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Research Article

Car Purchase Intention Modeling in the Context of COVID-19: An Integrated Analysis of Impact Range and Impact Asymmetry

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The car purchase intention of noncar owners is closely related to the growth of car ownership and may be changed in the context of COVID-19. This paper aims to investigate the decision-making mechanism of the car purchase intention before COVID-19 and the change of car purchase intention after COVID-19. The contributions of influencing factors are derived from the gradient boosting decision tree model and the asymmetric effects of attitudinal factors are further analyzed based on the three-factor theory. The comprehensive importance hierarchies of the two dependent variables are constructed through the integrated analysis of impact range and impact asymmetry. The results show that people who were previously more willing to buy cars are more likely to increase their willingness to buy after COVID-19. The pre–COVID-19 car purchase intention is primarily determined by shared mobility-related attitudes, while attitudes toward private car use have a greater impact on the post–COVID-19 intention change. These two attitudes are mainly manifested as intention relievers and discouragers before COVID-19, but they are more likely transformed into intention strengtheners and encouragers after COVID-19. The availability of shared mobility has the maximum comprehensive importance to the post–COVID-19 intention change. Therefore, maintaining and promoting the ridership of shared mobility will be the most important prerequisite for alleviating the car purchase intention after COVID-19 pandemic.

1. Introduction

With the acceleration of urbanization, car ownership has surged in many cities in developing countries [1]. As shown in Figure 1, the number of private cars in Beijing, the capital of China, remained at a low level when the per capita annual income was about 10,000 CNY (equal to 1,571 USD) (Stage I), and then increased significantly from 2000 to 2010 (Stage II) [2, 3]. Subsequently, some problems such as traffic congestion, environmental pollution, and parking space shortage come with it [4]. To address these challenges, policies such as license plate restrictions were gradually introduced, and the growth of automobiles began to slow down (Stage III) [5]. Nowadays, the car ownership rate in Beijing is 231 per 1000 inhabitants, higher than China's

average level (123/1000 inhabitants), but still far lower than developed countries such as the United States (797), the United Kingdom (450), Japan (591), and Germany (567) [5–7]. With the development of large-scale urbanization and motorization, noncar owners may change into potential car buyers in the future [8]. Therefore, the growth of car ownership is closely related to purchase intentions. The intention indicator can reflect residents' preferences for car-dependent lifestyle and interest in car ownership [9].

In order to slow the rapid growth of private car ownership and, meanwhile, compensate for the loss of accessibility caused by the license plate restrictions, the Chinese government has explored innovative shared mobility to make more efficient use of limited transportation resources [10]. Shared mobility, as an emerging alternative mode,
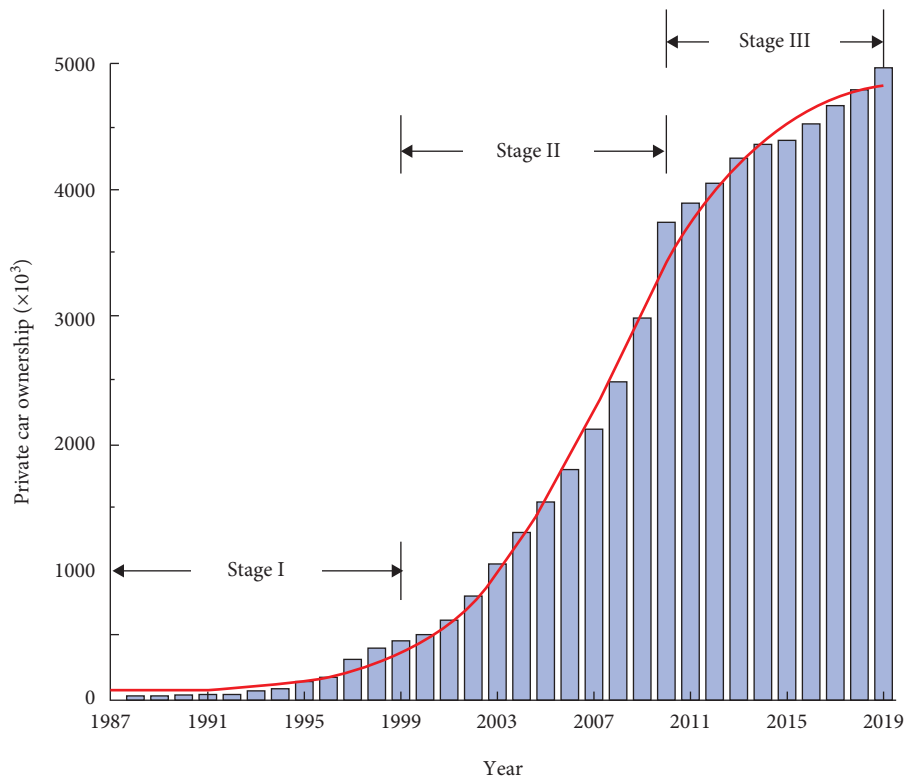
FIGURE 1: Private car ownership in Beijing.

separates the on-demand ride services from the fixed costs of car ownership [11]. Flexible and convenient mobility solutions can meet the high demand for motorized travel by providing more affordable accessibility to cars [12]. Existing studies show that shared mobility is mostly used by noncar owners and is beneficial in alleviating the potential demand for cars to some extent [8, 13, 14]. To promote the sustainable development of urban mobility landscape, it is worth considering what properties of shared mobility are more essential in reducing the individual intentions of purchasing cars.

Since late 2019, the global coronavirus (COVID-19) pandemic has had an unprecedented impact on the urban transportation and mobility patterns [15]. Due to the need for constant social distancing, the public transport use is suppressed and the private car use surges [16]. For instance, Hu and Chen [17] found that the pandemic led to an average 72.4% decline in the ridership at 95% of transit stations. Molloy [18] confirmed that the daily number of public transport trips fell by over 90% and a higher share of trips were performed using individual mobility [19] reported that 44.8% commuters using public transport switched to driving impacted by COVID-19. According to the report of Beijing Transport Institute [20], the use rate of private car in urban areas on weekdays in 2020 was 9.35% higher than that in 2019. Private car avoids people's close contact and is perceived as the least risky travel mode [19]. However, the car-free residents are unable to effectively avoid contact when traveling and are at higher risk of infection, resulting in complicated car purchase intentions in the post-COVID-19

periods. Additionally, the travel behavior for shared mobility is likely to change during the pandemic. The panic about shared spaces limits the utilization of new service, whereas some people are using it more for the reliability and avoiding in-car congestion [21]. Therefore, the relationship between shared mobility and car purchase intention needs further discussion in the context of COVID-19.

To provide more behavioral insights into the study of car purchase intention, it is crucial to discuss subjective attitudes, along with other factors, such as sociodemographics, gasoline prices, and trip attributes [9, 22]. Many studies have explored the determinants of purchase intention, while there is limited research on how purchase intention will change after the pandemic. The latter is conducive to mining the demand for car purchase and forecasting the car ownership in the recovery of daily life. Additionally, most studies believe that attitude has a linear effect on purchase intention [8, 23], while nonlinear relations will better explain the variation of behavioral intention.

