance behaviour. Another study found that perceptions about the 2009 H1N1 Influenza pandemic positively and significantly influence the adaptive behaviour of non-pharmaceutical intervention measures to control the disease (Lee et al., 2012). This behaviour strongly affected the intention to travel internationally for tourism purposes. An Australian study demonstrated that more than half of the population showed some concern about travel due to the 2009 H1N1 Influenza pandemic (Leggat et al., 2010). Considering the COVID-19 outbreak, recent studies investigate the impact on travel decisions due to the risk perception of contracting the virus. However, the majority of these studies have focussed on tourism-related travel decisions and not commuting or day-to-day travel (Bae and Chang, 2021; Li et al., 2020; Neuburger and Egger, 2021). These studies reveal the influence of perceived risk and perceptions about COVID-19 on the intention and decision to travel for tourism purposes. Governments and authorities worldwide have placed various travel restrictions that have affected daily travel, such as commuting and leisure trips. As a result, individuals have developed different perceptions of contracting the virus for different travel modes as revealed in various empirical studies (Jinjarak et al., 2020; Wielechowski et al., 2020). The research presented in the current paper investigates these perceptions considering two major aspects of risk associated with the pandemic and their impact on travel behaviour for different travel modes considering regular daily travel. The two focal aspects are: (1) the perceptions of individuals regarding the likelihood of contracting the virus and (2) the perceptions of travellers about the effectiveness of the enforced policies to restrict the pandemic. Given the highly infectious nature of COVID-19, it is imperative to scrutinise travel behaviour and its correlation with the perceived risk of the pandemic severity and the effect of mitigating policies. This will be valuable for policymakers to improve the planning and management of transport systems accounting for the possibility of future health crises.

Structural Equation Modelling (SEM) is implemented in this study. SEM is the statistical analysis method that involves a simultaneous analysis of the entire system of variables under consideration to determine the underlying structural relationships (Barillari et al., 2021; Blunch, 2008; Cao et al., 2007; Mokhtarian and Cao, 2008; Vale and Pereira, 2016; Wang and Law, 2007; Zaragoza et al., 2020). It encompasses the confirmatory approach for testing linear relationships among variables and considers the measurement error for all the variables, including the independent (explanatory) variables. Further, observed and latent variables can be incorporated into the SEM technique compared to other approaches for modelling multivariate relations. SEM has been widely used in the transport sector to examine the causal relationship between built environment characteristics, travel behaviour and attitudinal and lifestyle attributes (Bagley and Mokhtarian, 2002; Cao et al., 2007; Mokhtarian and Cao, 2008; Vale and Pereira, 2016). Currently, to the authors' best knowledge, only one study has employed an SEM approach to characterise risk perception in the context of COVID-19, and this study only focused on tourism travel behaviour (Bae and Chang, 2021). There has not been any comprehensive study evaluating the relationship of local day-to-day mobility patterns with the risk perception of contracting COVID-19 and the effectiveness of the enforced policies using the SEM approach. This study aims to fill this gap by providing insights across the nine surveyed countries.

3. Methodology

An overview of the methodology to carry out the analysis is shown in Fig. 1.SEM was the focal approach used in the study to uncover latent relationships in mode preferences during the COVID-19 pandemic. A comprehensive questionnaire survey data set gathered online responses from participants across nine countries (Australia, Brazil, China, Ghana, India, Italy, Norway, South Africa and the United States of America) and details about its collection can be found elsewhere (Barbieri et al., 2020). Each country is analysed separately to determine the latent factors that affect the perceptions towards travel modes in the context of the COVID-19 pandemic. The data set includes the responses of 9,394 participants of a questionnaire survey focussed on mobility prior to and during the enforcement of travel restrictions in light of the first wave of the COVID-19 pandemic. The survey was administered between the 11th and 31st of May 2020. The first part of the survey collected information regarding the frequency of use of all available transport modes before and after implementing COVID-19 restrictions. Two types of mobility patterns were considered in the survey. One was related to work/study and the other was related to the free-time and leisure mobility capturing the nature of all day-to-day travel. For the analysis, free-time and leisure mobility patterns are evaluated to determine the influence of risk perceptions. The foremost reason is that these mobility patterns represent diverse travel options with variable origins and destinations, allowing for a wider spectrum of modes to be used compared to travel associated with work or study. The second part of the survey asked questions regarding the perceived risk of infection whilst travelling during the pandemic and respondents' perspectives on the effectiveness of the travel restrictions. It is important to note that this study does not provide a descriptive analysis of mobility patterns across the countries as already done by Barbieri et al. (2021); instead, the focus is to understand further the perceptions of travel during a pandemic scenario. Fig. 2 presents the countries on the world map.

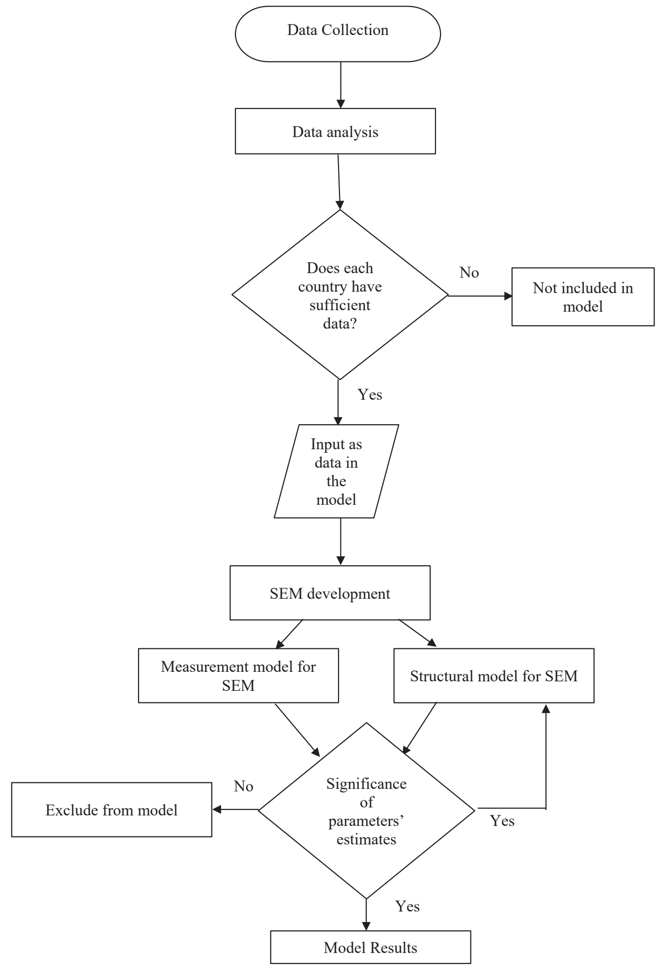

Fig. 1. Overview of the analysis.

