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Research article

Uncovering the behavioral determinants behind private car purchase intention during the new normal of COVID-19: An empirical investigation in China

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Abstract: Based on the Protection Motivation Theory (PMT), the Psychological Reactance Theory (PRT), and the Theory of Planned Behavior (TPB), we revealed the psychological impact factors of individuals' private car purchase intentions during the new normal of COVID-19. Structural equation modeling (SEM) and Bayesian network (BN) were used to analyzed the car purchase decision-making mechanism. A questionnaire survey was conducted to collect empirical data from April 20th to May 26th of 2020 in China. We investigated 645 participants and analyzed the data. The SEM results showed that conditional value, pro-car-purchasing attitude, and perceived behavioral control, health value, and cost factors have significant direct effects on car purchase intention. According to BN's prediction of purchase intention, the probability of high purchase intention grew by 47.6%, 97.3% and 163.0%, respectively, with perceived behavioral control, pro-car-purchasing attitude, and conditional value shifting from "low" to "medium" and "high". This study provided a new perspective for researchers to explore the purchase intention of cars during the epidemic. Meanwhile, we could provide a reference for the government and enterprises to develop measures related to the automobile market."

Keywords: Bayesian Network; COVID-19; Intention to purchase; Protection Motivation Theory; Psychological Reactance Theory

1. Introduction and literature review

1.1. Introduction

As one of the world's largest automobile markets [1], the automobile industry in China has become the backbone of the national economy [2]. However, an unexpected global pandemic, coronavirus (COVID-19), brought the automobile market to its knees [3]. As the global automobile industry slumped [4], China's automobile market sales fell 42% in the first quarter of 2020 compared with 2019 [5]. With the outbreak under effective control, China has entered the ongoing prevention and control stage by the end of April 2020 [6]. Although crowd-gathering activity is still restricted, people's work and daily life have returned to a new normal [6,7]. China's automobile market is on the road to recovery with the arrival of the new normal [8].

Nevertheless, the journey to recovery has not been smooth sailing. Without a complete understanding of the concerned factors when people decide to buy private cars, the development of the market will be seriously hampered [9]. At the crucial stage of recovery in the automobile market, it is significant for public policymakers, corporate marketers and researchers to re-understand the influence factors and internal mechanisms of people's car purchase intentions. This knowledge could be used to explain and predict the changes in people's car purchase needs, and then adjust sales strategies and related policies [10]. However, the world has not emerged an epidemic on this scale in over a century, and few existing consumer behavior studies could guide the work [11,12].

Previous research revealed consumers' purchasing intention towards different powered vehicles with the absence of infectious diseases, such as fully electric vehicles [13], new energy vehicles [14] and regular cars [15]. Limited research analyzed people's intentions to buy cars during the COVID-19 pandemic [10,16], while individual behavior has changed significantly in response to the epidemic [17]. Analyzing people's psychological changes could provide a better understanding of an individual's car purchasing behavior under the influence of COVID-19. On the one hand, restrictions on activities might create rebellious psychology that increases people's interest in travel [18,19]. Private cars with better isolation could reduce COVID-19 infection risk and protect individuals' health compared with public transport [20]. Therefore, people's desire for private car travel has been stimulated due to the attention to health, which may translate into the demand to purchase private cars [21,22]. On the other hand, the brutal blow of COVID-19 creates a disruption in economic health (e.g., earnings, jobs) [4,23], which may pent up consumers' demand to buy private cars [10]. Overall, people's private car purchase decision is a contradictory and complicated psychological process during the new normal of COVID-19. It is necessary to understand further the psychological factors that affect individuals' private car purchase intentions and decisions at this stage. From the perspective of individuals' psychology, this research makes the first attempt to explore the influence factors of their intentions to buy private cars during the new normal of COVID-19.

1.2. Literature review

A growing number of researchers have investigated consumers' intentions concerning car purchases from a psychological perspective. We have reviewed the previous studies for a more comprehensive understanding of the research status. Table 1 summarizes relevant studies in the field of car purchase intention.

Table 1. Consumers' purchasing behavior of vehicles in existing research.

Authors	Vehicles	Theoretical model	Mathematical model
Peters et al. [24]	Fuel-efficient vehicles	TPB	SEM
Yusof [25]	Environment-friendly automobile	/	SEM
Bockarjova and Steg [26]	Full electric vehicles	PMT	Multiple linear regression model
Afroz et al. [27]	Environmentally friendly vehicles	TPB	SEM
Wang et al. [15]	New energy vehicles	TPB	SEM
Ng et al. [28]	Electric vehicles	TPB	SEM
Mohiuddin et al. [29]	Green vehicles	TPB	SEM
He, Zhan, and Hu [30]	Electric vehicles	The valence framework	SEM
Lin and Wu [31]	Electric vehicles	TPB	Ordered logistic regression model
Huang and Ge [32]	Electric vehicles	TPB	SEM
Dong et al. [33]	Pure electric vehicles	TPB, Norm activation model (NAM)	SEM
Yan et al. [10]	Private cars	/	SEM
Sobiech-Grabka, Stankowska and Jerzak [34]	Electric vehicles	/	Machine learning methods
Vafaei-Zadeh et al. [35]	Electric vehicles	TPB, TAM	PLS-SEM
Krishnan and Koshy [36]	Electric vehicles	/	SEM
Zang, Qian and Jiang [37]	Electric vehicles	TPB, TAM, TRA	SEM
Lin and Shi [38]	New energy vehicles	/	PLS-SEM
Hamzah and Tanwir [39]	Hybrid vehicles	NAM, TPB	PLS-SEM
Lin, Wu and Xiong [40]	New energy vehicles	/	SEM
Shanmugavel and Micheal [41]	Electric vehicles	TAM	SEM
He et al. [42]	Electric vehicles	TPB	SEM
Ackaah, Kanton and Osei [43]	Electric vehicles	TPB	SEM
Marina et al. [16]	Private cars	TPB	PLS-SEM

Most research on "private car purchase intentions" has been modeled based on the structural equation model (SEM) based on the theory of planned behaviour (TPB). The results of previous studies have revealed the impact of different factors on individual car purchase intentions. Nevertheless, they have mainly focused on a normalized social order. The emergence of COVID-19 has brought new challenges to using and purchasing private cars. The research on private car purchase intention during COVID-19 is limited and insufficient. Marina et al. [16] explored the psychological factors influencing an individual's intention to purchase private cars during COVID-19, using TPB as the theoretical framework and modeling by PLS-SEM. Yan et al. [10] explored individual car purchase intentions during COVID-19 in terms of objective variables by the hybrid choice model.

Nevertheless, SEM could only measure linear relationships between variables, whereas it has poor predictive power. Bayesian network could remedy this gap. We integrated the two methods to provide more reliable modeling results. In addition, using TPB is not enough to explain car purchase intention during COVID-19. Considering the various nuisances that COVID-19 causes to people, we combined TPB, PMT and PRT to identify psychological factors that could influence consumers' intentions to buy private cars.

Based on the above analysis, we reviewed from two perspectives: mathematical model and theoretical framework. Moreover, demonstrate in detail the reliability of our methods.

In the modeling approach, existing research on car purchasing behaviors mostly used the structural equation model (SEM) to explore the interrelationship among various factors in the modeling approach. SEM deals with the interactions between latent (unobserved) variables presented in a linear combination of observed variables [44]. SEM can also quantitatively assess the combined effects of each influencing factor on target variables by measuring the correlations of independent variables [45,46]. Therefore, SEM provides us with an effective tool to analyze the interaction of various psychological factors that may affect an individual's car purchasing intention during the new normal of the COVID-19 pandemic. Nevertheless, SEM lacks predictive power mainly because it builds a linear relationship model. If these relationships are non-linear, the potential effect of the independent variable in explaining the variance of the dependent variable is not known with precision, leading to limitations in managerial decision support [47]. This limitation can be remedied by the BN. As with SEM, BN is a graphical model for depicting causal relationships with empirical data [48,49]. The difference is that the validity of the theoretical construction is evaluated by statistical hypothesis testing analysis in SEM, whereas BN is a model based on probabilistic reasoning from conditions to outcomes or from outcomes to conditions [50]. However, BN has a less theoretical explanation and cannot distinguish between latent variables and observed variables, which is achieved by using SEM with theoretical foundations [48,51].