This study aims to investigate the decision-making mechanism of noncar owners' purchase intentions. Two dependent variables are the car purchase intention before COVID-19 and the change of car purchase intention after COVID-19. The gradient boosting decision tree model and the impact asymmetry analysis are applied to deliver the impact range and impact asymmetry of influencing factors first, and then we construct the comprehensive importance hierarchies of the two dependent variables in this paper. Based on the survey data collected from Beijing, China, we address the following research questions:

(1) how do the influencing factors (e.g. attitudinal factors, sociodemographic characteristics, and trip attributes) contribute to the pre–COVID-19 car purchase intention and the post–COVID-19 intention change? (2) Does attitude have nonlinear and asymmetric effects on the two dependent variables? (3) What attitudinal factors are critical to alleviating the postpandemic car purchase intention? Three contributions are made in this paper. First, the driving tendency will be inevitable once people buy a car. Therefore, exploring purchase intentions of noncar owners is beneficial in introducing more appropriate adaptive policies and fundamentally reducing car dependence. Second, car purchase dissuasion measures based on attitudinal effects are weaker in compulsion and higher in acceptance than license plate restrictions. Third, this paper reveals the role of shared mobility in reducing car purchase intention.

The remainder of this study is organized as follows: Section 2 provides a brief review of the related literature. Section 3 describes the survey and model built in this study. Section 4 presents the analysis results. Section 5 discusses the key findings. Finally, Section 6 concludes and presents the policy implications.

2. Literature Review

2.1. Influencing Factors of Car Purchase Intention. According to the theory of planned behavior [24], intention reflects the motivation to perform a specific behavior. Due to the increasing purchase volume and consumption intention of cars in developing countries, car purchase intention is becoming an essential indicator to measure car dependence [25]. Existing literature has explored various factors influencing car purchase intention, such as social-demographics [26], social norms [27, 28], and the past travel experience [9, 29]. Table 1 summarizes the influencing factors in the literature.

Attitudinal factor has been identified as an important determinant of the car purchase intention [34]. For instance, Haustein [23] found that appreciating the car autonomy and necessity could form new purchase potentials of car-free households. Affective and symbolic factors contribute twice as much as functional factors to the intention to own a car [43]. However, those who are concerned more about high taxes, environmental sustainability, traffic congestion, and traffic accidents are less likely to buy a car [22]. In addition, perceptions of shared mobility use are also associated with the car purchase intention. Ikezoe et al. [44] pointed out that car-sharing need to be economical and have emotional incentives to reduce car purchase. The improvement of carpooling convenience, privacy, flexibility, and friendliness would postpone or cancel people's potential willingness to buy cars [8].

The above studies provide evidence on correlates of pre–COVID-19 car purchase intention. As for postpandemic era, Luan et al. [45] proved people's high desire for driving, while Olde Kalter et al. [46] found that the increased teleworking trends would reduce the car commuting rates. However, these studies mainly focused on the car use behavior. Analysis of the change in car purchase intention after COVID-19 remains limited and requires further research attention.

2.2. Study Methods of Car Purchase Intention. In terms of the study methods, several studies have analyzed the car purchase intention using statistical modeling. Krishnan and Koshy [26] evaluated the influence of various attitudinal factors on the electric vehicle purchase intention through structural equation modeling. Buranelli de Oliveira et al. [39] also took structural equation modeling and indicated that attitudes and emotions toward electric car had the highest predictive power for the intention to use. Tunçel [47] furthur adopted partial least square structural equation modeling and revealed that travelers' innovativeness and motivations led to a positive intention toward purchasing electric vehicles. Vafaei-Zadeh [48] combined the theory of planned behavior and the technology acceptance model and found that attitude, subjective norms, perceived behavioral control, price value, and environmental self-image had positive effects on the intention to purchase electric vehicles. Meena [22] determined that the future car ownership decisions by employing a principal component analysis and a subsequent binary logit model. Muromachi [9] conducted a retrospective questionnaire survey to explore the impact of past school travel experience on the future intentions of university students to purchase a car. An ordered probit model was established to conclude that locating schools in areas easily accessible by rail was helpful to promote a less car-dependent lifestyle. Belgiawan et al. [27] estimated and ordered hybrid choice models and proved that parents and university peers were significantly correlated with students' car purchase intentions.

The abovementioned methods have been used to examine the linear effects of influencing factors on car purchase intention. However, the linear variation of intention is inconsistent with the bounded rationality of decision-makers [49], and is queried by several studies [25, 50]. Some new techniques need to be proposed to explain the car purchase intention more realistically.

3. Methodology

3.1. Data and Variables. The data used in this study comes from a self-administered survey conducted in Beijing, China, in December 2020. The pandemic prevention has lasted for almost a year by this time, which means that travel habits have changed a lot [51]. The questionnaire consists of three parts:

(1) Sociodemographics: gender, age, annual income, home rental, household size, residential location, and car ownership. If the answer to the questionnaire on car ownership is zero, respondents need to retrospect their pre–COVID-19 car purchase intentions using five-point Likert scales (1 = extremely unwilling, 2 = unwilling, 3 = neither willing nor unwilling, 4 = willing, 5 = extremely willing). They are also asked to indicate changes in intentions after COVID-

TABLE 1: Summary of influencing factors in the literature.

Factor	Car purchase intention	Source
Gender	+	[9]
Age	−	[30, 31]
Annual income	+	[32, 33]
Home ownership	+	[34]
Household size	+	[23, 25]
Urban residence	−	[8]
Commuting time	+	[35]
Walking time to the nearest public transport station	+	[36, 37]
Affective well-being of car	+	[38, 39, 39]
Functionality of car	+	[27, 35]
Less-negative externalities of car	+	[22, 40]
Availability of shared mobility	−	[36, 41]
Frequency of using shared mobility	−	[31, 42]

Note. "+" indicates a positive correlation, and "−" indicates a negative correlation.

TABLE 2: Attitudinal statements and their statistics.