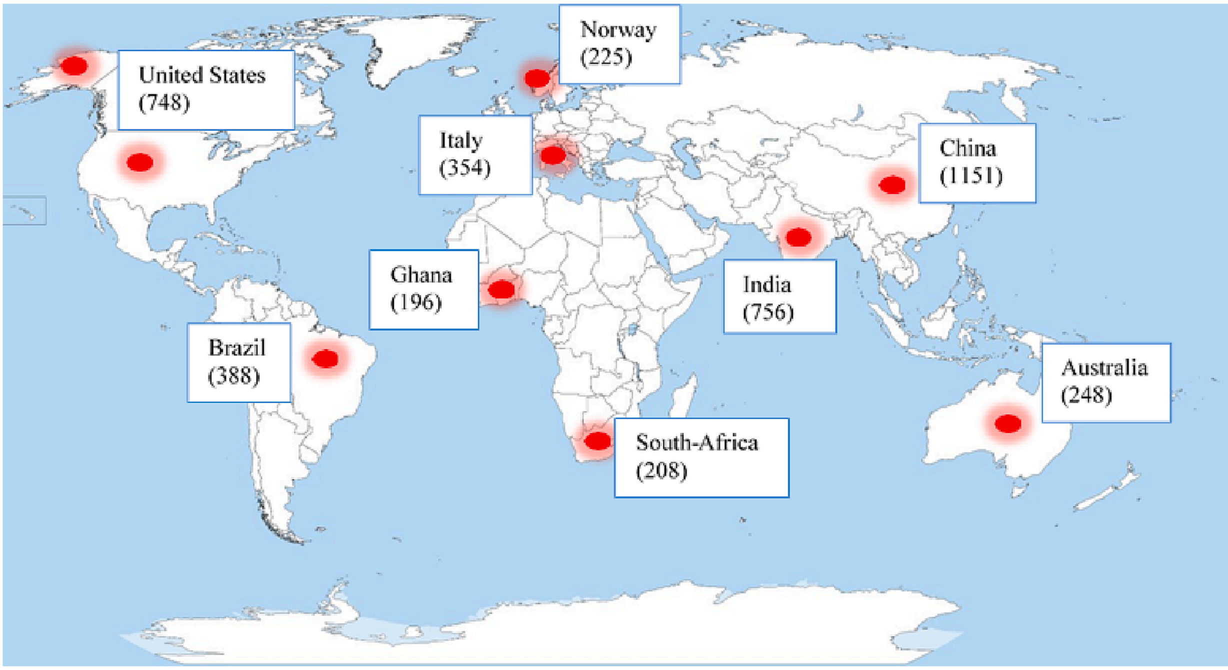

Fig. 2. Countries considered for the current study (Number of observations for each country are shown in brackets). (Source: https://www.freeworldmaps.net/political.htmlhttps://www.freeworldmaps.net/political.html).

4. Model formulation

The SEM approach analyses the influence of perceptions regarding the pandemic on mobility patterns. SEM broadly consists of two major parts. The first part defines the measurement model, which comprises the Confirmatory Factor Analysis (CFA) for investigating the relations between the sets of observed and latent variables. CFA determines the strength of regression paths of factor loadings for underlying latent constructs and the observed variables. It simply tests the significance of the observed variables in representing the latent constructs that are identified. In some cases, if there is limited knowledge of the latent constructs for any observed variables, Exploratory Factor Analysis (EFA) is carried out, providing insights into the underlying factors that account for covariance among observed variables. The second part of SEM specifies the regression or causal relationship among the latent variables and is defined as the structural part of the model. This study follows this two-step procedure for analysing the perceptions related to COVID-19 and mobility patterns. According to the survey, there were two questions related to perceptions of disease contraction and the effectiveness of the restrictions as follows:

(1) "*How would* ***you rate the probability of contracting COVID-19*** *using transportation modes?*"
(2) "*How would* ***you rate your region/province/state/county's restrictions on the transportation modes*** *to limit the COVID-19 spread?*".

These questions were asked regarding the following transport modes: walk, bicycle, motorbike/moped/quad, car (driving alone), car (with someone else), bus, subway/tram, train, ferry and airplane. Participants provided ratings based on a 7-point Likert scale. For question (1), the range of responses included: "extremely low", "very low", "low", "average", "high", "very high", and "extremely high" with the "not-available option" for modes that were not present. The values assigned to these ranges to be used in the model are 1 for "extremely high" to 7 for "extremely low". For question (2), the range of responses included: "extremely ineffective", "very ineffective", "ineffective", "average", "effective", "very effective", "extremely effective" and the other option being "there are no restrictions in the region/province/state/county where I am". For this question also, the values assigned to these ranges used in the model are 1 for "extremely effective" to 7 for "extremely ineffective". Participants who responded with the "other" options for both questions (mode not available or no restriction present) were removed from the data set as the analysis requires ordered data. Therefore, 4,374 observations were used for the study upon filtering the data. For these observations, exploratory factor analysis was carried out on the frequencies of using transportation modes during the COVID-19 epidemic for free-time mobility. The following questions were asked for the mobility patterns in the survey.

1. *How often do you go out for a walk or to do sports?* (answers: more than 3 times per week, 2 or 3 times per week, 1 time per week, 2 or 3 times per month, 1 time per month, less than 1 time per month, never)
2. *How often do you use a …?* (answers: more than 3 times per week, 2 or 3 times per week, 1 time per week, 2 or 3 times per month, 1 time per month, less than 1 time per month, never, I do not have one) – This question is asked for all transportation modes considered in the study.

EFA revealed the correlation between car (driving alone), walk and bicycle and between bus, subway and train travelling. Therefore, the frequencies for travelling in car (driving alone), walk and bicycle were termed latent variables for frequencies of travelling alone. Similarly, frequencies for travelling by bus, subway and train were termed latent variables for frequencies of travelling in public transport.

It is hypothesised that the mobility patterns with different travel modes are affected by the perceptions about the spread of COVID-19 and the policies to control it. The latent variables about the frequency of free-time and leisure mobility with travel modes are regressed on each latent variable for the perceptions about COVID-19 and travel. Each dependent variable also has the independent residual error term, estimated in the model. This residual term, also known as structural error, characterises the error in predicting free-time mobility (endogenous variable) from the latent variables (exogenous variables). It measures the impact of error in predicting the endogenous term in explaining the influence of exogenous variables. Separate SEM models were developed for each country as it is believed that inhabitants of the country have their own beliefs and perceptions about the pandemic. The model framework with all the included variables is shown in Fig. 3.

