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Research Article

Structure Analysis of Factors Influencing the Preference of Ridesplitting

Xinghua Li[1,2] **Feiyu Feng**[1,2] **Wei Wang**[1,2] **Cheng Cheng**[1,2] **Tianzuo Wang**[3] **and Pengcheng Tang**[4]

[1]*The Key Laboratory of Road and Traffic Engineering, Ministry of Education, Tongji University, Shanghai 201804, China*
[2]*China Transportation Institute at Tongji, No. 1239, Siping Road, Shanghai 200092, China*
[3]*Urban Mobility Institute, Tongji University, Shanghai 201804, China*
[4]*Chinaroads Communications Science & Technology Group Co., Ltd, No. 263, Zhujiang Avenue, Yuhua District, Shijiazhuang 050000, China*

Correspondence should be addressed to Cheng Cheng; michael_cheng1989@126.com

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Ridesplitting is a new form of for-hire service that riders with similar origins and destinations are matched to the same vehicle in real-time via Internet. However, the market share of ridesplitting only accounts for a small fraction of total travel. Understanding cognitive factors affecting ridesplitting preference would be helpful in designing its market measures, regulations, and incentives to achieve high-level customer attractions. This paper identifies the cognitive determinants affecting ridesplitting preference and their inner relationships via the structural equation model. The data from an online survey conducted in Shanghai were implemented for model calibration. The modal fitness results are reasonable, and the path coefficients are significant, exhibiting that the proposed hypothesis cannot be rejected. Specifically, attitude towards incentives and management issues, perceived benefit, and perceived usefulness appear to be strong active driving forces that encourage the desire to adopt ridesplitting.

1. Introduction

Ridesplitting is a new form of for-hire service that riders with similar origins, and destinations are matched to the same vehicle in real-time via Internet [1–3]. Compared with traditional carpooling, ridesplitting improves real-time matching probability. This new form of transportation service also reduces traffic congestion and emission since ridesplitting will make more efficient use of vehicles than ordinary taxis [4, 5].

Due to its commercial potential, transportation network companies such as Uber, Lift, and Didi have launched this service since 2014 [3]. However, within 6 years of development, the market share of ridesplitting only accounts for a small fraction of the total travel. According to Chen et al. [6], ridesplitting trips occupied only 17% only of Didi's ride-hailing trips in Hangzhou, China. Similarly, ridesplitting was not widely adopted compared with ridesourcing and taxi service in Los Angeles County as well according to Brown [7].

To figure out the causes of the low-level market share of ridesplitting among cities, researchers have devoted to investigating user characteristics and their effects on ridesplitting preferences. Mohamed et al. [8] investigated ridesourcing users by semistructured interviews to obtain characteristics of ridesplitting users. They found that ridesplitting was popular among students and travellers who preferred long-distance travel. Brown [7] studied Lyft's trip data from Los Angeles and figured out that people living in dense and lower-income neighborhoods would have a higher possibility to use ridesplitting. Dias et al. [9] presented a bivariate ordered probit model to estimate influential factors that affected ridesourcing and ridesplitting use frequency. The results indicated that young, well-educated, higher-income users and individuals residing in higher-density areas were major ridesourcing and ridesplitting users. Moody et al. [10] introduced a structural equation model to explore the influence of rider-to-rider discriminatory attitude on ridesplitting. It demonstrated that discriminatory attitude had a strongly negative influence on willingness to use ridesplitting.

Similarly, in the research field of traditional carpooling, Brownstone and Golob [11] presented an ordered probit discrete choice model to estimate the use frequency of carpooling. They discovered that women and individuals with multiple workers in family, long commutes, were more likely to use carpooling. Neoh et al. [12] adopted the meta-analysis to explore carpooling's influential factors and revealed that females and travels with fixed work schedules were strongly interested in adopting carpooling. Meyer and Shaheen [13] studied carpooling data from BlaBlaCar in France. The finding indicated that users with low income were more inclined to be passengers compared with high-income users. Delhomme and Gheorghiu [14] conducted an online survey to compare the characteristics of carpoolers with non-carpoolers. The results showed that women and travellers with children, positive attitudes toward public transport, and environmentally aware were more likely to be carpoolers.