No.	Variable	Statements	Mean	SD
Private car-related attitudes				
V1	Car-cost	It is difficult to purchase a car due to the expenses.	3.33	1.26
V2	Car-maintenance	Car maintenance is expensive for me.	3.24	1.24
V3	Car-parking	Parking fees would bring financial burden to me.	3.06	1.29
V4	Car-convenience	I think car is convenient for daily routines.	2.86	1.35
V5	Car-feeling	I enjoy the feeling of driving.	2.09	1.17
Shared mobility related attitudes				
V6	Shared-no-jam	Shared mobility can alleviate the traffic congestion.	4.31	1.01
V7	Shared-no-parking	Shared mobility would help me out of the parking difficulty.	4.31	1.00
V8	Shared-demand	Shared mobility can satisfy my travel demand.	4.09	1.02
V9	Shared-cost	I can easily afford travel costs of shared mobility.	4.03	1.07
V10	Shared-absence	I would buy a car if shared mobility is absent.	3.83	1.25
V11	Shared-comfort	I think shared mobility travel is more comfortable than driving.	2.66	1.18
V12	Shared-safety	I think shared mobility travel is safer than driving.	2.40	1.30
Psychology related attitudes				
V13	Flexibility-propensity	I hope to choose departure time and travel routes flexibly.	4.55	0.80
V14	Tech-savviness	I am familiar with using smartphone apps to manage my trip.	4.21	1.09
V15	Privacy-sensitivity	Having privacy is important during a journey.	4.16	1.03
V16	Environmental-awareness	I would choose environmental friendly travel modes as possible.	4.12	1.09
V17	Variety-seeking	I like discovering and trying something new.	3.93	1.12

19 (e.g., increased, unchanged, or decreased). Therefore, the respondents in the pre- and post-pandemic periods are the same ones.

(2) Trip attributes: commuting time, whether to tele-commute during COVID-19, total walking time from home/workplace to the nearest bus stop, total walking time from home/workplace to the nearest metro station, and frequency of using shared mobility before and during COVID-19.

(3) Attitudes related to private car usage, shared mobility usage, and psychology: seventeen statements (see Table2) are expressed with the five-level ordinal scale ranging from "extremely disagree" to "extremely agree."

The online survey was conducted with the assistance of a professional Internet survey company in China. A spatially stratified random sampling was adopted among the permanent residents in 16 districts of Beijing. We used the completion of questionnaires answered, response time limits, and trap questions to control the data quality. A total of 1007 valid questionnaires were collected, in which 369 participants without cars were selected as our research sample. As illustrated in Table 3, the gender distribution of the sample is consistent with that of the whole population of Beijing (51.63 : 48.37). Car-free participants were characterized by younger, living alone, settling in the urban area, and still commuting during COVID-19. Approximately 40% of the sample spends more than 40 min on commuting. The total walking time from home/workplace to the nearest bus stop less than 20 min accounts for 13.55%, while that to the nearest metro station only occupies 3.79%. Additionally, they tend to use shared mobility less frequently impacted by COVID-19. As shown in Figure 2, 12% of the sample

TABLE 3: Statistics of car-free participants.

Variable	Description	Percentage (%)
Sociodemographic characteristics		
Gender	1: Male	51.22
	0: Female	48.78
Age	(1): 18–29 years old	56.64
	(2): 30–39 years old	30.89
	(3): 40–49 years old	8.41
	(4): 50 years old and older	4.06
Annual income	(1): Under ¥ 20,000 ($ 3,150)	20.33
	(2): ¥ 20,000–60,000 ($ 3,150–9,450)	14.91
	(3): ¥ 60,000–100,000 ($ 9,450–15,750)	21.14
	(4): ¥ 100,000–150,000 ($15,750–23,625)	17.07
	(5): ¥ 150,000–200,000 ($23,625–31,500)	11.92
	(6): ¥ 200,000 ($ 31,500) and more	14.63
Home rental	1: Rent a house	46.88
	0: No rent a house	53.12
Household size	(1): 1 person	42.81
	(2): 2 persons	14.91
	(3): 3–4 persons	29.81
	(4): 5 or more persons	12.47
Residential location	1: Urban	63.96
	0: Suburban	36.04
Trip attributes		
Commuting time	(1): Within 20 min	34.96
	(2): 20–40 min	25.47
	(3): 40–60 min	18.16
	(4): 60 min and more	21.41
Telecommuting	1: Telecommuting during COVID-19	20.05
	0: Commuting during COVID-19	79.95
Walking_to_bus	Total walking time from home/workplace to the nearest bus stop	
	(1): Within 20 min	13.55
	(2): 20–40 min	36.31
	(3): 40–60 min	31.44
	(4): 60 min and more	18.70
Walking_to_metro	Total walking time from home/workplace to the nearest metro station	
	(1): Within 20 min	3.79
	(2): 20–40 min	44.17
	(3): 40–60 min	33.33
	(4): 60 min and more	18.71
Shared_fre_change	The frequency change of using shared mobility due to COVID-19	
	(1): Decreased	61.25
	(2): Unchanged	24.39
	(3): Increased	14.36

reported they had never used this new method of mobility before, whereas the proportion rose to 38% during the lockdown. The number of people who use it once or twice a week decreased from 26% to 17%.

Due to the impact of COVID-19, the number of car-free participates with increased, unchanged, and decreased car purchase intention, respectively, occupy 40%, 31%, and 29% (147/115/107). Figure 3 shows the relation between pre–COVID-19 car purchase intentions and post–COVID-19 intention changes. The values from 1 to 5 on the *x*-axis correspond to the five-point Likert scales of car purchase intentions in the survey. We find that 88% of those who are extremely reluctant to buy cars still do not change their purchase intentions after the pandemic outbreak. People who were previously more willing to buy cars are more likely to increase their willingness to buy after COVID-19. Therefore, if no preventive measures are taken, car ownership will rise sharply.

The descriptive summary of attitudinal statements is presented in Table 2. We can draw some conclusions from the table, for example, the expensive purchase cost has the highest consistency in the car-related attitudes. In terms of shared mobility, people have a deep consensus on its features of mitigating traffic jam and getting rid of parking. Among the psychology-related attitudes, flexibility is favored by most participants while traveling. Overall, the calculated
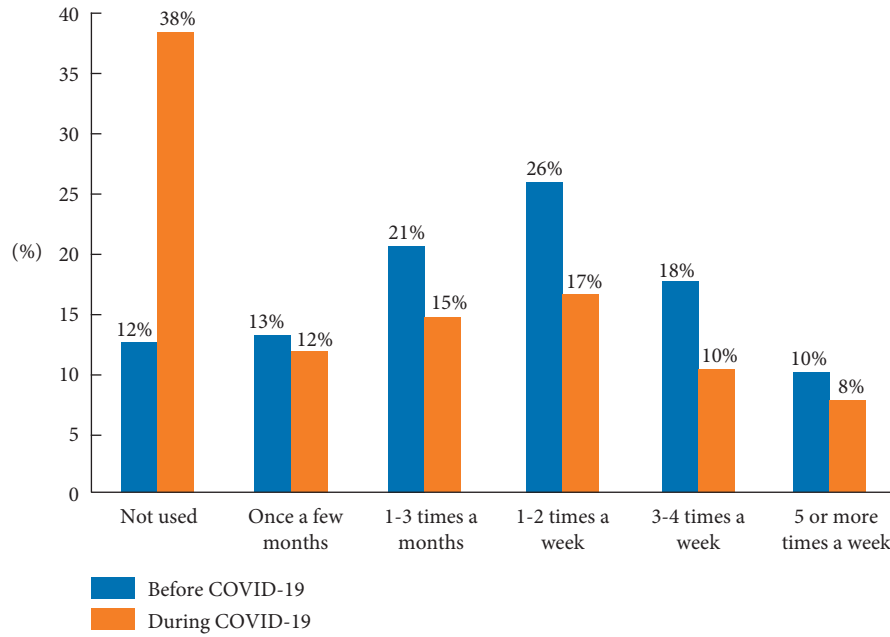
Figure 2: Frequency of using shared mobility before and during COVID-19 (abbreviated as "shared_frequency").
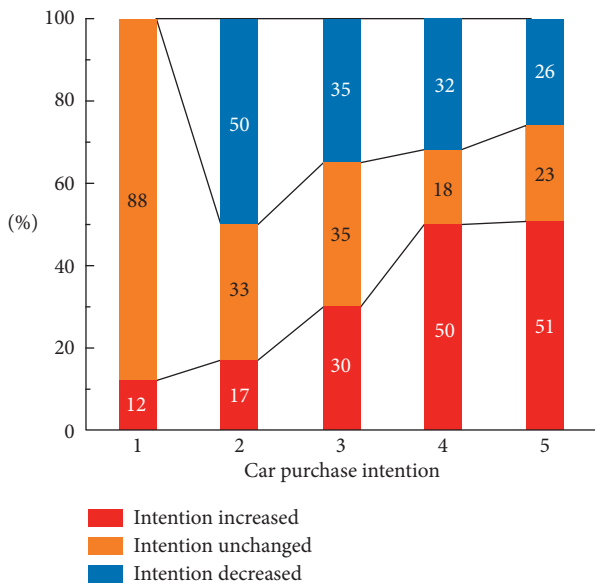

