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Spatial disparities in risk management in China: application of the theory of planned behavior

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Abstract
The application of risk management strategies is a common approach in emergency response scenarios. However, scant knowledge exists regarding its utilization in the specific context of an outbreak, both theoretically and practically. This study delves into the realm of risk management during the COVID-19 pandemic, focusing on four key measurements: risk avoidance (RA), risk reduction (RD), risk transfer (RT), and risk retention (RR). Using 800 valid responses collected from 31 provinces across China between August 1 and September 30, 2020, this study investigates spatial disparities in individuals' intentions towards risk management. To achieve this, an extended version of the Theory of Planned Behavior (E-TPB) is applied. The Structural Equation Model's path analyses revealed several findings: (1) discernible spatial disparities in RR, RA, and RD intentions between large and small cities; (2) RD and RR intentions were significantly associated with attitude, subjective norm, perceived behavioral control, and risk perception; (3) RA and RT intentions were significantly associated with attitude and risk perception; (4) risk perception exihibiting both direct and indirect effects on RA and RR intentions. This study contributs to the urban studies literature by extending the theoretical framework of risk management in the context of COVID-19. It enhances the measurement tools employed in the TPB model and scrutinizes spatial disparities in the adoption of preventative measures against COVID-19. The findings underscore the importance for local policymakers to consider geographical differences when formulating effective strategies for COVID-19 prevention.

Keywords Risk management, Risk avoidance, Risk reduction, Risk transfer, Risk retention, Risk perception

1 Introduction

The COVID-19 pandemic has resulted in significant human and financial losses worldwide. The case-fatality ratio was observed to be higher in rural areas compared to urban regions, as shown by the example in the United States (Iyanda et al. 2021). The global economic impact of pandemic-induced lockdowns is evident in the reported 7.3% decline in the growth of gross domestic product (GDP) in 2020 compared to 2019 (Sanchez 2021). Notably, middle-income countries experienced the largest GDP growth decline, with a percentage point change of 8.7% (Sanchez 2021). Despite the World Health Organization (WHO) emphasizing the importance of safe and effective COVID-19 vaccines in ending the pandemic, vaccination rates were lower in regions characterized by

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lower socioeconomic status (Mollalo and Tatar 2021). Given the virus's transmission through human contact, non-pharmaceutical interventions and protective measures, such as wearing face masks, handwashing, and practicing social distancing, have become essential policy options for controlling the spread (Yang et al. 2021).

Hence, it has become evident that the adverse effects of COVID-19 and the protective measures adopted to mitigate its impact may vary across regions (Huynh 2020; Mollalo and Tatar 2021; Trasberg and Cheshire 2021). These variations are likely influenced by how communities and individuals process or interpret information related to COVID-19, ultimately shaping their willingness to adopt preventive measures (Bae and Chang 2021; Caserotti et al. 2021). In such instances, psychological factors, including risk perception, play a crucial role in ensuring the effective implementation of risk management measures (Chan et al. 2020). The understanding of citizens' cognitive processes and the clarification of the spatial distribution of their intentions regarding risk management are pivotal for the development of effective and contextually appropriate policies to prevent the spread of COVID-19 (Hornik et al. 2021; Li et al. 2021a, b). This significance is particularly pronounced in countries with large populations, such as China.

Theoretical underpinnings of risk management find extensive application in emergency response scenarios (Krechowicz 2020; Sun and Yamori 2018). However, scant scholarly attention has been directed toward understanding its utilization within the context of pandemics, both in theoretical and practical dimensions. Addressing this gap, the present study enriches the existing literature on risk management by operationalizing and applying four distinct categories, namely risk avoidance (RA), risk reduction (RD), risk transfer (RT), and risk retention (RR), to the intricate landscape of the COVID-19 pandemic. Notably, this investigation stands as the pioneering empirical endeavor to formulate measures and scrutinize factors influencing risk management intentions in the context of a pandemic.

Furthermore, this study contributes to the domain of psychology by adopting an extended version of the Theory of Planned Behavior (E-TPB) to explore the determinants influencing the risk management intentions of Chinese citizens. The primary objectives of this research are fourfold: (1) to elucidate and define diverse metrics for assessing risk management concerning COVID-19; (2) to probe into the factors and pathways impacting individual intentions towards risk management; (3) to discern spatial differentials in COVID-19 risk management intentions; and (4) to propose efficacious policies aimed at curbing the proliferation of COVID-19. This investigative trajectory is poised to offer insights into reaching Chinese populations through targeted interventions, thereby augmenting the adoption of protective measures against COVID-19 and enhancing preparedness for potential future pandemics.

2 Literature review

2.1 Risk management measures for COVID-19

The protective measures against COVID-19 can be categorized into four types within the risk management framework: risk avoidance, risk reduction/mitigation, risk transfer, and risk retention (Fernandez-Muniz et al. 2014; Krechowicz 2020; Reim et al. 2016). While this classification of risk management measures is commonly utilized in the managing manufacturing and natural disaster risks (Reim et al. 2016; Tatano et al. 2004), it is rarely employed in studies focused on pandemics like COVID-19.

Risk avoidance involves reducing exposure to risks instead of implementing preventative actions (Eckerd 2014). Throughout the pandemic, measures of RA have been widely implemented and adopted by governments globally. Examples include community lockdowns, stay-at-home orders, and the reduction of unnecessary trips (Buffel et al. 2021; Wise et al. 2020; Sangiorgio and Parisi 2020). Cross-cultural and international comparative studies have revealed the mixed success of RA measures (Sun et al. 2021; Trasberg and Cheshire 2021). For instance, a recent study on cultural differences in social distancing measures reported that countries with a higher degree of uncertainty avoidance, according to the Hofstede index, were associated with a higher proportion of implementing social distancing measures (Huynh 2020).

Risk reduction involves the proactive implementation of preventive measures to diminish the causes and consequences of risks (Krechowicz 2020; Siegrist et al. 2021). Common RD measures for COVID-19 prevention include vaccination, sanitizing public places, and stockpiling face masks and ventilators. COVID-19 vaccines are widely regarded as potentially effective and safe prevention methods (WHO 2021). However, vaccine hesitancy prevails in many parts of the world, driven by perceptions of safety concerns and the belief that vaccination is unnecessary (Mollalo and Tatar 2021; Ward et al. 2020). For instance, Varotsos et al. (2021), utilizing global data on vaccination rates and socio-economic factors, reported that the correlation between the vaccinated population's level and COVID-19 deaths is not consistently evident. Additionally, individuals hold diverse perspectives on the importance and safety of wearing masks (Hornik et al. 2021).