The existing researches have confirmed the applicability of the combination of SEM and BN. Wipulanusat W et al. [52] examined the innovation process in the Australian Public Service (APS) using a BN founded on an empirically derived SEM. Kenett R S et al. [53] assessed the impact of pandemic management and mitigation policies on pandemic spread and population activity using BN and SEM. Gupta and Kim [48] adopted a two-step method integrating SEM and BN to analyze customer retention in virtual communities. They first set up the SEM to establish the causality in latent factors as the network structure of the BN modeling. Then, prediction and diagnosis in BN were implemented to provide managerial decision support. By applying the integrated approach, they examined what factors have causal effects on customer retention and how to support decision-making regarding customer retention with prediction and diagnosis. Subsequently, the combination of SEM and BN has been addressed in several studies on ecological modeling [54], career satisfaction [52], and red meat consumption [55]. However, few scholars applied SEM and BN simultaneously to the authors' knowledge regarding purchasing vehicles under the influence of the COVID-19 epidemic. We attempted to combine the SEM and BN to analyze the causal relationships among the influence factors of car purchase intention during the new normal of COVID-19 and reflect the influence degree. It is consistent with scenarios from previous studies. In general, the determining factors of car purchasing intention can be identified by using SEM, and the BN tells us how these factors will affect purchase intention. These two methods' integration is designed to provide a more reliable understanding of the primary reason influencing individual automobile consumption and provide a reference for management decisions.

Table 1 shows that most scholars used various theoretical models to explore the influence factors of car purchase intentions. Considering the theoretical model's importance, we proposed an integrated theoretical model based on previous studies to investigate consumers' car purchase intentions during the new normal of COVID-19. As seen in prior studies, theoretical integration can be regarded as a form of theoretical contribution. Lim et al. [56–59] integrate theories in the studies of consumer behavior; Katou [60] and Rahman [61] made a similar attempt in the field of human resource management. These studies provide us with inspiration for our own theoretical integration.

TPB aims to explain human behavior and has been widely used to predict individuals' intentions, such as pro-environmental intentions [62], health-related intentions [63] and re-purchase intentions [64]. These studies show that TPB has predictive power on an individual's intention. Therefore, we introduce TPB as our theoretical model to explore consumers' intention to buy private cars.

However, TPB may not be sufficient to explain car purchase intentions during the new normal of COVID-19. Yan et al. [10] pointed out that the COVID-19 poses a potential threat to human health and the public panic and fear in reaction to the breakout and prevalence of COVID-19 could be considered a health threat, causing people to build protection motivation and change behavior. Protection motivation theory (PMT) could explain and predict an individual's intention to take protective actions in fear-related cognitive processes [65]. Zhang et al. [66] examined the factors that influence the parental choice of school travel mode during COVID-19 on PMT. Thus, we make the first attempt to apply PMT to examine whether fear of the epidemic and self-protect consciousness would prompt people to buy private cars.

Besides, in response to the epidemic, the Chinese government restricted public transport on a large scale during the severe outbreak of COVID-19, causing inconvenience for people to travel [6]. According to the psychological reactance theory (PRT) [18], the individual reactance would be aroused when behavioral freedom is lost or threatened. Thus, the desire to be free again makes an individual motivated to reassert this freedom and related goods [19]. Private cars could ensure people's freedom of travel, which might become popular for individuals when there have some restrictions on travel. Therefore, we creatively use PRT to examine whether psychological reactance influences consumers' car purchase intentions.

To some extent, TPB complements PMT and PRT research. As mentioned earlier, PMT focuses primarily on exploring psychological pathways - describing the influence of fear appeals in attitude shaping, and PRT describes the influence of resistance psychology. While TPB measures the influence of consumers' internal beliefs and self-assessments on their intention to adopt a certain behavior. Lu et al. [67] emphasized that constructing a theoretical framework is a critical step to ensure measurement accurately, and it could better reflect and explain the interaction among predictor variables in behavior studies. Therefore, integrating these three theories provides us a better foundation for understanding individuals' private car purchase intentions.

In conclusion, we construct and examine a comprehensive theoretical model, which combined with TPB, PMT and PRT to identify psychological factors that could influence consumers' intentions to buy private cars. Also, we use health value and cost factors to reflect consumers' ambivalence to purchase private cars. Moreover, conditional value and fear are also employed to expand the theoretical model.

Therefore, to the best of our knowledge, limited research analyzed people's intentions to buy cars during the COVID-19 pandemic. Moreover, multiple mathematical approaches to uncovering relationships among variables and predicting the effects have not been studied enough. This manuscript aims the answer three research questions:

(1) During the new normal of COVID-19, how to model people's private car purchase intentions?

(2) What are the main concerns for people to buy private cars during the new normal of COVID-19?

(3) To what extent the factors could influence people's private car purchase intentions?

After answering these questions, the contributions of this research mainly include the following two aspects: A cross-domain integration of the PMT, the PRT, and the TPB built the comprehensive theoretical framework. The integrated theoretical framework provides research ideas for exploring people's intention to buy cars during the new normal of a pandemic. Moreover, the attempt to combine the SEM and BN to analyze the relationships among factors of car purchase intention during the new normal of COVID-19. The research paradigm could also provide new insight into consumers' purchase intention with the influence degree of independent variables.

The remainder of this paper is organized as follows: After the introduction, section 2 issues the hypotheses of this research. The data collection process and introduction to methodologies are described in section 3. Section 4 outlines the research results. Based on the results, section 5 discusses the research findings and implications. Finally, the research conclusions, limitations and potential opportunities for future research are put forward in section 6.

2. Hypotheses development

As described in Section 1, our study contributes to the understanding of individual' intentions to purchase a private car under the COVID-19. TPB, PMT and PRT are combined to provide a relatively comprehensive analysis of consumer psychological variables. Based on the integrated theoretical model, we propose fifteen hypotheses for this study.

2.1. Hypotheses based on TPB and PMT

As a theory originated from the TRA, TPB has the main goal to predict human behavior [68], which assumes that attitude and perceived behavioral control (PBC) are the key influence factors of individuals' behavioral intentions [69]. In this study, purchase intention (PI) is the dependent variable, defined as individual intentions to purchase private cars during the new normal of COVID-19. Attitude could reflect an individual's emotional position. This research uses pro-car-purchasing attitude (PA) to reflect individuals' emotional position of buying private cars. The more favorable an individual's attitude toward purchasing private cars during the new normal, the higher probability this person would intend to buy [15]. In this case, perceived behavioral control is the individuals' perceptions of their abilities to buy private cars in the context of COVID-19. Consumers' desire to purchase private cars would become more potent when they found the consumption is within their ability [32]. Based on the above viewpoints, we proposed the following hypotheses:

H1: Pro-car-purchasing attitude positively affects the purchase intention;

H2: Perceived behavioral control positively affects the purchase intention.

In being adapted from the expectancy-value theory, PMT explains individuals' psychological responses to potential threats [65]. It theorizes that individuals' intent to protect themselves from a noxious situation is formed by two appraisal channels: threat appraisal and coping appraisal [70]. The threat appraisal could be divided into perceived severity (PS) and perceived vulnerability (PV) [71]. In this study, perceived severity means an individual's judgment of the seriousness of COVID-19 and its consequences, and perceived vulnerability is defined as the estimation of the likelihood of infecting COVID-19. Generally, persons will adjust their response to the threat according to the risk level [72,73]. Accordingly, individuals' perceived severity and perceived vulnerability would promote their attitudes toward self-protection behavior [70,74]. The primary construct of the coping appraisal is response efficiency and self-efficacy [71]. Response efficiency (RE) is a person's belief that private cars will effectively reduce their infection probability in this research. In this case, self-efficacy means a persons' level of confidence that they could buy private cars. Individuals' attitudes towards countermeasures will change better when they realize it is practical and easy to take [71]. Therefore, the response efficiency and self-efficacy may advance the attitude towards self-protection behavior [70]. Furthermore, considering the same meaning of self-efficacy and perceived behavioral control, we integrate self-efficacy into perceived behavioral control [75,76]. In conclusion, the following hypotheses are drawn:

H3: Perceived severity positively affects pro-car-purchasing attitude;

H4: Perceived vulnerability positively affects pro-car-purchasing attitude;

H5: Response efficiency positively affects pro-car-purchasing attitude;

H6: Perceived behavioral control positively affects pro-car-purchasing attitude.

2.2. Hypotheses based on TPB and PRT

PRT posits that people believe they are free to engage in behaviors. If this behavioral freedom is threatened, eliminated, or reduced, they may experience psychological reactance, a state of motivational arousal. As a result, they are likely to act negatively to restore their threatened or lost freedom [74]. Specifically, PRT contains a four-stage process: freedom, threat to freedom, reactance and restoration of freedom [77,78]. Threat to freedom (TF) means any external stimulus like explicit and publicized persuasive messages may threaten an individual's freedom [79,80]. Such as classroom policies [81], climate change [82] and consumption restrictions [83]. Reactance is a motivational state that occurs when a person's freedom is lost or threatened [18]. It can be measured as anger and negative cognitions [77]. For instance, consumers feel that their ownership of seeking goods is threatened when they are restricted to touch products. Such perceptions of freedom threat may bring a reactance process and evoke a stronger desire to touch products [83].

