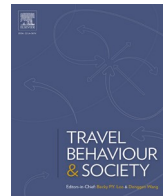




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Public transit travel choice in the post COVID-19 pandemic era: An application of the extended Theory of Planned behavior

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ABSTRACT

It is widely reported that the COVID-19 pandemic has reduced ridership and brought severe challenges to urban public transit systems in many countries. The impact of the COVID-19 pandemic on individual people's choice of public transit may continue for a while after the peak of the crisis. However, there is insufficient detailed knowledge of how individuals respond in the post-pandemic context and make choices on public transit travel. This paper contributes fresh evidence for this by looking at Beijing as a case. The theoretical framework of the Theory of Planned Behavior is used to model individuals' public transit travel choice-making processes along with three additional constructs representing the impact of the pandemic and the nature of urban mobility behaviors, namely perceived knowledge of COVID-19, the psychological risks of COVID-19, and travel habits. Structural equation modeling is used in model estimation. We point out that there may be potential differences between the effects and meanings of model constructs in the post-pandemic context and in normal daily context. Interestingly, despite the higher psychological risk's negative effects, higher perceived knowledge of COVID-19 has significantly positive effects on people's decision-making processes. A strong pre-pandemic personal habit of traveling by public transit has significant and positive effects on post-pandemic intention and perceived behavioral control. Group comparisons show that "captive" transit users have higher psychological risk of COVID-19 than "choice" transit users, yet their transit use decisions are less influenced by it. Based on the modeling results, more behavioral experiments are needed to further inform efficient policy-making.

1. Introduction

Public transit is essential to alleviating congestion and reducing carbon emissions in cities. As one of the most dynamic public facilities, it plays an important role in stimulating the urban economy and providing affordable mobility for inhabitants. However, the outbreak of the coronavirus pandemic has had severe negative effects on public transit systems worldwide. Demand has decreased dramatically as risk perception has risen among passengers, while social distancing regulations and service providers' loss minimization strategies have imposed serious constraints on the supply side (Gkiotsalitis and Cats, 2020). According to Google Mobility Reports data (Google, 2020), the drop in activity levels for public transit hubs during lockdown periods was 50%–85% in the world's major economies. Moreover, evidence suggests that the impact of COVID-19 on travel behavior is ongoing in the post-lockdown period (Gkiotsalitis and Cats, 2020). Passengers are reluctant to take public transit, and they are more anxious about public

hygiene issues than before the pandemic (Beck and Hensher, 2020; Labonté-LeMoyné et al., 2020).

There are some studies about public transit systems in the pandemic moment. Most of the existing literature focuses on analyzing the characteristics of (Zhang et al., 2020) and modeling the dynamics of (Li, 2020; Liu et al., 2020) changes in the public transit system from an aggregated and sometimes top-down view. For example, Zhang et al. (2020) found that Hong Kong Mass Transit Railway ridership reduced by 52.0% during the pandemic, and that people's travel behavior changes reduced the close contact rate and slowed the spread of the COVID-19 virus. Liu et al. (2020) fitted US transit demand data in the early stage of the pandemic using a logistic anti-growth process. Combining epidemiological models with the transportation system, Li (2020) built a robust simulator for the spread of COVID-19 in China that accounts for cross-infection in public transit systems. Furthermore, there is a growing literature on mass transit planning policy implications, such as a study by Bustamante et al. (2020) that estimated the maximum capacity of the

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busiest bus rapid transit station in Lima, Peru under COVID-19 security restrictions.

As many economies are now heading for recovery from this unprecedented crisis, studies on personal travel choice of public transit in the post COVID-19 pandemic era from a bottom-up perspective are becoming more urgent. Some studies have used individual or household measures to examine the influence of COVID-19 on public transit mode choice. Anke et al. (2021) investigated the changes in Germans' micro-mobility patterns via an online survey. They found that the main reason people shifted away from public transit was risk perception, while the effect of lockdown on travel mode choice was minor. In a survey by Przybyłowski et al. (2021), the most frequently mentioned reasons for reducing transit use were change of job or remote working and risk perception. Dong et al. (2021) built a model to predict public transit passengers' satisfaction levels. An influence chain can be derived from their results: those who pay more attention to COVID-19-related information are psychologically closer to the pandemic and are more anxious, feel less safe, and are less satisfied with transit service.

Although some studies have explored public transit in the post-pandemic moment, one important research gap still needs to be filled: how do individual people decide whether to travel by public transit in the post-pandemic context, and what is the pandemic's influence on their decision-making processes? Few previous studies have tapped into the individual's choice-making mechanism regarding transit use, and among those that have, the relationships between attitudes and intentions or behaviors has not been thoroughly discussed. There is thus an urgent need for systematic, theory-guided behavioral studies to uncover the internal structure of passengers' decision-making processes (Gkiotsalitis and Cats, 2020; Liu et al., 2020).

We aim to fill the research gap by using a behavioral model grounded in the Theory of Planned Behavior (TPB; Ajzen, 1991) to investigate passengers' intended and actual transit use in the post-pandemic era. TPB is one of the most commonly applied theoretical frameworks in the social and behavioral domain (Bosnjak et al., 2020). It has also been widely tested in urban transport studies (Bamberg et al., 2003a; Lo et al., 2016; Schoenau and Müller, 2017; Borhan et al., 2019). According to TPB, as Fig. 1 shows, the volitional factors attitude (ATT) and subjective norm (SN) and the nonvolitional factor perceived behavioral control (PBC) are the proximal determinants of intention, while intention and PBC act as the direct predictors of actual behavior (Ajzen, 1991). ATT indicates how positively or negatively the individual perceives the behavior in question (Zailani et al., 2016; Schoenau and Müller, 2017). SN captures the individual's perceived social pressure to perform the behavior (Bosnjak et al., 2020; Han et al., 2020). To be specific, SN could include injunctive norm and descriptive norm, referring respectively to individuals' beliefs that important others support the behavior or perform the behavior themselves (de Leeuw et al., 2015). PBC relates to

individuals' confidence in themselves to achieve a given behavior. It involves an evaluation of one's own strengths and limitations (Ajzen, 1991; Han et al., 2020). Intention stands for the individual's motivation to perform a certain behavior. It reflects how hard one is willing to try to carry out the behavior (Ajzen, 1991).

To analyze the pandemic's influence on people's decision-making process, we study the effects of two additional constructs on the original TPB framework: perceived knowledge of COVID-19 (PKC) and psychological risk of COVID-19 (PRC). PRC and PKC are introduced into the model because concerns about infection and related negative feelings are the most relevant reasons for transit riders to change their travel behavior, while awareness of pandemic-related facts serves as a reference when people make decisions. Apart from the pandemic's influence, since daily travel behavior is regularly performed, it is necessary to study the effect of people's pre-pandemic transit use habits on their post-pandemic travel choices; thus, travel habit (TH) is also absorbed into the modeling framework.

Based on the above, the objectives of the present study are (1) to untangle the decision-making mechanism of public transit passengers in the post-pandemic context using the behavioral framework of TPB, (2) to examine the effects of two pandemic-related constructs (perceived knowledge of COVID-19 and psychological risk of COVID-19) on individuals' decision-making process, and (3) to analyze the role of one construct reflecting the intrinsic nature of urban mobility (travel habit). In addition, in the post-pandemic context, the decision-making process of those who travel by transit willingly ("choice" users) and those who are less willing but must travel by transit ("captive" users) may be different. Therefore, another objective of the present study is (4) to study the difference between the decision-making mechanisms of "choice" and "captive" transit users.

This paper uses Beijing as a case. On the national level, China has entered the post-pandemic phase. New confirmed cases of COVID-19 dropped to <100 per day in early March 2020 and remained below 100 until early January 2021, when a minor wave of infection slightly raised the count. Zooming in, Beijing is a typical post-pandemic city. Many enterprises resumed production in March 2020. As of September 2020, all schools and higher education institutions returned to in-person instruction and the hospitality and entertainment industry operated at full capacity. Beijing has a large-scale public transit system consisting of bus and rail. It is usually crowded, especially during workdays. In 2019, the modal split rate for Beijing's public transit system was 31.8% (higher than the rate of 22.6% for private cars), making it an indispensable part of urban transportation. At the peak of the pandemic, Beijing's public transit system remained in operation with many preventive measures taken, but public transit ridership reduced to about 20% of the same period in 2019. Basically, public vehicles and transit stations were sterilized daily, strict flow restrictions and occupancy rate controls were

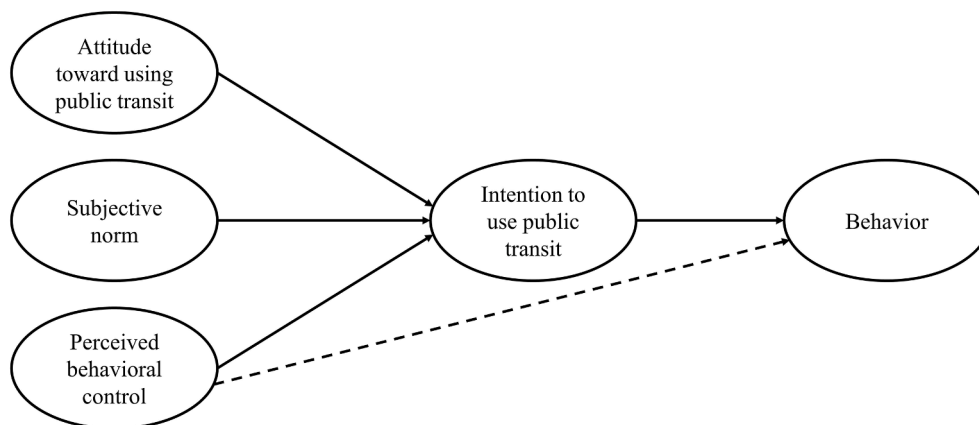


Fig. 1. The Theory of Planned Behavior. Source: Ajzen (1991)

enforced, passengers' body temperatures were taken, and they were required to wear masks. People only went out for essential trips, and many transit lines had very few passengers. As restrictions eased, ridership bounced back to around 80% in the post-lockdown period. To sum up, Beijing makes an ideal case for studying post-pandemic transit use behavior.

