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Effectiveness Analysis of Public Transit Pandemic Prevention Strategy Considering Traveler Risk Perception

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Abstract: Since the outbreak of COVID-19, there have been hundreds of millions of confirmed cases in the world, and people can strongly perceive the risk of infection with the virus in their daily lives, which has seriously affected people's life and travel, thus hindering the development of all sectors of society, especially the transportation sector. Taking China as an example, since the outbreak of the pandemic, China's overall public transportation passenger volume has decreased by about 37%, seriously affecting the normal running of the public transit. Therefore, the ways of ensuring the normal running of the public transport system during the pandemic has become the focus of this paper. In order to solve this problem, this paper constructed a SEM model based on pandemic risk perception, analyzed the impact of public transit pandemic prevention strategies (TPS) on risk perception (RP) and travel mode use according to the personal trip survey data in Harbin, China during the pandemic. The results showed that people's risk perception had a significant negative impact on car usage and transit usage. In other words, people's risk perception of virus infection had a great impact on travel, especially on the use of public transit. The transit pandemic prevention strategy had a significant negative impact on risk perception, and had a significant positive impact on people's use of transit. This showed that in the current pandemic outbreak period, the transit pandemic prevention strategy proposed by the Harbin authorities cannot effectively reduce transit usage, and can provide proven and effective transit pandemic prevention strategies. This provided an important support for ensuring the normal running of the public transit system and guiding the sustainable development of public transit during the outbreak of the pandemic.

Keywords: COVID-19; risk perception; transit pandemic prevention strategy; transit usage; car usage; SEM

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Citation: Li, X.; Xie, B.; Gong, D. Effectiveness Analysis of Public Transit Pandemic Prevention Strategy Considering Traveler Risk Perception. *Sustainability* **2023**, *15*, 4961. https://doi.org/10.3390/su15064961

Academic Editors: Xueming (Jimmy) Chen and Suwei Feng

Received: 8 February 2023
Revised: 6 March 2023
Accepted: 7 March 2023
Published: 10 March 2023

1. Introduction

Since the outbreak of COVID-19, the pandemic has kept rising all over the world, with hundreds of millions of confirmed cases of COVID-19, which has had a huge impact on people's physical and mental health and daily life, and has also had a very negative impact on the development of all sectors, especially the transportation sector. Under this background, the number of people taking public transit around the world has declined significantly, and the operation of urban public transit has also encountered serious obstacles. Taking China as an example, the public transit passenger volume in China declined by 37% due to the pandemic [1]. As an important travel mode for people, public transit undertakes the daily travel needs of most residents. Although China has entered a new stage of COVID-19 pandemic prevention in the present, pandemic events may also occur in the future. This study is of great significance to the sustainable development of public transit during the pandemic in the future. The ways of ensuring the normal run of the urban public transit system under the premise of controlling the pandemic is not only a widely discussed issue of many scholars, but also a key topic discussed in this paper. This paper further explains this problem from the following two aspects.

The pandemic has a great impact on all aspects of people's lives, especially people's travel. Travel is a necessary part of people's lives. People are more likely to perceive the risk of COVID-19 in enclosed buses. Passengers on closed public transit close to other passengers and touch handles, seats and other public facilities [2–4]. Therefore, some passengers turn to car travel to reduce the risk of infection, resulting in a rapid decline in the share rate of public transit [5], and a rapid decline in public transit travel preference [6]. At present, there are few studies on the impact of residents' risk perception on public transit travel, and few consider the indirect impact of cars on public transit travel during the pandemic. In addition, as the pandemic continues and the number of people vaccinated increases, the perceived pandemic risk is significantly reduced, the impact of the pandemic risk perception on public transit travel remains to be investigated at this moment [7]. Therefore, we analyzed the impact of the pandemic on people's daily use of cars and public transit from the perspective of risk perception. By exploring the relationship between people's risk perception and the use of travel modes and analyzing the impact of risk perception on public transit choices from a more refined perspective, we hope to improve the public transit sharing rate during the pandemic by proposing risk reduction strategies to ensure the normal running of public transit.

On the other hand, during the outbreak of the pandemic, the pandemic prevention strategies adopted by the transportation authorities reduced the public transport service level, thereby affecting the public transit service level and attractiveness. The authorities have taken some pandemic response measures to reduce the impact of vehicles on the spread of the virus, such as suspending the operation of some vehicles, changing routes, shortening the stay time, and requiring passengers to wear masks and gloves. These measures reduce the risk of taking public transit while also reducing public transit services [8–12], which reduces the willingness of residents to use public transit [13]. Therefore, the pandemic prevention strategy that is adopted can effectively reduce people's risk perception in the process of travel, and also ensure the normal running of public transit and the prevent the decline in service level during the pandemic, which has become the main content of this research topic.

In general, we took Harbin, China, to investigate the travel characteristics of people during the pandemic period. This survey reflected the perceived risk of the pandemic and people's travel choices at the current outbreak, and provided good data support for this paper to discuss the public transit operation during the pandemic. We judge whether these public transit pandemic prevention strategies can reduce risk perception without reducing the residents' preference for the use of public transit. In other words, we evaluated the effectiveness of public transportation pandemic prevention strategies. This study of transit pandemic prevention strategies will contribute to the normal operation of public transit and the sustainable development of transport during the pandemic.