Previous studies have researched the relationship between threat to freedom and reactance. Threat to freedom is considered an antecedent to reactance [77,84]. In particular, Dillard and Shen [77] have proposed an intertwined model, which showed that threat to freedom could be used as an exogenous variable to predict reactance. The authors emphasized that a higher freedom-threatening would induce a higher level of reactance.

In our study, threat to freedom means individuals feel their travel freedom has been reduced, manipulated, or threatened due to the restrictions on crowd gathering activities, and the inconvenience of public transportation during the new normal of COVID-19. These types of restrictions lead to more cravings for outdoor activities than usual, which refers to the meaning of reactance in this study. Therefore, we propose:

H7: Threat to freedom positively affects reactance.

Previous studies have also shown that reactance could facilitate outcome variables like attitudes and behavioral intention in the context of persuasive messages [77,78]. For example, Feng et al. [78] found that users' psychological reactance to the way new technologies popularized directedly influence their attitudes and adoption intention. In our study, reactance toward travel restrictions will generate the desired behavior change associated with travel. Specifically, COVID-19 has a significant scaling down of crowd activities, public transportation becomes inconvenient because of the restrictions, such as wearing masks and showing health codes [85]. The restrictions on public travel induce people's psychological reactance, given an increasing desire to travel freely [9]. Under the circumstances, people are eager to buy related goods that could assist them to restore freedom of travel [22]. And private cars could ensure people's freedom of travel during the new normal of COVID-19, which might become a popular good for individuals. Hence, this research expects that the desire for travel freedom can result in consumers' car purchase intentions. The following hypotheses are proposed:

H8: Reactance positively affects pro-car-purchasing attitude;

H9: Reactance positively affects the purchase intention.

2.3. Cost factors, health value, conditional value and fear

The outbreak of COVID-19 has a detrimental effect on the economy, which leads to the decline of some family incomes. When consumers concern their economic situation, they will not tend to purchase durable goods like cars [86]. Hence, the cost factors (CF) are involved in the research model to reveal the negative influence of buying private cars during the new normal of COVID-19. Referring to the research of Dong et al. [33], cost factors in this study include private car price, price of fuel, parking cost, and the cost of private car maintenance. The hypothesis is introduced as follow:

H10: Cost factors negatively affect purchase intention.

Health value (HV) is usually used to reveal the attention that individuals care about their health. A previous study noted that health value might regulate the behavior intentions of individuals [87].

Zhang et al. [74] suggested that individuals' health value positively influences the behavioral intention to use mobile health services. In this research, health value is involved in estimating individuals' intentions to buy private cars due to the concern about their health during COVID-19. We assume that the higher individuals place value on their health, the more likely they exert effort to take measures to protect themselves from infection with COVID-19. Compared with public transport [16], private cars with better isolation have a lower probability of infection with COVID-19 and protect individuals' health. Meanwhile, health value could be used as a positive factor influencing consumers' car purchase intentions during the new normal of COVID-19, which could compare with cost factors. Hence, the following hypothesis is proposed:

H11: Health value positively affects the purchase intention.

Subsidies from both central and local governments could reduce the cost of car purchases and affect the intention to buy private cars [88]. Previous studies used conditional value to describe government subsidies or preferential treatment from automobile enterprises [89,90]. The definition of conditional value (CV) is the choice maker's perceived utility when they face a specific situation or circumstance [91]. It has been found that conditional value is a powerful influence predictor of consumers' choice behavior [92]. Some researchers analyzed new energy vehicles' purchase intention, which involved the conditional value factor. The results of these studies indicated that financial subsidies and discounts are the primary motivations for consumers to buy new energy vehicles [92,93]. Consumers can not realize the conditional value until the condition changing the behavior emerges [94]. Under the particular condition of COVID-19, the financial subsidies and discounts from automobile enterprises are likely to ease the individuals' pressure on car purchases and drive consumers to buy vehicles. Hence, the following hypothesis is developed:

H12: Conditional value positively affects the purchase intention.

In a previous study, fear was conceptualized as an emotional state, which could stimulate individuals to escape or avoid harmful events, and arouse the individuals' protection motivation [65]. Ronald C. and Nick [95] used PMT to estimate the dietary change behavior to prevent cardiovascular disease, which concluded that fear arousing protection motivation significantly affects perceived severity, perceived vulnerability and response efficiency. Mesch and Schwirian [96] examined vaccination behavior during the Ebola outbreak, which suggested that individuals may engage in self-protective behavior when they fear an infectious disease. The more fearful individuals are, the more likely they are willing to get a vaccination for Ebola. In this research, fear describes the fear of COVID-19, which may drive people to engage in self-protective behavior. Hence, we propose:

H13: Fear positively affects perceived severity;

H14: Fear positively affects perceived vulnerability;

H15: Fear positively affects response efficiency.

Figure 1 shows the basic constructs and variable relationships of the research model in this study. The dependent variable is the individuals' intentions to buy private cars during the new normal of COVID-19. The fundamental constructs of the proposed conceptual model are based on TPB, PMT, and PRT.

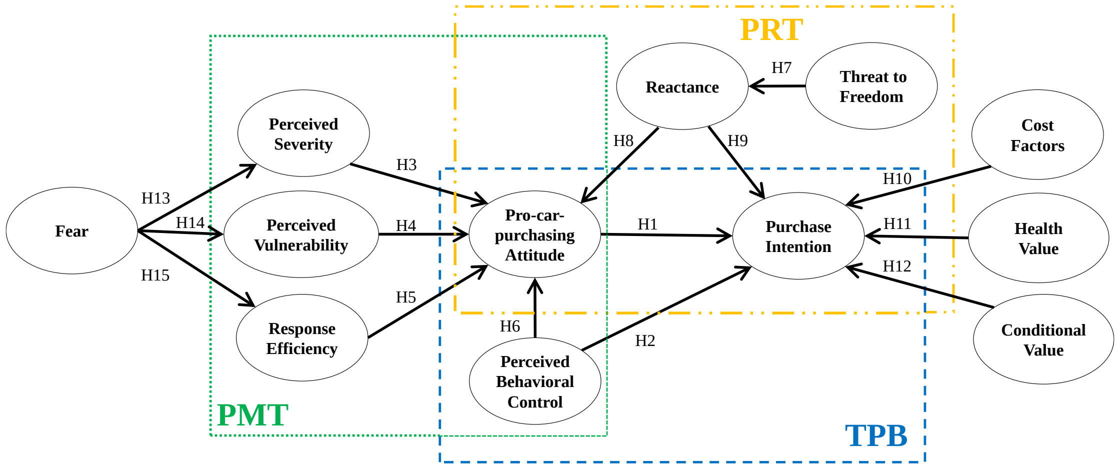


Figure 1. The proposed conceptual model and research hypotheses.

3. Methodology

We used questionnaires to collect the data for this study, and 645 questionnaires were collected from 29 provincial administrative regions. The SEM was used to test the correlation between the variables, which the model fitted well. The value of the discrete nodes was obtained by the factor score approach of the SEM as raw data for the BN modeling. Mplus and Netica were used to model the SEM and the BN, respectively.

3.1. Data and sample collection

A questionnaire survey was conducted to collect empirical data from April 20th to May 26th of 2020 in China. During the survey period, it is an appropriate time to conduct a questionnaire on car purchase intention during the new normal of COVID-19. Informed consent was obtained from all subjects involved in the study. Figure 2 showed a flow chart of the data sampling and processing. First, the questionnaire was proposed in the preliminary design stage after retrieving and summarizing the relative literature. The content of the questionnaire includes four parts: (1) a basic introduction to the purpose and background of the investigation; (2) sociodemographic characteristics; (3) psychological factors that may affect individuals' intention to buy a private car; (4) individual's WTP for purchasing a private car. Each psychological construct was measured with several items using a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree, with four serving as neutral). Appendix A presents the twelve constructs and items.

Second, we conducted a pre-investigation. A total of 104 volunteers were invited to complete the questionnaire. Some necessary adjustments and modifications have been made according to the feedback collected. Third, we used simple random sampling, in which consumers' car purchase intentions during the new normal of COVID-19. Considering that the face-to-face communication survey on the streets was inappropriate in a unique Chinese period of COVID-19 pandemic prevention and control work, we took an online survey to gather empirical data via Sojump (www.sojump.com).