The remainder of this study is organized as follows: Section 2 presents a literature review and our research hypotheses. Section 3 offers a research design including a brief introduction of the case city, data collection, and measurements. Section 4 provides our modeling results and analysis. Section 5 discusses the study's key findings, practical implications, limitations, and future research prospects. Section 6 summarizes our conclusions.

2. literature review and research hypotheses

2.1. Effects of the COVID-19 pandemic on public transit travel behavior

During the pandemic, public transit modes were among the most affected modes of urban transportation. People avoided public vehicles to keep social distance, causing transit ridership to drop dramatically (Google, 2020; Zhang et al., 2020), and transport modal split to shift away from public transit. Anke et al. (2021) found that in Germany, regular passengers of public transit turned to walking, cycling, or using private cars. In China, the percentages of people using public transit, bicycles, and electric bicycles decreased during the pandemic, while the percentages traveling by walking or cars (either private cars or taxis) significantly increased (Jiang et al., 2020).

Infection risk is frequently linked with people's reluctance to travel by transit. On the one hand, compared with other modes, there was a higher level of perceived risk associated with public transit during the pandemic. In a study of ten countries on six continents, Barbieri et al. (2021) found that airplanes and buses had the highest perceived risks of infection among all transportation modes. Beck and Hensher (2020) found perceptions that trains and buses were the least comfortable options for Australians during the pandemic. On the other hand, individuals more mentally susceptible to risk may be more reluctant to take public transit. As indirect evidence, Asselmann et al. (2020) found that students with less emotional stability tend to take public transit less often. While risk has been explored in some surveys conducted during the pandemic, an opposite concept, safety perception, has also been used in other studies (e.g., Dong et al., 2021; Przybyłowski et al., 2021). Risk and safety are two sides of the same coin.

In the post-pandemic era, although government restrictions have been lifted, passengers might still tend to trade time for less crowding (Gkiotsalitis and Cats, 2020). A study in Korea compared transit users' crowding impedance levels before and after the pandemic and found that the crowding impedance in November 2020 was higher than in October 2018 (Cho and Park, 2021). Another study in Australia found that in the early days of the post-lockdown period, people were still reluctant to travel by transit (Beck and Hensher, 2020). It is possible that in the long run, the negative effect of infection risk will fade away. For example, a survey by Ehsani et al. (2021) found that people's expected post-pandemic travel by public transit did not significantly differ from their pre-pandemic travels. However, in the short run, the impact of COVID-19 on people's choice to use public transit still stands out.

2.2. Travel mode choice and the Theory of Planned behavior

Many existing literatures use traditional discrete choice models to study travel mode choice (Li and Zhao, 2015; Zhao and Wan, 2020). These studies have identified factors that influence people's mode choice behavior. However, it is also important to analyze how these factors affect the internal mechanisms of individual decision-making processes (Zhao and Zhang, 2018). In recent years, transportation researchers have begun to use behavioral variables to reveal the internal

structure of the travel choice black box and to improve model explanatory power (Temme et al., 2008). The present study extends TPB to study people's post-pandemic public transit mode choices.

TPB assumes that ATT, SN, and PBC directly influence intention, and that intention and PBC have direct effects on behavior (Ajzen, 1991; Liu et al., 2017; Han et al., 2020). Many case studies exploring transit use behavior (Heath and Gifford, 2002; Nordfjærn et al., 2014a; Zailani et al., 2016), switching intention from private vehicles to public transit (Chen and Chao, 2011; Lourdes and Dima, 2019) and the related topic of low-carbon transportation behavior (Eriksson and Forward, 2011; Liu et al., 2017) have shown the capacity of TPB in modeling individual mobility. Note here that much of the TPB-assisted literature, including many of the studies mentioned above, was interested only in explaining intentions. However, to get a broader picture of transit use in the post-pandemic context, it is necessary to bring the behavior construct into the model. Thus, the following hypothesis is adopted:

H1. The relationships between attitude, subjective norm, perceived behavioral control, intention, and behavior in the original TPB framework still stand.

This specifically suggests that (a) the more positive the attitudes are regarding using public transit; (b) the higher the subjective norm to use public transit is; (c) the stronger the perceived behavioral control is regarding using public transit, the stronger the intention is to travel by public transit in the post-pandemic era. Also, (d) the stronger the intention to travel by public transit; (e) the stronger the perceived behavioral control regarding using public transit, the more likely the behavior of traveling by public transit in the post-pandemic era is to occur.

2.3. Perceived knowledge of COVID-19

Perceived knowledge is an important factor that can enhance the reasoning-based component of our theoretical framework. Perceived knowledge represents the individual's awareness of the given behavior and its consequences. In a study on museum visitors' pro-environmental behavior, Han and Hyun (2017) found that more environmental knowledge enables people to gain further access to the emotions they might have once they perform or avoid the behavior, helping them become surer of what to do. Sufficient awareness can enhance people's judgements and self-confidence when making decisions. This suggests that perceived knowledge is vital in determining people's intentions and behavior. Therefore, perceived knowledge of COVID-19 is included in the research model. It is the participants' awareness of COVID-19-related facts, represented by their self-rated knowledge level of COVID-19, and it is consistent with definitions in previous studies that also looked at post-COVID behaviors, such as Han et al. (2020).

Under the TPB framework, perceived knowledge of COVID-19 influences ATT and PBC by encouraging objectivity and confidence in individual people. To be specific, those who are more aware of the facts about the pandemic are more likely to rule out the influence of irrational thoughts and make rational risk assessments; thus, they tend to hold more positive attitudes towards transit use. In the post-pandemic context, public transit stands out from other daily travel modes in that it is still most associated with infection risks and is subject to the strictest preventive measures; therefore, when considering how easy or difficult it is to take public transit, people tend to relate to the troubles or difficulties induced by COVID-19 control measures in addition to accessibility factors. Since people with higher PKC are more familiar with and more understanding towards suitable protection measures and more confident in dealing with additional trouble, they may find it easier to use public transit. Many empirical studies in the fields of health-related behaviors (Meadowbrooke et al., 2014), tourist behaviors (Han et al., 2020), and pro-environmental behaviors (Han and Hyun, 2017; Zhu et al., 2020) have analyzed the role of perceived knowledge. For example, perceived knowledge's effects on ATT and PBC are found in Meadowbrooke et al. (2014) and Zhu et al. (2020). Based on the above,

the present study examines PKC's influence on ATT and PBC through the following hypothesis. The direction of PKC's effects is not presupposed because it still needs exploration:

H2. In the post-pandemic era, perceived knowledge of COVID-19 affects (a) attitudes regarding using public transit; and (b) perceived behavioral control regarding using public transit.

2.4. Psychological risk of COVID-19

In the post-pandemic context, risk perception is another core factor influencing people's attitudes and perceptions regarding public transit, one that has been noted but not thoroughly discussed in the existing literature. The present study introduces a most relevant facet of perceived risk, psychological risk, into the reasoning-based part of the research model. In our study context, psychological risk of COVID-19 means feelings of mental discomfort or anxiety caused by traveling in a public vehicle (Garner, 1986; Labonté-LeMoyne et al., 2020). It reflects the negative effect of the pandemic on the individual's peace of mind. The concept is derived from Perceived Risk Theory: a commonly accepted notion is that there are six facets of risk stemming from the general idea of perceived risk, namely social, financial, physical, performance, time, and psychological risk (Garner, 1986). In public transportation, physical, psychological, and performance risks stand out among the other kinds of risks. A regression analysis by Labonté-LeMoyne et al. (2020) found that these three risks explain 34% of the variation in intended transit use among commuters in Canada. The present study mainly focuses on psychological risk because it is the most readily accessible facet of perceived risk for public transit passengers. After the peak of the pandemic, people's psychological vulnerability has become a major obstacle to restoring social and economic order, and quantifying its influence is of practical significance.

The results of existing research (Anke et al., 2021; Przybylowski et al., 2021) suggest that perceived risk is an important influencer of people's transit mode use decisions in the pandemic moment. To incorporate the psychological risk of COVID-19 into the TPB framework, we assume it can influence people's intentions and behavior through ATT. People with higher levels of psychological risk tend to exaggerate the dangers of using public transit in the post-COVID context; thus, they hold less positive attitudes towards transit use. By proposing the following hypothesis, we can test PRC's effects:

H3. In the post-pandemic era, the higher the psychological risk of COVID-19 is, the less positive attitudes are regarding using public transit.

2.5. Travel habit

As daily travel mode choices are usually performed repeatedly in stable contexts, they are considered to be habitual (Verplanken and Aarts, 1999; Gärling et al., 2001; Thøgersen, 2006; Gardner, 2009). Therefore, we add travel habit into the research model. Habit is a non-deliberate behavioral response cued by a certain stable situation (Triandis, 1977; Wood et al., 2002; Wood and Rüniger, 2016; Haggart et al., 2019), and its features include a history of repetition, automaticity, and (for some kinds of behaviors) expressing identity (Verplanken and Orbell, 2003; Wood and Rüniger, 2016). In a broader sense, it is also referred to as inertia effect or psychological inertia (Goodwin, 1977; Gärling and Axhausen, 2003; González et al., 2017; Gao et al., 2020; Thorhaug et al., 2020). Friedrichsmeier et al. (2013) categorized the concept of habit into two embranchments based on the level of generality: the association view and the script-based view. The "associationist" approach (e.g., Wood et al., 2002; Wood et al., 2005; Neal et al., 2006) understands habit as a connection between specific context and behavior formed through repetitively performing behavior in context, while the "schema or script-based" approach (e.g., Verplanken et al., 1994; Verplanken et al., 1997; Verplanken and Aarts, 1999; Fujii and Gärling, 2003) regard habit as a behavioral script linked to a behavioral

goal, and this script can be built on past enactment or socialization, and can be effective in a wider range of situations.