The risk transfer refers to the complete or partial transfer of risks to others (Legault and Chasserio 2012). This method is commonly used in the business sector to mitigate financial losses by spreading the risk across multiple partners (Legault and Chasserio 2012; Tatano et al. 2004). The most common RT measures are buying insurance and shifting financial losses to insurance companies (Tallaki and Bracci 2021). The uncertainty accompanied with the COVID-19 pandemic, such as causes and consequences of the infection, waiting line of treatment, and health rehabilitation cost, along with high mortality rate, have significantly increased people's willingness to buy health insurance (Qian 2021; Seino et al. 2021). Applying for bank loans is also an effective way of transferring temporary financial risks (Mirakhor et al. 2017). The central banks of many countries have adopted monetary stimulus policies (e.g., small business financing) to lessen the economic recession (Ma et al. 2021). In China, bank loans for small businesses have been made more flexible and larger in areas that have been more severely affected by the pandemic (Song et al. 2021).

The risk retention means accepting the risk and increasing contingency plans (Krechowicz 2021). Individuals who use RR measures are usually better prepared to handle the risk; they can even profit from retaining the risk by pricing their offering accordingly (Reim et al. 2016; Spring and Araujo 2009). When there are economic crises and emergency events (e.g., natural disasters), individuals reduce their consumption as a RR measure to lessen the financial risk (Sarmento et al. 2019). Evidence from China shows that people who are closer to the outbreak epicenter have a lower perception of the risk of infection, leading to less irrational consumption behavior such as stockpiling food (Li et al. 2021a, b). Furthermore, people with low-status consumption goals currently tend to purchase fewer luxury hospitality products than those with high-status consumption goals (Peng and Chen 2021). Individuals' attitude towards the efficacy and cost of the actions are key to the dissemination of RR measures (Siegrist et al. 2021; Trifiletti et al. 2021).

Until now, Chinese citizens' intentions to adopt measures of RA, RD, RT, and RR during the pandemic have not been known. It can be beneficial to clarify the potential predictive factors on these intentions to design effect and appropriate COVID-19 prevention policies.

3 Research hypotheses

The model of Theory of Planned Behavior (TPB) states that three predictive factors shape the behavioral intention to prevent risks: attitude toward the behavior (*attitude*), subjective norm (*sub_norm*), and perceived behavioral control (*per_control*) (Rezaei et al. 2019; Shi and Kim 2020; Trifiletti et al. 2021). Behavioral intention refers to an individual's willingness to try and motivation to exert an effort, in order to perform the behavior (Ajzen 1991). In this study, intention refers to a person's willingness and motivation to adopt the four types of COVID-19 risk management measures (e.g., RA, RD, RT, and RR).

According to the TPB, *attitude* refers to the degree to which an individual has a favorable or unfavorable evaluation or appraisal of the behavior; *sub_norm* refers to the perceived social pressure to perform or not to perform the behavior; *per_control* refers to the perceived ease or difficulty of performing the behavior (Ajzen 1991, 2011). In the current study, we use the following definitions: (1) *attitude* is the degree to which a person has a positive or negative view of performing COVID-19 risk management measures; (2) *sub_norm* is the degree to which a person believes that significant others (e.g., family and friends) and the community would approve and support these risk management measures; (3) *per_control* is the degree to which a person has the ability and resources (e.g., vaccine, body immunity) to carry out these risk management measures. The more favorable the *attitude* and *sub_norm*, and the greater the *per_control* concerning behavior, the stronger an individual's intention should be to perform that behavior (Ajzen 1991; Armitage and Conner 2001). Drawing on the TPB model, the following hypotheses are proposed:

> H1: The attitude towards COVID-19 protective behavior is positively associated with the intention to adopt risk management measures.
> H2: The subjective norm regarding COVID-19 protective behavior is positively associated with the intention to adopt risk management measures.
> H3: The perceived behavioral control regarding COVID-19 protective behavior is positively associated with the intention to adopt risk management measures.

In risk management studies, risk perception has long been acknowledged as a robust predictive factor for people's intentions to take preventive action (Siegrist et al. 2021; Taylor and Snyder 2017; Wang et al. 2018). However, few studies have used risk perception as an additional explanatory variable in the TPB model to obtain a comprehensive understanding of individuals' intentions for risk management (Shi and Kim 2020; Trifiletti et al. 2021). Recently, a study in Italy reported that risk perception is significantly associated with individuals' willingness to perform COVID-19 preventive behavior (e.g., social distancing) (Trifiletti et al. 2021). Hence, drawing on the TPB model and previous studies, we construct an E-TPB model to predict Chinese citizens' intentions of taking COVID-19 risk management measures. The theoretical framework is shown in Fig. 1. The following hypotheses are proposed:

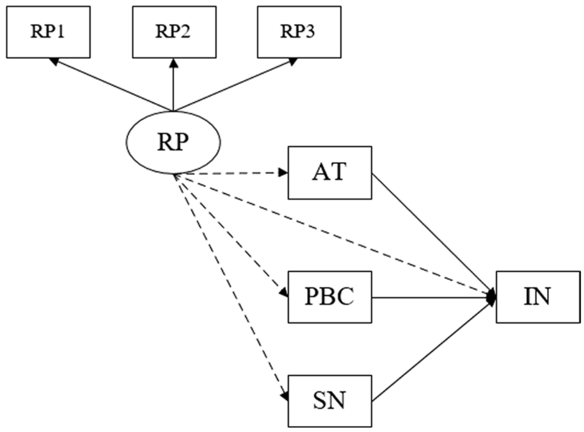


Fig. 1 Theoretical framework of an E-TPB model. RP = risk perception; AT = attitutde; PBC = perceived behavioral control; SN = subjective norm; IN = intention

> H4-1: Risk perception has a direct positive association with the intention to adopt risk management measures.
> H4-2: Risk perception has an indirect positive association with the intention to adopt risk management measures.