Eventually, 645 questionnaires were collected from 29 provincial administrative regions in China. Moreover, after eliminating the invalid questionnaires with repeated IP addresses, logical errors, consistent answers and overlong or short filling time, 327 complete surveys were obtained with an efficient rate of 50.70%.

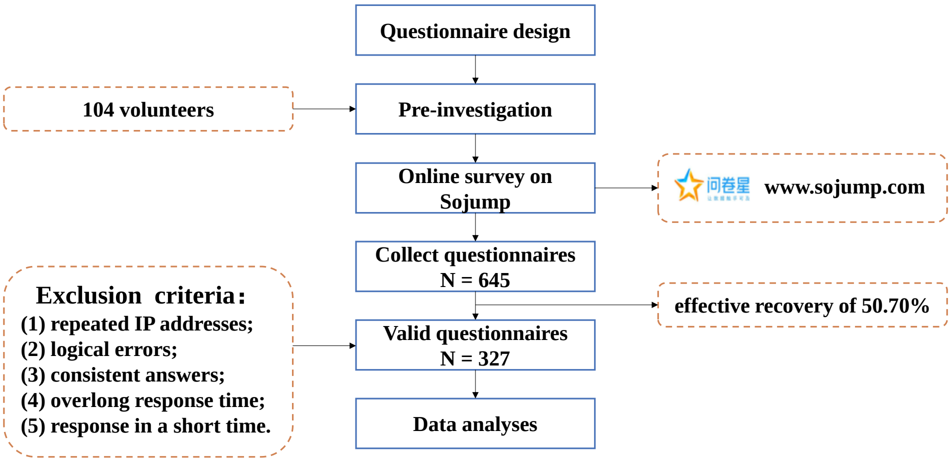


Figure 2. flow chart of data collecting and processing.

The socio-demographic information, including gender, age, education level and monthly income, is presented in Table 2. Specifically, the proportion of males (49.24%) and females (50.76%) in the sample is the same. Participants whose age distributes evenly between 20 and 49 have an equal proportion distribution, which the similar distribution is shown in the Chinese population [97]. More specifically, the ratio among 18-29 years old, 30-39 years old and 40-49 years old are 1.51:1.10:1, while the ratio of Chinese population among 18-29 years old, 30-39 years old and 40-49 years old are 1:1.20:1.21. Most of the sample respondents (52.9%) are middle-income and earn between 441 USD and 1323 USD per month.

To measure participants' WTP for private cars, we adopt the contingent valuation method (CVM) [83]. Participants were asked the question: "Assuming you will purchase a new private car during the new normal of COVID-19, how much are you willing to pay?" The question is adapted from the work of Kyriakidis and Happee [84] and Liu et al. [83]. A total of 11 alternatives are provided, from "8,085 USD" to " > 47,775 USD". The specific content is shown in Figure 3. According to WTP for private cars during the new normal of COVID-19, participants could be roughly grouped into three categories: participants were willing to pay less than 12,495 USD (13.79%), willing to pay for between 12,495 and 30,135 USD (66.67%), and willing to pay for more than 30,135 USD (19.57%). The second category's proportion was the highest, especially the WTP for 12,495–16,905, which accounted for 23.79%.

Table 2. Descriptive statistics of participant characteristics (N = 327).

Demographic variables		Sample size	Percentage
Gender	Male	161	49.24%
	Female	166	50.76 %
Age	18-29 years old	121	37.01%
	30-39 years old	88	26.91%
	40-49 years old	80	24.46%
	≥50 years old	38	11.62%
Education	Senior middle school or below	32	9.79%
	Junior college	86	26.30%
	Bachelor's degree	187	57.19%
	Master's degree or above	22	6.73%
Monthly income (USD)	<441	81	24.77%
	441-882	97	29.66%
	882-1323	76	23.24%
	1323-1764	44	13.46%
	>1764	29	8.87%
Number of vehicles at home	0	116	35.47%
	1	201	61.47%
	2	9	2.75%
	3	1	0.31%

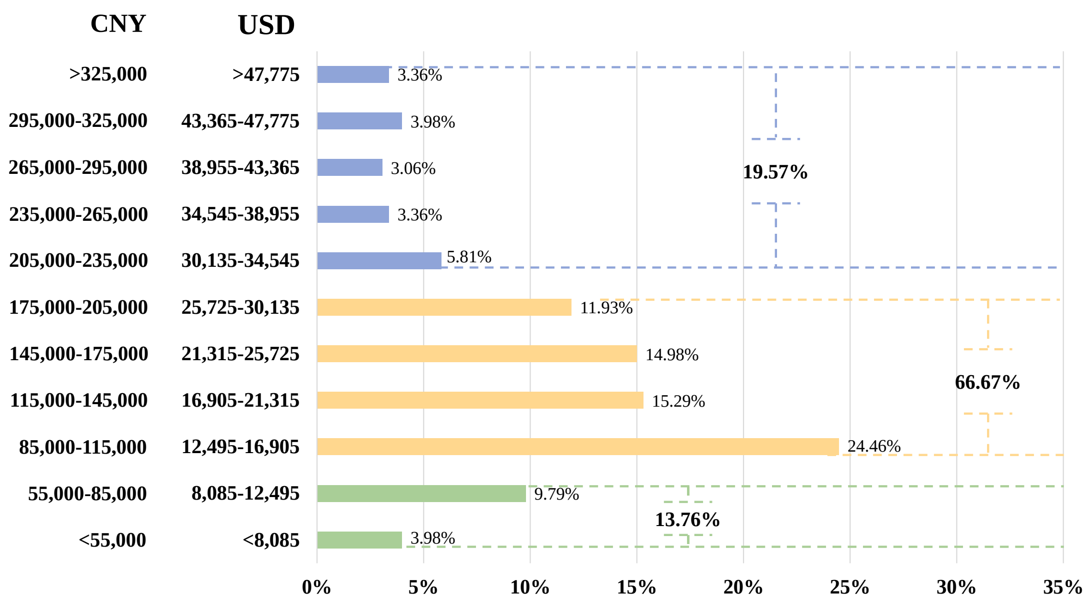


Figure 3. Participants' WTP for a private car.

3.2. Measurement model of SEM

SEM is a statistical method for analyzing the relationships between variables based on their covariance matrices. SEM typically includes the following three matrix equations:

$$\beta = A\beta + T\lambda + \xi \quad (1)$$

$$Y = \Delta y\beta + \varepsilon \quad (2)$$

$$X = \Delta x\lambda + \nu \quad (3)$$

Equation (1) is a structural model, where β refers to endogenous latent variable and λ an exogenous latent variable, A and T are the coefficient matrices and ξ is the error vector for each variable. Equations (2) and (3) are the measurement models, where Y is the observed variable of the endogenous latent variable, and Δy represents the correlation coefficient matrix between the endogenous variable and the observed variable, X is the observed variable of the exogenous latent variable, Δx is the correlation coefficient matrix between the exogenous variable and its observed variable; ε and ν refer to the measurement error.

First, this study performs a confirmatory factor analysis (CFA) to test the measurement model's reliability and validity. The standard loadings of items were above 0.6. A reliability test is used to measure the reliability and the internal consistency coefficient on the survey data. Appendix B shows that the Cronbach's alpha coefficients of all variables range from 0.74 to 0.90 which exceed the cut-off value of 0.70, indicating that this scale's design was reliable [98].The formula for Cronbach's alpha is:

$$\alpha = \frac{n}{n-1}\left(\sigma^2{}_X - \sum \sigma^2{}_i\right) \Big/ \sigma^2{}_X\ , \quad (4)$$

where n is the number of items, $\sigma^2{}_X$ is the total test score variance and $\sigma^2{}_i$ is the item variance.

The construct reliability (CR) values of all constructs range from 0.78 to 0.91, better than the recommended benchmark of 0.70. These results reveal that each construct's multi-measurement indicators' internal consistency was quite right, and the measurement model has adequate reliability [99]. The formula for CR is:

$$CR = \frac{(\Sigma\lambda)^2}{[(\Sigma\lambda)^2 + \Sigma\theta]}, \quad (5)$$

where λ is normalized parameters of the observed variables on the latent variables, θ is error variances of indicator variables and $\sum$ is sum of indicator variable values for potential variables.