Generally, in a stable environment, people with stronger habits of using a specific travel mode or weaker habits of using complementary modes are more inclined to take this travel mode in the future. Previous case studies and meta-analysis studies on individual mobility using TPB confirmed this hypothesis (Thøgersen, 2006; Nordfjærn et al., 2014a; Şimşekoğlu et al., 2015; Zailani et al., 2016; Zhao et al., 2016; Hoffmann et al., 2017). However, the effect of habit is more complicated when decision context changes. According to the habit discontinuity hypothesis, a disturbance in decision context can weaken individuals' old habits and provide a window for them to consciously (re)consider their choice of action and even establish new habits (Verplanken et al., 2008; Walker et al., 2015; Verplanken and Roy, 2016). Studies have found that old travel habits are weakened after context shifts such as work relocation (Walker et al., 2015) and home relocation and public transit-promoting interventions (Bamberg et al., 2003b; Bamberg, 2006; Eriksson et al., 2008; Verplanken et al., 2008). Nevertheless, in many circumstances past habits can still last even if important contextual changes render the habitual choice less desirable (Wood et al., 2002), and new habits does not necessarily replace old ones (Wood and Rüniger, 2016). Many studies examining travel behavior after residential relocation (often combined with interventions aimed at changing travel behavior) (e.g., Fatmi and Habib, 2017; Zarabi et al., 2019), the introduction of a new travel mode option (e.g., González et al., 2017), transport reorganization (e.g., Lattarulo et al., 2019), or important life-course events (e.g., Busch-Geertsema and Lanzendorf, 2017) have found that pre-change habits still influence post-change behaviors, and Gao et al. (2020) also found that this influence is more evident in a mild context change than in an overturning change.

The outbreak of the COVID-19 pandemic created a low-travel period in early 2020, separating pre-pandemic from post-pandemic periods, and the post-pandemic world is still under the influence of COVID cases and temporary lockdowns. This sudden interruption and consistent uncertainty could be viewed as a context change, pushing people to reexamine their travel goals and to invest more thought in their travel choices. Nevertheless, this change of environment is milder than that studied in previous research, thus pre-COVID travel habits may influence people's post-COVID intention and behavior. Also, those who were used to traveling by transit before the pandemic are familiar with the public transit system and its facilities, so it is easier for them to use transit and deal with the additional troubles caused by strict preventive measures. Based on the above, the following hypothesis is used to test the effects of TH in the TPB model:

H4. In the post-pandemic era, the stronger the habit is to use public transit, (a) the more likely the behavior of traveling by public transit in the post-pandemic era is to occur; (b) the stronger the intention is to travel by public transit; and (c) the stronger the perceived behavioral control is regarding using public transit.

Figure 2 summarizes this research model. Considering the possible effects of background factors, we also introduced gender, age, educational level, employment status, monthly family income after tax, and access to a private car into the model.

3. Research design

3.1. Case city

The present study was carried out in Beijing, the capital city of China. It is one of the largest cities in China (Ning et al., 2021). Beijing has jurisdiction over 16 districts with a total administrative area of 16,410.5 km². As of the end of 2019, its permanent population (those who have lived in Beijing for more than six months) was 21.5 million (86.6% urban). It is also one of China's most developed cities. In 2019, Beijing's per capita GDP reached 164,220 RMB (equivalent to 23,805 USD), and its built-up area reached 1,469.1 km².

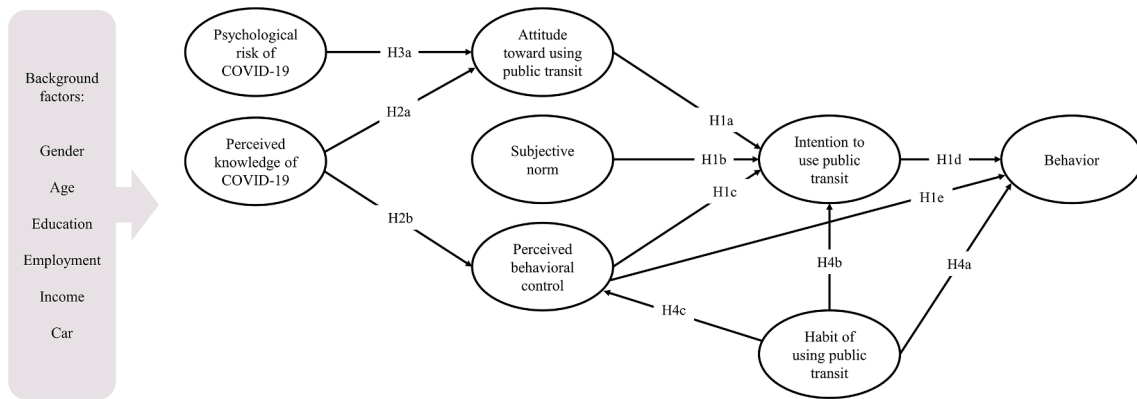


Fig. 2. Research model. Source the authors.

The public transportation system of Beijing consists of buses (including trolley buses) and rail transit (light rail and subway). According to data from 2019, the total length of operating lines, the number of operating lines, and the number of operating vehicles reached 27,632 km, 1,158, and 23,010 for bus transit and 699 km, 23, and 6,449 for rail transit, respectively; the total passenger volume reached 1311.7 million person-time and 3962.4 million person-time for bus and rail transit, respectively. The data came from the [Beijing Statistical Yearbook \(2020\)](#) and the [China Statistical Yearbook \(2020\)](#).

Beijing’s spatial structure and transportation system are shown in Fig. 3.

Like most cities around the world, Beijing’s public transit system has been hit hard by the COVID-19 outbreak. Fig. 4 shows the negative effect of the pandemic on both bus and rail transit ridership. On a national scale, the first confirmed case was reported in December 2019. In February, more cases were revealed as the result of large-scale tests. Since March, the number of new cases has decreased. Although there are still ups and downs, the incidence rate of COVID-19 has leveled off. As for Beijing, in line with national trends, the first wave of the pandemic occurred in January and February 2020. In the meantime, ridership of buses and rail transit decreased by 77.9% and 88.7%, respectively. Then, ridership increased despite a smaller wave in March due to increased imported cases from abroad. As of May, ridership rose to around half of that of the previous year, before being interrupted by a third wave in June due to a cluster of infections that emerged in Xin Fa Di Market. After that, Beijing entered a five-month low-risk period until a small number of confirmed cases was reported in late December 2020 and January 2021. Transit ridership continued to increase in August and September as social and economic orders gradually restored normalcy. Ridership then stabilized at around 20% below pre-pandemic levels until another drop in January 2021.

3.2. Data collection

The data were collected using a self-administered questionnaire. The questionnaire had two parts: (a) filter questions and basic sociodemographic questions, and (b) measures for the study constructs.

Participants were asked two filter questions: “Since the outbreak of the COVID-19 pandemic (since January 2020), have you been living in Beijing (apart from temporary departures for business trips, family visits, vacations etc.)” and “Before the outbreak of the COVID-19 pandemic, on average, how many times in a week did you travel by public transit (a single trip from the starting point to destination counts as one time, e.g., taking the bus and then transferring to subway to work is one time, returning by the same route after work is another one time).”.

For sociodemographic attributes, we collected the gender, age, educational level, employment status, monthly family income after tax,

and access to private car information.

The measurement items for study constructs were based on the existing literature and were customized to suit the local context and language habits. The meanings of important terms are repeatedly indicated in the questionnaire. In particular, “public transit” = buses (including trolleybuses) and rail transit (light rail and subway); “before the pandemic” = before January 2020; “the new post-pandemic normal” = from the time the educational and economic sectors resumed in-person activity (September 2020) to the time when COVID-19 vanishes or vaccines are widely available; “when the pandemic is over” = after COVID-19 vanishes or vaccines are widely available.

From November 27 to 30, 2020, an intensive online surveying campaign took place. A period including a weekend was chosen to increase the participation rate. This period was also ideal for reflecting people’s attitudinal and behavioral states in the new post-COVID normal because it came after a four-month low-infection period and before the rise of confirmed cases in December (Fig. 4). Public transit ridership has largely recovered, and the pace of life has returned to normal, although COVID-19-preventive measures are still in place. The questionnaire was uploaded to and released via a professional online survey platform. It was then distributed through WeChat (one of the most popular social platforms in China), and a convenience sampling method was used.

During the data collection process, all questions required an answer, and questionnaires with one or more blank answers were not returned. A total of 1,360 completed questionnaires were returned. To control for quality, we dropped 152 questionnaires that were completed in <6 min (according to a small-scale test run, it takes a minimum of approximately 6 min to read and answer the questionnaire carefully). We then manually inspect the responses for illogical answers and dropped another 106 questionnaires. After that, we excluded 341 questionnaires with answers of “no” to the first filter question or “0” to the second filter question. Therefore, 761 effective responses were obtained, yielding an effective response rate of 56.0%.

The places of residence of most participants are within the boundary of the inner suburban area (Fig. 3). This area consists of six districts, is densely populated with 52.2% of the city’s total population ([Beijing Statistical Yearbook, 2020](#)), and has the best public transit coverage in Beijing.