Figure 3: Statistics of pre-COVID-19 car purchase intentions and post-COVID-19 intention changes.

Cronbach's alpha of 0.768 is greater than the recommended benchmark of 0.7, thus the measurement has acceptable internal consistency reliability [52].

3.2. Gradient Boosting Decision Tree Model. This study applies the gradient boosting decision tree (GBDT) model to, respectively, examine the relative importance of influencing factors to the pre–COVID-19 car purchase intention and the post–COVID-19 intention change. As an ensemble machine learning method, GBDT is a generalization of boosting to arbitrary differentiable loss functions [53]. It combines successive decision trees, and each new added tree is trained to reduce the residual errors of the former trees [54]. Existing literature has introduced GBDT into travel behavior research, such as mode choice, ride satisfaction, and car ownership [1, 55, 56], while few studies have analyzed car purchase intention using this approach.

Due to three advantages, the GBDT model is suitable for regression in this study. First, different from traditional regression models (e.g., generalized linear models) and discrete choice models, GBDT is known to address the multicollinearity, accommodate various types of independent variables (e.g., categorical, continuous, count, with missing values, and with outliers), and describe nonlinear effects of correlates. Second, it provides a higher prediction accuracy than other machine learning models, such as support vector machine, random forest, and neural networks [57–60]. Third, this approach is effective on relatively small datasets [56]. Fang et al. [61] explored service attributes' contribution to the satisfaction of 193 choice bus riders. Wu et al. [62] used 360 observations to explore the relationship between built environment elements and CO_2 emissions. The sample size in the two studies is comparable to our study of 369 noncar owners.

In the GBDT model, the training dataset consisting of N samples is denoted by $\{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\}$, where x_i and y_i are the independent and dependent variable values of the i th sample, respectively. The base learners of this algorithm are M decision trees, and the m th tree $T(x; \theta_m)$ is added to minimize the loss function $L(y, f(x)) = (y - f(x))^2$. A detailed mathematical solution of GBDT is as follows:

First, the predicted value is initialized as a constant c, expressed as follows:

$$f_0(x) = \text{argmin}_c \sum_{i=1}^{N} L(y_i, c). \tag{1}$$

Second, for the m th iteration $(m = 1, 2, ..., M)$, the residual is estimated with the negative gradient of loss function, specified as (2). Then $T(x; \theta_m)$ is used to fit the constructed training sample $\{(x_1, r_{m1}), (x_2, r_{m2}), ..., (x_N, r_{mN})\}$. The gradient descent step size is calculated as (3), and the iterative model is updated as (4).

$$r_{mi} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]_{f(x) = f_{m-1}(x)}, \tag{2}$$

$$\alpha_m = \arg\min_\alpha \sum_{i=1}^{N} L(y_i, f_{m-1}(x_i) + \alpha T(x_i; \theta_m)), \tag{3}$$

$$f_m(x) = f_{m-1}(x) + \alpha_m T(x; \theta_m). \tag{4}$$

Third, the loop is performed until reaching the maximum number of iterations or specified convergence conditions. To address the overfitting issue, the contribution of each tree is scaled by introducing a learning rate ξ $(0 < \xi \leq 1)$, stated as (5). Generally, a balance exists between the learning rate and the tree number, and more trees are needed with a smaller learning rate. The final model is computed as (6).

$$f_m(x) = f_{m-1}(x) + \xi \alpha_m T(x; \theta_m), \tag{5}$$

$$f(x) = f_M(x). \tag{6}$$

3.3. Three-Factor Theory and Impact Asymmetry Analysis. Three-factor theory is the theoretical basis for the impact asymmetry analysis. As shown in Figure 4(a), it previously identifies three categories of positive factors influencing customer satisfaction, including basic factors, performance factors, and excitement factors [63]. Basic factors are minimum requirements that need to be met, since they do not lead to satisfaction if implemented, while cause dissatisfaction once not fulfilled. Performance factors are associated with both satisfaction and dissatisfaction, depending on whether they are fulfilled. Excitement factors do not enhance dissatisfaction if absent, while increase satisfaction if delivered. Wai Lai et al. [64] extended the negative factors affecting the customer satisfaction, as shown in Figure 4(b). Negative basic factors cause dissatisfaction if present, but their absence will not generate satisfaction. Negative performance factors affect both satisfaction and dissatisfaction. The existence of negative excitement factors does not contribute to dissatisfaction, but the absence will cause satisfaction.

Satisfaction is considered to be a prerequisite for the behavioral intention [65–67], thus intention may exhibit the similar factor structure. Therefore, this paper conducts the impact asymmetry analysis of attitudinal factors influencing car purchase intention based on the extended three-factor theory. The penalty-reward contrast analysis is adopted to test asymmetric effects of attitudes on the pre–COVID-19 car purchase intention and the post–COVID-19 intention change. Each attitudinal variable (see Table 2) has a penalty category and a reward category, corresponding to the low and high performance of the variable. GBDT is employed to generate the penalty index and the reward index input for impact asymmetry analysis, detailed as follows:

First, for each attitudinal variable in Table 2, scales 1 and 2 are included in the penalty category (recoded as -1), scales 4 and 5 are included in the reward category (recoded as 1), and scale 3 is the reference category (recoded as 0).