2. Literature Review

As mentioned in the introduction, people's use of public transit during the pandemic was seriously affected by the risks of virus infection and the pandemic prevention policies. This section first summarized the impact of risks factors on the transport use verified by researchers and the pandemic prevention strategies proposed by scholars in detail. Secondly, the relationship between individual socio-demographic factors and the use of transport modes was analyzed, which provided a theoretical basis for the selection of control variables in this paper.

Anwari et al. compared travel purpose, travel mode, and travel frequency in Bangladesh during and before the pandemic, and found that COVID-19 could reduce the frequency of leisure travel and transit choices [3]. Pawar et al. found that 41% of commuters stopped traveling during the pandemic, 51.3% of commuters did not change their travel mode and 5.3% of the commuters switched their travel mode from bus to car [5]. Kreetzer et al. believed that the pandemic has a severe effect on public transit operation and reduces public transit users by 95% [6]. It could be concluded from this that the pandemic had a large impact on the operation of public transit. Ensuring the normal running of public transit during the pandemic is the main topic of this paper. Considering the impact of people's pandemic risk perception on travel, the personal heterogeneity of travelers' travel mode use and the status of research by scholars, we explored the effectiveness of public transit pandemic prevention strategies in the case of cities from the perspective of travel mode use. The risk perception of COVID-19 can increase people's travel anxiety, reduce travel demand, and thus, affect the use of traffic modes [14]. Ozbilen et al. found that people perceived the risk of public transit (bus, car appointment and carpool) to be greater than that of car travel [15]. This proved that risk perception is an important reason for people to choose cars instead of public transit during the pandemic. This explains why people's travel mode changed from shared public transport to cars and motorcycles during the pandemic [16]. According to the research of scholars, people affected by the pandemic believe that there are many risks in their daily life. The travel process is an essential part of people's lives and is also a hotspot for the spread of the virus. Public transport is the area where the virus is most likely to spread, and people are more likely to be aware of these risks, thus affecting their travel behavior. The most current studies have compared the changes of only one travel mode choice before and after the pandemic. These studies have not yet explored the frequency of multiple trips. Travel frequency is the number of times people use different travel methods, which more accurately reflects people's daily travel preferences. However, the current research has not explored the impact of risk on travel from the perspective of travel frequency, which is a supplementary aspect discussed in this paper.

In order to reduce the impact of the pandemic on people's travel, many scholars gradually began to be concern about the pandemic prevention strategies in the field of transportation. Taking Singapore as a case study, Mo et al. established a heterogeneous network structure to simulate the spread of COVID-19 through public transport based on the data of the Singapore smart card [17]. The results showed that closing some bus lines could not prevent the spread of the pandemic, while identifying infected passengers as soon as possible could effectively reduce the spread of the pandemic. Dzisi et al. thought that bus is a high-risk region for the spread of the pandemic and recommended that operators control the number of boarding passengers and impose fines on passengers without masks [18]. By investigating the traffic pandemic prevention strategies of Bangladesh, it was found that the authorities provided pandemic prevention support to bus companies. Strategies proposed by the authorities to support pandemic prevention could improve the possibility of using transit and the profitability of transit companies [3]. UITPa also proposed some pandemic prevention strategies, such as reducing the number of bus passengers, requiring passengers to wear masks and gloves and providing protective equipment for drivers [13]. To reduce the contact between passengers, Gkiotsalitis et al. proposed some bus pandemic prevention measures, such as changing the bus stops, routes and vehicle schedules [19]. Based on the differences in the risk perception of COVID-19 by different passengers, Naveen et al. established a pandemic prevention framework [12]. Tirachini et al. believed that public transport should be frequently ventilated and that passengers should wear masks, and that keeping a physical distance of 1 m will reduce the probability of infection among staff and passengers [10]. Zhang et al. recommended some measures to ensure the normal operation of public transit under the pandemic, such as adjusting bus frequency, maintaining the physical distance between passengers, dynamic stop hopping, reducing waiting time, controlling speed and the timely sharing of information [9]. Tian C A et al. established a knowledge graph-based passenger infection tracking method based on multi-source public transport data, which was beneficial in reducing the spread of the pandemic [20]. In order to not increase the risk of transmission of the virus on public transit, Muren et al. proposed an integer programming model, which considered the number of trips and the efficiency of pandemic prevention, and implemented the commuting peak travel strategy, indicating that in this way the risk of cross infection among commuters could be reduced to a certain extent [21]. Thus, scholars proposed many public transport pandemic prevention strategies, but have not evaluated the effectiveness of these strategies. Therefore, we explored the effectiveness of public transit pandemic prevention strategies implemented in Harbin from the perspective of travel mode use.