5. Estimation results

5.1. Measurement model

EFA was first performed on the dataset to gather insights for the latent constructs based on the covariance of the observed variables and their related factor loadings. The two perceptions related to the pandemic described above, for different transport modes, were considered to perform EFA. Two latent factors were identified for each question asked in a survey related to perceptions about the pandemic. It is found that people have different perceptions about the probability of contracting the disease when using public transport. In other words, when people travel together in groups (train, bus, airplane, ferry, subway) or alone (walk, bicycle, car, motorbike), they have different perceptions about the probability of contracting the disease. The same finding is revealed for the perceptions about the effectiveness of policies restricting the pandemic concerning different transport modes. Furthermore, two latent variables are considered for different frequencies of travel modes during an epidemic for free-time or leisure mobility. The first one is about the frequency of travelling alone and is measured by the frequencies of travelling by walk, bicycle and car (drive-alone). The second latent variable is the frequency of travelling in public transport, measured by the frequencies of travelling by bus, train and subway/tram. CFA is then conducted to analyse the factor loadings for the latent constructs identified by EFA and the extent to which they are related to the observed variables. For statistical identification, one of the regression paths of observed variables for each latent factor is kept as a reference and constrained to be 1. Each observed variable is associated with the measurement error, which determines the adequacy of measuring the underlying latent factors. In the SEM specification, the variance and regression path cannot be estimated simultaneously. The error variance related to each observed variable is essential to estimate, so the regression path of this error is fixed and not estimated. The estimates for these observed variables and the critical ratios are presented in Table 1, which indicates that all the estimates are positive and significant. It is revealed in the results that the observed variables are significantly related to the underlying latent constructs. The hypothesis that was developed as an outcome of EFA is not rejected as implied by CFA results.

5.2. Structural model

The collated results of the SEM modelling across all countries considered in the study are shown in Tables 3 to 11. The goodness of fit criteria is evaluated for each model in order to present how well the model fits the data. Each of the models is over-identified, which means that the number of estimated parameters is less than the observed data points, giving positive degrees of freedom. Other goodness of fit statistics includes comparing the current hypothesised model, independent (zero relations among variables) and saturated model (where the number of estimated parameters is the same as the number of data entries). These statistics have been supported by the previous literature (Byrne, 2010). Some of the most recommended criteria are discussed as follows:

CMIN measures the minimum discrepancy between the restricted and unrestricted sample covariance matrix. It is also known as the chi-square statistic and the chi-square divided by the degree of freedom of

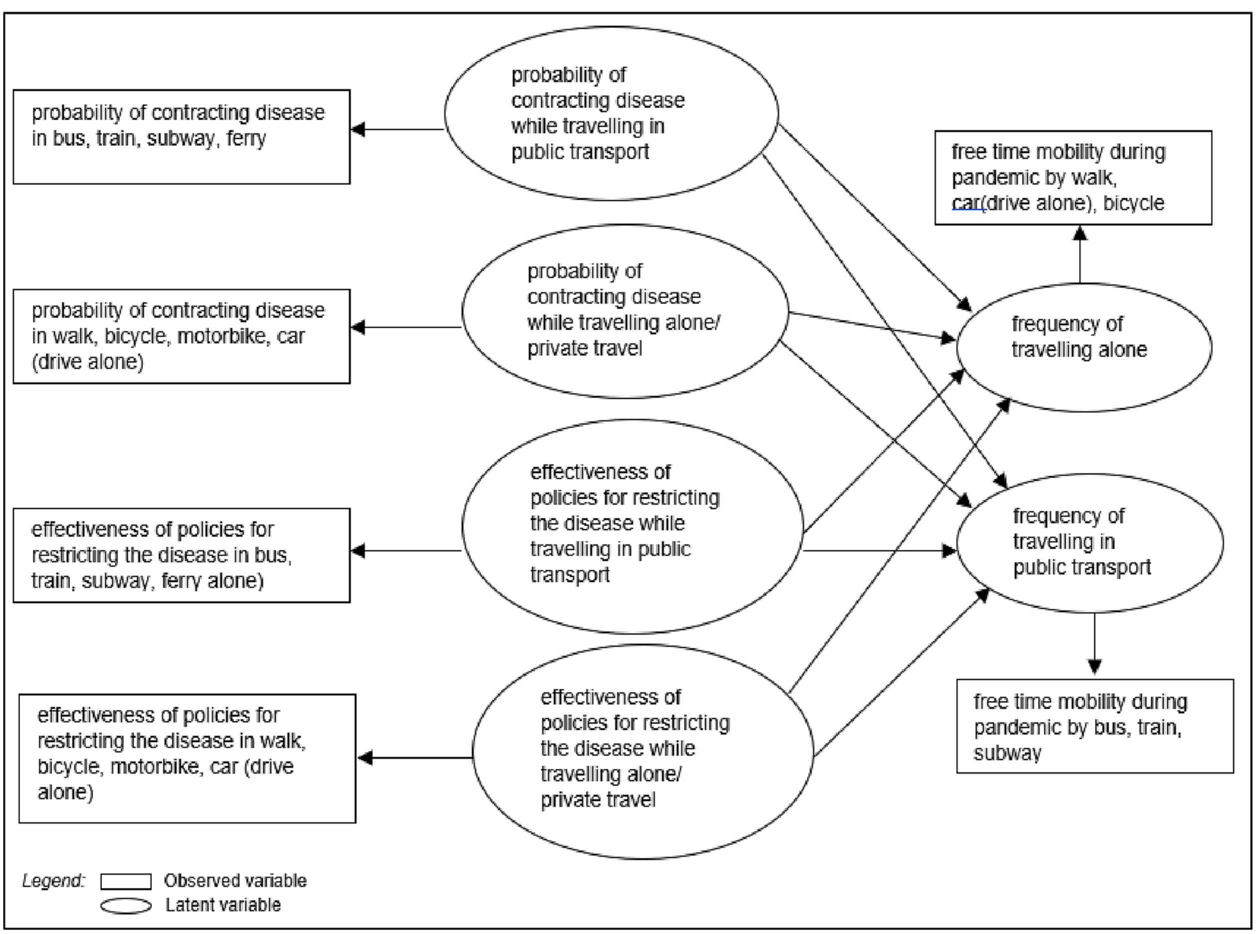

Fig. 3. Model framework.

