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Research Article

Risk Perception in Public Transport Mobility During the Pandemic in The Literature Published From 2020 To 2024 In International Repositories

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Abstract

Mobility policies in public transport were guided by the distancing of people during the pandemic. However, its effect on users' risk perception was not fully established as a discussion axis in the research agenda. Therefore, the study aimed to address this gap by comparing the theoretical structure against the empirical structure analyzed in a systematic review. A cross-sectional and correlational work was carried out with a sample of experts who evaluated the prevalence of the categorical dimensions of risk perception in public transport mobility using the Delphi technique. The results confirm a second-order factor that makes the model extension essential to the state of the art where prevention is highlighted, with practical implications for public health and transport policy.

Keywords: confirmatory factor analysis; covid-19; transport mobility; risk perception; confinement and distancing policies

Introduction

The COVID-19 pandemic has significantly impacted human mobility patterns and risk attitudes (Chan *et al*., 2020). Studies have shown that the marked decline in mobility following the World Health Organization's declaration of the pandemic can be attributed to risk attitudes. Several research efforts have been undertaken to assess the spatial and temporal risk of COVID-19 transmission based on mobility data (Rahimi *et al*., 2021). Using human mobility models to assess transmission risk resulted in generating heat maps indicating the risk of exposure under different scenarios (Jiang *et al*., 2021). Similarly, a technique for assigning spatial and temporal risk scores uses high-resolution mobility data, focusing on location density and mobility behavior (Lawal & Nwegbu, 2022). Furthermore, studies have explored the use of mobility data for early detection and risk prediction of COVID-19 outbreaks (García *et al.*, 2023). A data-driven framework for assessing neighborhoods and predicting infection risks ahead of outbreaks (*Zachreson et al.,* 2021). In addition, a procedure for producing spatial transmission risk assessments uses population mobility data, highlighting the utility of aggregated human mobility data for estimating transmission risk (Martin & Bergmann, 2021). In addition, the impact of interventions such as mask mandates on mobility behavior and risk compensation has been investigated. Analyzing mobility data to assess the risk-offsetting effects of mask mandates emphasizes the importance of understanding how interventions influence human behavior during the pandemic (Pullan *et al*., 2020). Overall, research on COVID-19 risk mobility has focused on leveraging mobility data to assess transmission risk, predict outbreaks, and evaluate the impact of interventions on human behavior and risk attitudes (Freudendal-Pedersen & Kesselring, 2021). By using high-resolution mobility data and human mobility models, researchers seek to improve understanding of the spatial and temporal dynamics of COVID-19 transmission and improve response strategies to mitigate the spread of the virus.

Dimension	Description	Examples of factors	Impact during the pandemic
Risk of contagion	Concern about the likelihood of exposure to the virus when using public transportation.	- Proximity to other people - Inadequate ventilation - Use of masks	Increased fear of contagion, reduced use of public transport, and implementation of distancing measures.
Hygiene and disinfection	Evaluation of cleaning and disinfection measures in public transport.	- Cleaning frequency - Availability of disinfectants and visible cleaning	There is an expectation of increased cleaning and disinfection and an increased demand for visible sanitization in stations and vehicles.
Accessibility and capacity	Perception of the availability and efficiency of public transport.	- Reduced capacity due to social distancing - Reduced hours	Reduced access due to reduced capacity and schedules mainly affects vulnerable groups.
Perceived comfort	Evaluation of the comfort experience during travel.	- Limited available seats - Crowds at peak times	Decreased comfort due to capacity restrictions and fear of crowds in confined spaces.
Physical security	Perception of safety in the event of possible violence or accidents in public transport.	- Increased stress and anxiety - Fear of robbery or attacks at stations or vehicles	Increased stress, with a more excellent perception of insecurity due to tense situations caused by health restrictions.
Trust in the authorities	Level of confidence in the measures implemented by the government and transport companies to ensure the safety of users.	- Clear public policies - Effective communications	Confidence varies depending on the effectiveness of the government response and compliance with health protocols.
Cost and economic viability	Concern about the economic impact on users due to increased costs, reduced income, or changes in transport mode.	- High rates - Loss of employment or income - Alternative options	Economic imbalance in specific sectors affects mobility and favors cheaper means of transport.
Environmental impact	Awareness of the ecological impact of using different modes of transport, including public transport versus private options.	- Reduction in the use of mass transportation - Increase in the use of private cars	Greater environmental awareness is needed, but private transport tends to be used for fear of contagion, which can increase emissions.