Second, this study tests the measured variables' structural validity, including two crucial aspects: convergent and discriminant validity. Convergent validity (CV) is determined by evaluating CR and average variance extracted (AVE) [100]. All variables have AVE that exceeds the critical value of 0.5, proving that the measurement model has good convergent validity [99]. The formula for AVE is:

$$AVE = \frac{\left(\Sigma\lambda^2\right)}{\left[\left(\Sigma\lambda^2\right)+\Sigma\theta\right]}, \tag{6}$$

where λ is normalized parameters of the observed variables on the latent variables, θ is error variances of indicator variables and $\sum$ is sum of indicator variable values for potential variables.

Moreover, discriminant validity is the level at which a construct differs from other constructs. The values of AVE's root-squared for all constructs are greater than the correlation among the constructs, indicating that the measurement model has acceptable discriminant validity [99], as shown in Table 3. Thus, the CV and DV of the measurement tools in this study are favorable, indicating that this study's questionnaire has good structural validity and can be further analyzed.

3.3. Model construction of BN

BN uses prior probabilities and probabilities in the sample space to estimate posterior probabilities. Further, the posterior probability distribution of a variable is calculated from the new observations. In the graph, each parent represents the cause of an event, the children represent the results. The arrows indicate causality and the arrows between nodes indicate a Directed Acyclic Graph (DAG). Using parent (D) to denote the set of parents of D, the joint distribution of node values can be written as the product of the local distribution of each node and its parent, as follows.

$$P(A,B,C,D) = \prod p(D|parents(D)) \tag{7}$$

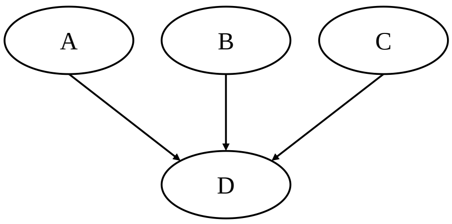


Figure 4. Example Diagram of Bayesian Network.

Structural learning and conditional probability estimation are two essential steps in BN modeling [101]. In this study, the structure through the SEM hypothesis testing will be the basic structure of the BN. In addition, discretization of nodes is needed before the conditional probability estimation, including determining the number of states and the cut-off values of the discrete states [54]. Specifically, in this research, the value of the discrete nodes was obtained by the factor score approach of SEM 123 as raw data for the BN modeling. In the next step, the number of states was classified as low, medium, and high using the method applied in Carfora et al. [55] based on a seven-point Likert scale:

(1) factor score range of 1–2 is considered "low";

(2) factor score range of 3–5 is considered "medium";

(3) factor score range of 6–7 is considered "high."

Table 3. Discrimination validity.

Construct	PS	PV	RE	Reactance	TF	HV	CV	Fear	CF	PA	PI	PBC
PS	0.772											
PV	0.227	0.722										
RE	0.223	0.205	0.740									
Reactance	0.063	0.058	0.057	0.822								
TF	0.151	0.139	0.136	0.419	0.776							
HV	0.154	0.141	0.138	0.066	0.159	0.762						
CV	0.225	0.207	0.203	0.195	0.465	0.397	0.768					
Fear	0.498	0.456	0.448	0.127	0.304	0.309	0.453	0.767				
CF	-0.005	-0.004	-0.004	0.046	0.110	-0.044	-0.108	-0.009	0.799			
PA	0.367	0.329	0.529	0.223	0.333	0.226	0.481	0.514	-0.235	0.807		
PI	0.211	0.192	0.232	0.158	0.308	0.354	0.628	0.376	-0.328	0.586	0.864	
PBC	0.175	0.161	0.158	0.143	0.343	0.220	0.561	0.352	-0.407	0.702	0.635	0.813

Table 5. Diagnosis of purchase intention.

State (high = 1)	**Variables**																					
	PS		**PV**		**RE**		**Reactance**		**TF**		**HV**		**CV**		**Fear**		**CF**		**PA**		**PBC**	
	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP
Low	0	0	0.02	0.02	0	0	0.14	0.13	0.04	0.04	0	0	0.02	0.01	0.05	0.04	0.12	0.13	0.02	0.02	0.09	0.09
Medium	0.22	0.20	0.79	0.78	0.38	0.34	0.65	0.65	0.63	0.63	0.18	0.18	0.54	0.39	0.73	0.72	0.81	0.80	0.63	0.50	0.59	0.46
High	0.78	0.80	0.19	0.20	0.62	0.66	0.21	0.22	0.33	0.33	0.82	0.82	0.44	0.60	0.22	0.24	0.07	0.07	0.35	0.48	0.32	0.45

Note: PCP: prior conditional probability, NCP: new conditional probability.

Table 4 shows the prior probability distribution of each node and state from the questionnaire. For the node "purchase intention," 6% of participants had "low" purchase intention, 57% and 37% of them were at "medium" and "high" levels of purchase intention, respectively.

Table 4. The prior probability distribution of each variable.

States	Variables											
	PS	**PV**	**RE**	**Reactance**	**TF**	**HV**	**CV**	**Fear**	**CF**	**PA**	**PI**	**PBC**
Low	0	0.02	0	0.14	0.04	0	0.02	0.05	0.12	0.02	0.06	0.09
Medium	0.22	0.79	0.38	0.65	0.63	0.18	0.54	0.73	0.81	0.63	0.57	0.59
High	0.78	0.19	0.62	0.21	0.33	0.82	0.44	0.22	0.07	0.35	0.37	0.32

The conditional probabilities can be estimated using algorithms from the dataset [52]. Since the network structure included latent variables that were not from direct observation, causing incomplete data in the BN system [102]. However, the expectation-maximization (EM) algorithm can process missing data and automatically calculate the conditional probability table (CPT) in BN [54]. Therefore, this research applied the EM algorithm in Netica software to develop and update the BN modeling. The updated network is presented in Figure 5.

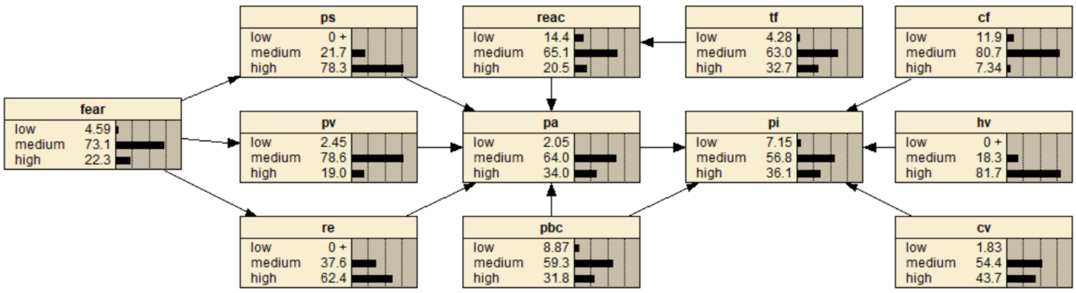


Figure 5. Updated BN using the EM algorithm.

After the BN modeling was determined, the predictive accuracy of the model should be evaluated. Error rate and confusion matrix are frequently used to test the BN performance. The sample dataset was randomly divided into 80% training data and 20% testing data in our study. Table 6 gives the validation results. The BN constructed in this study can predict the low state of purchase intention with 100% accuracy and predict 91.89% and 65.38% of the cases with medium and high purchase intention, respectively. The overall error rate is 18.46%. Besides, Spherical payoff, logarithmic loss and quadratic loss are effective indices that evaluate the performance of the BN [103]. A higher spherical payoff (close to one), a lower logarithmic loss (close to zero) and quadratic loss (close to zero) represent a better forecasting accuracy [103]. In this case, the values are 0.8648, 0.3851 and 0.2406, respectively. From the above indicators, we can conclude that the BN proposed in this study can provide a good prediction ability for the public's intention to purchase private cars during the new normal.

Table 6. Confusion matrix of the BN modeling.

Confusion matrix				Error rate	Total error rate
Predicted			Actual		
Low	Medium	High			
2	0	0	Low	0%	
1	34	2	Medium	8.11%	18.46%
0	9	17	High	34.62%	

3.4. Software description

We used Mplus and Netica as our analysis tools in this research. Mplus is used for SEM modeling, and Netica is used for BN analysis.

Mplus is a powerful multivariate statistical analysis software that integrates several latent variable analysis methods into a unified general latent variable analysis framework. These methods include exploratory factor analysis, structural equation modeling, item response theory analysis, latent class analysis, latent transition analysis, survival analysis, growth modeling, multilevel analysis, complex survey data analysis, monte carlo simulation, etc. Compared to other common software on the market, such as LISERL, EQS, AMOS, etc., Mplus has the most comprehensive function and is easy to operate. Thus, we choose Mplus to model the structural equation model.