Table 1
Estimation results for measurement part of SEM for each country (critical ratios are shown in brackets).

Parameters		Latent variables	Australia	China	USA	South Africa	Brazil	India	Italy	Ghana	Norway
			Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Probabilityof contracting disease in:	Subway	Probability of contracting disease while travelling in public transport	1.032 (28.036)	0.926 (25.339)	0.979 (55.683)	1.00 (fixed)	0.936 (43.57)	0.951 (56.806)	1.00 (fixed)	1.00 (fixed)	0.975 (28.924)
	Ferry		1.00 (fixed)	1.00 (fixed)	0.869 (36.068)	1.017 (31.54)	0.941 (27.77)	0.975 (63.72)	1.02 (27.17)	1.072 (28.736)	0.828 (16.771)
	Train		1.043 (30.798)	0.874 (24.068)	1.00 (fixed)	0.968 (34.011)	1.00 (fixed)	1.00 (fixed)	1.038 (38.329)	1.092 (27.424)	1.00 (fixed)
	Bus		0.940 (19.261)	0.797 (24.528)	0.869 (36.385)	0.714 (13.74)	0.737 (19.746)	0.860 (35.046)	0.835 (19.18)	0.934 (12.964)	0.935 (22.22)
	Walk	Probability of contracting disease while travelling alone/private travel mode	1.00 (fixed)	1.00 (fixed)	0.864 (54.34)	0.915 (12.057)	0.863 (20.688)	0.953 (42.42)	0.912 (18.49)	1.032 (14.86)	1.02 (13.265)
	Motorbike		0.951 (15.298)	0.964 (18.478)	0.886 (32.474)	0.934 (23.23)	0.956 (29.39)	0.875 (38.62)	0.753 (22.654)	0.968 (18.239)	0.802 (12.935)
	Bicycle		1.032 (15.85)	0.969 (17.893)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)
	Car (driving alone)		0.476 (7.756)	0.787 (15.791)	0.695 (19.071)	0.415 (7.264)	0.544 (13.852)	0.630 (15.95)	0.389 (12.101)	0.562 (8.369)	0.393 (8.681)
Effectiveness of policiesfor restrictingthe disease in:	Subway	Effectiveness of policies for restricting the disease while travelling in public transport	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	0.981 (29.075)	1.005 (113.22)	0.951 (75.362)	1.01 (46.208)	1.00 (fixed)	0.975 (38.538)
	Ferry		0.937 (34.819)	0.992 (20.176)	0.946 (55.856)	1.012 (28.652)	0.908 (47.304)	0.955 (76.211)	0.966 (48.959)	1.033 (42.03)	0.720 (18.467)
	Train		0.990 (79.55)	1.180 (21.121)	1.011 (73.251)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.027 (37.334)	1.00 (fixed)
	Bus		0.797 (17.739)	0.902 (16.685)	0.670 (22.618)	0.563 (8.715)	0.862 (26.324)	0.716 (24.935)	0.745 (16.694)	0.740 (10.104)	0.609 (10.457)
	Walk	Effectiveness of policies for restricting the disease while travelling alone/private travel mode	0.934 (27.298)	0.935 (19.432)	0.969 (54.341)	0.987 (20.747)	0.983 (50.948)	0.953 (42.42)	0.857 (28.495)	1.043 (19.441)	0.997 (41.499)
	Motorbike		0.994 (35.32)	0.958 (20.031)	0.939 (51.62)	1.009 (25.016)	0.949 (51.043)	0.875 (38.62)	0.825 (27.992)	1.00 (fixed)	0.952 (37.37)
	Bicycle		1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.051 (22.095)	1.00 (fixed)
	Car (driving alone)		0.896 (20.45)	0.750 (15.614)	0.870 (8.056)	0.917 (16.679)	0.853 (25.112)	0.815 (29.20)	0.742 (20.54)	0.980 (14.953)	0.941 (24.71)
Frequencyof travelling by:	Walk	Frequency of travelling alone	1.1.52 (2.219)	0.211 (3.718)	2.279 (4.177)	0.728 (3.130)	1.344 (3.096)	0.791 (7.651)	4.869 (1.591)	0.22 (3.288)	1.00 (fixed)
	Bicycle		1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	0.821 (3.199)	0.955 (7.482)	1.00 (fixed)	1.00 (fixed)	0.004 (0.017)
Car (driving alone)			0.756 (1.859)	0.559 (5.153)	1.661 (4.203)	1.234 (3.628)	1.00 (fixed)	1.00 (fixed)	1.1.20 (4.418)	1.130 (6.887)	0.005 (0.017)
Bus		Frequency of travelling in groups/public transport	1.891 (6.336)	0.939 (22.941)	0.985 (29.553)	0.884 (9.391)	0.753 (4.753)	1.152 (21.55)	1.401 (10.604)	0.671 (11.316)	2.053 (4.610)
Train			1.749 (6.015)	1.01 (21.480)	1.055 (41.54)	0.954 (44.838)	0.291 (5.237)	1.063 (23.578)	0.746 (10.22)	0.972 (80.05)	0.851 (4.621)
Subway			1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)	1.00 (fixed)

the model should be less than 3 for a good model fit.

Goodness of Fit Index (GFI) measures sample variance and covariance explained by the population's variance and covariance. Values closer to 1.0 provides better goodness of fit.

Comparative Fitness Index (CFI) and Normative Fitness Index (NFI) also compares the hypothesised and the independent model with the null hypothesis. Values of CFI and NFI greater than 0.95 indicates a better model fit (Bae and Chang, 2021).

RMSEA is the root mean square error of approximation. It measures the discrepancy between the population covariance matrix and the hypothesised model. Values of RMSEA between 0.05 and 0.08 indicate a good fit (Kline, 2015).

Apart from these statistics, the statistical significance of the estimates was also assessed using the critical ratio. The critical ratio is the statistic generated by the division of parameter estimate and its standard error. It is otherwise known as the z-statistic and to have the probability level of 0.05, its value should be greater than ±1.96. In the current analysis, the parameters with a significance level of at least 80% (probability level of 0.20) have been included in the model, while the rest are excluded. The SEM results of each country are discussed, compared and contrasted in the following subsections.