To evaluate the effectiveness of public transit prevention strategies from the perspective of individuals' travel mode use, it is also necessary to pay attention to the influence of individuals' socio-demographic characteristics on the use of traffic mode. Chakrabarti's research found that car ownership is related to transit choice preferences. A total of 90% of travelers with a driver's license were less likely to choose public transit than travelers without a driver's license [22]. A deeply explored the factors affecting the use of travel modes. The results showed that older and lower-income groups were more sensitive to travel costs and were more inclined to use public transit [23]. Han et al. found that passengers with higher monthly incomes and educational levels are more likely to choose cars [24]. Kaffashia et al. studied the travel behavior of people in the Klang Valley region of Malaysia, and found that high-income levels increase car ownership, increase the tendency to use cars and decrease the use of public transportation [25]. Yao et al. analyzed the interaction between bus and car use based on bus service levels and car ownership; bus use and car use were mutually exclusive [26]. Given the influence of socio-demographic attributes on the mode usage, we selected these variables as control variables to explore the transit and car usage during the pandemic. Furthermore, we explored the effect of public transit pandemic prevention strategies on the use of travel modes after considering the impact of individual socio-demographic factors, that is, the effectiveness of public transit pandemic prevention strategies.

The remainder of this paper was organized as follows. Section 1 introduces the research questions. In Section 2, we summarize the related research literature. In Section 3, we analyze the methods, variables and data used in the model calculation. In Section 4, the model calculation results are discussed. We conclude this paper in Section 5.

3. Materials and Methods

Since 2019, COVID-19 has become more and more prevalent around the world. As of 11 January 2022, around 600 million people worldwide have been infected with the virus, including China. Medical experts found that the virus spreads more easily in low temperatures. Harbin is located at 44°04′–46°40′ N, and the temperature in January is below −25°, as shown in Figure 1. This is very suitable for the survival of viruses. In December 2020, COVID-19 emerged again in Harbin, in the meantime, we conducted a two-month personal trip survey from 26 January 2021 to 11 February 2021, including the transit pandemic prevention strategies. Affected by the pandemic, we conducted an online travel survey of residents living in areas affected by the pandemic in Harbin, including 14 medium- and high-risk areas, such as Hulan District, Xiangfang District and Daoli District. The questionnaire, as shown in Table 1, was designed using the Likert scale. We received 461 answered questionnaires and 435 were valid, the effective rate of the questionnaires was 94.36%. This is similar to the study sample size of Yao [26].

Figure 1. Study area.

Table 1. Variables of RP, TPS and mode usage.

Variables	Observation Variable	Symbol	Evaluation
RP	I think contracting the virus is a serious threat to lives.	RP1	1 to 5
	I think contracting the virus can seriously affect at work.	RP2	1 to 5
	I think contracting the virus can cause serious economic damage.	RP3	1 to 5
	I think contracting the virus can seriously affect mental health.	RP4	1 to 5
TPS	I think it's good to control the space with passengers.	TPS1	1 to 5
	I think it's good to have pandemic prevention training for bus drivers.	TPS2	1 to 5
	I think it's good to ventilate and disinfect the bus in time.	TPS3	1 to 5
	I think it's good to have temperature checks for drivers and passengers.	TPS4	1 to 5
TU	Average number of transit trip per day on weekdays.	TU1	1 to 4
	Average number of transit trip per day on weekends.	TU2	1 to 4
CU	Average number of car trip per day on weekdays.	CU1	1 to 4
	Average number of car trip per day on weekends.	CU2	1 to 4

Risk perception can measure people's perceptions severity of contracting COVID-19, which indicates the level of psychological panic. As the pandemic has a great impact on all aspects of people's lives, especially people's travel. Travel is a necessary part of people's lives. People are more likely to perceive the risk of COVID-19 in enclosed buses, thus affecting their choice of travel mode. The risk variables include life safety, economic loss and psychological burden [16]. So, according to the Brati's research [16], we obtained the risk perception variables of people during the pandemic, as shown in Table 1.

Transit pandemic prevention strategies (TPS) represent people's perceived preference for public transit travel after the TPS were adopted by the government or enterprises [13]. Through the questionnaire survey of Harbin in 2021, the following major TPS were obtained: controlling passenger spaces, training drivers in pandemic prevention, disinfecting the buses and taking passengers' temperature, as shown in Table 1.

Travel frequency reflects the amount of travel mode usage. The travel feature of weekdays and weekends is quite different. Travel time and destination on weekends are more diversified and flexible than those on weekdays. Travel time is relatively concentrated on weekdays. Compared to weekdays, there is an insignificant morning/evening peak hour on weekends. Moreover, the frequency of transit trips varies greatly between weekdays and weekends [27]. Therefore, considering the difference in the performance of transit trips between weekends and weekdays, we used the frequency of transit usage (TU) to characterize people's daily transit travel choices.

Similar to variables of transit usage, the number of car trips on weekdays and weekends was used to measure car usage (CU), as shown in Table 1 [27].

3.1. Framework and Hypotheses

According to the variables collected in Tables 1 and 2, this paper established the analysis framework of travel mode usage. Similar to [23,28,29], we also set the nominal variables in Table 2 as exogenous control variables to analyze the transit public use during the pandemic under the influence of socio-demographic variables. We hoped to explore whether the transit pandemic prevention strategies (TPS) are effective from the perspective of the use of people' travel mode during the pandemic. TPS and socio-demographic variables were exogenous variables, while travel mode usage (TU and CU) and RP were endogenous variables, as shown in Figure 2. Through the establishment of this model, based on the analysis of residents' perceived risk and socio-demographic factors affecting the use of traffic mode, we explored the impact of the public transit pandemic prevention strategies on the use of transport modes, and then discussed its effectiveness.