Many cross-sectional and international investigations report that people's intentions of taking risk management measures vary between regions (Vick et al. 2019; Yalçin et al. 2021) and countries (Appleby-Arnold et al. 2021). By comparing the disaster preparedness of urban and rural hospitals in New York State, Vick et al. (2019) found that differences were seen in disaster plan development, available materials and resources, and disaster education. A study in China reported that the factors that predicted COVID-19 preventive behaviors differed between urban and rural areas. For example, checking of face mask wearing by policemen in public places was positively associated with protective actions in rural areas but not in urban areas (Zhang et al. 2021). Drawing on previous findings, the current study investigates spatial disparities in citizens' intentions of taking COVID-19 risk management measures based on whether they are in large or small cities. Generally, the ranking of cities in China are calculated based on their economic development, infrastructure, and transportation system, and can be categoried into first-, second-, third-, and fourth-tier cities (Zhang et al. 2016). For instance, first-tier cities (e.g., Beijing, Shanghai) are featured with large amout of GDP, and high-quality resource aggregation such as medical resource. In the current study, large cities refer to first- and second-tier cities, and small cities refer to third- and fourth-tier cities. Using the place of residence as a variable, the following hypothesis is proposed:

> H5: The relationships between the E-TPB constructs (attitude, subjective norm, perceived behavioral control, and risk perception) and the intention to adopt risk management measures vary depending on the place of residence.

4 Constructs and data collection

4.1 Development of measurements

The constructs for the E-TPB model are taken from existing risk management studies (Krechowicz 2020; Rubin et al. 2009; Zhang et al. 2020a, b). They have been carefully designed to fit the context of the COVID-19 pandemic in China. A five-point Likert scale is used for the responses, ranging from "strongly disagree = 1" to "strongly agree = 5". Appendix A shows the survey items.

It is worth noting that, numerous constructs allow for both reflective and formative measurements (Bagozzi 2011; Christophersen and Konradt 2012). According to Christophersen and Konradt (2021), in a reflective measurement model, the observed indicators are assumed to be caused by the latent variable, leading to an expectation of high internal consistency between the indicators. Conversely, in a formative measurement model, the observed indicators are assumed to cause the latent variable, and therefore, high correlations between the indicators are not generally expected. Hence, a measurement model based on risk management intentions may be determined by formative indicators, each representing a unique and distinguishable aspect of the construct. Given that the current study categorizes risk management measures into four types, each type offers a unique perspective on preventive behaviors related to COVID-19. These four categories are not interchangeable and cannot be combined into a single domain (Christophersen and Konradt 2012). In this study, formative indicators are applied to elucidate the TPB constructs, represented by the sum of the related indicators. Reflective indicators are employed to uncover the construct of risk perception because COVID-19 risk perception can be derived from an infinitive domain of items, such as the perceived likelihood of harm (Brewer et al. 2007; Shi and Kim 2020).

4.2 Data collection and sample description

A cross-sectional online questionnaire was used to collect data on Chinese citizens' intentions of taking risk management approaches to respond to the pandemic. A pilot test of the survey was conducted, which garnered eight responses, and the findings were used to refine the survey items. Using geographical location (that is, the province as stratum), a stratified sampling method was used to distribute the questionnaires and ensure the representativeness of the place of residence. A survey company, Wenjuan, was paid to help with the data collection from August 1 to September 30, 2020. Respondents might have received financial incentives.

Respondents were at least 18 years of age and provided consent before accessing the survey. A total of 800 valid responses were collected from 31 out of 34 provinces and areas. Any invalid/uncompleted responses were not provided by Wenjuan. The research protocol was approved by the China University's Ethics Committee.

The demographics of the respondents are shown in Table 1. The gender distribution indicates a higher percentage of females (54.9%) compared to males (45.1%). The majority of respondents fell within the age range of 21 to 40, with only 13.9% being older than 40. Additionally, most respondents had completed either a three-year college or a four-year undergraduate degree. The survey included 450 respondents residing in large cities and 350 respondents residing in small cities.

4.3 Data analysis

The assessments of the measurement model and structural model were carried out using R (Ver.4.0.5, Lavaan package). The maximum likelihood (ML) estimate was adopted and the confidence interval for indirect effects was estimated using bootstrapping with 5000 samples. The model fit indices in this study were based on the comparative-fit index (CFI) (Bentler 1990) and the root mean square error of approximation (RMSEA) (Browne and Cudeck 1992).

Table 1 Demographic statistics (N = 800)

Variables	N	%
Gender		
Male	361	45.1
Female	439	54.9
Age (year)		
21–30	318	39.7
31–40	371	46.4
41–50	89	11.1
51 +	22	2.8
Education		
Less than high school	17	2.2
Three-year college	301	37.6
Four-year undergraduate	446	55.7
At least master degree	36	4.5
Place of residence		
Large-scale city	450	56.2
Small-scale city	350	43.8

The correlation matrix for all variables is provided in Appendix B, revealing substantial internal correlations whithin the variables of four intra-groups: RA, RD, RT, and RR. Additionally, internal correlations were observed among variables between inter-groups; however, correlation coefficients were notably higher within intra-groups than between inter-groups. For instance, within the RD intra-group, coefficients for RD_*attitude*, RD_*per_control*, RD_*sub_norm*, and RD intention were 0.66, 0.55, 0.55, respectively. In contrast, coefficients between RD_*attitude*, RD_*per_control*, RD_*sub_norm*, and RA intention were 0.41, 0.32, 0.34, respectively. Although inter-group correlations suggested potential impacts of RD_*attitude*, RD_*per_control*, and RD_*sub_norm* on intentions of RA, RT, or RR, the significance of these impacts was considerably lower compared to RD intra-group impacts. As highlighted in the literature review section, prior studies often examined factors influencing risk management without extending their exploration to those four dimensions of risk management (Brewer et al. 2007; Caserotti et al. 2021). The present results affirm the appropriateness of establishing four Structural Equation Models (SEMs) in this study to investigate the factors influencing individuals' intentions in RA, RD, RT, and RR, respectively. Notably, this study is the first attempt to unveil influencing factors on each dimensions of risk management. Furthermore, it is observed that the constructs of *attitude*, *sub_norm*, and *per_control* can be appropriately measured using formative indicators with intermediate internal consistency. Additionally, the construct of risk perception can be effectively measured using reflective indicators, exhibiting high internal consistency.