5.2.1. Australia

Table 2 indicates that individuals who perceive the probability of contracting the disease is more likely when travelling on public transport, tend to travel less on buses and trains. This result aligns with previous studies, revealing that public transport use significantly decreases if people deem it unsafe during the COVID-19 pandemic (Przybylowski et al., 2021; Michał Wielechowski et al., 2020). However, the results indicate that the propensity of walk or cycle is unaffected with insignificant estimated parameter values. People who perceive that the probability of contracting COVID-19 is higher when travelling alone tend to walk, cycle, and use a car less and to use bus or train more as their mode of transport. However, the perceptions of the effectiveness of the policies for restricting the disease considering various transport modes by their country do not play a significant role in mobility. In this case, only one aspect is found important: if they perceive that the policies of controlling the disease are more effective by travelling on public transport, they still tend to travel less on buses. This could be due to the reduced capacities of buses and the greater likelihood of overcrowding on buses in Australia. It also indicates that the restrictions have not significantly affected the risk perceptions of mode choice in the context of COVID-19. Overall, this model has an acceptable goodness of fit according to the CMIN, CFI and RMSEA metrics.

5.2.2. China

The model estimates for China are shown in Table 3. It is observed that individuals who perceive contracting the disease is more likely while travelling in groups tend to travel alone less and, similarly to the results from Australia, there is less desire to use public transport modes. On the other hand, individuals who perceive disease contractions are more likely when travelling alone in private modes tend to use public transport. Interestingly, when individuals perceive the restrictions as more effective on public transport, there is a significant tendency to not travel in any transport mode. This result suggests that though the community perceives those restrictive measures as adequate, restrictions themselves have limited travel, which is reflected in the strict criteria applied in China.

5.2.3. USA

Table 4 presents the results of the modelling of the data from the USA. The results indicate that individuals who perceive contracting COVID-19 is more likely when travelling in groups are less likely to travel by public transport modes. In contrast, those who perceive contracting COVID-19 is more likely when travelling alone, tend to have lower probabilities of travelling alone and increased utilisation of travelling by public transport modes. Similar to Australia, the perception of the effectiveness of policies has little significance on the decision to use any travel mode.

5.2.4. South Africa

The result of the structural model estimates for South Africa, displayed in Table 5, reveals a lower probability of travelling by bicycle, train and bus if the individuals perceive that the probability of contracting disease in public transport is more, a reflection of the other countries analysed. If they think that the chance of contracting the

Table 2
Estimation results for the structural component of SEM - Australia.

<u>Australia</u>					
(1) How would you rate the probability of contracting COVID-19 using transportation modes?					
Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/ transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	n.a.	−0.060		−0.226	0.048
Critical ratio	n.a.	−1.939		−2.516	1.347
P-value	n.a.	0.053		0.01	0.17
*(2) How would **you rate your region/province/state/county's restrictions on the transportation modes** to limit the COVID-19 spread?*					
Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/ transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	n.a.	−0.040		n.a.	n.a.
Critical ratio	n.a.	−1.390		n.a.	n.a.
P-value	n.a.	0.16		n.a.	n.a.
GFI = 0.869, CMIN = 2.512, CFI = 0.953, NFI = 0.915, RMSEA = 0.068					

Table 3
Estimation results for the structural component of SEM - China.

China					
How would you rate the probability of contracting COVID-19 from using transportation modes?					
Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/ transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	−0.329	−0.518		0.136	0.405
Critical ratio	−4.676	−10.9		2.112	8.466
P-value	0	0		0.035	0
*How would **you rate your region/province/state/county’s restrictions on the transportation modes** to limit the COVID-19 spread?*					
Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	−0.242	−0.253		n.a.	−0.083
Critical ratio	−2.804	−4.566		n.a.	−2.235
P-value	0.005	0		n.a.	0.024
GFI = 0.956, CMIN = 3.132, CFI = 0.949, NFI = 0.927, RMSEA = 0.043					

Table 4
Estimation results for the structural component of SEM - USAl.

USA					
How would you rate the probability of contracting COVID-19 from using the transportation modes?					
Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	n.a.	−0.056		−0.184	0.288
Critical ratio	n.a.	−2.765		−4.189	11.431
P-value	n.a.	0.004		0	0
*How would **you rate your region/province/state/county’s restrictions on the transportation modes** to limit the COVID-19 spread?*					
Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/ transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	−0.025	n.a.		n.a.	−0.034
Critical ratio	−1.343	n.a.		n.a.	−1.504
P-value	0.179	n.a.		n.a.	0.133
GFI = 0.928, CMIN = 3.369, CFI = 0.970, NFI = 0.958, RMSEA = 0.056					

disease is higher while travelling alone, there is less likelihood of travelling by car, bicycle and walk. If individuals perceive that South Africa’s policy effectively restricts disease in public transport, they tend to travel less by public transport modes. However, if they perceive that policies are more effective for travelling alone, they significantly have a lower probability of using bus, train and even bicycle and walk. This result also indicates that the individuals prefer to travel less overall, even if they perceive that policies are effective for travelling alone or in groups.

5.2.5. Brazil

Table 6 presents the SEM results for Brazil, which present a suitable

Table 5
Estimation results for the structural component of SEM - South Africa.

South Africa

How would you rate the probability of contracting COVID-19 from using the transport modes?

Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/ transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	−0.109	−0.167		−0.182	n.a.
Critical ratio	−1.943	−4.021		−3.248	n.a.
P-value	0.052	0		0.001	n.a.

*How would **you rate your region/province/state/county's restrictions on the transportation modes** to limit the COVID-19 spread?*

Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	n.a.	−0.059		−0.203	−0.099
Critical ratio	n.a.	−1.787		−3.189	−2.077
P-value	n.a.	0.07		0.001	0.038
GFI = 0.867, CMIN = 1.808, CFI = 0.962, NFI = 0.919, RMSEA = 0.062					

Table 6
Estimation results for the structural component of SEM - Brazil.

Brazil

How would you rate the probability of contracting COVID-19 from using the transportation modes?

Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	−0.113	n.a.		n.a.	n.a.
Critical ratio	−1.808	n.a.		n.a.	n.a.
P-value	0.071	n.a.		n.a.	n.a.

*How would **you rate your region/province/state/country's restrictions on the transportation modes** to limit the COVID-19 spread?*

Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	−0.10	n.a.		n.a.	n.a.
Critical ratio	−1.552	n.a.		n.a.	n.a.
P-value	0.071	n.a.		n.a.	n.a.
GFI = 0.928, CMIN = 3.369, CFI = 0.970, NFI = 0.958, RMSEA = 0.056					

goodness of fit, where all key statistics are within the acceptable thresholds. The estimation indicates that if individuals perceive that the probability of contracting COVID-19 is higher by travelling in public transport, they tend to travel alone less. There is no significant influence on mobility with any travel mode if the individuals perceive that contracting the disease is more likely while travelling alone. If individuals perceive that policies are effective for travelling alone, there is less tendency to travel alone by walk, bicycle and private car. Mobility in other transport modes is not influenced significantly if the travellers perceive that policies effectively restrict the disease.