Table 1. Comparison of the dimensions of risk perception in public transport mobility during the pandemic

However, studies on mobility and risks have not focused on policies and their effects on risk perception (Luo *et al.,* 2021). Therefore, the objective of this study was to conduct a systematic literature review to reveal metropolitan mobility and peri-urban health policies, focusing the discussion on the effects of public transport safety on users' health. Are there significant differences between risk policies regarding the perception of risks of contagion, illness, and death from COVID-19 in the literature from 2020 to 2024? Given that distancing and confinement policies impact risk perception, significant differences are expected between the literature published from 2020 to 2024 regarding the relative dimensions of public transport's performativity as a route of transmission of COVID-19.

Method

A cross-sectional and correlational study was conducted with a non-probabilistic selection of indexed sources published in international repositories from 2020 to 2024 and searched with keywords. The PRISMA format (see Annex A) was used for the systematic review of the literature, considering seven dimensions related to exposure to risks of contagion, illness, and death from COVID-19 (Rambhatla *et al*., 2022). Reliability ranged between 0.645 and 0.756 for each of the mobility risk dimensions. Validity was established between 0.337 and 0.561. The sphericity test was significant, and the adequacy exceeded the minimum indispensable value of 0.60. Data were captured in Excel and processed in Google Colab (see Appendix B). Reliability, adequacy, sphericity, validity, adjustment, and residual coefficients were estimated to test the hypothesis regarding significant differences. Values close to one were considered evidence of non-rejection of the null hypothesis.

Results

The analysis of covariances suggests the introduction of other indicators and factors in the model (Figure. 1). The covariances between the dimensions were close to zero, which suggests the inclusion of other indicators and factors not contemplated in the instrument.

	CD	EP	HW	RI	SC	WEG	PJI
CD	0						
EP	.07	0					
HW	.2	.21	0				
RI	.16	.05	.11	0			
SC	.04	.05	.18	.01	0		
WEG	.02	.08	.03	.02	.02	0	
PJI	.01	.01	.01	.04	.01	0	0

Figure 1. Covariances between the first-order factors

The structural analysis captures the relationships between first- and second-order factors (Fig. 2). The findings indicate that the second-order factor, related to risk perception, is indicated by seven factors reported in the literature on mobility policy and transport risk.

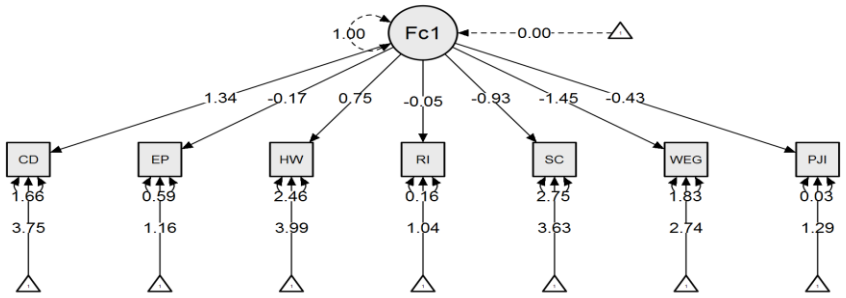

Figure 2. Confirmatory factor analysis of the transportation risk policy in Mexico City

The fit and residual values $[\chi 2 = 34.332(14\ gl)p > 0.002; CFI = 0.994; MFI = 0.902; RMSEA = 0.015; RMSR = 0.071]$ suggest that the hypothesis regarding significant differences between the theoretical structure and the empirical analysis is not rejected.

Discussion

This study's contribution to the state of the art lies in establishing an empirical model to compare with the theoretical model reported in the literature regarding mobility and risk perception in transport during the pandemic. The results highlight the emergence of a second-order factor that the literature identifies as risk perception. Mobility policies reveal the prevention of risk events' effects on users' health (Chang *et al*., 2021). The data supporting the non-exposure to risk events are derived from mobility policies on public transport safety and users' health (Gibson, 2021). Mobility policies focused on the effects of transport safety on users' health do not recognize the risks of exposure or the short-, medium--, and long-term consequences.

Unlike the state of the art in which mobility policies are not evaluated from the perspective of risk perception, this work suggests that from the literature reviewed, it is possible to infer risk perception as an effect of confinement and distancing policies. In this sense, it is recommended that the study be extended to the dimensions of mobility and overcrowding to anticipate a scenario of risks of contagion, illness, and death from COVID-19.

Conclusion

The purpose of the study was to compare the theoretical structure reported in the literature from 2020 to 2024 regarding mobility policies concerning an empirical structure analyzed from the perception of risk as an effect of distancing and confinement policies. The results demonstrate the prevalence of a second-order factor that the literature identifies as the perception of mobility risk. In the state of the art in which the association between distancing and confinement policies as axes of mobility in public transport is demonstrated, this work suggests including a second-order factor that the literature identifies as risk perception. It is recommended that the study be extended to the impact of mobility on public transport mediated by the distancing of people.

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