According to the literature review, existing studies have investigated the effects of socioeconomic characteristics on passengers' travel preferences and provided insights for ridesplitting adoption estimation. However, these studies hardly reveal the key cognitive factors to influence travellers' preference on ridesplitting. Cognitive factors have been demonstrated as important issues in people's decision process, including choosing travel modes [15–22]. The research to identify cognitive determinants of ridesplitting would be helpful in designing its market measures, regulations, and incentives to achieve high-level customer attraction.

In this paper, we identify the cognitive determinants affecting ridesplitting preference and their inner relationships via the structural equation model. Attitudes towards incentives, such as discounts, surge pricing, and management issues, including implementation of HOV lane and etc., are considered in the model as well. An online survey was conducted in Shanghai to capture traveler's attitudes and preferences on ridesplitting and the survey data were implemented for model calibration. Estimation results could identify those important factors affecting ridesplitting preference and may present useful information for ridesplitting service development.

The remainder of this paper is organized as follows. An overview of the questionnaire design and sample feature is presented in Section 2. Section 3 introduces the modeling method of structural equation model and its adopted variables and hypotheses. Section 4 discusses the results of the model estimation, followed by the conclusions in Section 5.

2. Questionnaire and Sample Feature

2.1. Questionnaire Design and Data Collection. Questionnaire is designed to collect traveler's basic information and attitude towards factors that may influence travel preference on ridesplitting. The questionnaire is designed as two sections: the sociodemographic characteristic investigation section and the user attitudes investigation section. In the sociodemographic characteristic investigation section, respondents are asked to provide their personal information such as age, income, gender, education, household vehicle ownership, and single-trip commuting distance. In the user attitude investigation section, user attitudes towards ridesplitting service and some relative issues are investigated by using Likert Scales ranging from 1 ("strongly disagree") to 7 ("strongly agree"). Referring to the research results of Ajzen [16] and Davis et al. [18], we designed the relative issues, including perceived usefulness (PU), perceived benefit (PB), attitude towards incentives and management issues (AIM), attitude towards public transport (APT), and ridesplitting preference (RP), into the questionnaire.

PU captures the perceived utility of ridesplitting for the traveller, which is closely related to the service efficiency, service quality, and riding environment. PB is defined as the anticipated benefit when using ridesplitting, which is related to the consumption characteristics of ridesplitting. AIM describes the effectiveness of incentives or traffic management measures when using the measures to encourage traveller to adopt ridesplitting. APT describes satisfaction with the service level of surrounding public transport. RP describes the travellers' willingness to adopt the ridesplitting. The details of each category are shown in Table 1.

The online questionnaires were distributed randomly to the residents in Shanghai from 7 to 21, April 2020. 1187 respondents participated in the survey, and 848 investigation results passed the consistency and quality checks. The effective sample size is greater than 150, which is the minimum size of SEM analysis (Bagozzi and Yi [23]) and thus can be adopted by the structural equation model calibration.

2.2. Sample Feature. According to the survey data, over 60 percent of the respondents are male. The age of participants is ranging from 18 to 60, and the percentage of respondents below 41 years is nearly 80 percent. For the education statistic results, 74.76% of the respondents own bachelor or higher degree. For the revenue part, respondents with monthly income ranging between CNY 5000 and CNY 10000 occupy the highest proportion (42.92%). Over 65% of the respondents claim that they own household vehicles. The investigated results of single-trip commuting distance distribute relatively stable, while the travellers with distance ranging from 6 to 10 km account for 35 percent of the total sample. Compared to the Shanghai statistical yearbook [24], the survey respondents are generally younger and better educated than the average population in Shanghai. Meanwhile, the survey sample adequately covered the diversity of Shanghai residents concerning sociodemographic characteristics, household vehicle ownership, and single-trip commuting distance; sample features are shown in Table 2.

Table 1: Questions in user attitudes investigation section.