5.2.6. India

Table 7 presents the SEM results related to India. The results indicate that if travellers perceive that contracting the disease is more likely

Table 7
Estimation results for the structural component of SEM - India.

India

How would you rate the probability of contracting COVID-19 from using the transportation modes?

Independent variable	Travelling in groups (public transport)			Travelling alone (private transport)	
Dependent Variables	Frequencyof travelling alone	Frequency travelling groups/ transport	of in public	Frequencyof travelling alone	Frequencyof travelling in groups/ public transport
	Walk,Bicycle, Car (drive alone)	Train, Subway	Bus,	Walk,Bicycle, Car (drive alone)	Train, Bus, Subway
Coefficient	−0.108	−0.117		−0.139	−0.044
Critical ratio	−3.096	−4.798		−2.887	−1.313
P-value	0.002	0		0.004	0.18

How would ***you rate your region/province/state/county's restrictions on the transportation modes*** *to limit the COVID-19 spread?*

Independent variable	Travelling in groups (public transport)			Travelling alone (private transport)	
Dependent Variables	Frequencyof travelling alone	Frequency travelling groups/ transport	of in public	Frequencyof travelling alone	Frequencyof travelling in groups/ public transport
	Walk,Bicycle, Car (drive alone)	Train, Subway	Bus,	Walk,Bicycle, Car (drive alone)	Train, Bus, Subway
Coefficient	−0.147	−0.130		−0.165	−0.130
Critical ratio	−3.991	−5.127		−3.70	−5.127
P-value	0	0		0	0

GFI = 0.937, CMIN = 3.163, CFI = 0.971, NFI = 0.958, RMSEA = 0.054

while using public transport, they tend to travel less with all travel modes. If travellers perceive that the probability of contracting the disease is more by travelling alone, they walk less, use bicycle and private car less frequently and have a lower likelihood of travelling by public transport as well. The respondents from India, irrespective of their perceptions towards restriction effectiveness, are more likely to travel less on any mode available. This result is quite similar to that observed in China.

5.2.7. Italy

Table 8 presents the results of SEM estimates for Italy which have a suitable goodness of fit across all the key metrics. Individuals in Italy tend to travel less by public transport when public transport (travelling in groups) is considered more likely to spread COVID-19. The opposing view reveals no influence on travelling alone and by public transport modes. Similar to the results in India and China, Italy also shows a general aversion to travel regardless of the perception of the disease

Table 8
Estimation results for the structural component of SEM - Italy.

Italy

(1) How would you rate the probability of contracting COVID-19 using the transportation modes?

Independent variable	Travelling in groups (public transport)			Travelling alone (private transport)	
Dependent Variables	Frequencyof travelling alone	Frequency travelling groups/ transport	of in public	Frequencyof travelling alone	Frequencyof travelling in groups/ public transport
	Walk,Bicycle, Car (drive alone)	Train, Subway	Bus,	Walk,Bicycle, Car (drive alone)	Train, Bus, Subway
Coefficient	−0.054	−0.116		n.a.	n.a.
Critical ratio	−1.289	−2.973		n.a.	n.a.
P-value	0.197	0.003		n.a.	n.a.

(2) *How would* ***you rate your region/province/state/county's restrictions on the transportation modes*** *to limit the COVID-19 spread?*

Independent variable	Travelling in groups (public transport)			Travelling alone (private transport)	
Dependent Variables	Frequencyof travelling alone	Frequency travelling groups/ transport	of in public	Frequencyof travelling alone	Frequencyof travelling in groups/ public transport
	Walk,Bicycle, Car (drive alone)	Train, Subway	Bus,	Walk,Bicycle, Car (drive alone)	Train, Bus, Subway
Coefficient	n.a.	n.a.		n.a.	−0.03
Critical ratio	n.a.	n.a.		n.a.	−1.24
P-value	n.a.	n.a.		n.a.	0.2

GFI = 0.899, CMIN = 2.225, CFI = 0.960, NFI = 0.930, RMSEA = 0.059 restriction's effectiveness for public or private transport modes.

5.2.8. Ghana

Table 9 presents the SEM estimation results for Ghana, reflecting the goodness of fit results similar to China and the USA. If individuals perceive that disease contraction is more likely while travelling alone, they tend to travel less by private and public transport modes. There is no significant influence of travelling alone and by public transport on the individual's perceptions about contracting the disease by travelling in public transport. Unlike some other countries examined in this study, Ghana's travel behaviour is significantly influenced by perceptions of disease restriction. If individuals perceive the policies are more effective while travelling in public transport, they tend to travel more by public transport modes and also by car, bicycle and walk. However, if the individuals perceive that the disease mitigation strategies are effective for travelling alone, they are reluctant to travel alone and by public transport.

5.2.9. Norway

Table 10 presents the results of SEM estimates for Norway. Individuals who perceive the probability of contracting a disease higher in public transport tend to travel less in public transport modes and have a lower likelihood of travelling alone. Individuals who perceive the probability of contracting a disease while travelling alone are more prone to use public transport and private modes. Similar to the results in Australia and USA, individuals' perceptions about the effectiveness of their country/region policies to restrict the disease do not play a significant role in travelling by any of the identified modes of transport.

6. Summary of findings

Considering the diversity of the sample across all countries, the findings suggest a dramatic change in travel patterns due to the pandemic for leisure time free mobility. Fig. 4 presents the graphical summary of each analysed country's SEM findings. The results suggest that people in each country sampled tend to travel less if they perceive a severe probability of contracting the disease while travelling in public transport. However, there are some countries where people tend to travel on public transport if they perceive there is more probability of contracting the virus while travelling alone or in private car. These countries include Australia, China, the USA and Norway. While India tends to travel less by public transport, the rest of the countries (South Africa, Ghana, Brazil and Italy) do not have a statistically significant parameter for travelling by public transport when the people in these countries perceive more possibility of contracting the virus while travelling in private car. This suggests that these countries need to revise their public transport policies to utilise sustainable modes better during the pandemic. Travel behaviour is more influenced by the perception of contracting the disease than the perceptions about the government's effectiveness of policies for disease restriction. This suggests a lack of trust by the people in their respective country's government policies to restrict the spread of disease. Only inhabitants of Australia and Ghana tend to travel more on public transport if they perceive the policies to restrict the disease on public transport are adequate. China, South Africa and India tend to travel less by public transport. Other countries (USA, Brazil, Norway, Italy) are not significantly influenced by their perceptions of the effectiveness of policies restricting the disease on public transport. These results also suggest that the policies need to be revised in countries like India, China, South Africa, the USA, Brazil, Norway and Italy to improve people's perceptions about travel safety by public transport during the pandemic times.