Netica is the most used Bayesian network analysis software in the world. The development principle of this software is simple, reliable and efficient. This software supports system risk analysis, system failure simulation modeling, and other functions. Thus, we choose Netica for Bayesian network analysis due to its comprehensive functions and convenient operation.

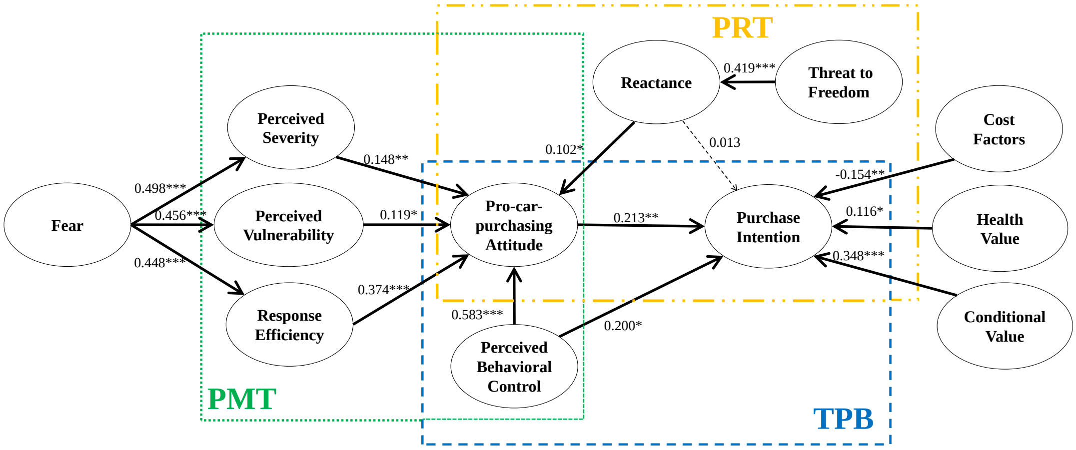
After analyzing our research methods and comparing the available software options, we chose to use these two softwares in our research, and their application has achieved excepted effect.

4. Results

The SEM results revealed what key factors affect individuals' intention to purchase vehicles under the normal of COVID-19. The results showed that the direct effect of reactance was not significant, while the rest were significant. The BN showed how these factors shape car purchasing intention. We give positive inferences about changes in purchase intentions for 11 factors. The variables of CV, PBC and PA have measurable effects on purchase intentions.

4.1. Structure model and hypothesis tests

The purpose of this study is to explore the influence of psychological factors on people's car purchase intention under the background of COVID-19. We constructed a theoretical model and used SEM to explore the relationships of psychological factors among the intention of purchasing cars during the new normal of COVID-19. The model is shown in Figure 6 SEM is a multivariate statistical tool, which can explore the relationship between latent variables and analyze the influence mechanism among them [104].



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

The dotted line indicates that the path is not significant.

Figure 6. Results of the structural model.

To test the validity of the model, evaluating the fitting effect is necessary. Previous studies have shown that the chi-square with degrees of freedom (χ^2/df) value is between 1 and 3, comparative fit index (CFI) and Tucker Lewis index (TLI) values are greater than 0.90 and the root mean square error of approximation (RMSEA) is smaller than 0.08, so the overall model would be regarded as excellent. Table 7 shows the fitting effect of the model. The results show that the model fitting effect is satisfactory (χ^2/df = 1.72, RMSEA = 0.047, CFI = 0.919, TLI = 0.926). The formulas are:

$$\chi^2 = \frac{N-1}{F\left(S;\hat{\Sigma}\right)}, \qquad df = \frac{k(k+1)}{2} - t \tag{8}$$

where N is the number of samples, $F\left(S;\hat{\Sigma}\right)$ is the value of the fitness function for estimating the post-model aggregation, S is the covariance matrix of the sample data, $\hat{\Sigma}$ is the covariance matrix implied by the hypothetical model, k is the number of observed variables and t is the number of estimated parameters. Further,

$$RMSEA = \sqrt{\frac{F_0}{df}} = \sqrt{\max\left(\frac{F_{ML}}{df} - \frac{1}{N}, 0\right)}, \tag{9}$$

where F_0 is the value as a function of overall variance and F_{ML} is the value of the fitness function estimated by the maximum likelihood method. Additionally,

$$CFI = \frac{\left(\chi^2_{null} - df_{null}\right) - \left(\chi^2_{test} - df_{test}\right)}{\chi^2_{null} - df_{null}} \tag{10}$$

$$TLI = \frac{\chi^2_{null}/df_{null} - \chi^2_{test}/df_{test}}{\chi^2_{null}/df_{null} - 1}, \tag{11}$$

where χ^2_{null} is the Chi Square value of the null model, χ^2_{test} is the Chi Square value of the hypothetical model, df_{null} is the degree of freedom of the null model and df_{test} is the degree of freedom of the hypothetical model.

Table 7. Results of the goodness of fit for the theoretical model.

Fit index	χ^2/df	RMSEA	TLI	CFI
Measured value	1.72	0.047	0.919	0.926
Standard value	$1 < \chi^2/df < 3$	<0.05	>0.90	>0.90
Adaptation judgment	Yes	Yes	Yes	Yes

Table 8. The result of path coefficients for each causal relationship.

Hypothesis	Path	Standardized Estimate	S.E.	*p*-value	Support
H1	PA → PI	0.213	0.079	0.007	Yes
H2	PBC → PI	0.200	0.091	0.028	Yes
H3	PS → PA	0.148	0.057	0.009	Yes
H4	PV → PA	0.119	0.051	0.020	Yes
H5	**RE → PA**	**0.374**	**0.059**	**0.000**	**Yes**
H6	**PBC → PA**	**0.583**	**0.047**	**0.000**	**Yes**
H7	**TF → Reactance**	**0.419**	**0.057**	**0.000**	**Yes**
H8	Reactance → PA	0.102	0.048	0.033	Yes
H9	Reactance → PI	0.013	0.050	0.797	No
H10	CF → PI	-0.154	0.053	0.004	Yes
H11	HV → PI	0.116	0.053	0.030	Yes
H12	**CV → PI**	**0.348**	**0.067**	**0.000**	**Yes**
H13	**Fear → PS**	**0.498**	**0.057**	**0.000**	**Yes**
H14	**Fear → PV**	**0.456**	**0.058**	**0.000**	**Yes**
H15	**Fear → RE**	**0.448**	**0.057**	**0.000**	**Yes**

Note: The bold content is path hypotheses, and their significance level is at $p < 0.001$.

Figure 6 shows the hypothetical paths' test results. The thick lines represent the significant paths, and a thin line represents the non-significant path. The specific test results of the hypothetical paths are shown in Table 8. The results show that all the hypotheses except H9 are supported at the significance levels of 0.05 and 0.001.

In order to ensure the stability and reliability of our model and hypothesis, a robustness check is conducted. We removed perceived behavioral control in our hypothesis path, and the results are presented in Table 9. It can be observed that the signs and significance levels of all the coefficients are pretty close to that in Table 8. After a modification of the hypothesis path, it is normal that the values of the coefficients are different. Therefore, we deem that the results we get are robust and credible.

Table 9. The result of the robustness checks.

Hypothesis	Path	Standardized Estimate	S.E.	*p*-value	Support
H1	PA → PI	0.360	0.060	0.000	Yes
H2	PBC → PI	-	-	-	-
H3	PS → PA	0.198	0.064	0.002	Yes
H4	PV → PA	0.127	0.058	0.029	Yes
H5	RE → PA	0.562	0.057	0.000	Yes
H6	PBC → PA	-	-	-	-
H7	TF → Reactance	0.418	0.056	0.000	Yes
H8	Reactance → PA	0.238	0.052	0.000	Yes
H9	Reactance → PI	0.020	0.055	0.712	No
H10	CF → PI	-0.224	0.050	0.000	Yes
H11	HV → PI	0.110	0.057	0.032	Yes
H12	CV → PI	0.413	0.063	0.000	Yes
H13	Fear → PS	0.499	0.057	0.000	Yes
H14	Fear → PV	0.459	0.057	0.000	Yes
H15	Fear → RE	0.453	0.056	0.000	Yes

4.2. Prediction and diagnosis

The SEM results can reveal what key factors affect individuals' intention to purchase vehicles during the new normal of the COVID-19 pandemic. While the BN modeling tells us how these factors shape car purchasing intention, expressing the causality between variables in graphs.