Table 2. The detailed description of socio-demographic variables.

Variables	Question Description	Range	Frequency
Gender (G)	What's your gender?	1: Male 2: Female	58.90% 41.10%
Age (A)	What is your age?	1: <18 year 2: 18–40 year 3: 41–60 year 4: >60 year	0.50% 46.20% 43.90% 9.40%
Income (I)	What is your monthly income?	1: <3000 2: 3001–6000 3: 6001–9000 4: >9000	16.10% 43.20% 24.80% 15.90%
Car ownership (CO)	How many vehicles do your family own?	1: NO 2: YES	29.00% 71.00%
Education level (E)	What's your level of education ?	1: Below junior high school 2: High school 3: Undergraduate 4: Graduate student	6.44% 13.79% 32.64% 42.75%
Occupation (O)	What's your occupation?	1: Public officials 2: Self employed and freelance 3: Migrant workers 4: Student 5: Retiree and others	71.27% 8.97% 0.69% 5.75% 13.34%

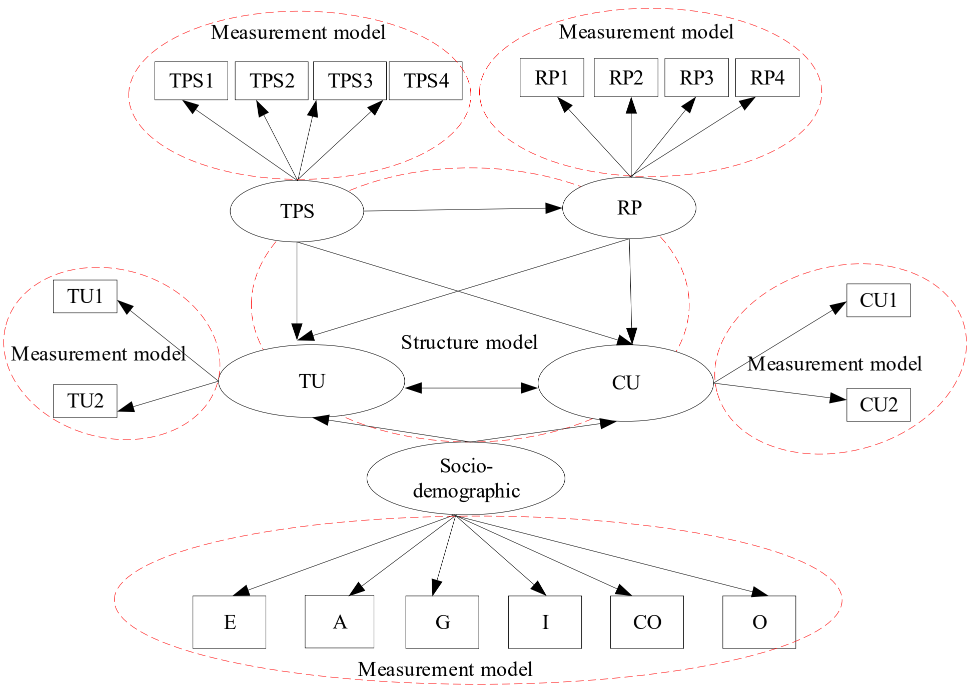

Figure 2. Model of framework.

Through the detailed analysis of the model established in Figure 2 and the existing scholars' research on TPS, RP, transit (TU) and car usage (CU), we established Hypotheses 1–7, as shown in Table 3 and Figure 3.

Table 3. The source and description of the hypotheses.

Hypothesis	Source	Description
H1	[15]	RP has a negative impact on transit usage.
H2	[14]	RP has a negative impact on car usage.
H3	[27]	TPS has a negative impact on RP.
H4	[30–33]	TPS has a negative impact on car usage.
H5	[3]	TPS has a positive impact on transit usage.
H6	[33]	Transit usage has a negative effect on car usage.
H7	[26]	Car usage has a negative effect on transit usage.

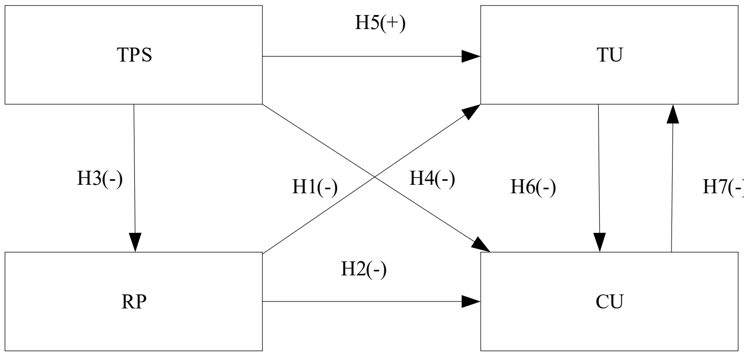

Figure 3. Model hypothesis.