7. Discussion and concluding remarks

This study investigated the role of risk perceptions regarding COVID-19 on nine countries' free time mobility patterns. Two important aspects related to risk perception were considered in the study. One was associated with the contraction of the disease in different travel modes, and the second considered the effectiveness of policies to restrict the disease in different travel modes. Free-time and leisure mobility patterns were considered in the study, which provided a broad spectrum for travel activities rather than restricting to a singular travel purpose. A structural equation model was developed to explore the latent constructs and the dependency of mobility patterns on the risk perceptions of travellers.

Table 9

Estimation results for the structural component of SEM - Ghana.

Ghana					
(3) How would you rate the probability of contracting COVID-19 using the transportation modes?					
Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/ transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	−0.592	−0.622		n.a.	n.a.
Critical ratio	−4.519	−5.937		n.a.	n.a.
P-value	0	0		n.a.	n.a.
(4) *How would **you rate your region/province/state/county's restrictions on the transportation modes** to limit the COVID-19 spread?*					
Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/ transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	0.197	0.187		−0.255	−0.346
Critical ratio	1.523	1.703		−1.848	−2.954
P-value	0.12	0.089		0.06	0.003
GFI = 0.804, CMIN = 3.062, CFI = 0.918, NFI = 0.884, RMSEA = 0.103					

Table 10
Estimation results for the structural component of SEM - Norway.

Norway					
How would you rate the probability of contracting COVID-19 from using the transportation modes?					
Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/ transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	−0.216	−0.159		0.345	0.363
Critical ratio	−2.007	−3.518		2.276	3.100
P-value	0.045	0		0.023	0
*How would **you rate your region/province/state/county's restrictions on the transportation modes** to limit the COVID-19 spread?*					
Independent variable	**Travelling in groups (public transport)**			**Travelling alone (private transport)**	
Dependent Variables	**Frequencyof travelling alone**	**Frequency travelling groups/ transport**	**of in public**	**Frequencyof travelling alone**	**Frequencyof travelling in groups/ public transport**
	Walk,Bicycle, Car (drive alone)	**Train, Subway**	**Bus,**	**Walk,Bicycle, Car (drive alone)**	**Train, Bus, Subway**
Coefficient	n.a.	n.a.		n.a.	n.a.
Critical ratio	n.a.	n.a.		n.a.	n.a.
P-value	n.a.	n.a.		n.a.	n.a.
GFI = 0.850, CMIN = 2.119, CFI = 0.942, NFI = 0.896, RMSEA = 0.071					

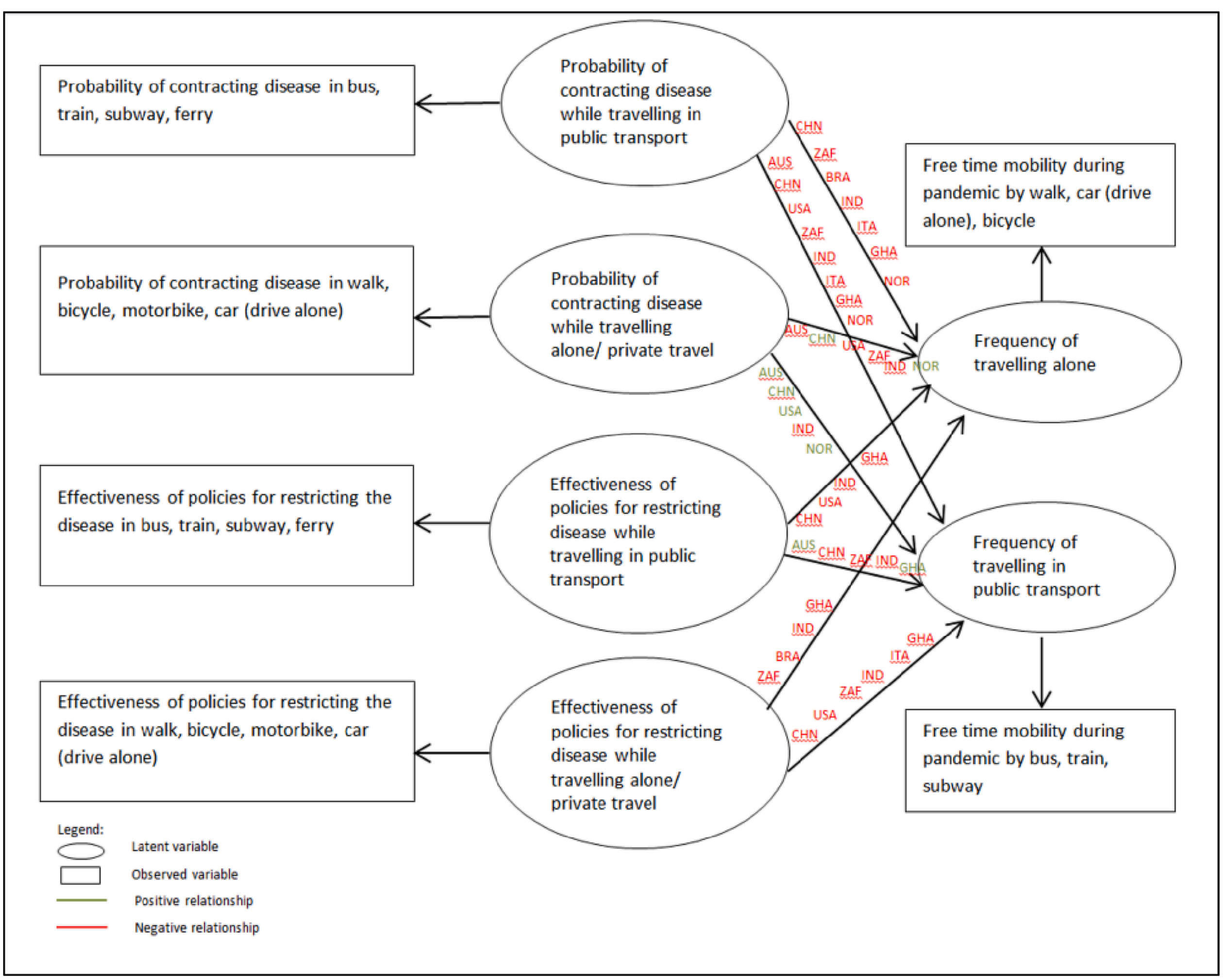

Fig. 4. Graphical summary of structural model results for each country.