The socio-demographic characteristics of our sample are in Table 1. The valid sample consists of 761 individuals, with the percentage of female participants (60.7%) being somewhat greater than that of male participants (39.3%). Some 73.6% of them are middle-aged (30–49 years old), 75.9% have a bachelor’s degree or higher, and 80.4% were employed at the time of inquiry. Family income is more spread out, as people from all income levels were surveyed. In addition, 58.7% stated that they or their families owned at least one private car, while the rest did not have access to private cars. The characteristics of our sample differs to some extent from the population statistics of Beijing; the

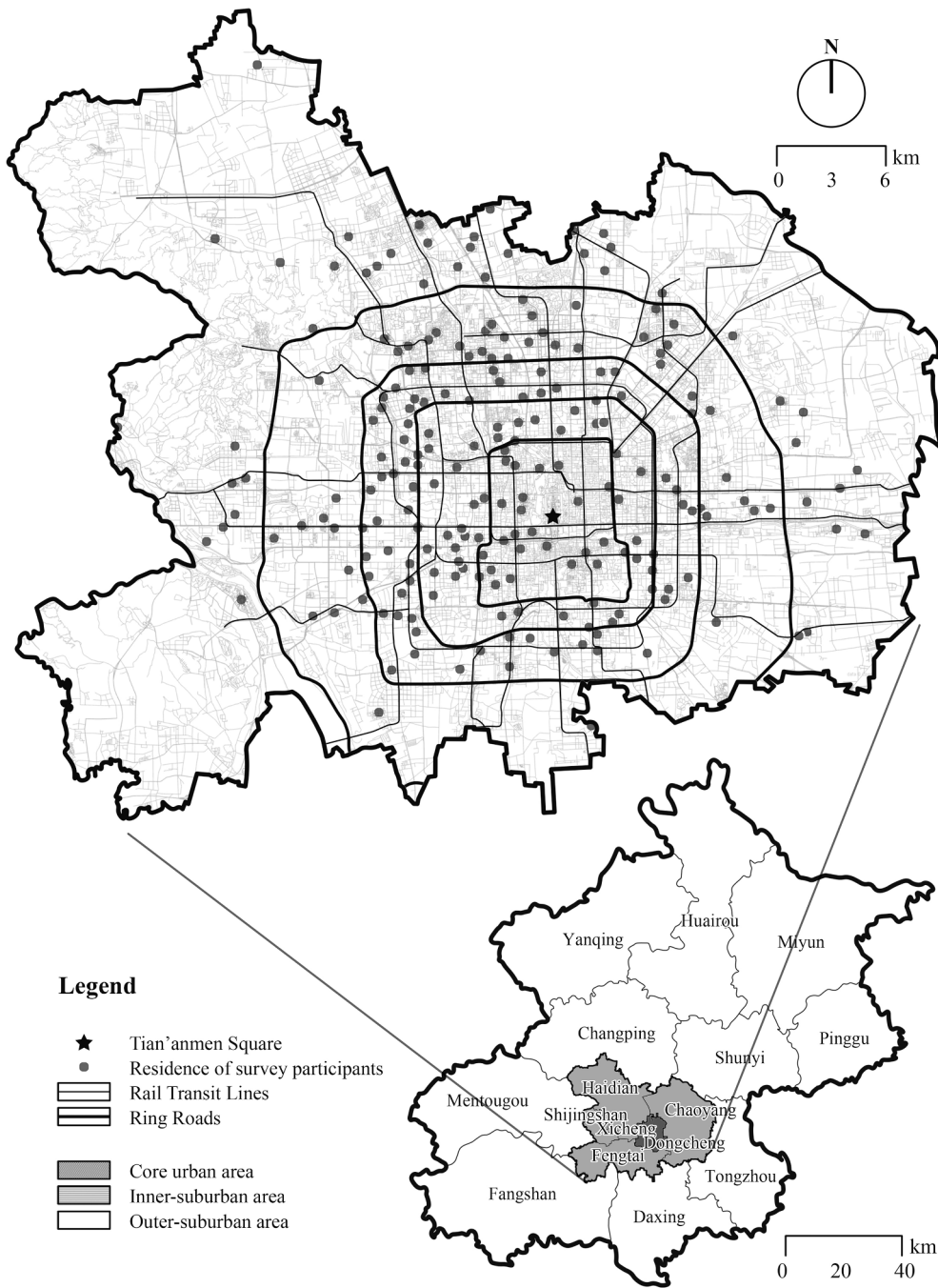


Fig. 3. Urban structure and transportation system of Beijing. Source: the authors; road network base map is from [OpenStreetMap \(2021\)](#).

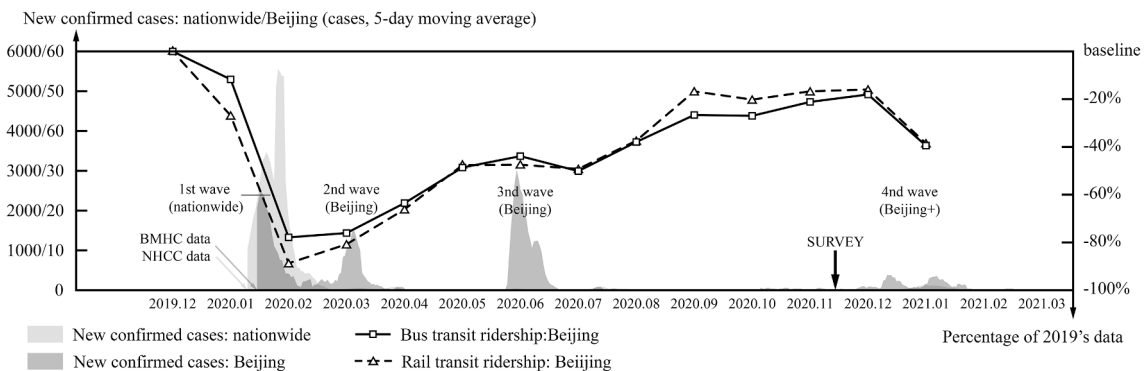


Fig. 4. The course of the COVID-19 pandemic and public transit ridership in Beijing. Data sources: National Health Commission of the People's Republic of China (NHCC, 2020–2021), Beijing Municipal Health Commission (BMHC, 2020–2021), Ministry of Transport of the People's Republic of China (2019–2021).

Table 1
Sample socio-demographic characteristics (total N = 761).

Item	N (sample)	Percentage (sample)	Percentage (Beijing)	Item	N (sample)	Percentage (sample)	Percentage (Beijing)
Gender				Employment status			
Male	299	39.3%	51.1%	Employed	612	80.4%	57.5%
Female	462	60.7%	48.9%	Student	30	3.9%	18.40%
Age				Retired	48	6.3%	24.10%
Under 18 years	4	0.5%	13.5%	Other	71	9.3%	
18–29 years	119	15.6%	16.0%	Monthly family income after tax			
30–39 years	359	47.2%	21.2%	Under 5 k RMB	60	7.9%	Average =
40–49 years	201	26.4%	14.7%	5–10 k RMB	153	20.1%	19.4kRMB
50–59 years	48	6.3%	14.8%	10–15 k RMB	152	20.0%	
60 years and above	30	3.9%	19.7%	15–20 k RMB	124	16.3%	
Educational level				20–30 k RMB	147	19.3%	
Primary school and below	6	0.8%	7.7%	30–50 k RMB	89	11.7%	
Secondary school	80	10.5%	44.7%	Above 50 k RMB	36	4.7%	
Junior college	97	12.7%	15.2%	Family (including self) own private car			
University graduate	322	42.3%	24.7%	Yes	447	58.7%	53.0%
Postgraduate	256	33.6%	7.7%	No	314	41.3%	47.0%

Note: Population statistics of Beijing is from Beijing Statistical Yearbook (2021). Some percentages do not add up to 100% because of rounding errors. Due to age group inconsistencies, the percentage (Beijing) of age group “under 18 years” is calculated as percentage of groups “0-4”+“5-9”+“10-14”+“15-19”*0.6 from statistical year book, and the percentage (Beijing) of age group “18-29 years” is calculated as percentage of groups “15-19”*0.4+“20-24”+“25-29” from statistical year book; the percentage (Beijing) of different educational levels are based on permanent population aged 15 or over; average monthly family income of Beijing is calculated with per capita disposable income and average permanent population per household; the percentage (Beijing) of “student” includes primary school secondary school and higher education students, and the percentage (Beijing) of “retired” and “other” is calculated as 100% - “employed” - “student”.

impact of this on our understanding of the modeling results are further discussed in Section 5.

3.3. Variables and measurements

A total number of 18 items capture intention, behavior, ATT, SN, PBC, PKC, PRC, and TH. Another item was used to distinguish between “choice” and “captive” transit users. The original TPB constructs were measured following Ajzen’s (2006) guidelines for questionnaire design and previous studies (Heath and Gifford, 2002; Han et al., 2020). The measurements for TH were selected from the Self-Report Habit Index (Verplanken and Orbell, 2003; Nordfjærn et al., 2014b), and the source of survey items for PKC and PRC was Han et al. (2020). All items were measured using a five-point Likert-type scale.

To measure the public transit use behavior, we asked, “In the context of the new post-pandemic normal, on average, how many times in a week do you travel by public transit?” We converted the answer to a scale of 1–5 and used it as an indicator of behavior (B1).

The intention to use public transit in the post-lockdown period was captured by two items. I1: “I plan to travel by public transit in the next 7 days” and I2: “I will try to travel by public transit in the next 7 days.” We measured both on a scale of totally disagree (1)—totally agree (5).

Attitude was derived from three items: “In the context of the new post-pandemic normal, I think traveling by public transit is” ATT1: “bad (1)—good (5),” ATT2: “foolish (1)—wise (5),” ATT3: “unpleasant (1)—pleasant (5).”