5 Results and discussion

The results of the theoretical model estimation are presented in Table 2. The model fit indices of the CFI are 0.970, 0.999, 0.979, 0.991. They show a close fit as the suggested value of the CFI is above the threshold of 0.950 (Bentler 1990). The model fit indices of the RMSEA are 0.085, 0.017, 0.055, 0.047. They show appropriate fit as the suggested value of RMSEA is lower than the threshold of 0.080 (Bentler 1990). Since the current study aims to understand the path analysis of influencing factors on risk management intentions, the R-squared value of the theoretical model for RA, RD, RT, and RR is reported. It shows that the variance of risk management intentions can be explained by the constructs of *attitude*, *sub_norm*, *per_control*, and risk perception.

5.1 Test of risk avoidance hypotheses

The results of the model regarding the direct effect of risk perception on RA intentions are as follows:

Table 2 Estimation results of theoretical model

		Risk avoidance		Risk reduction		Risk transfer		Risk retention	
		Standardized coefficient	***p*-value**	**Standardized coefficient**	***p*-value**	**Standardized coefficient**	***p*-value**	**Standardized coefficient**	***p*-value**
Direct effect	*Attitude* → intention	0.384	< 0.001	0.448	< 0.001	0.286	< 0.001	0.414	< 0.001
	Sub_norm → intention	0.283	< 0.001	0.145	< 0.001	0.014	0.727	0.138	< 0.001
	Per_control → intention	0.013	0.700	0.201	< 0.001	0.034	0.420	0.089	0.015
	Risk perception → intention	0.198	< 0.001	0.137	< 0.001	0.161	< 0.001	0.320	< 0.001
Indirect effect	Risk perception → *attitude* → intention	0.056	0.001	0.019	0.353	0.014	0.257	0.045	0.014
	Risk perception → *sub_norm* → intention	0.083	< 0.001	0.005	0.429	< 0.001	0.751	0.010	0.109
	Risk perception → *per_control* → intention	0.004	0.699	0.014	0.120	0.002	0.462	0.014	0.031
	CFI	0.970		0.999		0.979		0.991	
	RMSEA	0.085		0.017		0.055		0.047	
	R-squared	0.459		0.504		0.129		0.464	

attitude (beta = 0.384, $p < 0.001$), *sub_norm* (beta = 0.283, $p < 0.001$), and risk perception (beta = 0.198, $p < 0.001$) have a significant positive effect on RA intentions. The results of the model regarding the indirect effect of risk perception on RA intentions are as follows: risk perception has a significant positive effect on RA intention through *attitude* (beta = 0.056, $p = 0.001$) and *sub_norm* (beta = 0.083, $p < 0.001$). These results indicate that H1 (attitude is positively associated with risk management intention), H2 (subjective norm is positively associated with risk management intention), and H4-1 (risk perception is directly associated with risk management intention) are fully supported. H4-2 (risk perception is indirectly associated with risk management intention) is partly supported. H3 is rejected (Fig. 2).

These findings are consistent with previous studies (Chan et al. 2020). RA strategies, such as avoiding travel and steering clear of large gatherings during an outbreak, have already been confirmed to be effective (Aledort et al. 2007). However, the legitimacy of such strategies may vary between countries (Sun et al. 2021). In such circumstances, *sub_norm* such as the autonomous organization of the community and the people around, as well as people's attitudes toward the value of RA strategies, strongly impace behavioral intentions (Zhai et al. 2021). Meanwhile, the perceived risk of COVID-19, influenced by the lack of effective medical treatment, can lead individuals to intend to avoid contact with people or events associated with COVID-19 (Wise et al. 2020). However, *per_control* which typically requires additional resources or abilities for individuals to perform certain actions, is not a necessary factor when it comes to implementing RA strategies. In other words, individuals do not have to exert any additional effort to avoid performing protective behaviors. Therefore, when encouraging people to perform RA strategies, *attitude*, *sub_norm*, and risk perception are the most significant influencing factors. Policymakers should consider measures such as illustrating the risks of COVID-19 to the public, educating them about the values of avoidance actions, and motivating the local community to agree on shared RA strategies.

5.2 Test of risk reduction hypotheses

The results of the model regarding the direct effect of risk perception on RD intentions are as follows: *attitude* (beta = 0.448, $p < 0.001$), *per_control* (beta = 0.201, $p < 0.001$), *sub_norm* (beta = 0.145, $p < 0.001$), and risk perception (beta = 0.137, $p < 0.001$) have a significant effect on RD intentions. The results of the model regarding the indirect effect of risk perception on RD intentions show that risk perception has no significant effect on the intentions. These results indicate that H1 (attitude is positively associated with risk management intention), H2 (subjective norm is positively associated with risk management intention), H3 (perceived behavioral control is positively associated with risk management intention), and H4-1 (risk perception is directly associated with risk management intention) are fully supported. H4-2 is rejected.

These findings are inconsistent with previous studies (Zhang et al. 2020a, b). RD measures, such as getting a vaccination against COVID-19 or stockpiling face masks require individuals to have additional resources and abilities. As *per_control* also requires extra effort, it is easy to understand the positive relationship between *per_control* and risk management intention. Meanwhile,