Second, recoded attitudinal factors, together with sociodemographics and trip attributes, are used as inputs and modeled with GBDT to quantify their effects on the pre–COVID-19 car purchase intention and the post––COVID-19 intention change. The model parameters are determined by applying a fivefold cross-validation. In the training stage, we used the fivefold cross-validation method to train the model for three main parameters, including the learning rate, the maximum number of trees, and the tree depth. A learning rate of 0.001 is generally recommended by the existing studies as it makes the model more robust and prevents over-fitting, thus the corresponding tree number needs to be more than 1000 [25, 57]. With the learning rate of 0.001, a variety of tree number 1000, 2000, 3000, 4000, 5000, 6000 and tree depth 2, 4, 6, 8, 10 was tested in this paper until the value of root mean square error of approximation (RMSEA) reached the minimum level and the model outputs were stable. Through grid search, the final model was obtained with learning rate = 0.001, maximum tree number = 6000, and tree depth = 6.

Third, GBDT is used to calculate the predicted car purchase intention (PCPI) corresponding to penalty, reference, and reward categories of each attitudes. Thus, the penalty index and the reward index are specified as Equations (7) and (8). Additionally, if $\text{PCPI}_{\text{reward}} > \text{PCPI}_{\text{penalty}}$, the attitudinal factor is a positive correlate, while if $\text{PCPI}_{\text{reward}} < \text{PCPI}_{\text{penalty}}$, the factor is a negative correlate.

$$\text{penalty}_{\text{index}} = \left|\text{PCPI}_{\text{reference}} - \text{PCPI}_{\text{penalty}}\right|, \tag{7}$$

$$\text{reward}_{\text{index}} = \left|\text{PCPI}_{\text{reward}} - \text{PCPI}_{\text{reference}}\right|. \tag{8}$$

According to the three-factor theory [63, 64], if the penalty index and the reward index are approximately equal, such variable would be a performance factor. For positive correlates, the penalty index of a basic factor is larger, and that of an excitement factor is smaller. Oppositely, the reward index of a negative basic factor is larger and that of a negative excitement factor is smaller.

In reference to the satisfaction generating process described in [64, 68], the impact asymmetry (IA) index is used to further classify factors influencing intention, calculated as Equations (9)–(12). The range of impact on car purchase intention (RICPI) is the sum of reward index and penalty index. The intention increasing potential (IIP) and the intention decreasing potential (IDP) of a positive factor are proportions of reward index and penalty index to RICPI, while the calculation is reversed for negative factors. The IA
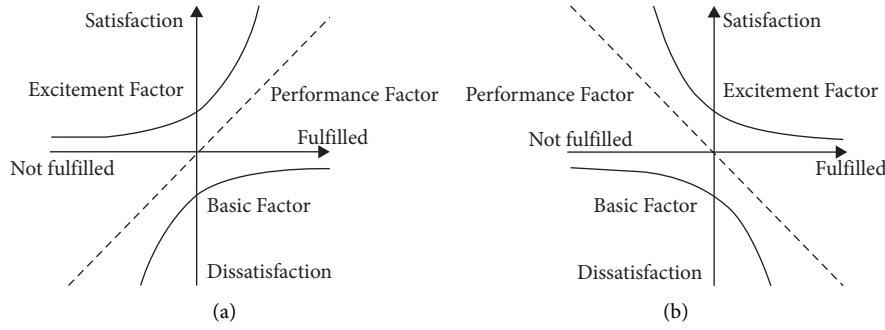
Figure 4: Three-factor theory of customer satisfaction. (a) Positive correlations. (b) Negative correlations.

indexes of both positive and negative correlates are the difference of IIP and IDP. Each correlate can be classified into one of the five factors: encourager ($IA > 0.6$), strengthener ($0.2 \leq IA \leq 0.6$), hybrid ($-0.2 < IA < 0.2$), reliever ($-0.6 \leq IA \leq -0.2$), and discourager ($IA < -0.6$).

$$RICPI = reward_{index} + penalty_{index}, \tag{9}$$

$$IIP_{positive} = \frac{reward_{index}}{RICPI}, \quad IDP_{positive} = \frac{penalty_{index}}{RICPI}, \tag{10}$$

$$IIP_{negative} = \frac{penalty_{index}}{RICPI}, \quad IDP_{negative} = \frac{reward_{index}}{RICPI}, \tag{11}$$

$$IA = IIP - IDP. \tag{12}$$

4. Results

4.1. Impact Range of Influencing Factors. The contributions of influencing factors to the pre–COVID-19 car purchase intention and the post–COVID-19 intention change are measured by the relative importance derived from GBDT, see Table 4.

For social-demographic characteristics, the residential location (6.83%) has the greatest impact on the pre–COVID-19 car purchase intention. The annual income (4.02%) is more crucial for the post–COVID-19 intention change. This importance of income is consistent with [40], in which most people preferred to travel by car if they can afford it. Affected by the pandemic, it will be more difficult to reduce the purchase intention once the economic conditions are improved.

In terms of trip attributes, the commuting time accounts for 4.15% of the pre–COVID-19 car purchase intention, while the telecommuting (4.03%) has a stronger effect on the post–COVID-19 intention change due to the home quarantine policy. Besides, public transport is unpopular due to its difficulty of keeping social distancing, thus the walking time to the nearest station (8.76%) contributes less to the intention change. The relative importance of shared-frequency and shared-free-change is 2.60% and 3.65%, respectively, which further proves the correlation between shared mobility usage and car purchase intention in the existing studies [31, 42].

Attitudes to private car use only contribute 2.01–3.53% to the pre–COVID-19 purchase intention, while have the greatest influence (28.85%) on the post–COVID-19 intention change. This means that the pandemic has shifted the attention of noncar owners from shared mobility to private car. The importance of car-cost (10.20%) ranks first, thus the affordability of car is most concerned. Car-convenience (7.77%) contributes more than car-feeling (3.46%), thus the functionality is more influential than the affective well-being to the change of car purchase intention after COVID-19.

The pre–COVID-19 car purchase intention is primarily determined by shared mobility related attitudes (37.47%). The availability and affordability of shared mobility are most influential since the importance of shared-absence (17.12%) and shared-cost (9.63%) ranks in the top two. This result confirms the critical role of shared mobility in alleviating car purchase intention in the previous studies [8, 36, 41]. However, these two attitudes are less effective for the post–COVID-19 intention change, which means that the pandemic has weakened the role of shared mobility due to travelers' panic about shared spaces. Shared-comfort (5.94%) and shared-safety (2.59%) contribute more to the intention change, thus noncar owners are concerned more about the affective well-being of shared mobility in the context of COVID-19. In addition, most functionalities of shared mobility are less concerned since the contributions of shared-no-parking and shared-demand are declined.