For subjective norm, both descriptive (SN1 and SN2) and injunctive (SN3) measures were used. SN1 reflects the influence of important people from the individual’s private life and is the average of two separate sub-items: “In the context of the new post-pandemic normal, my family members/friends never (1)—always (5) travel by public transit.” SN2 inspects social perceptions induced by public relationships and is also the average of two separate sub-items: “In the context of the new post-pandemic normal, my colleagues or classmates/boss or teachers never (1)—always (5) travel by public transit.” SN3: “In the context of the new post-pandemic normal, the government and media advocate traveling by public transit: totally disagree (1)—totally agree (5).”

Perceived behavioral control was measured by a single item,

following a straightforward approach by Heath and Gifford (2002). PBC1: “In the context of the new post-pandemic normal, for me traveling by public transit is easier than by other means of transportation: totally disagree (1)—totally agree (5).” Note that according to Ajzen (2006), the measure for PBC should cover meanings of capacity and autonomy, and many studies have used a two-item measure including one question about how easy it is for the individual to travel by public transit, and one question about the individual’s freedom of choice when it comes to using transit (e.g., Bamberg et al., 2003b; Nordfjærn et al., 2014a; Zailani et al., 2016). However, the latter question is somewhat confusing and ambiguous in the study context, and that such statements could lead to invalidity and unreliability in participants’ responses. Thus, the present study integrates the meaning of the second question into the first (“for me traveling by public transit is easy...”) so that PBC1 is able to tap into both capacity and autonomy aspects; this is achieved by adding a comparative component (“... easier than by other means of transportation”) which can cue respondents to think about alternative modes and the freedom of choice between these modes and public transit and can also make their thoughts more accessible.

Perceived knowledge of COVID-19 was rated by three items: PKC1: “compared with the average person,” PKC2: “compared with people who are important to me (such as family and friends),” PKC3: “compared with other people who travel by public transit,” “I know more about the facts of the COVID-19 pandemic (ways of transmission, protective methods etc.).” All items were measured on a scale of totally disagree (1)—totally agree (5).

Psychological risk of COVID-19 was assessed using two items: “In the context of the new post-pandemic normal, the thought of traveling by public transit” PRC1: “makes me nervous,” PRC2: “makes me mentally uncomfortable,” PRC3: “makes me feel stressed.” All items were measured on a scale of totally disagree (1)—totally agree (5).

To assess transit-using habit, we select two items from Verplanken’s Self-Report Habit Index (SRHI) (Verplanken and Orbell, 2003; Nordfjærn et al., 2014b). TH1: “Before the pandemic, I never (1)—always (5) traveled by public transit.” TH2: “Before the pandemic, I often chose to travel by public transport without much thought: totally disagree (1)—totally agree (5).” Unlike the “habit strength” measure proposed by Wood et al. (2005) that belongs to the association view of habit and the Response Frequency Measure (RFM) proposed by Verplanken et al.

(1994) that belongs to the script-based view, the SRHI cannot be classified into either association or script-based view. The SRHI is built on the idea that habit is not only past behavior, but also a psychological construct with three facets, namely repetition, automaticity, and identity (Verplanken and Orbell, 2003). The present study uses TH1 to access the repetition facet and TH2 to access the automaticity facet; we did not include the identity facet because the identity facet is not always relevant (Verplanken and Orbell, 2003), and in the context of the present study, habit concerning public transit travel choice is hardly connected with personal identity, thus a combination of TH1 and TH2 would be theoretically sufficient to capture people's public transit use habit strength.

Another item was used to assess the motivation (MO) for transit users. "Choice" users are those who take public transit willingly, and "captive" users are those who must use transit for practical reasons. Since these reasons are usually complicated, for example involving the inability to afford private vehicles, constraints caused by family members' travel plans and health conditions, etc., we asked a direct question to capture the motives. MO1: "In the context of the new post-pandemic normal, I am not willing to travel by public transit, but for various reasons (such as no private car and long travel distance), I have to travel by public transit: totally disagree (1)—totally agree (5)."

The background factors were derived from sociodemographic characteristics. Gender was recoded 1 for male and 0 for female. Age was recoded 15 for under 18 years, 25 for 18–29 years, 35 for 30–39 years, 45 for 40–49 years, 55 for 50–59 years, and 65 for 60 years and above. Education is the years of education corresponding to educational level: 6 years for primary school, 9 or 12 years for secondary school (9 years for middle school, 12 years for high school and secondary specialized school), 15 years for junior college, 16 years for university graduate, and 19 years for postgraduate. Employment was recoded 1 for employed (including full-time employed and studying on the job) and 0 for student, retired, and other (including full-time housewife/househusband, unemployed, and other). Income was recoded from monthly family income after tax, with 2.5 for under 5 k RMB, 7.5 for 5–10 k RMB, 12.5 for 10–15 k RMB, 17.5 for 15–20 k RMB, 25 for 20–30 k RMB, 40 for 30–50 k RMB, and 60 for above 50 k RMB. Car was recoded from access to private car, with 1 for yes and 0 for no.

4. Analysis

Based on the above study design, we first conducted descriptive statistics analysis on the collected data. Then, we followed the commonly used two-step approach (Anderson and Gerbing, 1988) to analyze the data: Step 1 was to test the reliability and validity of the data using confirmative factor analysis (CFA), and Step 2 was to test the research hypotheses and to conduct group comparisons using structural equation modeling (SEM). Covariance-based SEM was used. The software package Mplus 7.4 and its maximum likelihood estimation with robust standard errors (MLR) estimator were used to determine the models. MLR is a frequently used estimator and is robust to non-normal distribution of data.

The results of CFA should satisfy the following suggested requirements before SEM can be conducted. To satisfy scale reliability requirements, Cronbach's α should be greater than or equal to 0.7 (Nunnally, 1978). All standardized factor loadings (SFL) should be 0.5 or greater and statistically significant, the composite reliability (CR) of all model constructs should be greater than 0.7, and the average variance extracted (AVE) should exceed 0.5 to secure satisfactory convergent validity as suggested by Hair et al. (2006) and Kuo and Tang (2013). The squared correlation among the constructs should be less than the corresponding AVEs to ensure acceptable discriminant validity (Fornell and Larcker, 1981).

The results of CFA and SEM should satisfy the following suggested rules to indicate good model fit. We used chi-square degrees of freedom ratio (χ^2/df), root mean square error of approximation (RMSEA),

comparative fit index (CFI) and Tacker-Lewis Index (TLI) to assess model fit. The recommended cut-off points for χ^2/df and RMSEA are 0.5 and 0.06 respectively (Hu and Bentler, 1998; 1999). McDonald and Ho (2002) suggested that 0.08 should be taken as an acceptable threshold value for RMSEA, and a value <0.05 indicated a good fit. Moreover, models with CFI and TLI values greater than 0.9 are generally considered acceptable (Wang, 2014).

4.1. Descriptive findings

Descriptive statistics for the research constructs and background factors are presented in Table 2. On average, the participants travel by public transit 5.33 times per week (SD = 4.35). In Table 2, this is presented by M = 1.53 and SD = 0.44 because we rescaled the behavior construct to 1–5. The mean values of intention, ATT, SN, PBC, habit, and PKC are all greater than 3, the midpoint of their theoretical range, indicating that participants have positive perceptions of using public transit in the post-pandemic period. The average score for PRC is below 3, suggesting that participants have a low level of perceived risk of COVID-19; however, this does not mean that people's post-pandemic PRC is lower than the pre-pandemic level—according to our observation, residents in Beijing are generally more nervous using public transit after than before the pandemic.

Interestingly, the correlation between PKC and PRC is negative and the correlations between PKC and all other psychological constructs except MO are positive, meaning that people with more perceived knowledge are less concerned with the risk of infection and more willing to take public transit. This is quite unusual, because often, the more aware of the facts people are about a risky behavior, the more cautious they feel about performing it. One explanation is that since the infection rate is low in post-pandemic Beijing, those who have higher levels of perceived knowledge are less blindly afraid and more confident to reclaim daily mobility and its social and economic benefits by using public transit, especially when the local economy is starting to pick up and life is returning to normal. Further explanation follows in Section 5.

Looking at the differences between "choice" and "captive" transit users, MO is negatively correlated with behavior, intention, ATT, SN, and PKC, indicating that less willing users tend to have less perceived knowledge and more negative perceptions of using public transit in the post-pandemic period. MO is also negatively and weakly correlated with PBC, and it has little correlation with TH. It is worth noting that MO and PRC have a relatively large and significant correlation, meaning that less willing users have much higher psychological risk scores than more willing users.

4.2. Confirmative factor analysis

Confirmative factor analysis was conducted (Table 3). The model-fit indices for the measurement model ($\chi^2/df = 2.073$, RMSEA = 0.038, CFI = 0.980, TLI = 0.971) meet all the requirements, indicating a good fit. Reliability and validity indices are shown in Table 3. Cronbach's α estimates, all above the threshold of 0.7, ranged from 0.747 to 0.898, which confirms reliability. Convergent validity was also achieved: SFLs all exceed 0.5, and the estimates for CR and AVE exceed their respective cut-off points of 0.7 and 0.5. The square roots of AVE of each model construct are greater than its correlation with other constructs (Table 2), meaning that the requirement for discriminant validity is satisfied. Thus, the structure of the measurement model is validated, which enabled us to build a reliable structural model on top of it.

4.3. Structural equation modeling and hypotheses testing

Before building our proposed model, we conducted structural equation modeling to test the efficacy of the original TPB framework. As expected, TPB is capable of modeling participants' transit use intention and behavior in the post-lockdown phase ($\chi^2/df = 2.898$, RMSEA =

Table 2
Descriptive statistics.