The two applications in BN are prediction and diagnosis [103]. Prediction refers to forwarding inference from cause to effect and can be used to learn the effect of the variation of various factors on the target node [47,52]. In the BN modeling, the actual implementation is to set the low, medium and high state of an influencing factor as 1.00, respectively, and observe the revised probability of the consequent node in the same three states. Figure 7 illustrates the forward inference in the changing of 11 factors on purchase intention. Conditional value, perceived behavioral control and attitude have a measurable effect on purchase intention. For example, as the node "pro-car-purchasing attitude" shifts from "low" to "medium" to "high", the low state of purchase intention has been falling steadily from 27.1% to 8.1%, the high state of purchase intention shows a rapid upward trend from 26.2% to 51.7%. When the probability of high-cost factors is 1.00, the chance of low purchase intention reaches 17.9%.

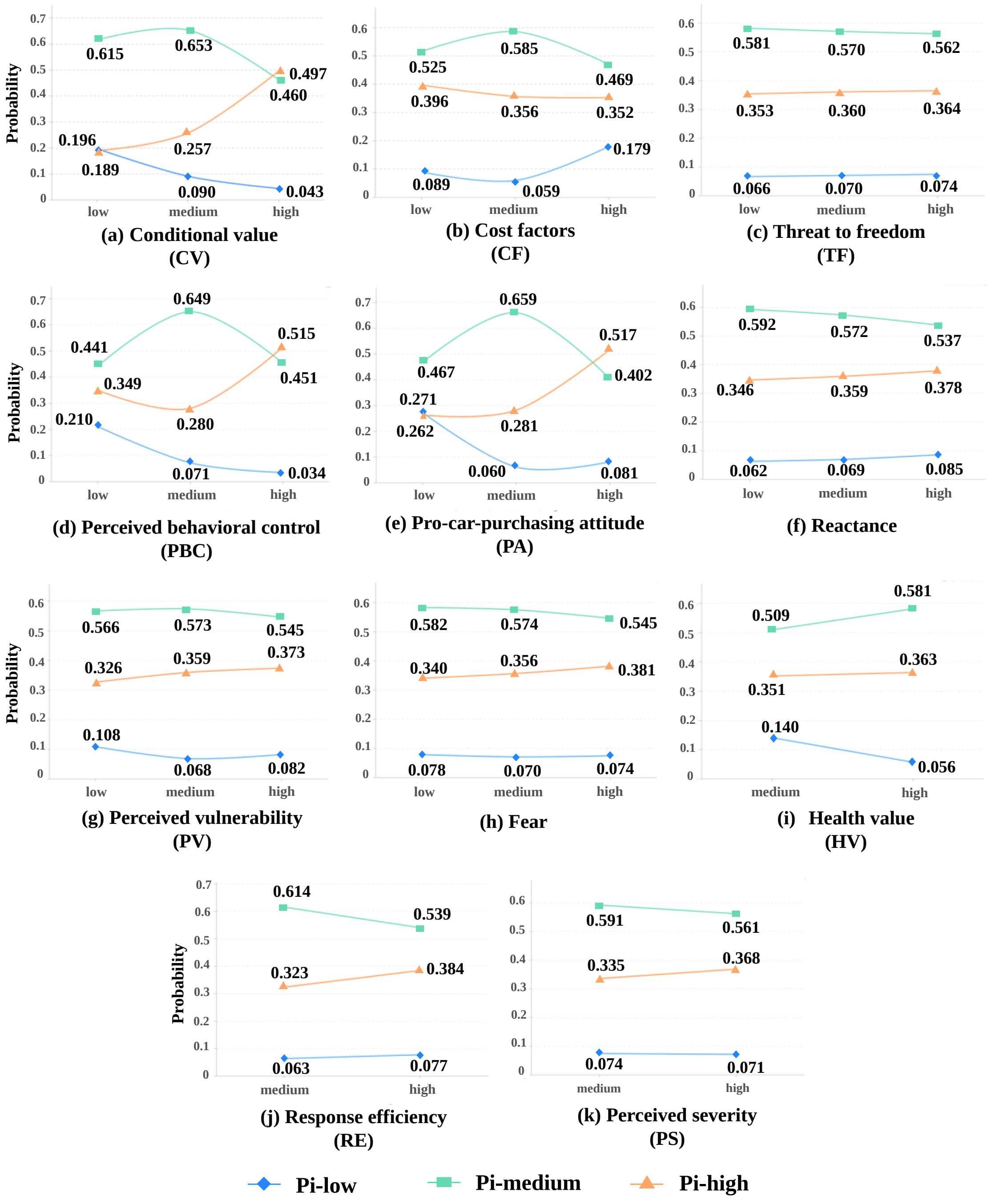


Figure 7. Prediction of purchase intention.

Diagnosis is a form of backward inference to be reasoned from effect to cause [47,52]. The approach in BN is to set the probability of the low and high state of the target node as 1.00, respectively, and observe the change of antecedents. Diagnosis enables decision-makers to understand what scenarios can achieve the 100% chance of high state occurrence of the specific node. It can be seen from Table 5 that there is a rising trend of the high state of all the variables, assuming a 100% probability rate of high purchase intention. The "high" number of perceived behavioral control has increased by 40.6% compared to the prior conditional probability, followed by pro-car-purchasing attitude (39.4%) and conditional value (38.2%), becoming the most influential factor.

5. Discussion

Few empirical studies currently exist elucidating what factors may affect individuals' private car purchase intentions during the new normal of a serious pandemic. This study investigates the psychological factors that may influence private cars' purchase intentions during the new normal of COVID-19 to address this caveat. The empirical findings provide new insights into the psychological factors that affect individuals' private car purchase intentions. The results of the survey are discussed below.

5.1. Theoretical implications

This research aims to study the psychological mechanism behind individuals' private cars purchase intention during the new normal of the COVID-19 pandemic. A theoretical framework includes PMT, PRT and TPB that was constructed according to 327 samples from an online survey. SEM was used to identify the determinants of purchase intention, and BN was adopted to analyze how these factors affect individuals' car-buying decisions. The combination of SEM and BN has been applied in previous studies in different areas [47,52,54]. This research carried out the causal modeling method of Gupta and Kim [47] on linking SEM to BN. The performance evaluation showed that the model could accurately predict the actual cases with an 18.46 error rate. Integrating the two methods could provide a more reliable explanation of the primary reasons affecting individuals' automobile consumption intentions.

5.1.1. Influence mechanism of cost factors and health value

The purchase of private cars is a contradictory and complicated process during the new normal of COVID-19. Traveling in a private car could effectively reduce contact with others and reduce the possibility of COVID-19 infection. People's emphasis on health may prompt people to buy private cars. However, the impact of COVID-19 on the economy may bring some economic pressure to people's purchase of cars and restrain the intention to buy cars. Therefore, people's emphasis on health and the economic pressure brought by COVID-19 are likely to affect intentions to buy cars, simultaneously.

Nevertheless, it is not yet known which of the two has a more substantial influence on purchase intention. Solving this problem could provide strong theoretical support for the government and enterprises to launch relevant market recovery policies and measures. Filling up this research gap is one of the essential purposes of this study.

This study introduces two important psychological variables to achieve the research goal: health value and cost factors. Health value reflects the degree of people's importance to health. The cost factors reflect the economic pressure on people brought by COVID-19. We use SEM to study the influence mechanism of health value and cost factors on intentions to buy cars, and use path coefficient β to analyze the strength of influence of different variables [104]. The results show that health value has a significant positive effect on intention ($\beta = 0.116, p < 0.05$), while the cost factors have a negative effect on intention ($\beta = -0.154, p < 0.01$).

People seem to pay more attention to cost factors than health value when buying private cars. We can conclude that intentions to buy private cars are likely to be more affected by economic pressures during the new normal of COVID-19. It is worth noting that the research results may be related to the research period. During this study, COVID-19 injured the economy as a whole so that people could pay more attention to the cost factors. However, people might pay more attention to health value if the investigation occurs during a severe outbreak of COVID-19. In general, people may be more affected by the economic pressure brought by COVID-19 when they buy a car under the background that COVID-19 has been controlled to a certain extent. This study may be the first to reveal the result of the game between health factors and economic factors in car purchase behavior during the new normal of COVID-19.

5.1.2. Influence mechanism of the extended PMT

To have in-depth knowledge about how people's self-protection awareness affects their intention to buy private cars during the new normal of COVID-19, we combine PMT with TPB and expand fear. Meanwhile, conditional value is also employed in the research model for considering the adjustment made by the government and automobile enterprises to the private car purchase market during the epidemic period. Our findings contribute to the theory in the following three aspects based on the integration of PMT and TPB expanded with fear and conditional value. First, we proved that the psychological factors related to threat appraisal and coping appraisal have strong explanations for the private car purchase intention during the epidemic outbreak. Second, we found that fear of the epidemic has a strong predictive effect on the variables of PMT, which is rarely taken into account by previous studies. Finally, the positive roles played by the government and automobile enterprises in the car purchase market during the epidemic period have also been confirmed.