Construct	
Perceived Usefulness	
PU1	I think ridesplitting can improve the quality of daily travel
PU2	I think ridesplitting can save my waiting time and energy in travel
PU3	I think ridesplitting can provide a comfortable and relaxed riding environment
PU4	I think ridesplitting can improve daily travel efficiency
PU5	In a word, ridesplitting is very useful for me
Perceived Benefits	
PB1	I think ridesplitting can save money on daily travel
PB2	In terms of money, I think ridesplitting is worthwhile
PB3	I think ridesplitting has a good performance-price ratio
Attitude towards Public Transport	
APT1	The distance I walk to the surrounding metro/bus stops is acceptable
APT 2	I do not think it will take too much time by public transportation
APT 3	I think the riding environment of public transportation is acceptable
APT 4	I think surrounding public transportation facilities are very convenient for daily travel
Attitude towards Incentives and Management Issues	
AIM1	I would like to choose ridesplitting with reasonable discounts or subsidies
AIM2	I would like to choose ridesplitting when surge pricing happens during rush hours
AIM3	I would like to choose ridesplitting when the increase in fuel or parking charge executed
AIM4	I would like to choose ridesplitting when providing high occupancy vehicle lane
Ridesplitting Preference	
RP1	In the future, I will use ridesplitting.
RP2	I would like to use ridesplitting in my daily travel.
RP3	I would like to recommend ridesplitting to my family members/friends
RP4	I am going to use ridesplitting as far as possible
RP5	Compared with other travel modes, I prefer ridesplitting

Table 2: Detail of sample feature.

Variables	Description	Size	Proportion (%)
Gender	Males	512	60.38
	Females	336	39.62
Age	[18, 25]	171	20.17
	[26, 30]	200	23.58
	[31, 40]	300	35.38
	[41, 60]	177	20.86
Education	High school	78	9.20
	Less than a bachelor's degree	136	16.04
	Bachelor's degree	543	64.03
	Graduate degree and above	91	10.73
Monthly income	5000 CNY below	176	20.75
	[5.000, 10,000) CNY	364	42.92
	[10,000, 15,000) CNY	201	23.70
	15,000 CNY and above	107	12.62
Household vehicle	0 (no vehicles)	243	28.66
	1	520	61.32
	2 and above	85	10.02
Single-trip commuting distance	5km and below	174	20.52
	[6, 10] km	297	35.02
	[11, 15] km	214	25.24
	16 km and above	163	19.23

3. Methods

3.1. Introduction of Structural Equation Modeling. Structural equation modeling (SEM) is a multivariate statistical method to analyse the relationship among variables based on the covariance matrix of variables, which can reveal the causal relation [23]. This method has been adopted to identify the key factors influencing customer preference in many market areas [15–22]. Thus, it is suitable to capture the cognitive factors that may influence ridesplitting preference.

SEM is composed of a measurement model and a structural model.

3.1.1. Measurement Model. The measurement model is primarily adopted to describe and evaluate the relationship between latent variables and observed variables (measurement items) and ensure that each latent variable has a reasonable explanatory ability, equations which are shown as follows:

$$\begin{aligned} X &= \Lambda_x \xi + \delta, \\ Y &= \Lambda_y \eta + \varepsilon, \end{aligned} \tag{1}$$

where Λ_x is the loading matrix of exogenous variable X on exogenous latent variable ξ; δ is the measurement error vector of exogenous variable; Λ_y is the loading matrix of endogenous variable Y on endogenous latent variable η; and ε is the measurement error vector of endogenous variable.

3.1.2. Structural Models. The structural model is primarily used to capture and estimate the relationship between exogenous variables and endogenous variables, which can be reflected by the path diagram. Its equation is as follows:

$$\eta = B\eta + \Gamma\xi + \zeta, \tag{2}$$

where B is coefficient matrix of endogenous latent variable; Γ is coefficient matrix of exogenous latent variable; and ζ is the residual vector of the structural model.

3.2. Definition of Variables. To reveal the determinants affecting ridesplitting preference, both sociodemographic variables and cognitive variables are considered in the modeling process. The model variables are defined in Table 3.

3.3. Theoretical Hypotheses. Since the correlation between cognitive variables may exist, this paper proposed several hypotheses to describe the relationship between the cognitive variables. The details of proposed hypotheses are presented in Table 4. The structural equation model of ridesplitting preference based on these hypotheses is then developed and is presented in Figure 1. The arrow in Figure 1 indicates the unidirectional influence of a cognitive factor on the other. The ID of each hypothesis is posed on its corresponding arrows for the sake of understanding.

3.4. Criterion of Model Fitness. The AMOS 21 and SPSS 21 are implemented to conduct the model calibration process. Different indicators are adopted to validate the fitness of measurement model and structural model [23, 25]. In the measurement model, factor loading, square multiple correlations (SMC), composition reliability (CR), and average variance extracted (AVE) values, were implemented for model validation. The thresholds of these indicators are set to be 0.6, 0.36, 0.7, and 0.5, respectively. The consistency between the model and the sample data in the structural model is tested by degree of freedom ratio ($\chi 2$/DF), root-mean-squared error of approximation (RMSEA), goodness of fit index (GFI), adjusted goodness of fit index (AGFI), and comparative fit index (CFI). The consistency threshold details are set to be $\chi^2/\mathrm{DF} < 3$, RMSEA<0.08, GFI>0.9, AGFI>0.9, and CFI>0.9.