Variable	Mean	SD	Behavior	Intention	ATT	SN	PBC	PKC	PRC	TH	MO	Gender	Age	Education	Employment	Income	Car
Behavior	1.53	0.44	-														
Intention	3.90	1.07	0.493***	0.901													
ATT	3.78	0.84	0.245***	0.705***	0.839												
SN	3.76	0.87	0.299***	0.729***	0.810***	0.836											
PBC	3.89	1.06	0.390***	0.696***	0.642***	0.645**	0.864										
PKC	3.96	0.76	0.132**	0.451***	0.570***	0.565***	0.425***	0.837									
PRC	2.32	1.08	-0.169***	-0.383***	-0.585***	-0.396***	-0.253***	0.837	0.837								
TH	4.13	0.91	0.382***	0.712***	0.454***	0.551***	0.676***	0.348***	0.786	0.786							
MO	3.11	1.34	-0.103**	-0.155***	-0.359***	-0.256***	-0.080*	-0.114**	0.535***	0.020	-						
Gender	-	-	0.092*	-0.001	-0.019	-0.039	-0.042	-0.006	-0.056	-0.016	-0.099**	-					
Age	38.42	9.66	-0.127***	0.035	0.094**	0.042	0.051	0.038	0.004	0.063	0.067	0.047	-				
Education	16.33	2.48	0.011	0.000	-0.011	0.034	0.018	0.033	0.018	-0.024	0.016	-0.013	-0.033	-			
Employment	-	-	0.197***	0.007	-0.082*	-0.034	-0.076*	-0.030	-0.001	-0.063	-0.021	0.187***	-0.237***	0.052	-		
Income	19.40	13.96	0.005	-0.135***	-0.103**	-0.155***	-0.132***	-0.041	-0.045	-0.146***	-0.108**	0.078*	-0.015	0.021	0.257***	-	
Car	-	-	-0.180***	-0.143***	-0.089*	-0.075*	-0.242***	-0.049	0.007	-0.222***	-0.088*	0.002	0.031	-0.014	0.057	0.237***	-

Note: the ranges of behavior, intention, ATT, SN, PBC, PKC, PRC, TH and MO are 1–5, the range of age is 15–65 years old, the range of education is 6–19 years of education, the range of income is 2.5–60 k RMB; for the correlation coefficient matrix, * p < 0.05, ** p < 0.01, *** p < 0.001; the numbers on the diagonal of the correlation coefficient matrix are the square roots of AVE.

Table 3
CFA, reliability, and convergent validity.

Construct	Item	Cronbach's α	SFL	CR	AVE
Behavior Intention	B1	0.896	1.000	0.896	0.812
	I1		0.894		
	I2		0.908		
ATT	ATT1	0.877	0.790	0.877	0.704
	ATT2		0.849		
	ATT3		0.875		
SN	SN1	0.865	0.901	0.873	0.698
	SN2		0.876		
	SN3		0.718		
PBC	PBC1	0.898	1.000	0.899	0.747
	PKC1		0.839		
	PKC2		0.891		
PRC	PKC3	0.874	0.862	0.875	0.701
	PR1		0.784		
	PR2		0.897		
TH	PR3	0.747	0.826	0.761	0.618
	TH1		0.875		
	TH2		0.686		
MO	MO1	-	1.000	-	-

0.050, CFI = 0.980, TLI = 0.969). The explained variance in intention (62.6%) is greater than that in behavior (23.6%). This means the intention-behavior gap commonly found in previous studies (Ajzen, 2015; Nordfjærn et al., 2014a; de Leeuw et al., 2015) is also present in the current study. One reason for this is that the thoughts that occur to people when making decisions in a real situation may differ from those when responding to a survey (Ajzen, 2015). After adding TH, the model still has good fit ($\chi^2/df = 3.044$, RMSEA = 0.052, CFI = 0.974, TLI = 0.960) and the explained variance in intention increases from 62.6% to 70.4%. This model predicts PBC and behavior by 45.0%, and 23.8%, respectively. After adding PKC and PRC, the model fit indices improved ($\chi^2/df = 2.285$, RMSEA = 0.041, CFI = 0.976, TLI = 0.967), and the model predicts ATT, PBC, intention, and behavior by 54.6%, 49.4%, 70.6% and 23.8%. By adding background factors, our research model is completed. Indices reflect a good fit ($\chi^2/df = 2.233$, RMSEA = 0.040, CFI = 0.964, TLI = 0.955), and the model's predictive power increases for intention (71.6% explained) and behavior (31.3% explained).

The modeling results are summarized in Table 4 and Fig. 5. All hypotheses are supported except for H4a. Of the TPB variables, ATT, SN, and PBC all show significant and positive effect on intention (H1a, H1b, H1c), and intention has significant and positive influence on behavior (H1d). PBC also has a significant and positive influence on behavior (H1e), although the value of the path coefficient is small, meaning that this relationship is comparatively weak. The model also supports PKC's significant and positive influence on ATT and PBC (H2a, H2b), while PRC shows significant and negative influence on ATT (H3a). TH has significant and positive effects on intention and PBC (H4b, H4c).

Background factors also have some effects on the model and help to increase explanatory power. Older people and people who have access to a private car travel less by public transit in the post-pandemic era. The employed use public transit more than others; it is possible that employed people are generally younger and have more travel needs, so they need to resort to transit from time to time.

The direct, indirect, and total effects of the key variables on public transit use behavior and intention are summarized in Table 5. Original TPB constructs all have positive and significant total effects on intention and behavior. HT is obviously an important predictor of intention and behavior, and the total effects of PKC and PRC on intention and behavior are also significant though in opposite directions.

The above analysis revealed the decision-making mechanism for the whole sample. Now we employ group comparison analysis to study the difference in this decision-making process between “choice” and “captive” transit users. We split the whole sample into two groups using the measurement item for MO: those with MO1 ≤ 3 were identified as “choice” or willing transit users (N = 449), and those with MO1 > 3 were

Table 4
SEM and hypotheses testing.

Hypothesis	B	S.E.	P-value	Inference	
H1	H1a: ATT → Intention (+)	0.311	0.060	***	Supported
	H1b: SN → Intention (+)	0.176	0.068	**	Supported
	H1c: PBC → Intention (+)	0.123	0.061	*	Supported
	H1d: Intention → Behavior (+)	0.361	0.054	***	Supported
	H1e: PBC → Behavior (+)	0.092	0.041	*	Supported
H2	H2a: PKC → ATT	0.459	0.039	***	Supported
	H2b: PKC → PBC	0.224	0.038	***	Supported
H3	H3a: PRC → ATT (-)	-0.485	0.039	***	Supported
H4	H4a: TH → Behavior (+)	0.073	0.050	0.141	Not supported
	H4b: TH → Intention (+)	0.391	0.063	***	Supported
	H4c: TH → PBC (+)	0.593	0.044	***	Supported
Controlling for confounding variables					
Gender → Behavior	0.068	0.032	*	-	
Age → Behavior	-0.111	0.030	***	-	
Education → Behavior	-0.002	0.027	0.928	-	
Employment → Behavior	0.159	0.029	***	-	
Income → Behavior	0.057	0.029	0.052	-	
Car → Behavior	-0.107	0.033	**	-	
Gender → Intention	-0.017	0.025	0.492	-	
Age → Intention	0.002	0.022	0.933	-	
Education → Intention	0.000	0.023	0.998	-	
Employment → Intention	0.084	0.025	**	-	
Income → Intention	-0.041	0.026	0.112	-	
Car → Intention	0.025	0.024	0.291	-	

Note: *p < 0.05, **p < 0.01, ***p < 0.001; the path coefficient for H1e was relatively small.

identified as “captive” or not-so-willing transit users (N = 312). We then conducted a series of invariance tests. The results are shown in Table 6.

The baseline model (1) was estimated without constraints, allowing

all model parameters to be different across groups. It has good fit, indicating that configural invariance holds. The equal loadings model (2) was estimated with equality constraints for the factor loadings of the two groups. The chi-square difference test result is not significant (p > 0.05), meaning that adding equal loading constraints does not significantly reduce model fit; therefore, measurement invariance holds.

After confirming measurement invariance, we can test structural invariance by adding equality constraints to all or some of the path coefficients and conducting chi-square difference tests. Model (3) was estimated with all path coefficients constrained to be equal. The test result is significant (p < 0.05), meaning that the path estimates for “choice” and “captive” users are not exactly the same. Furthermore, we tested the cross-group invariance of single path coefficients. Model (4) was estimated with only one path coefficient (PRC → ATT) constrained to be equal. The test result is significant, and the estimated coefficient for “choice” users is larger in absolute value than that for “captive” users, which suggests that the effect of psychological risk on attitude is greater for “choice” users than for “captive” users. Besides, from PRC → ATT, we also tested all other paths in the research model and found nonsignificant results.

5. Discussion

As introduced, this paper investigates the determinants of personal travel mode choice of public transit in the context of the post-COVID era. In particular, the impacts of three key factors, transit travel habit, perceived knowledge of COVID-19 and psychological risk are examined by an updated TPB framework. The following important points are discussed according to the analysis results above.

First, although the effects of the original TPB constructs do not show any abnormalities, some context-related issues should still be discussed.