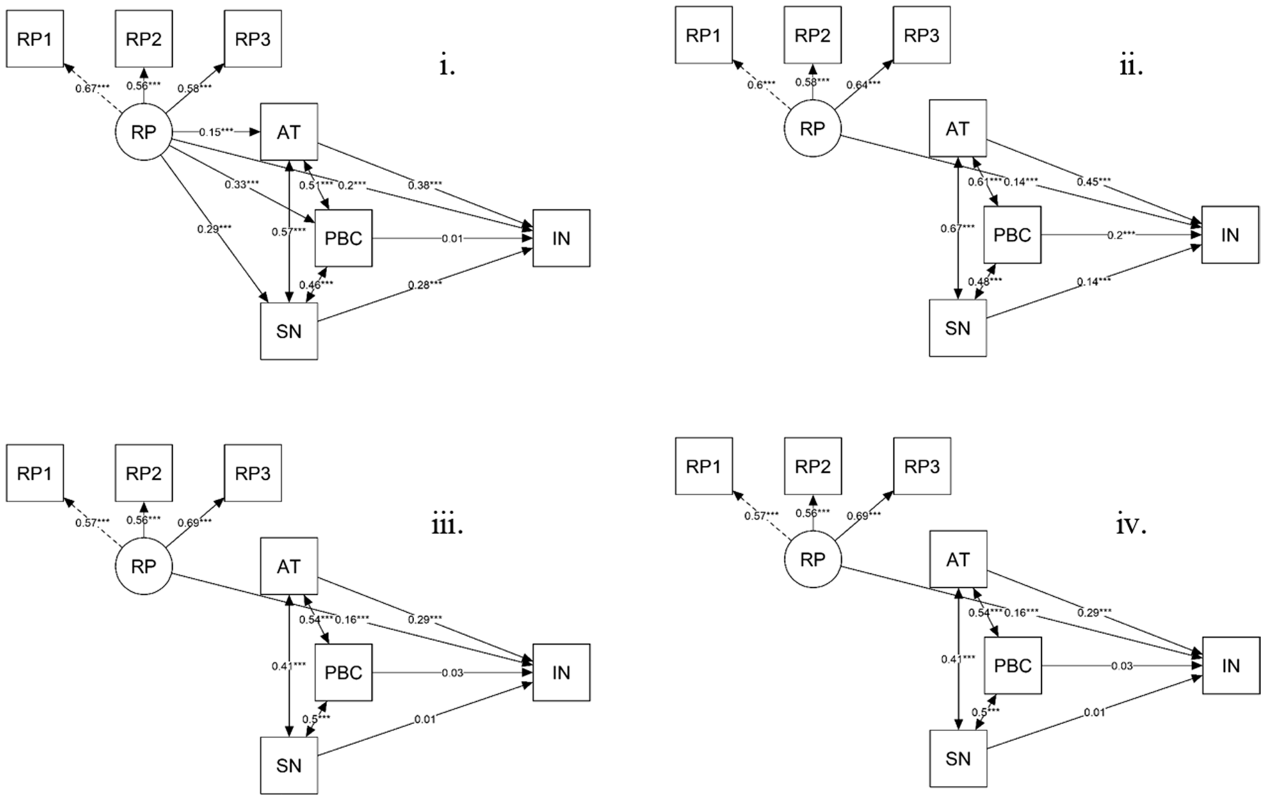


Fig. 2 Association between E-TPB constructs and risk management intention. **i** RA intention; **ii** RD intention; **iii** RT intention; **iv** RR intention

unlike RA strategies which have been confirmed to be effective (Aledort et al. 2007), RD strategies regarding COVID-19 (e.g., stockpiling face masks, using disposable chopsticks) have a limited effect when it comes to combating COVID-19 (Maclntyre et al. 2009). Thus, individuals' recognition of the values of RD strategies, along with the pressure exerted by the people around them, would encourage them to implement RD strategies. In addition, worries about COVID-19 infection and financial risks can encourage the adoption of RD strategies (Fadel et al. 2021). Policymakers should show the public the effectiveness of adopting RD strategies. Nevertheless, since individuals must have additional resources, policymakers should make sure that the opportunities for adopting RD strategies are fair, open, and transparent.

5.3 Test of risk transfer hypotheses

The results of the model regarding the direct effect of risk perception on RT intentions are as follows: *attitude* (beta = 0.286, $p < 0.001$) and risk perception (beta = 0.161, $p < 0.001$) have a significant effect on RT intentions. The variables of *per_control* and *sub_norm* do not affect RT intentions. The results of the model regarding the indirect effect of risk perception on RT intentions were that risk perception has no significant effect on RT intentions. These results indicate that H1 (attitude is positively associated with risk management intention) and H4-1 (risk perception is directly associated with risk management intention) are fully supported. H2, H3, and H4-2 are rejected.

These findings are consistent with previous studies (Dorfman 1998; Reim et al. 2016). In risk management science, RT measures are generally related to financial issues and can cause extra risks to counterparts (Krechowicz 2021). To deal with personal financial risks, only the internal attributes such as personal recognition and understanding of the financial situation have legitimate effects (Dorfman 1998). It is quite easy to understand that the internal attributes of individuals' attitudes and risk perception would motivate them to perform RT strategies. However, because *sub_norm* involves external social pressures, it sometimes has a weak influence on RT intentions. The *per_control* is sometimes influenced by external resources (e.g., stable income and mutual trust). Nevertheless, as resources such as mutual trust are sometimes affected by internal characteristics, further analysis on the relationship between *per_control* and RT intentions is needed. When it comes to RT strategy, therefore, policymakers should encourage financial agents such as banks to take the risks away from individuals during a pandemic.

5.4 Test of risk retention hypotheses

The results of the model regarding the direct effect of risk perception on RR intentions are as follows: *attitude* (beta = 0.414, $p < 0.001$), *per_control* (beta = 0.089, $p = 0.015$), *sub_norm* (beta = 0.138, $p < 0.001$), and risk perception (beta = 0.320, $p < 0.001$) have a significant effect on RR intentions. The results of the model regarding the indirect effect of risk perception on RR intentions are as follows: risk perception has a significant positive effect on RR intentions through *attitude* (beta = 0.045, $p = 0.014$) and *per_control* (beta = 0.014, $p = 0.031$). These results indicate that H1 (attitude is positively associated with risk retention intentions), H2 (subjective norm is positively associated with risk retention intentions), H3 (perceived behavioral control is positively associated with risk retention intentions), and H4-1 (risk perception is directly associated with risk retention intentions) are fully supported. H4-2 is partly supported.

In risk management science, RR strategy involves both internal and external attributes (Spring and Araujo 2009). An individual who uses RR strategy usually has a strong ability to handle the risk, or they have additional resources to profit from retaining the risk (Krechowicz 2021; Spring and Araujo 2009). Therefore, it is easy to understand the significant relationships between the internal attributes (e.g., *attitude* and risk perception), external attributes (e.g., *per_control* and *sub_norm*), and risk retention intention. In contrast to the other three risk management strategies, RR strategies are usually formed through private markets (Reim et al. 2016). Thus, policymakers need to understand the situation regarding RR intention. They must take appropriate measures like providing subsidies for face mask factories to ensure there is adequate supply during the pandemic.