3.2. SEM

To quantify the effectiveness of transit pandemic prevention strategies considering risk perception, the structural equation model (SEM) was used to test the hypothesized correlation between RP, TPS and mode usage. SEM was developed with the efforts of many scholars, path analysis was proposed by Wright and then SEM was divided into two parts: measurement model and structure model [34,35]. Furthermore, the general covariance as the main components of SEM was adopted by Bollen to optimize the measurement model and structure model [36]. The measurement model showed the relationship between latent variables and observed variables, as shown in Equations (1)–(4). The structure model described the relationship between multiple variables including latent variables, as shown in Equations (5)–(6).

$$A = \gamma_1 RP + \xi_1 \tag{1}$$

$$B = \gamma_2 TPS + \xi_2 \tag{2}$$

$$C = \gamma_3 TU + \xi_3 \tag{3}$$

$$D = \gamma_4 CU + \xi_4 \tag{4}$$

$$TU = \beta_{11} RP + \beta_{12} TPS + \beta_{13} CU + \beta_{14} G + \beta_{15} CO + \varepsilon_1 \tag{5}$$

$$CU = \beta_{21} TPS + \beta_{22} RP + \beta_{23} TU + \beta_{24} A + \beta_{25} G + \beta_{26} I + \beta_{27} CO + \varepsilon_2 \tag{6}$$

where A is the column vector of the observed variables of RP; B is the column vector of the observed variables of TPS; C is the column vector of the observed variables of TU; D is the column vector of the observed variable of CU. $\gamma_1, \gamma_2, \gamma_3$ and γ_4 are the load coefficient matrices between the latent variables and their observed variables; ξ_1, ξ_2, ξ_3 and ξ_4 are the column vectors of the measurement error terms of the observed variables A, B, C and D. β_{11}, β_{12}, β_{13}, β_{14} and β_{15} represent the parameters of RP, TPS, CU, G and CO to TU, respectively. β_{21}, β_{22}, β_{23}, β_{24}, β_{25}, β_{26} and β_{27} represent the parameters of RP, TPS, TU, A, G, I and CO to CU, respectively.

3.3. Data

Table 4 shows the distribution of the observed variables of RP and TPS. The scores of the observed variables of RP were all concentrated on agree or strongly agree. Meanwhile, the scores of the observed variables of TPS were all concentrated on disagree or neither agree or disagree.

Table 4. Data distribution of risk perception (RP) and transit pandemic prevention strategies (TPS).

Observed Variables	1	2	3	4	5
RP1	6.7	5.7	11.7	46.4	29.4
RP2	5.7	5.3	6.9	47.4	34.7
RP3	6.2	4.6	11.3	45.1	32.9
RP4	6.4	4.6	10.8	44.8	33.3
TPS1	20.0	43	27.4	6	3.7
TPS2	19.5	40.7	28.7	7.8	3.2
TPS3	19.1	40.5	27.8	9	3.7
TPS4	19.1	42.5	28	7.4	3.0

Note: 1 is strong disagree; 2 is disagree; 3 is neither; 4 is agree; 5 is strongly agree.

Figure 4 shows the frequency distribution of public transit usage and car usage on weekdays and weekends. The frequency distribution of public transit usage was obviously different from car usage, while it differed a little between weekdays and weekends. The frequency of transit usage was mostly distributed in 0–2 times/day [28]. During the pandemic, the frequency of trips by car/day was mostly less than or equal to twice.

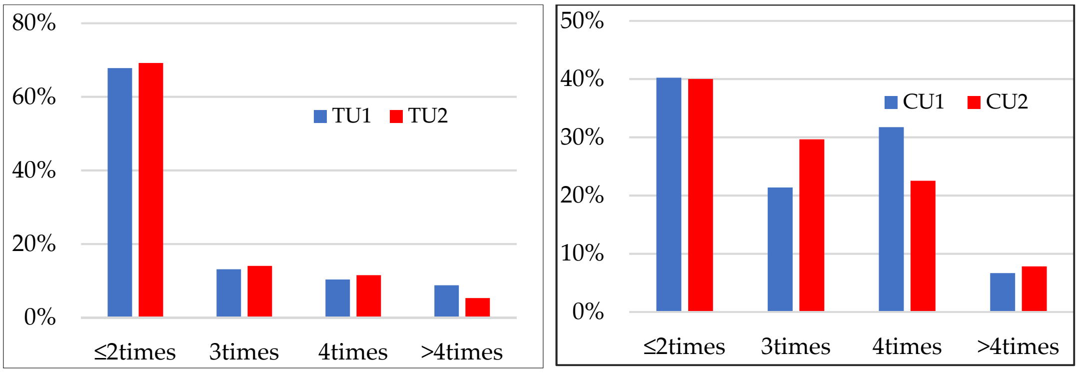

Figure 4. The distribution of public transit and car usage.

4. Results

AMOS software and SEM were used to measure the hypothetical relationship between TPS, RP, TU and CU. Considering the limited research sample, we used a bootstrap method to select randomly n times samples and calculate the standard error. Bootstrap is a non-parametric estimation method that enables samples to make statistical inferences about the population [37,38], which can solve the non-normal distribution of variables and small sample size, and ensure the rationality of the results. This calculation mainly addressed the following three questions: (1) Is the hypothesized relationship valid? (2) Are these transit pandemic prevention strategies effective? (3) Was the transit pandemic prevention strategy effective after considering the control effect of socio-demographic variables?