The original TPB constructs attitude, subjective norm, and perceived behavioral control all have significant effects on public transit travel intention and behavior in the post-pandemic era, which proves (again) the effectiveness of the TPB; nevertheless, there may be potential differences between people’s decision-making mechanisms in the post-pandemic context and in normal daily context. In the unstable post-pandemic environment, the role of reason-based factors may be different. For example, due to uncertainty, people might rely more on others’ opinions or actions when making decisions; this phenomenon can be more prominent in China and some other countries where society promotes a collective culture that values social impressions and social outcomes. Also, the meanings of reason-based factors might have

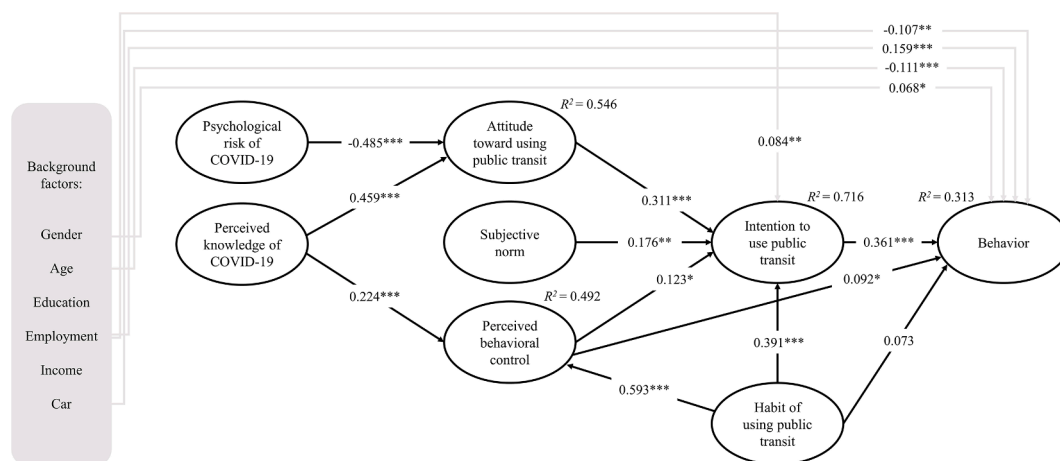


Fig. 5. Modeling results. Source: the authors. Notes: * p < 0.05, ** p < 0.01, *** p < 0.001; to avoid overloading the diagram, correlations between the research constructs are not shown: they are 0.533*** between ATT and SN, 0.419*** between ATT and PBC, 0.273*** between SN and PBC, 0.308*** between TH and ATT, 0.546*** between TH and SN, 0.564*** between PKC and SN, 0.338*** between PKC and TH, -0.226*** between PKC and PRC, -0.398*** between PRC and SN, -0.171*** between PRC and TH, -0.144** between PRC and PBC. Effects from background factors to intention or behavior that are not significant are not shown.

Table 5
Direct, indirect, and total effects.

	Behavior			Intention		
	Direct	Indirect	Total	Direct	Indirect	Total
ATT		0.112***	0.112***	0.311***		0.311***
SN		0.064*	0.064*	0.176**		0.176**
PBC	0.092*	0.044 (<i>p</i> = 0.058)	0.136**	0.123*		0.123*
PKC		0.082***	0.082***		0.170***	0.170***
PRC		-0.054***	-0.054***		-0.151***	-0.151***
TH	0.073 (<i>p</i> = 0.141)	0.222***	0.295***	0.391***	0.073*	0.464***
Intention	0.361***		0.361***			

Note: **p* < 0.05, ** *p* < 0.01, *** *p* < 0.001.

Table 6
The two numbers in the “Choice” users column and the “Captive” users column (-0.558 and -0.359) should be -0.558*** and -0.359***. (The “***”s indicate significance.)

Model	χ^2	df	RMSEA	CFI	TLI	Nested	χ^2 difference test	“Choice” users	“Captive” users	Inference
(1) Baseline	726.803	422	0.044	0.958	0.948					Configural invariance holds.
(2) Equal loadings	729.255	432	0.043	0.959	0.950	(2)-(1)	<i>p</i> > 0.05			Measurement invariance holds.
(3) Equal loadings and equal structural	775.327	455	0.043	0.956	0.949	(3)-(2)	<i>p</i> < 0.05			Structural invariance does not hold.
(4) Equal loadings and partial equal structural	PRC → ATT 752.121	433	0.044	0.956	0.947	(4)-(2)	<i>p</i> < 0.05	-0.558	-0.359	Partial structural invariance does not hold for the influence of PRC on ATT

Note: The present study used the MLR estimator, and the MLR chi-square difference test is slightly different from the regular way: the *p*-values are calculated using the method described on the Mplus website and excel ($p\text{-value} = \text{chidist}\left(\frac{(T_0c_0 - T_1c_1)(d_0 - d_1)}{d_0c_0 - d_1c_1}\right)$ where “T” denotes χ^2 value, “d” denotes degrees of freedom, “c” denotes scaling correction factor, “0” denotes the nested model, and “1” denotes the comparison model, source: <http://www.statmodel.com/chidiff.shtml>). Columns “‘Choice’ users” and “‘Captive’ users” contain the estimated path coefficients and significance levels for each of the two groups, derived from (2) equal loadings model, **p* < 0.05, ** *p* < 0.01, *** *p* < 0.001.

changed in the post-pandemic era. For instance, when making travel mode choices in the post-COVID context, safety has become a dominant component of personal attitude, and most residents in Beijing prioritize safety over other aspects they usually consider (accessibility, cost, speed, and the level of physical comfort). Perceived behavioral concern may also be laced with pandemic-related components such as the capacity to deal with troubles due to COVID prevention measures.

Second, a higher level of perceived knowledge of COVID-19 is a positive influence on people’s public transit use intention in the post-pandemic context, while the higher psychological risk of COVID-19 is a negative influence.

Higher perceived knowledge of COVID-19 has significant and positive effects on transit use intention, mediated by attitude and perceived behavioral control. Many studies available to us (Meadowbrooke et al., 2014; Han and Hyun, 2017; Han et al., 2020; Zhu et al., 2020) convey the idea that higher levels of perceived knowledge mean higher levels of risk aversion. For example, Han et al. (2020) found that more perceived knowledge of COVID-19 positively influenced international travelers’ intention to travel to a safer destination through its positive effects on attitude and subjective norm. However, the results of the present study suggest that higher levels of perceived knowledge mean stronger will to travel by public transit, i.e., higher levels of risk appetite. This contradiction can be explained when viewed from a rational decision perspective (instead of a risk avoidance one) combined with the research context. A risk behavior contains a choice between two options: taking or not taking the risk. People with more perceived knowledge have a clearer picture of which side poses less expected loss and thus are more likely to make the rational decision. In most previous studies, participants with more perceived knowledge chose not to take the risk because this choice had less expected loss. For example, the survey by Han et al. (2020) was conducted in mid-April, when the pandemic was still spreading rapidly around the world; under this circumstance, the

possible reduction in travel experience by changing to a safer destination appeared to cause much less harm than the possibility of catching a novel virus in a foreign country. However, our survey was conducted in a relatively low-risk post-pandemic environment in Beijing. Participants with more perceived knowledge are more aware of the effectiveness of prevention measures and how unlikely it is to get infected on a public vehicle. Therefore, they choose a small possibility of catching COVID-19 using public transit over reduced mobility and subsequent damage to their economic and social welfare caused by avoiding public transit. This is also a rational decision. In this sense, our results are in fact very consistent with previous research. The present study proves that the role of higher perceived knowledge level is to help people to react more rationally and constructively to risk rather than to promote risk aversion.

Higher psychological risk of COVID-19 has a significant and negative effect on transit use intention, mediated by attitude. There is little literature about psychological risk’s influence on TPB constructs. Many past attempts have mainly focused on the general idea of perceived risk (Featherman and Pavlou, 2003; Pearson and Hamilton, 2014; Zhu et al., 2020). Our results are consistent with the only available and relevant study by Seol et al. (2015), in that more psychological risk has an indirect and negative effect on intention.

Both perceived knowledge and psychological risk of COVID-19 reflect individuals’ perceptions of the risk of using public transit in the post-pandemic period, yet they affect transit use intention in opposite directions. Perceived knowledge represents a rational part of the individual, and psychological risk stands for an irrational part. A higher level of perceived knowledge means enough awareness or vigilance to respond to risk in an objective and constructive manner; in contrast, a higher level of psychological risk means excessive anxiety that can only damage people’s peace of mind and prevent them from confronting the problem. It is recommended that future research continue to explore

perceived knowledge and psychological risk's role in influencing people's decision-making processes.

Third, the habit of travelling by public transit has a long-term impact on people's public transit mode choice-making mechanism even when an outbreak event, such as COVID-19, intervenes in their intention and thus behavior.

Pre-pandemic public transit use habit has significant effects on people's post-pandemic transit use intention and behavior. The present study involves three different contexts: pre-COVID-19, during COVID-19, and post-COVID-19; since daily mobility was largely suppressed during the pandemic, participants' pre-pandemic travel habits were measured and used to predict their post-pandemic travel intentions. Our results are in line with many previous studies that have also found significant effects of old habits on travel behavior after context change (e.g., Busch-Geertsema and Lanzendorf, 2017; Fatmi and Habib, 2017; González et al., 2017; Lattarulo et al., 2019; Zarabi et al., 2019). Nevertheless, this does not mean it is unnecessary to study people's post-pandemic travel habits. The habit discontinuity hypothesis states that a disruption in decision context may lead to discontinuity in habit and eventually habit change (Verplanken et al., 2008; Walker et al., 2015; Verplanken and Roy, 2016). In this process, old habits do not disappear suddenly but gradually fade away over time, and new habits also take time to build (Walker et al., 2015). Moreover, new habits do not always replace old habits (Wood and Rünger, 2016). Therefore, from the finding of pre-pandemic habit's influence on post-pandemic intention and behavior alone, it is hard to distinguish if old habits have survived the context change and will continue to be strong, or old habits have been gradually replaced by new ones but are still strong enough to make an impact, or old habits are coexisting with new ones. After the pandemic, some transit riders might turn to private cars to avoid crowding, and some others might favor cycling. It is important for future studies to provide more information on travel habit change before and after the pandemic, and to study ways to promote desirable new habits while suppressing unwanted ones.