Among the psychology-related attitudes, privacy-sensitivity (4.78%), and tech-savviness (3.90%) are the most powerful predictors for the pre–COVID-19 purchase intention. This is consistent with the results of existing studies [8, 26, 40]. Flexibility-propensity (7.20%) has a significant effect on the post–COVID-19 intention change. The reason may be that the pandemic has led to the suspension of some public transportation stations and lines, thus noncar owners are unable to choose departure time and travel routes flexibly, resulting in the change of car purchase intention after COVID-19.

4.2. Impact Asymmetry of Attitudinal Factors. Fang et al. [61] believes that variables with the relative importance less than 2% usually have little impact, and thus they are ignored in the analysis of impact asymmetry. From Table 4, we can conclude that the excluded attitudinal factors are shared-no-

TABLE 4: The relative importance of influencing factors to the pre–COVID-19 car purchase intention and the post–COVID-19 intention change.

Variable	Pre–COVID-19 car purchase intention		Post-COVID-19 intention change	
	Rank	Relative importance (%)	Rank	Relative importance (%)
Sociodemographic characteristics				
Gender	21	2.09	26	1.04
Age	10	3.10	19	2.51
Annual income	19	2.38	9	**4.02**
Home rental	27	0.63	20	2.37
Household size	16	2.57	27	0.87
Residential location	3	**6.83**	21	2.29
Sum of relative importance		17.60		13.10
Trip attributes				
Commuting time	7	**4.15**	12	3.48
Telecommuting	—	—	8	**4.03**
Walking_to_bus	4	5.33	13	**3.47**
Walking_to_metro	5	5.31	6	**5.29**
Shared_frequency	15	**2.60**	—	—
Shared_fre_change	—	—	11	**3.65**
Sum of relative importance		17.39		19.92
Private car-related attitudes				
Car-cost	13	2.86	1	**10.20**
Car-maintenance	9	3.53	15	3.10
Car-parking	18	2.21	7	4.32
Car-convenience	12	2.77	2	**7.77**
Car-feeling	23	2.01	14	**3.46**
Sum of relative importance		13.38		**28.85**
Shared mobility-related attitudes				
Shared-no-jam	25	1.34	10	3.72
Shared-no-parking	20	2.34	28	**0.66**
Shared-demand	17	2.42	24	**1.36**
Shared-cost	2	**9.63**	17	2.67
Shared-absence	1	**17.12**	5	5.81
Shared-comfort	11	2.94	4	**5.94**
Shared-safety	24	1.68	18	**2.59**
Sum of relative importance		**37.47**		22.75
Psychology-related attitudes				
Flexibility-propensity	26	0.63	3	**7.20**
Tech-savviness	8	**3.90**	22	2.27
Privacy-sensitivity	6	**4.78**	23	2.02
Environmental-awareness	22	2.01	16	2.74
Variety-seeking	14	2.84	25	1.15
Sum of relative importance		14.16		15.38

jam (1.34%), shared-safety (1.68%), and flexibility-propensity (0.63%) for the pre–COVID-19 car purchase intention, and are shared-no-parking (0.66%), shared-demand (1.36%), and variety-seeking (1.15%) for the post–COVID-19 intention change. We divide the remaining attitudes into positive and negative correlations, and then analyze their asymmetric effects, respectively. The IA indexes of attitudinal factors affecting the two dependent variables are summarized in Tables 5 and 6. Based on IA indexes, the asymmetric attitudinal factor structures are shown in Figures 5 and 6. The hybrids of both pre–COVID-19 car purchase intention and post–COVID-19 intention change only account for 2/14, indicating the nonlinearity of the attitudinal effects.

Excitement factors (e.g., encouragers and strengtheners) are the primary factors to reduce car purchase intention, as their increase also leads to an increase in intention. Performance factors (e. g., hybrids) are less important. Basic factors (e. g., discouragers and relievers) are the least important as they have a limited effect on the intention. Therefore, the order of these factors' importance is excitement factors (encouragers > strengtheners) > performance factors (hybrids) > basic factors (relievers > discouragers).

For the pre–COVID-19 car purchase intention, the importance of private car-related attitudes is in the order of car-feeling > car-convenience > car-parking > car-maintenance > car-cost. The last three are basic factors, which means noncar owners will not increase their intentions to buy cars even if there is a discount. While for the post–COVID-19 intention change, the order is car-convenience > car-parking > car-feeling > car-cost > car-maintenance, thus the affordability is less influential than the

TABLE 5: The IA indexes of attitudinal factors influencing the pre–COVID-19 car purchase intention.

Variable	Reward index	Penalty index	RICPI	IIP	IDP	IA
Positive factors						
Privacy-sensitivity	0.209	0.015	0.224	0.933	0.067	0.866
Tech-savviness	0.224	0.044	0.268	0.836	0.164	0.672
Car-feeling	0.160	0.048	0.208	0.769	0.231	0.538
Variety-seeking	0.162	0.128	0.290	0.559	0.441	0.118
Car-convenience	0.041	0.046	0.087	0.471	0.529	−0.058
Shared-absence	0.478	0.763	1.241	0.385	0.615	−0.230
Negative factors						
Environmental-awareness	0.011	0.061	0.072	0.847	0.153	0.694
Shared-comfort	0.023	0.082	0.105	0.781	0.219	0.562
Shared-demand	0.123	0.063	0.186	0.339	0.661	−0.322
Car-parking	0.077	0.038	0.115	0.330	0.670	−0.340
Shared-cost	0.589	0.130	0.719	0.181	0.819	−0.638
Shared-no-parking	0.165	0.010	0.175	0.057	0.943	−0.886
Car-maintenance	0.187	0.008	0.195	0.041	0.959	−0.918
Car-cost	0.186	0.008	0.194	0.041	0.959	−0.918

TABLE 6: The IA indexes of attitudinal factors influencing the post-COVID-19 intention change.