The reliability test of the questionnaire was a necessary process of the research, which was used to measure the consistency and stability of the results. Cronbach's alpha was considered the most popular measure indicator, which assessed the internal consistency among variables [39].

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \Psi_i^2}{\Psi_T^2}\right) \tag{7}$$

where k is the total number of question items of potential variables; Ψ_i^2 is the variance of all respondents' answers to question item i; Ψ_T^2 is the variance of all respondents' answers to all question items. The value of Cronbach's alpha (α) is between 0 and 1. The larger the value, the higher the reliability of the measurement. If the value is greater than 0.7, the result is acceptable [39].

The results of the reliability test, as shown in Table 5, showed that Cronbach's alpha coefficients for all latent variables exceeded 0.7, indicating that the questionnaire had good reliability. On this basis, we used SEM to measure the model. Table 6 provided the fit indices for SEM, which suggested that the model had good fitness and complied fully with the criteria. For instance, if CFI > 0.9, the test is eligible. The result of the model calculation showed that the CFI value was 0.956, which suggested that the result complied with the test requirements.

Table 5. Model reliability analysis.

Latent Variable	Observed Indicator	Standard Load	*p*-Value	Cronbach's Alpha
TPS	TPS 4	0.956	***	0.955
	TPS 3	0.892	***	
	TPS 2	0.894	***	
	TPS 1	0.935	***	
RP	RP4	0.909	***	0.95
	RP3	0.915	***	
	RP2	0.940	***	
	RP1	0.881	***	
CU	CU2	0.898	***	0.889
	CU1	0.892	***	
TU	TU1	0.952	***	0.743
	TU2	0.777	***	

***: $p < 0.01$, means passed the significance test.

Table 6. Fitting of structural equation model.

Measure	χ^2/df	NFI	RFI	IFI	TLI	CFI	RMSEA
Threshold Value	<5	>0.90	>0.90	>0.90	>0.90	>0.90	>0.05 and <0.1
	3.732	0.941	0.919	0.956	0.939	0.956	0.079

Table 7 and Figure 5 showed the standardized results between the model variables, which indicated the causality between the variables. Additionally, the results validated the hypotheses we proposed. It was concluded that the impact of risk perception (RP) on public transit usage was significantly negative (−0.112). Hence, Hypothesis 1 was supported by the result. Similar to transit usage, the impact of risk perception (RP) on car usage was significantly negative (−0.120), indicating the negative effect of risk perception on car usage. This finding was consistent with Ozbilen B' study [15], which indicated that the risk significantly reduced travel motivation during COVID-19. From this, Hypothesis 2 can be confirmed. It is suggested that the authorities took measures to control the spread of COVID-19 [12], ensure the safety of travelers, and reduce travel risks and risk perceptions of COVID-19. Meanwhile, it was necessary to maintain the normal operation of transit to ensure daily travel needs.

Table 7. Estimation results of the SEM model. _Hlk119681370.

Path	Estimate	S.E.	*p*
RP←TPS	−0.531	0.049	***
CU←RP	−0.120	0.038	0.005
CU←Car-ownership	0.463	0.088	***
CU←Age	−0.089	0.046	0.010
CU←Income	0.206	0.034	***
TU←Car ownership	−0.835	0.408	***
TU←Gender	0.119	0.11	0.034
CU←Gender	−0.183	0.062	***
TU←TPS	0.298	0.071	***
TU←RP	−0.112	0.063	0.091
CU←TPS	−0.084	0.042	0.057
TU←CU	0.383	0.100	0.091
CU←TU	−0.524	0.052	***

Note: *** representative coefficient value passed the significance test at the 99% level.

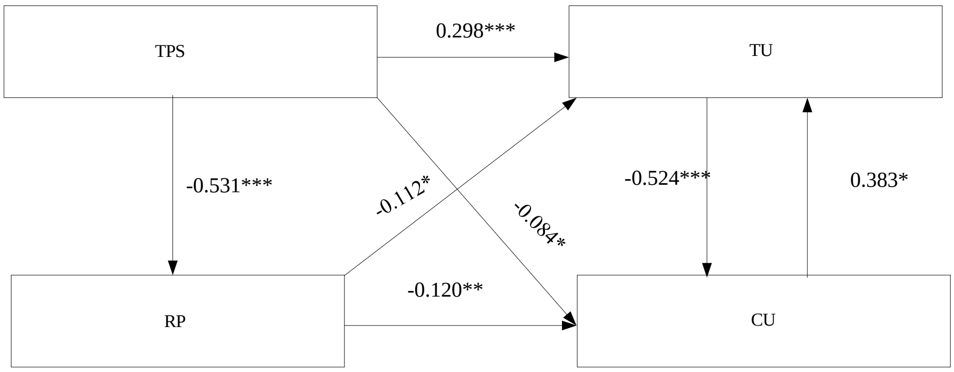

Figure 5. Structural equation results on RP, TPS, CU and TU. Note: *** representative coefficient value passed the significance test at the 99% level; ** representative coefficient value passed the significance test at the 95% level; * representative coefficient value passed the significance test at the 90% level.