5.5 Test of spatial disparity hypotheses

The measurement invariance and equivalence of the structural models between groups living in large and small cities were tested. The factor of the place of residence (*place*) was used to measure any spatial disparities in individuals' intention of taking risk management measures. A set of nested models was established. Model *place*1 was a baseline model, in which all the factor loadings and path coefficients in the measurement model were estimated freely. Compared to *place*1, model *place*2 examined the invariance of the factor loadings, in which all factor loadings in the measurement model were made to be equal. Compared to *place*2, model *place*3 examined the invariance of the path coefficients of the TPB constructs, in which all the path coefficients of the TPB constructs were made to be equal. Compared to *place*3, model *place*4 examined the invariance of the path coefficients of the E-TPB constructs, in which all the path coefficients of the E-TPB constructs were made to be equal.

The results in Table 3 reveal that, when it comes to risk management intentions, there were only significant spatial disparities in RR intentions (*place*2, $p = 0.017$). For the pathways of the TPB constructs relating to risk management intentions, significant spatial disparities were seen in RA intentions (*place*3, $p = 0.021$). For the pathways of the E-TPB constructs relating to risk management intentions, significant spatial disparities were seen in RD intentions (*place*4, $p = 0.007$). No significant spatial disparities were seen in RT intentions. Therefore, H5 (the relationships between E-TPB constructs and risk management intention are variant across the place of residence) was partly supported.

The reasons for the spatial disparities in RR intentions (e.g., saving money and reducing consumption) may be that people living in large cities have higher incomes and higher levels of consumption than those living in small cities (Tang et al. 2020). The rational provided was that the dummy variable of residential place (large city vs. small city) might exhibit a notable correlation with individuals' income.This proposition is grounded in the hierarchical classification of cities in China, which is organized into first-, second-, third-, and fourth-tier categories. This classification primarily hinges on factors such as economic development, infrastructure, and transportation systems specific to each city (Zhang et al. 2016). Also, people who have ample resources and stable wages could afford losses during the COVID-19 pandemic and so could adopt risk retention measures. However, in small cities, people typically keep their consumption levels low because they have lower incomes. Therefore, they cannot afford to reduce consumption further.

The reasons for the spatial disparities in RA intentions (e.g., avoiding the consumption of imported food and avoiding travel) may be that people living in large cities have to change their lifestyle when performing RA measures, while those living in small cities do not. For people who live in large cities and have guaranteed incomes and holidays, consuming imported food and traveling periodically have become part of life (Li et al. 2021a, b). For people in small cities, due to the slow development of industry, low income and unstable holidays are a part of life. Therefore, taking RA measures would cost less money and be less emotional for people in small cities than for people in large cities. Moreover, the exploration of disparities across residential locations was a prevalent theme in the context of COVID-19 research. Numerous prior studies employed residential place as a variable to investigate spatial disparities in COVID-19

Table 3 Multi-group analysis results between large and small cities

Model	df	AIC	BIC	Chi-square	Chi-square difference	df difference	*p*-value
risk_avoid							
Model *place*1	16	17,077.194	17,330.163	66.912	NA	NA	NA
Model *place*2	18	17,075.764	17,319.363	69.482	2.570	2.000	0.277
Model *place*3	24	17,079.509	17,309.054	79.227	9.745	3.000	0.021
Model *place*4	23	17,077.557	17,288.364	85.275	6.048	4.000	0.196
risk_reduc							
Model *place*1	16	18,918.741	19,171.710	20.199	NA	NA	NA
Model *place*2	18	18,917.237	19,160.836	22.695	2.496	2.000	0.287
Model *place*3	24	18,912.895	19,142.441	24.354	1.659	3.000	0.646
Model *place*4	23	18,919.138	19,129.945	38.596	14.242	4.000	0.007
risk_trans							
Model *place*1	16	18,162.045	18,415.014	48.758	NA	NA	NA
Model *place*2	18	18,160.866	18,404.466	51.579	2.821	2.000	0.244
Model *place*3	24	18,159.882	18,389.428	56.595	5.016	3.000	0.171
Model *place*4	23	18,161.174	18,371.982	65.887	9.292	4.000	0.054
risk_reten							
Model *place*1	16	17,995.674	18,248.643	40.180	NA	NA	NA
Model *place*2	18	17,999.869	18,243.468	48.374	8.194	2.000	0.017
Model *place*3	24	17,994.508	18,224.054	49.013	0.639	3.000	0.887
Model *place*4	23	18,000.502	18,211.309	63.007	13.994	4.000	0.007

case fatality ratios and COVID-19 vaccination coverage in the US (Murthy et al. 2021), as well as in knowledge, behavior, and mental health in China (Zhang et al. 2021). Consequently, the current study aligns with and builds upon the insights gleaned from these antecedent investigations, focusing on discerning spatial disparities in risk management intentions. Importantly, the formulation of COVID-19 policies has been primarily tailored to the unique circumstances of local cities. Indeed, over the past three years, distinct cities in China have implemented markedly different strategies to curb the pandemic (Sun et al. 2023). The findings of our study furnish academic support for the development of future pandemic policies tailored to diverse regions.

The reason for the spatial disparities in RD intentions (e.g., vaccination, stockpiling face masks) might be that it is easier for people living in large cities to access to medical equipment because the logistics and market systems are better developed than those in small cities. With the rapid development and authorization of COVID-19 vaccines, safety and effectiveness have become the main concerns among Chinese people, especially among people with higher levels of education in large cities (Chen et al. 2021). Additionally, the huge difference of socioeconomic status between large and small cities (Zhang et al. 2016) may also contribute to spatial disparities in taking RD measures.

5.6 Limitations

An evident limitation within the current study pertains to the novel methodologies employed for assessing the four delineated categories of risk management in the context of a pandemic. The study operationalized four risk management categories—namely, risk avoidance, risk reduction, risk transfer, and risk retention—and extended their applicability to the context of COVID-19. However, the methodologies employed for the measurement of these categories are innovative and relatively recent. Consequently, the study utilized formative indicators to gauge constructs within the TPB model, resulting in a diminished level of internal consistency. Subsequent to this observation, it is imperative to underscore the necessity for further theoretical refinement in the measurement protocols.

Moreover, the study employed cross-sectional survey data to validate the efficacy of the E-TPB model. It is crucial to acknowledge that the outcomes of this approach may be susceptible to data bias. In light of this, it is recommended that future investigations consider the adoption of longitudinal datasets to discern causal relationships between indicators in the E-TPB model. Such longitudinal analyses would provide a more robust foundation for understanding the temporal dynamics and causal pathways associated with the constructs under investigation.