| Variable	Reward index	Penalty index	RICPI	IIP	IDP	IA
Positive factors						
Shared-absence	0.262	0.041	0.303	0.865	0.135	0.730
Car-convenience	0.330	0.052	0.382	0.864	0.136	0.728
Tech-savviness	0.038	0.010	0.048	0.792	0.208	0.584
Shared-comfort	0.173	0.052	0.225	0.769	0.231	0.538
Car-feeling	0.118	0.039	0.157	0.752	0.248	0.504
Privacy-sensitivity	0.012	0.027	0.039	0.308	0.692	−0.384
Flexibility-propensity	0.031	0.242	0.273	0.114	0.886	−0.772
Negative factors						
Car-parking	0.036	0.178	0.214	0.832	0.168	0.664
Shared-safety	0.059	0.177	0.236	0.750	0.250	0.500
Shared-no-jam	0.055	0.084	0.139	0.604	0.396	0.208
Car-cost	0.199	0.273	0.472	0.578	0.422	0.156
Car-maintenance	0.056	0.043	0.099	0.434	0.566	−0.132
Environmental-awareness	0.086	0.011	0.097	0.113	0.887	−0.774
Shared-cost	0.070	0.007	0.077	0.091	0.909	−0.818
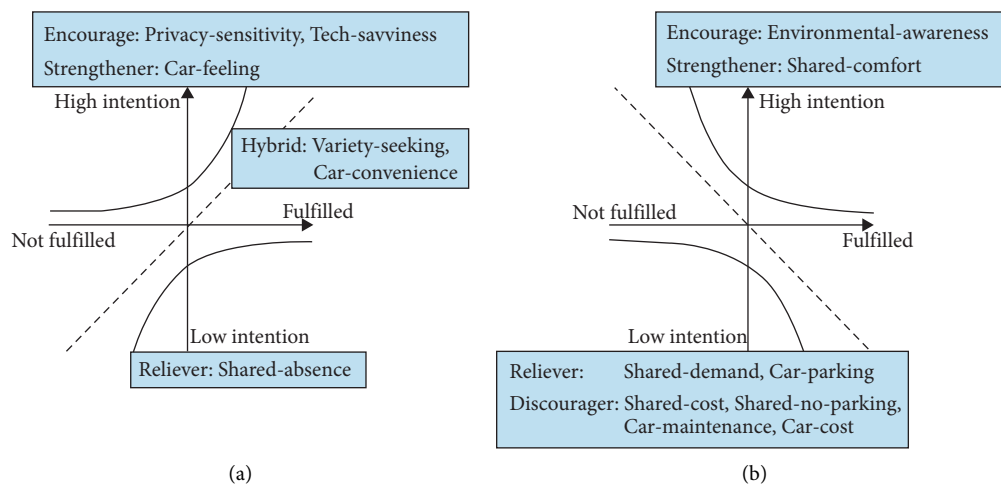
FIGURE 5: The asymmetric factor structure of the pre-COVID-19 car purchase intention. (a) Positive correlations. (b) Negative correlations.
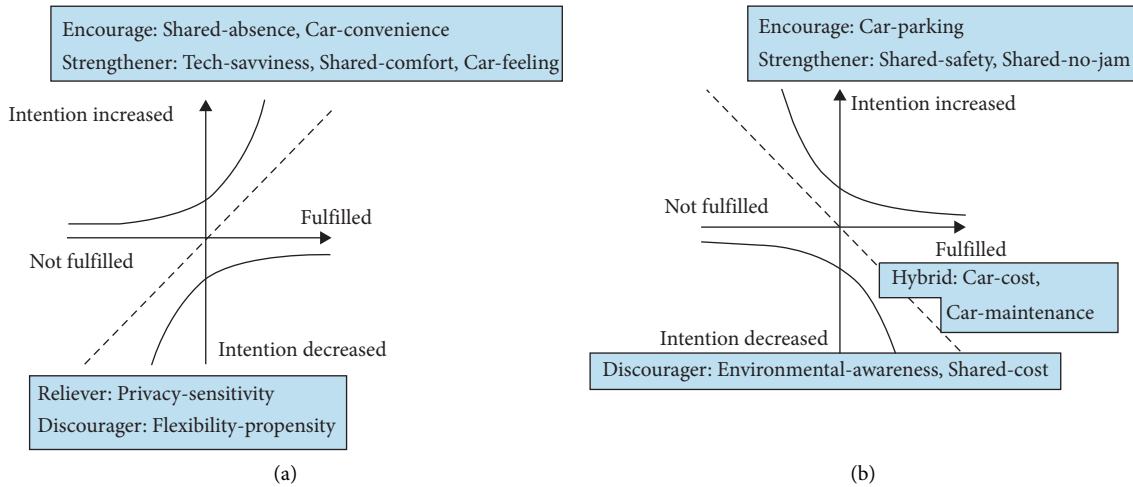
FIGURE 6: The asymmetric factor structure of the post-COVID-19 intention change. (a) Positive correlations. (b) Negative correlations.

functionality and the affective well-being of car. At this time, all private car-related attitudes are excitement and performance factors; therefore, they have been more important due to the pandemic.

The importance of shared mobility related attitudes is in the order of shared-comfort > shared-absence > shared-demand > shared-cost > shared-no-parking before COVID-19. All factors except shared-comfort are basic factors, thus, they are only associated with the intention decrease. While the order is shared-absence > shared-comfort > shared-safety > shared-no-jam > shared-cost after COVID-19. All these factors except shared-cost are excitement factors, thus, the availability of shared mobility and its most attributes have been more significant to reduce car purchase intention impacted by the pandemic. Besides, the affective well-being of shared mobility needs more attention than its functionality. Interestingly, shared-comfort positively affect the postintention increase, thus, it is unnecessary to improve the existing comfort level of shared mobility.

In terms of psychology-related attitudes, the pre-COVID-19 importance order is privacy-sensitivity > environmental-awareness > tech-savviness > variety-seeking, while the post–COVID-19 order is tech-savviness > privacy-sensitivity > flexibility-propensity > environmental-awareness. Most factors are excitement factors for the pre–COVID-19 car purchase intention, while they have turned to basic factors and have been less important due to the pandemic.

5. Discussion

The analysis of impact range and impact asymmetry results in different importance orders of influencing factors. By integrating these analytic approaches, we construct the comprehensive importance hierarchies of the pre–COVID-19 car purchase intention and the post–COVID-19 intention change, see Figures 7 and 8. The low-, medium-, and high-impact, respectively, correspond to the relative importance of 2–3%, 3–5%, and more than 5% in Table 4.

Excitements with higher impacts usually have greater comprehensive importance. An excitement factor with a medium impact is more crucial than a basic factor with a high impact, while a performance factor with a low impact is less crucial than that with a high impact [61]. As shown in Figure 7, the psychology-related attitudes have the greatest influence on the pre–COVID-19 car purchase intention. The comprehensive importance of private car-related attitudes is in the order of car-feeling > car-convenience > car-parking ≈ car-maintenance > car-cost, thus the affective well-being of car is more important than the functionality and affordability before COVID-19. The comprehensive importance of shared mobility-related attitudes is in the order of shared-absence≈shared-comfort > shared-cost > shared-demand > shared-no-parking, thus the availability and affective well-being of shared mobility is the most significant, followed by the affordability and functionality.

As shown in Figure 8, the psychology-related attitudes are less effective for the post–COVID-19 intention change, except for the flexibility-propensity. The comprehensive importance order of private car-related attitudes is car-convenience > car-parking > car-feeling≈car-cost > car-maintenance, thus the functionality of car has a stronger effect than the affective well-being and affordability. The importance order of shared mobility-related attitudes is shared-absence > shared-comfort > shared-no-jam > shared-safety > shared-cost, thus, the affordability is the least essential factor in the context of COVID-19.

From the above comprehensive importance hierarchies, we find that the variables of shared-absence, car-convenience, car-parking, car-feeling, shared-no-jam, car-cost, and car-maintenance need to be more concerned after COVID-19. The availability of shared mobility has the highest comprehensive importance among all attitudinal factors. Therefore, maintaining and promoting the ridership of shared mobility is the most important prerequisite for reducing the post–COVID-19 car purchase intention.