The impact of transit prevention strategies (TPS) on risk perception (RP) was obviously negative (−0.531). This indicated that Hypothesis 3 was valid, which implied that transit prevention strategies (TPS) could be effective in reducing people's risk perception (RP) during the pandemic [27]. TPS had a quite significant positive effect on public transit usage (0.298), indicating that Hypothesis 5 was supported. It was clear that the transit prevention strategies (TPS) established by the authorities were related to the increase in transit usage. Moreover, the impact of transit pandemic prevention strategies on public transit usage was much greater than that on car usage, and had a weak negative impact on car usage (−0.084). This showed that the implementation of transit pandemic prevention strategies can effectively prevent people from using public transit during the pandemic, although it cannot evidently reduce car travel. That is, the transit pandemic prevention strategies adopted by the authorities of Harbin during the pandemic, such as controlling the spatial distance of passengers, providing pandemic prevention training to drivers, disinfecting public transit vehicles and taking the passengers' temperature, could effectively improve people's preference for public transit during the pandemic [9,10,20].

Public transit usage had a significantly negative impact on car usage (−0.524). Hypothesis 6 was established, that is, when public transit usage increased, the frequency of car usage decreased. On the contrary, the impact of car usage on transit usage was significantly positive (0.383), and Hypothesis 7 was valid, which was inconsistent with the negative effect of transit usage on car usage in Yao' findings [26]. For the control variables, the gender had significant positive and negative effects on transit and car usage (0.119, −0.183), indicating that women prefer to public transit. The age variable had a significant positive effect on car usage. That is, with age, people were not inclined towards car usage [28]. The effect of car ownership on public transit usage [40] and car usage was quite different, which was −0.835 and 0.463, respectively [41]. This suggested that car ownership is significantly relevant to the increase in car usage, and the authorities should take measures to curb the growth in car ownership. The effect of income on car usage was significantly negative, which was consistent with the present study's finding. High-income groups were more likely to purchase and use cars.

The standardized total effects between variables are shown in Table 8. The total effect is equal to the sum of direct effects and indirect effects. The results showed that the direct effects and indirect effects of risk perception on public transit and car usage were significant. For transit usage (TU), the direct effects and indirect effects on public transit were −0.112 and −0.020, respectively. For car usage (CU), the direct effect on car usage was negative (−0.120), while the indirect effect was positive (0.069). The total effect was −0.051 = −0.120 + 0.069. Obviously, the risk perception was related to the increase in car usage. The reason for this result was that people reduce public transit usage and shift to the usage of cars to reduce the travel risk during the pandemic. Transit prevention strategies (TPS) had a direct effect on risk perception, while it had obvious direct and indirect effects on public transits and cars usage, and the direct effect was greater than the indirect effect. Specifically, with other exogenous variables remaining constant, for each unit of increase in TPS, the risk perception was decreased by 0.531, transit usage was increased by 0.292 and car usage was decreased by 0.173. Therefore, it was suggested that transit prevention strategies contribute in the prevention of people's travel from shifting to car. It can also be understood that the transit pandemic prevention strategies proposed in this paper were significantly related to the increase in transit usage.

Table 8. The direct effects, indirect effects and total effects.

	Total Effect			**Direct Effect**			**Indirect Effect**		
	RP	**TU**	**CU**	**RP**	**TU**	**CU**	**RP**	**TU**	**CU**
TPS	−0.531	0.292	−0.173	−0.531	0.298	−0.084	None	−0.070	−0.089
RP	None	−0.131	−0.051	None	−0.112	−0.120	None	−0.020	0.069
TU	None	−0.167	−0.436	None	None	−0.524	None	−0.167	0.087
CU	None	−0.319	−0.167	None	0.383	None	None	−0.064	−0.167

A group of alternative models was constructed for comparative analysis to test the effectiveness of the above results, which is applied by Yao [26], as shown in Figure 6. These models were based on the model established in Figure 2, and the reliability of the results in Figure 5 was re-verified without considering the impact of socio-demographic variables. Their goodness of fit results are shown in Table 9. By eliminating some paths in the modified models, we obtained Models 1–7. Compared with other models, Model 3 performed the best. This was consistent with the hypothetical model constructed in this paper. Therefore, the results were be extremely reliable and reasonable. This showed that the transit pandemic prevention strategies (TPS) directly affected transit usage (TU), and affected car usage (CU) by affecting transit usage (TU).

Table 9. Goodness of fit measures of the alternative model.