Another constraint inherent in this study pertains to the absence of transnational comparative research. Given that our data were exclusively derived from Chinese sources, the prospect of cross-national comparisons was precluded. Nevertheless, empirical evidence underscores the adoption of notably stringent measures by China in response to the COVID-19 crisis, including the implementation of mandatory policies to ensure public compliance (Sun et al. 2023). These obligatory directives may exert a discernible influence on individuals' proclivities towards embracing protective behaviors against COVID-19. It is recommended that future investigations extend their research ambit to encompass multinational comparisons, thereby addressing this inherent limitation and advancing a more nuanced understanding of the intricacies surrounding the adoption of protective behaviors in the context of a pandemic.

6 Conclusion

To understand Chinese people's intentions to take risk management measures during the pandemic, this study has clarified and developed measurements for four categories of risk management. The study has empirically examined an E-TPB model that describes how attitude, subjective norm, perceived behavioral control, and risk perception affect risk management intentions for those four categories.

The major findings in this study are as follows. First, attitude has the most substantial direct positive effect on risk management intentions. Second, risk perception has direct and indirect effects on risk avoidance and risk retention intentions. Third, both subjective norm and perceived behavioral control positively affect risk reduction and risk retention intentions, and subjective norm also positively affects risk avoidance intention. Fourth, there were spatial disparities in risk transfer, risk avoidance, and risk reduction intentions between large and small cities.

This study contributed to the literature concerning risk management by applying the four categories of risk management to the situation of COVID-19 pandemic. To our knowledge, this is the first study that has empirically developed measures and examined factors affecting risk management intentions for COVID-19. This study also contributed to the literature by extending the TPB framework to an E-TPB model. The findings of the E-TPB model provide further empirical support for Trifiletti et al. (2021), who have reported that risk perception was a significant predictor of social distancing. Nevertheless, our study categorized detailed risk management measures, providing a more comprehensive account. From the perspective of geographical studies, this study has illustrated how the place of residence affects risk management intention. The results of the study show that local policymakers should consider geographical differences when designing preventive strategies for COVID-19. The effectiveness of those strategies can be improved by controlling for the place of residence.

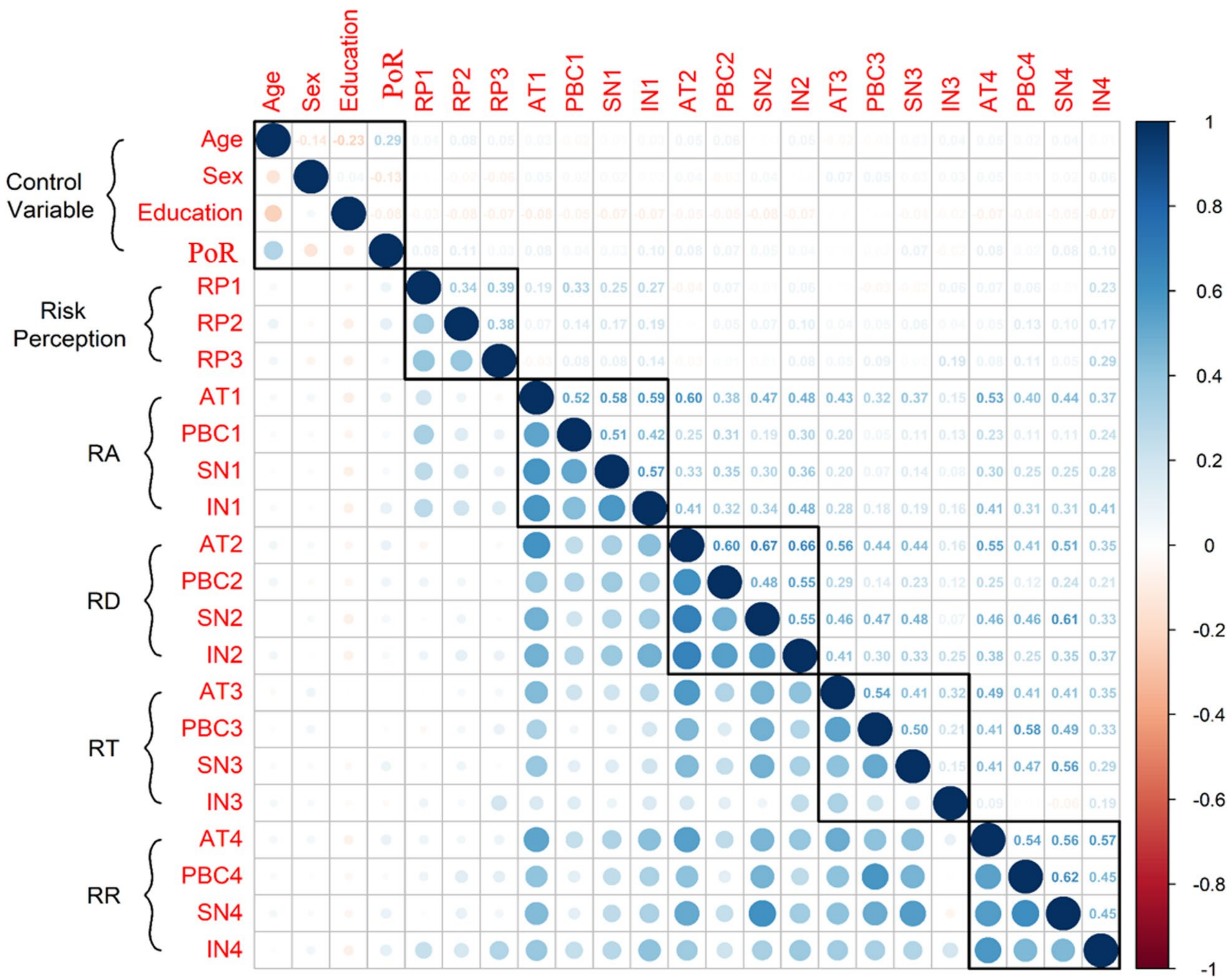
From a practical standpoint, this study can help those responsible for managing the spread of COVID-19 to understand four categories of risk management. The following suggestions could be worth considering when implementing strategies for containing COVID-19. Risk managers should educate the public about the value of performing risk reduction and risk retention measures such as social distancing and saving money. This is because attitude toward that strategy is a significant factor for behavioral intention. Following this, risk managers should emphasize the values of performing a strategy for the community as a whole. They should cultivate a shared sense of responsibility in society. In this way, the subjective norm of performing protective behaviors would be encouraged, which would have a significant effect on behavioral intention. Furthermore, risk managers can provide additional resources and budgets such as face masks to enhance individuals' abilities to adopt risk reduction measures. Thus, the perceived behavioral control of performing protective strategies would be strengthened, which would have a significant effect on behavioral intention. Meanwhile, risk managers should highlight the risks of COVID-19 infection and the risks of long-term COVID-19 containment to the public. This is because risk perception has been found to have a positive effect on behavioral intention.