Some limitations still remain in this study. First, these results are based on the survey data in Beijing. It is necessary to extend the sampling to more cities suffered from COVID-
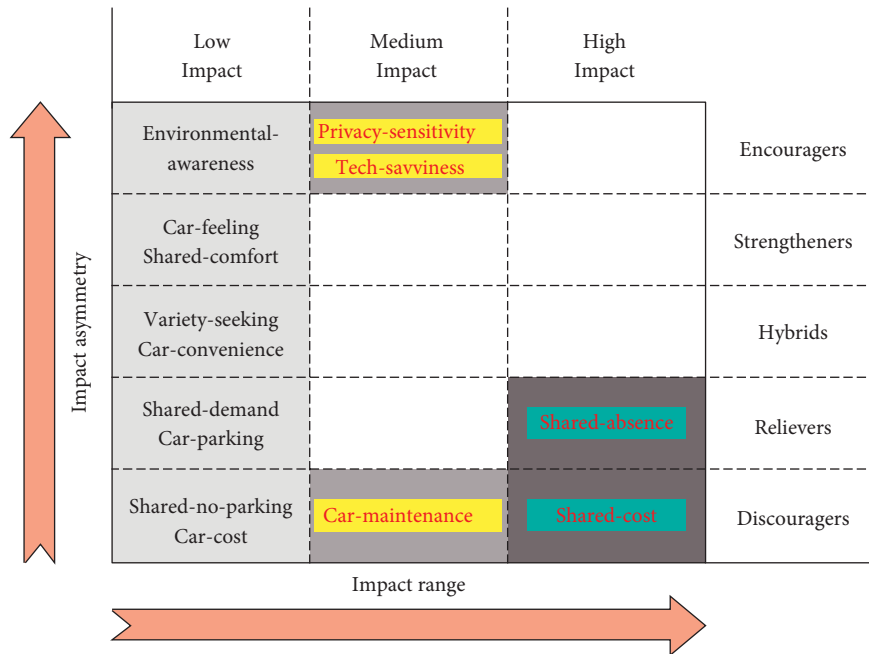
FIGURE 7: The comprehensive importance hierarchy of the pre-COVID-19 car purchase intention.
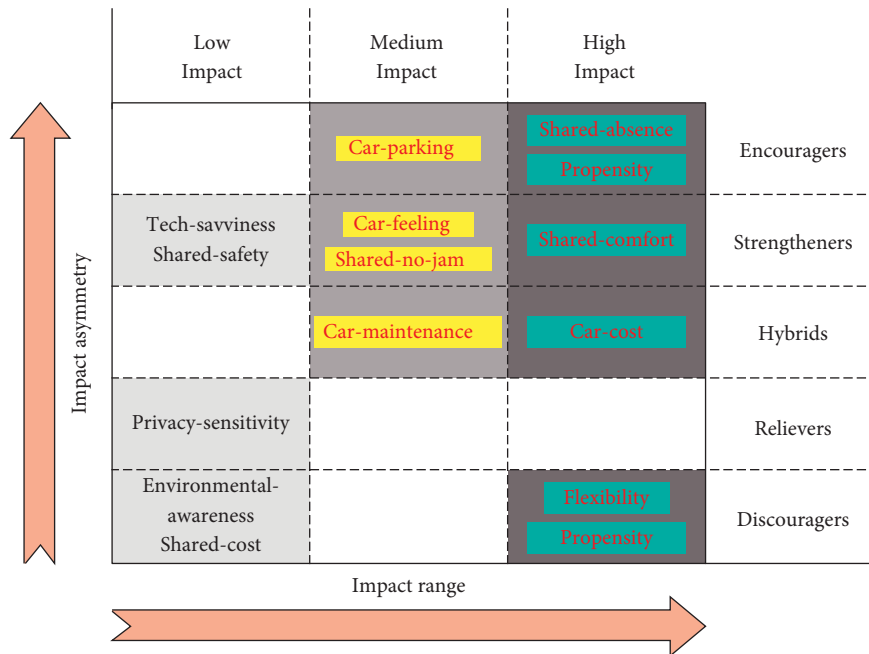

FIGURE 8: The comprehensive importance hierarchy of the post-COVID-19 intention change.

19 to obtain more generalized results. Second, this study considers the attitudes toward overall shared mobility. People hold various attitudes toward multiple shared mobility services, and these services would be impacted by COVID-19 to varied extent. We will further investigate the contributions of differentiated services to the car purchase intention, and thus purpose more personalized developing strategies for shared mobility.

6. Conclusions

This paper provides insights for the decision-making mechanism of the car purchase intention before COVID-19 and the change of car purchase intention after COVID-19. To be specific, based on the data collected from a self-administered survey, the GBDT model is applied to derive the impact range of influencing factors. Second, based on the

three-factor theory and the impact asymmetry analysis, the attitudinal variables are categorized into excitement factors (e.g., encouragers and strengtheners), performance factors (e.g., hybrids), and basic factors (e.g., relievers and discouragers). Third, by integrating two above analytic approaches, the comprehensive importance hierarchies of the two dependent variables are constructed.

According to the survey results, people who were more willing to buy cars before are more likely to increase their willingness to buy after COVID-19. The impact range analysis based on the GBDT model shows that the pre–COVID-19 car purchase intention is primarily determined by shared mobility-related attitudes, in which the availability and affordability of shared mobility are most concerned. However, the post–COVID-19 intention change is mostly influenced by the attitudes to private car use, especially the affordability and functionality of cars.

The asymmetric factor structure shows that excitement factors (e.g., encouragers and strengtheners) are the primary factors to reduce car purchase intention, as their increase also leads to an increase in intention. From the impact asymmetry analysis of attitudinal factors, we find that private car and shared mobility-related attitudes are mainly manifested as intention relievers and discouragers before COVID-19, but they are more likely transformed into intention strengtheners and encouragers after COVID-19. The affordability of car is less influential than its functionality and affective well-being, and the affective well-being of shared mobility needs more attention than its functionality and affordability.

Through the integrated analysis of impact range and impact asymmetry, we find that the availability of shared mobility has the greatest comprehensive importance to the post–COVID-19 intention change. Therefore, to reduce the post–COVID-19 car purchase intention, we need to maintain and promote the ridership of shared mobility despite the impact of COVID-19. First, transportation network companies need to optimize the vehicle distribution and response speed to improve the convenience of shared mobility usage. Second, encourage people use shared mobility to save the fixed costs for car ownership, maintenance, and parking. Third, popularize car-sharing service to satisfy people's driving taste. Fourth, emphasize the role of shared mobility in alleviating the road congestion. Finally, enhance the safety of shared mobility and protect passengers from the pandemic infection.

Data Availability

The data can be obtained from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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