Model	χ^2/df	**NFI**	**RFI**	**IFI**	**TLI**	**CFI**	**RMSEA**
Model1	5.010	0.949	0.934	0.959	0.946	0.959	0.096
Model2	1.616	0.984	0.979	0.994	0.992	0.994	0.186
Model3	0.997	0.990	0.987	1.000	1.000	1.000	0.000
Model4	4.794	0.952	0.937	0.962	0.949	0.962	0.093
Model5	1.395	0.986	0.982	0.996	0.995	0.996	0.030
Model6	1.001	0.990	0.987	1.000	1.000	1.000	0.002
Model7	1.015	0.990	0.987	1.000	1.000	1.000	0.006

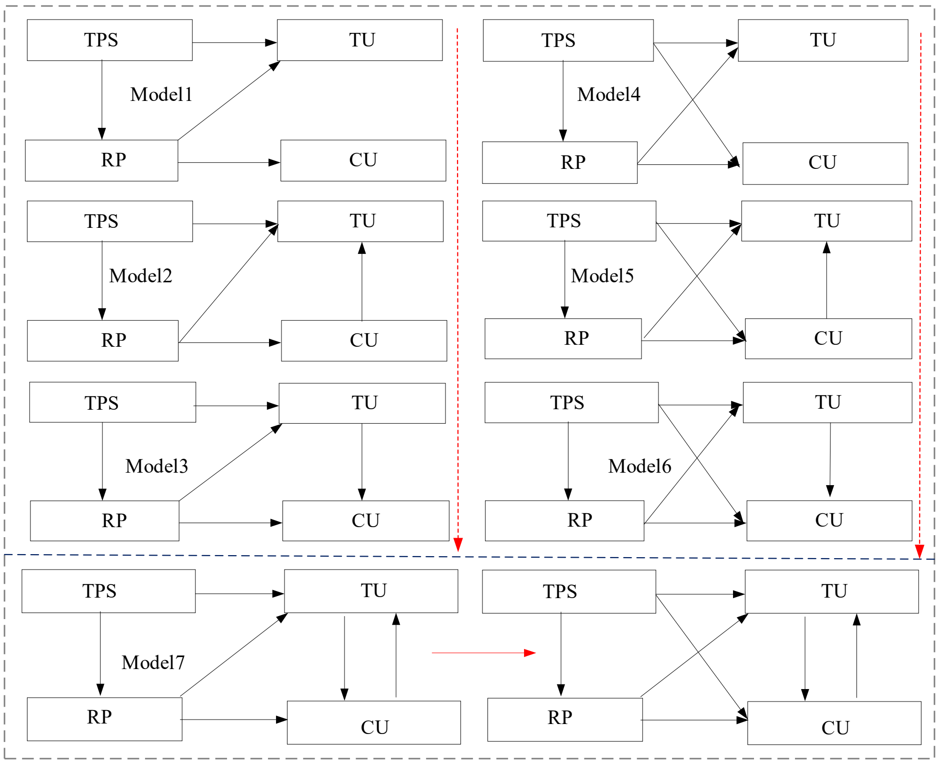

Figure 6. Comparison diagram of sub model results.

5. Conclusions

In order to ensure the normal operation of transit during the pandemic, maintain traveler safety during transit, and prevent people's travel choices shifting to car use during the pandemic, we specially evaluated the effectiveness of public transit strategies. By evaluating the impact of public transit pandemic prevention strategies on the use of people's travel modes, we judged whether these strategies can effectively reduce the transit choice preference of passengers during the pandemic, which was the focus of this paper. Therefore, a framework for assessing the relationship of risk perception, transit pandemic prevention strategies, car usage and transit usage was established. We used AMOS.24 to measure the framework, the results are as follows:

This paper explored the impact of these strategies on public transit travel, evaluated the effectiveness of major public transit prevention strategies implemented in China, and extended the empirical theories in this research field. Meanwhile, our research findings could have universal implication for areas under the thread of a pandemic and in need of rapid development of public transit.

Based on the proven hypothesis relationship, both risk perception and transit pandemic prevention strategies had a great relationship with transit usage. The authorities should implement reasonable public transit pandemic prevention strategies to reduce the psychological impact of the pandemic on travelers, especially controlling the distance between passengers on public transit, and measuring the temperature of passengers and drivers. This finding was of great significance to promote people's pandemic use of public transit and guide the sustainable development of urban transport during the pandemic. Moreover, through the study of control variables, it was found that car ownership had an obvious positive effect on car travel during the pandemic. This suggested that some step of restricting car purchases and use should be taken, such as increasing car purchase tax, controlling the number of the driver's licenses issued and so on.

This paper includes research on transit pandemic prevention strategies and risk perception in Harbin, without considering car ownership preferences, perceived behavior control, social norms, bus speed, bus stops distribution, bus departure rate and so on. These factors may affect travel mode usage and the operation of public transit to a certain extent. Studying these factors is conducive to a more serious and comprehensive analysis of bus usage. Therefore, we will explore the impact of these factors on the use of public transit travel during the pandemic in future research.

Author Contributions: Conceptualization, B.X. and X.L.; methodology, X.L. and D.G.; analysis, X.L.; investigation, D.G.; writing and editing, B.X. and X.L.; supervision, B.X. All authors have read and agreed to the published version of the manuscript.

Funding: This study aims to achieve the sustainable development of transit transport under normalization by proposing pandemic prevention strategies. The work is supported by two funds, National Natural Science Foundation of China (71974043) and the Science and Technology Innovation Committee of Shenzhen under Grant (JCYJ20210324133202006).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are not applicable to this paper.

Acknowledgments: We are very grateful to the editors and reviewers for their suggestions for this manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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