Finally, when it comes to risk avoidance and risk transfer measures, risk managers should focus on the attitude of individuals towards the pandemic and their perception of risk. This is because these internal attributes have a significant effect on behavioral intention. Although no material resources from individuals are necessary to perform risk avoidance and risk transfer measures, self-sacrifice on freedom such as avoiding travel or social distancing is strongly required. Therefore, to motivate risk avoidance and risk transfer measures, risk managers should explore new ways of management based on local needs.

Appendix A. Survey instrument

Construct/Item	Mean	S.D
Intention (IN) IN_*risk_avoidance*		
IN1 I will avoid consuming imported food (e.g., seafood) which may has coronavirus	3.79	0.85
IN2 I will avoid travelling in the next few months	3.68	0.97
IN_*risk_reduction*		
IN3 I will get vaccinated ASAP when a COVID-19 vaccine is officially approved	3.34	0.85
IN4 I will stockpile face masks and disinfection in the next few months	3.78	0.95
IN5 I will use disposable chopsticks when eat outside in the next few months	3.74	0.94
IN_*risk_transfer*		
IN6 I will borrow money from banks or friends in the next few months	2.59	0.97
IN7 I will buy multiple medical insurance in the next few months	3.23	0.92
IN_*risk_retention*		
IN8 I will save money in the next few months	3.88	0.93
IN9 I will reduce consumption in the next few months	3.61	0.94
Attitude (AT) AT_*risk_avoidance*		
AT1 I do not think avoid consuming imported food would reduce the choices of delicious food	3.60	1.03
AT2 I do not think avoid travelling would restrict personal freedom	3.69	1.05
AT_*risk_reduction*		
AT3 I do not think get a COVID-19 vaccine would undermine the health status	3.39	1.11
AT4 I do not think stockpile face masks and disinfection is waste of money	3.91	1.10
AT5 I do not think use disposable chopsticks would violate dining etiquette	4.01	1.08
AT_*risk_transfer*		
AT6 I think borrow money from banks or friends is necessary and possible	3.30	1.03
AT7 I think buy multiple medical insurance is beneficial	3.86	1.02
AT_*risk_retention*		
AT8 I do not think save money is out of date	3.82	1.01
AT9 I do not think reduce consumption is out of date	3.70	1.02
Subjective norm (SN)		
SN_*risk_avoidance*		
SN1 When I plan to avoid consuming imported food, I hope my family/friends are willing to avoid together	3.59	0.90
SN2 When I plan to avoid travelling, I hope my family/friends are willing to avoid together	3.52	0.89
SN_*risk_reduction*		
SN3 When I plan to vaccinate against COVID-19, I hope my family/friends are willing to vaccinate together	3.36	0.88
SN4 When I plan to stockpile face masks and disinfection, I hope my family/friends are willing to stockpile together	3.88	1.02
SN5 When I plan to use disposable chopsticks, I hope my family/friends are willing to use together	3.74	1.10
SN_*risk_transfer*		
SN6 When I plan to borrow money from banks or friends, I hope my family will not look down on me	3.13	1.19
SN7 When I plan to buy multiple medical insurance, I hope my family/friends will buy together	3.54	1.06
SN_*risk_retention*		
SN8 When I plan to save money, I hope my family/friends will save together	3.90	1.01
SN9 When I plan to reduce consumption, I hope my family/friends will reduce together	3.65	1.06
Perceived behavioral control (PBC) PBC_*risk_avoidance*		
PBC1 I can resist the temptation and avoid consuming imported food during the pandemic	3.62	0.91
PBC2 I can resist the boring and avoid travelling during the pandemic	3.17	0.89
PBC_*risk_reduction*		
PBC3 I can accept the side effect and vaccinate against COVID-19	3.26	0.97
PBC4 I can buy and stockpile face masks and disinfection during the pandemic	3.55	0.86
PBC5 I can insist using disposable chopsticks during the pandemic	3.83	0.91
PBC_*risk_transfer*		
PBC6 I can borrow money from banks or friends during the pandemic	3.05	1.08
PBC7 I can buy multiple medical insurance during the pandemic	3.74	1.06
PBC_*risk_retention*		
PBC8 I can insist saving money during the pandemic	3.65	1.10
PBC9 I can insist reducing consumption during the pandemic	3.43	1.06
Risk perception (RP) RP1 I'm worried about infecting with COVID-19	3.39	0.99
RP2 I'm worried about the sequel from COVID-19 infection	3.72	0.99
RP3 I'm worried about the interruption of career development from COVID-19	3.56	0.97

Appendix B. Correlation matrix (ranges from — 1 to 1)



Abbreviations

GDP	Gross domestic product
WHO	World Health Organization
TPB	Theory of planned behavior
E-TPB	An extended version of the Theory of Planned Behavior
SEMs	Structural equation models
ML	Maximum likelihood
CFI	Comparative-fit index
RMSEA	Root mean square error of approximation
RA	Risk avoidance
RD	Risk reduction
RT	Risk transfer
RR	Risk retention

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XJ research design, methodology, data analysis. XW questionnaire design, data collection. YS literature review, methodology, text writing. LY questionnaire design, methodology, data collection. ZL questionnaire design, data collection. SS text revision. All authors contributed to and have approved the final manuscript.

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Data availability
The datasets collected and analysed in the current study are not publicly available due to respondents' privacy, but are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that the work has not been published previously, that it is not under consideration for publication elsewhere, that its publication is approved by all authors, and that, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.

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