The results reveal that fear significantly and positively affected perceived severity ($\beta = 0.498$, $p < 0.001$), perceived vulnerability ($\beta = 0.456$, $p < 0.001$) and response efficiency ($\beta = 0.448$, $p < 0.001$). As confirmed in the extended model, fear of infection with COVID-19 may arouse individuals' motivation to protect themselves, similar to the previous study [96]. Moreover, it is found that perceived severity ($\beta = 0.148$, $p < 0.01$) and perceived vulnerability ($\beta = 0.119$, $p < 0.05$) have significant effects on individual's pro-car-purchasing attitude during the new normal of COVID-19. This finding is consistent with the research results by Yang et al. [70]. The more serious the threat individuals face, the more likely protective measures would be taken. Perceived severity and perceived vulnerability are both threat appraisals, which describe individuals' feelings about COVID-19. Persons who think COVID-19 is the severity and vulnerable are more likely to have a positive attitude toward private cars purchase, leading to a car purchase intention. Meanwhile, as a factor revealing the coping appraisal, response efficiency ($\beta = 0.374$, $p < 0.001$) significantly influences individuals' pro-car-purchasing attitudes, which supports the claim of Yang et al. [70]. The result implies that people who think private cars could avoid infection when they travel are more likely to buy private cars, and travel by car is believed to effectively avoid infection with COVID-19.

An interesting finding is that perceive behavioral control, a critical factor that combines PMT and TPB has the most significant effect on pro-car-purchasing attitude among PMT variables. Additionally, perceived behavioral control could also significantly influence purchase intention in a positive way ($\beta = 0.200$, $p < 0.05$), which is consistent with the results of Huang and Ge [32]. These findings mean that the degree of easer perceived by consumers regarding purchasing private cars will improve their attitudes toward purchasing private cars and the intentions to buy them. Otherwise, we have verified the positive impact of conditional value on purchase intention ($\beta = 0.348$, $p < 0.001$), which is equal to Teoh and Nor Azila [93], and Zailani et al. [105]. This result reflects government subsidies, and automobile enterprise promotions would promote individuals' private car purchase intentions.

5.1.3. Influence mechanism of PRT and TPB

One of this study's primary objectives was to explore whether individuals' psychological reactance toward travel restriction influences car purchase intention during the new normal of COVID-19. Therefore, we advanced a combined model by applying both TPB and PRT. The empirical findings suggest that threat to freedom significantly influences reactance positively ($\beta = 0.419$, $p < 0.001$). It indicates that individuals with higher threatening travel freedom might experience relatively high reactance. The result is in line with previous researches [77]. Therefore, COVID-19 would cause a great deal of inconvenience on individuals' daily travel and induce their growing desire to travel more.

Following Dillard and Shen [77] and Feng et al. [78], this study hypothesized that reactance could lead to attitude and behavioral intention, two TPB variables. An interesting observation is that reactance does not significantly impact purchase intention. At the same time, it is positively associated with pro-car-purchasing attitude ($\beta = 0.102$, $p < 0.05$). Inconsistent with previous works, our result reveals that the desire to travel affects individuals' pro-car-purchasing attitudes, but not enough to affect their purchase intention. The explanation may be the individuals' concerns for car prices. In other words, consideration of car prices would decrease their intention to buy private cars, especially since there are adverse effects COVID-19 has on individual income. However, the strong demand for travel does make a difference in individuals' attitudes toward car purchases. People might be thinking about buying private cars out of travel restrictions. Notably, Dillard and Shen [77] and Feng et al. [78] attributed that psychological reactance can result in negative attitudes. In their studies, attitudes were defined as a response to the freedom-threatening message. Therefore, their adoption intention diminished due to resistance to the advocacy of new technologies and flossing. However, in this research, attitude is described as a propensity for car purchases. In the context of travel restrictions, car purchase is a behavior change that can be viewed as a fight to reestablish individuals' threatened travel freedom. Hence, the positive effect of reactance on pro-car-purchasing attitude is reasonable.

In sum, while reactance does not significantly influence purchase intention, the results provide empirical implications for integrating TPB and PRT to predict consumers' car purchase intentions during the new normal of COVID-19.

5.2. Practical implications

This research offers certain practical implications. First, the results could provide insights for estimating individuals' price expectations on private cars during the new normal of COVID-19. Second, our findings identify the dominant psychological factors that explain individuals' car purchase intentions during the new normal of a serious pandemic. Conditional value, pro-car-purchasing attitude and public behavioral control are the crucial factors that influence car purchase intention. It means that government subsidies on private cars effectively stimulate individuals' car purchase intentions under the new normal of COVID-19. It is worth noting that the subsidies should be adjusted according to the recovery process of the automobile market. The monetary subsidy for fuel vehicles could be reduced after the steady recovery of the car market, avoiding traffic and environmental problems caused by a large number of fuel vehicles on the road in the future. Subsidies for new energy automobiles could be deferred the reduction, taking the COVID-19 as an opportunity to promote the use of new energy vehicles [106]. Moreover, building pro-car-purchasing attitude through promotional campaigns and/or car design is essential. For example, private cars should be designed with anti-epidemic parts to optimize epidemic prevention and reduce the risk of people's infection [10]. Promotional campaigns should be proactive, providing concrete information about the sufficiently good anti-epidemic performance of the private car and its advantage that could ensure travel freedom when public transportation is inconvenient. Furthermore, automobile enterprises could reduce the difficulty of purchasing private cars, fulfilling individuals' purchase demands during the new normal. For example, referring to Tesla's practice, we suggest that automobile enterprises promote online car purchase mode to provide convenient channels for consumers to buy cars [8].

6. Conclusions, limitations, and future research

By expanding the theoretical basis of TPB, PMT and PRT, this research proposed, and empirically tested, a structural model to reveal individuals' car purchase intentions during the new normal of COVID-19. The combination of SEM and BN was first incorporated as a mathematical model in the field of car consumption to quantify the influence degree of factors on car purchase intention.

6.1. Conclusions

Main findings: The results of SEM showed that conditional value, pro-car-purchasing attitude, and perceived behavioral control, health value and cost factors have significant direct effects on car purchase intention. Among these, pro-car-purchasing attitude could be affected by the variables of PMT and PRT, providing the possibility for the combination of the three theoretical models. The negative impact of cost factors on car purchase intention is more significant than the positive impact of health value. The analytical results of BN found that perceived behavioral control, pro-car-purchasing attitude and conditional value played the most vital role in the formation of car purchase intention during the new normal of COVID-19. With perceived behavioral control, pro-car-purchasing attitude and conditional value shifting from "low" to "medium" and "high," the probability of high purchase intention grew by 47.6%, 97.3%, and 163.0%, respectively.

Implications: The results are essential in gaining a more nuanced understanding of the private car purchase intentions and attitudes during the new normal of a pandemic. Our study provided theoretical support for the integrated of TPB, PMT and PRT. Then, this research could contribute to the government and enterprises to formulate measures related to the automobile market. Under the new normal of COVID-19, the government could effectively stimulate consumers' purchase intention through subsidies for private cars. Auto enterprises could build pro-car-purchasing attitude by increasing publicity, running promotions or improving the design with anti-epidemic.

6.2 Limitations and future research

There are some limitations to this study study. First, this research is required to maintain confidentiality and anonymity. The researchers cannot interfere with the participants during the testing process. The general disadvantage of employing questionnaires in the study could not be avoided.

Second, the questionnaire survey was conducted during COVID-19, and, thus, we could only analyze individuals' private car purchase intentions during the outbreak. However, individuals' car purchase intentions and needs might change during the post-pandemic period, which is also significant for public policymakers, corporate marketers and researchers to understand.

Additionally, this study analyzed consumers' purchase intention on private cars, which did not distinguish between vehicle categories. The government issues subsidies policy to encourage the purchase of new energy vehicles. The effect of subsidies policy stimulus on consumers may change due to financial stress during the outbreak of COVID-19.

Future research directions could focus on survey data and specific vehicle types based on the above research limitations. On the one hand, future research could investigate the data in the post-COVID-19 period and conduct a comparative analysis of the influence factors of car purchase intention during and after COVID-19. On the other hand, further research on car purchases could focus on a specific type of vehicle.

In addition, future research could consider introducing behavioral control theory [107] and social influence theory [108] to explain the private car purchase intention during the new normal of COVID-19.

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Conflict of interest

On behalf of all authors, the corresponding authors state that there is no conflict of interest.

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