Fourth, "captive" transit users' level of psychological risk is higher than that of "choice" transit users, yet their decision-making mechanism is less reactive to psychological risk than that of "choice" transit users.

The descriptive statistics show that those who are less willing to take public transit by choice in the post-pandemic era also tend to experience higher psychological risk of COVID-19 (the correlation between motivation and psychological risk of COVID-19 is 0.535, $p < 0.001$). Naturally, this is consistent with our distinguishing criteria between "choice" and "captive" users. The results from the group comparison analysis indicate that motivation has moderating effects on the influence of psychological risk of COVID-19 on attitude, and that the influence of psychological risk is smaller for "captive" transit users than for "choice" users. Additional Wald chi-square tests also showed that psychological risk of COVID-19's total effects on intention and behavior for "choice" users is significantly larger than for "captive" users (total effect PRC \rightarrow Intention: for "choice" users = -0.223 , $p < 0.05$; for "captive" users = -0.089 , $p < 0.05$, Wald test $p < 0.05$. Total effect PRC \rightarrow Behavior: for "choice" users = -0.073 , $p < 0.05$; for "captive" users = -0.033 , $p < 0.05$, Wald test $p < 0.05$). This means that despite the way concerns about infection risks could negatively influence their state of mind, "captive" transit users are to some extent still bound to make the same choices, making them underprivileged in the post-pandemic era.

The contributions of the present study are threefold: (1) It provides the needed behavioral knowledge of individual public transit travel choice-making after the COVID-19 pandemic. The negative influence of COVID-19 on public transit systems is unprecedented, and the impression that public transit is no longer only a way of transportation, but also a route of transmission for potential health risks induced by people's pandemic experiences is likely to affect their transit travel choices throughout and beyond the post-pandemic era. In light of this, the present study provides an insight into people's decision-making mechanisms after the pandemic using the TPB framework, and it studies

factors that can influence this mechanism, i.e., perceived knowledge of COVID-19 and psychological risk of COVID-19. To the best of our knowledge, the present study is one of the first TPB-guided studies on transit use behavior in the post-pandemic world. (2) It tests habit's effect in a post-pandemic environment, and found that pre-pandemic habits can influence post-pandemic intention and behavior. Many past studies have examined the influence of old habits on behavior after decision context change. However, the types of context change studied mostly belong to categories of home relocation (often combined with travel behavior intervention) (e.g., Bamberg et al., 2003b; Bamberg, 2006; Verplanken et al., 2008; Fatmi and Habib, 2017; Zarabi et al., 2019), job relocation (e.g., Walker et al., 2015; Gao et al., 2020), travel behavior intervention (e.g., Bamberg et al., 2003a; Eriksson et al., 2008), new travel mode option (e.g., González et al., 2017; Gao et al., 2020), transport reorganization (e.g., Lattarulo et al., 2019), or important life-course events (e.g., Lanzendorf, 2010; Busch-Geertsema and Lanzendorf, 2017), while context change due to a global pandemic is rarely discussed. Transport reorganization such as banning car use or road-blocks have similarities with the pandemic situation, as they both cause temporary shutdowns in certain travel modes; yet apart from lockdowns and negative effects on public transit ridership, the COVID-19 pandemic has also brought public health concerns and increased risk perception, therefore it is different from traffic control. The present study provides information of habit's effect in a distinctive kind of context change seldom studied by previous research. (3) It has potential implications that might be valuable for public transit promoting "nudge" interventions. For example, increasing perceived knowledge of COVID-19 and lowering psychological risks might be a promising direction; some measures may include informing the public about how small the possibility of infection on a post-pandemic public vehicle is, and adhering to effective protective measures such as mask-wearing in public spaces and regular disinfection of public vehicles. Another possible direction is to discourage unfavorable old habits and foster positive new ones during this period of contextual change. Also, the inequality between choice and captive transit users should not be neglected; ways to ease captive users' psychological stress might include offering special services such as subway by appointment and customized bus routes. However, we should be fully aware of the gap between psychological/behavioral studies and the efficacy of behavioral interventions derived from them. Respondents do not always genuinely show their thoughts and intentions thus self-report surveys could be misleading, and the influence of nudges could vary across different categories of behaviors, not to mention in some situations more heavy-handed measures are needed to shake stubborn habits (Kristal and Whillans, 2020). This calls for more comprehensive and solid behavioral experiments to pinpoint effective policies.

There are limitations to the present study. First, there are some methodological limitations. We used a single item to measure perceived behavioral control and only two items to access travel habit. Although theoretically the items we used should be adequate to measure these constructs and also be suitable for the study context, it is still recommended that future studies use more items to improve robustness of the measures. Moreover, we also applied an alternative measure for habit based on the Response Frequency Measure (RFM) by Verplanken et al. (1994) to test the research model. The participants were asked to select their most frequently used travel mode before the pandemic from a list of all possible modes (bus, rail transit, private car, taxi, motorcycle, electric bicycle, bicycle owned by self, shared-bike, or other) for five different travel purposes: RFM1: going to work/school, RFM2: going shopping at supermarkets or markets, RFM3: going to shopping malls or other places of entertainment, RFM4: going to exercise or places of leisure/relaxation, and RFM5: going to the hospital or clinic); public transit travel habit strength was calculated as the number of times public transit (bus or rail transit) is chosen, and was rescaled to 1–5. Using this measure for habit, we re-estimated the research model and found that important findings discussed above remained consistent. Some

differences exist, such as the RFM habit strength has smaller effects on perceived behavioral control and intention and larger and more significant effect on behavior; this might be because the two measures of habit were carried out in different psychological context of the respondents – the RFM questions (RFM1 – RFM5) were asked with objective questions like sociodemographic attributes, while the main habit questions (TH1 – TH2) were asked with other psychological items. Another difference is that along with motivation's moderating effect on psychological risk of COVID-19's influence on attitude, there is also a moderating effect of motivation on perceived knowledge of COVID-19's influence on perceived behavioral control, and captive transit users' perceived behavioral control is less influenced by their perceived knowledge of COVID-19; this further confirms that travel mode choices of captive users are less flexible and that they are rendered underprivileged in this sense. Second, we used the convenience sampling method and the sample collected may contain potential bias. Consequently, the generalization of the findings will be limited by our specific sample, and the modeling results should be interpreted with caution. Table 1 presents a comparison of sample characteristics and population statistics of Beijing. Generally, our sample reflects a highly educated young-to-middle-aged employees with average monthly family income and private car ownership that are slightly higher than the whole population. The sample also consists of a larger proportion of women than the whole population. However, since group comparison analysis for the research model (without gender) between male and female groups indicates measurement invariance and structural invariance, meaning that the model estimation is not significantly different for men and women, the imbalanced female/male ratio should have little impact on our interpretation of modeling results (note that in Table 4 and Fig. 5, gender makes a contribution to explaining behavior, but its effect is very small; thus, this is still in line with the group comparison analysis results). The 30 s and 40 s age groups, which are the backbone of labor market, consist of 73.6% of the sample but only 35.9% of the whole population; this could explain the dominance of employed participants (they consist of 80.4% in sample but 57.5% in the whole population). These employees could be regular commuters with stronger and more persistent public transit use habits than others, thus based on this sample the model could have over-estimated the effects of habit. However, existing research suggests that older people and people with less cognitive-control are less competent in seizing the opportunity of context disruption to change habits (de Wit et al., 2014; Otto et al., 2015; Wood and Rünger, 2016), while young-to-middle-aged people can be more adaptive and fast-learning and may change their old habits faster after context change (Qin et al., 2019); therefore, it is also possible that the lack of juveniles and old people in the sample would cause underestimates of habits' effects. Our sample also has a high percentage of university graduates and postgraduates (75.9% in sample but only 32.4% in the whole population). Highly educated people tend to be more rational and assertive than average population, thus they might have smaller psychological risk and more perceived knowledge, and they might be less affected by these COVID-related factors. Therefore, we could have under-estimated the effects of psychological risk of COVID-19 and perceived knowledge of COVID-19's influence. High educational levels and large percentage of employed workers can explain the sample's higher average monthly family income (19.4kRMB compared with 16.2kRMB in the whole population) and private car ownership (58.7% compared with 53.0% in the whole population). This sample mainly reflected main-stream urban transit riders but did not include enough old/young people and those with lower educational levels and lower income. The travel choices of these groups are also important for understanding post-pandemic transit use. Future studies could use a random sample to further generalize the results. Finally, public transit travel is considered as a whole, yet people's travel mode choice-making mechanisms could be different for trips with different purposes. Therefore, it is necessary for future research to examine the pandemic's influence on people's willingness to take public transit for

commuting, shopping, recreational, and other purposes.

6. Conclusion

The present study builds a theoretical framework based on TPB to examine the mechanism behind the individual's choice to travel or not to travel by public transit in the post-pandemic era. We shed light on individual people's post-COVID public transit travel choice-making processes and examined perceived knowledge of COVID-19, psychological risk of COVID-19, and pre-COVID travel habit's influence on it. We analyzed the effects of the model constructs on transit use intention and behavior, discussed the role of vital constructs, and compared the decision-making process of "captive" and "choice" transit users. The key findings are as follows. Although modeling results confirms the effectiveness of TPB, the effects and meanings of original TPB constructs may be potentially different in the post-pandemic context than in normal daily context; psychological risk has a negative effect on people's decision-making process, while perceived knowledge can offset this negative effect; people's pre-pandemic travel habit as an enduring effect on their post-pandemic transit use; "captive" transit users must use transit despite their higher psychological risk than "choice" users. This study calls for solid behavioral experiments to further examine potential implications on behavioral interventions.

CRedit authorship contribution statement

Pengjun Zhao: Conceptualization, Supervision, Writing – review & editing. **Yukun Gao:** Methodology, Writing – original draft.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

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