The modelling and analysis conducted in the research utilised the responses to a global survey that had more than 8,000 participants responding to their mobility actions and perceptions. As a country-by-country analysis was conducted, there was an imbalance in the sampling, especially relative to each country's population. Furthermore, the survey was distributed using online platforms and social media, resulting in responses from people with access to the internet who were also interested in supporting this type of research. The last significant limitation of the collected data was that participants completed the survey in May 2020, before accessible vaccination programs. Vaccination against any infectious disease can provide greater confidence for people to interact in mobility or other social settings, which could change responses. However, the survey responses to date have provided significant insights into overall travel utilisation (Barbieri et al., 2021), psychological impacts (Passavanti et al., 2021) and environmental impacts (Lou et al., 2022), highlighting the value of the data-gathering process. In addition, the data gathered can still provide significant insights regarding risk perceptions in an uncertain and uncontrolled pandemic environment.

Interesting findings were evident for the countries considered and are summarised in Table 11. Overall, individuals tend to travel less by trains and buses if they perceive the risk of contracting the disease is higher in public transport modes. This finding is in line with the previous studies documenting that the risk of contracting the disease prompts engaging in disease prevention measures (Brewer et al., 2007; Glanz et al., 2008). However, there is another important point of view regarding decline in public transport travel. Many studies related to pandemic indicated that several measures were taken by the governments and institutions to restrict public transport travel, thus limiting the supply of public transport. For example, Washington Metropolitan Area Transit Authority minimised its service frequencies by more than half, sealed more than 20% of its metro stations, and restricted the operations of daily metro services (WMATA, 2020). Transport of London (TfL) closed about 40 metro stations that did not interconnect with other lines and suspended the night tube service as well (TfL, 2020). In Netherlands, the train capacity was reduced to limit passenger numbers and service frequencies were also reduced markedly (Gkiotsalitis, 2021). Existing literature also indicates that the decline in public transport travel can be attributed to the restrictions and limitations imposed by the countries to restrict the virus spread. The modelling presented in this paper does not account for the reduction in supply of transport services, and thus investigation into controlling for this aspect would be valuable as a future research project. Moreover, since public transport has been considered one of the leading media for the spread of COVID-19 because of its physical distancing challenges, its mobility has been affected most during the pandemic (Abu-Rayash and Dincer, 2020; Gutiérrez et al., 2020; Wielechowski et al., 2020). To revive the more sustainable ways of travel, such as the use of public transport, policymakers need to consider individuals' risk perception and formulate the measures that can compel a mode shift towards public transport.

Countries displayed a spectrum of individual perceptions towards the effectiveness of policies in restricting the spread of the disease. For example, as shown in Table 11, countries like Australia, the USA, Brazil and Norway indicate that there is no statistically significant perception related to the effectiveness of policies in restricting the spread of the disease in the context of leisure mobility. However, in countries like India, Brazil, Italy, and South Africa, even if individuals perceive that the policies were effective in restricting the disease, they tend to travel less across most transport modes, especially public transport. This indicates a gap between individuals' mobility decisions and their perceptions about the effectiveness of policies for controlling the disease that needs to be addressed. In this research, the frequencies of travelling by walk and bicycle are measured along with car (drive alone) as one latent variable of travelling alone. Most countries exhibit lesser tendencies to travel alone if the individuals perceive that the probability of contracting the disease is higher while travelling in public transport. Most respondents do not tend to travel alone even if they perceive the policies for restricting the disease are effective in public transport modes or travelling alone. In general, it can be concluded that the virus's perceived risk did not significantly affect the active travel frequency. It has more effect on the mobility patterns related to bus, train, and car-alone driving. This result leads to an important conclusion that individual's behaviours should be targeted more regarding active travel during the pandemic considering their perceptions about the disease mitigation policies. The importance of active travel is more comprehensively discussed in previous literature that explores the fact that more opportunities for walking and bicycling should be created by policymakers who can physically and emotionally enhance public health during the pandemic (Laverty et al., 2020).

The structural equation modelling in this paper provides valuable insights for transport planning practitioners in aligning behavioural perceptions with pandemic mitigation policies. Extensions of the research can consider longitudinal and panel surveys to capture long-term impacts. These surveys can be designed to focus on commuter behaviour, which is fundamental to the functionality of a transport system. Future policy development can leverage the findings from this research and extensions to create environments with a more positive perception across the community leading to better outcomes in disease management of transport infrastructure. Another potential direction of future research is developing a detailed policy and stakeholder analysis for each country depending on the SEM findings.

CRediT authorship contribution statement

Kiran Shakeel: Conceptualization, Data curation, Formal analysis, Visualization, Methodology, Writing – original draft, Writing – review & editing. **Kasun Wijayaratna:** Conceptualization, Data curation, Methodology, Writing – original draft, Writing – review & editing. **Diego

Table 11
Summary of SEM results.

	Frequency of Travelling Alone			Frequency of Travelling in Public Transport		
	Positive Relationship	**Negative Relationship**	**Insignificant**	**Positive Relationship**	**Negative Relationship**	**Insignificant**
Contracting disease (Public Transport)		China, South Africa, Brazil, India, Italy, Ghana, Norway	Australia, USA		Australia, China, USA, South Africa, India, Italy, Ghana, Norway	Brazil
Contracting disease (Private Transport)	China, Norway	Australia, USA, South Africa, India	Brazil, Italy, Ghana	Australia, China, USA, Norway	India	South Africa, Brazil, Italy, Ghana
Effectiveness of policies (Public Transport)	Ghana	China, USA, India	Australia, South Africa, Brazil, Italy, Norway	Australia, Ghana	China, South Africa, India	USA, Brazil, Italy, Norway
Effectiveness of policies (Private Transport)		South Africa, Brazil, India, Ghana	Australia, China, USA, Italy, Norway		China, USA, South Africa, India, Italy, Ghana	Australia, Brazil, Norway

Maria Barbieri: Conceptualization, Data curation, Methodology, Writing – review & editing. **Baowen Lou:** Conceptualization, Data curation, Methodology, Writing – review & editing. **Taha Hossein Rashidi:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition, Project administration, Resources.

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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