4. Results and Discussion

4.1. Model Fitness. According to the model tests, measurement items, such as PU3, PU5, RP1, RP4, AIM3, and APT1, are statistically insignificant and thus dropped from the original model. The results of measurement model are presented in Table 5. Both factor loading and square multiple correlations (SMCs) are greater than their corresponding threshold, indicating the reliability of the measurement model. The composition reliability (CR) is over 0.7, and the average variance extracted (AVE) value is greater than 0.5. Therefore, convergent validity can be certified. The model fitness results of structural model are shown in Figure 2. The R^2 values for perceived usefulness, perceived benefit, and ridesplitting preference are 0.73, 0.71, and 0.51, respectively. Moreover, fitness indices, such as chi-squared/df (2.504), CFI (0.975), GFI (0.958), AGFI (0.944), and RMSEA (0.042) meet its recommended value, indicating that model fitness is reasonable and estimation results can be further interpreted.

4.2. Analysis of Results of the Measurement Model. From the results of measurement model in Table 5, the loadings of PU1, PU2, and PU4 are positive. These results denote that measures to improve service quality, travel efficiency, and saving waiting time would exert positive effects on the perceived usefulness. Also, the loadings of PB1, PB2, and PB3 are positive and the loading of PB2 is the largest, signifying that saving money, reasonable price, and cost performance have positive effects on perceived benefit and reasonable pricing is essential to increase the perceived benefit. The loading of AIM2 is the largest, followed by AIM1 and AIM3, suggesting that the surge pricing on ridesourcing will exert the strongest positive influence on ridesplitting usage attitude, followed by ridesplitting discounts and the implementing HOV lane. Meanwhile, loadings of ATP4 and ATP3 are positive and their loading values are close, indicating that convenience of public transportation facilities and comfort of riding environment will share similar positive influences on the attitude towards public transport. The loadings of RP2, RP3, and RP5 are positive, exhibiting that willingness to use in the daily travel, willingness to recommend to the family, and travel preference on ridesplitting are suitable to describe the travellers' preference to adopt the ridesplitting.

4.3. Analysis of Results of the Structural Model. According to the regression results of structural model, the coefficient and significance results are shown in Figure 2. The estimated results of significance (t value) are lower than 0.05, meaning the H1–H7 hypothesis cannot be rejected within 95% confidence interval. Also, age, education, and gender have a

Table 3: Model variables.

Variable	Description
Gender	1 = males; 0 = female
Age	1 = individual 18–25 years old; 0 = above 25
Education	1 = graduate degree; 0 = below graduate degree
Income	
Low	1 = monthly income of 2500–5000 CNY; 0 = else
Medium	1 = monthly income of 5000–10000 CNY; 0 = else
High (reference)	1 = monthly income of above 10000 CNY; 0 = else
Distance	
short (Reference)	1 = average distance of below 5 km; 0 = else
Medium	1 = average distance of 5–10 km; 0 = else
Long	1 = average distance of above 10 km; 0 = else
Perceived usefulness	Measured by items from PU1 to PU5 in Table 1, ranging from 1 to 7
Perceived benefit	Measured by items from PB1 to PB3 in Table 1, ranging from 1 to 7
Attitude towards incentives and management issues	Measured by items from AIM1 to AIM4 in Table 1, ranging from 1 to 7
Attitude towards public transport	Measured by items from APT1 to APT4 in Table 1, ranging from 1 to 7

Table 4: Model hypotheses.

Description
H1: perceived benefit exerts a significant positive effect on perceived usefulness
H2: perceived benefit exerts a significant positive effect on ridesplitting preference
H3: attitude towards incentives and management issues has a significant positive effect on perceived usefulness.
H4: attitude towards incentives and management issues has a significant positive effect on ridesplitting preference
H5: attitude towards incentives and management issues has a significant positive effect on perceived benefit.
H6: perceived usefulness has a significant positive impact on ridesplitting preference
H7: attitude towards public transport has a significant negative impact on ridesplitting preference

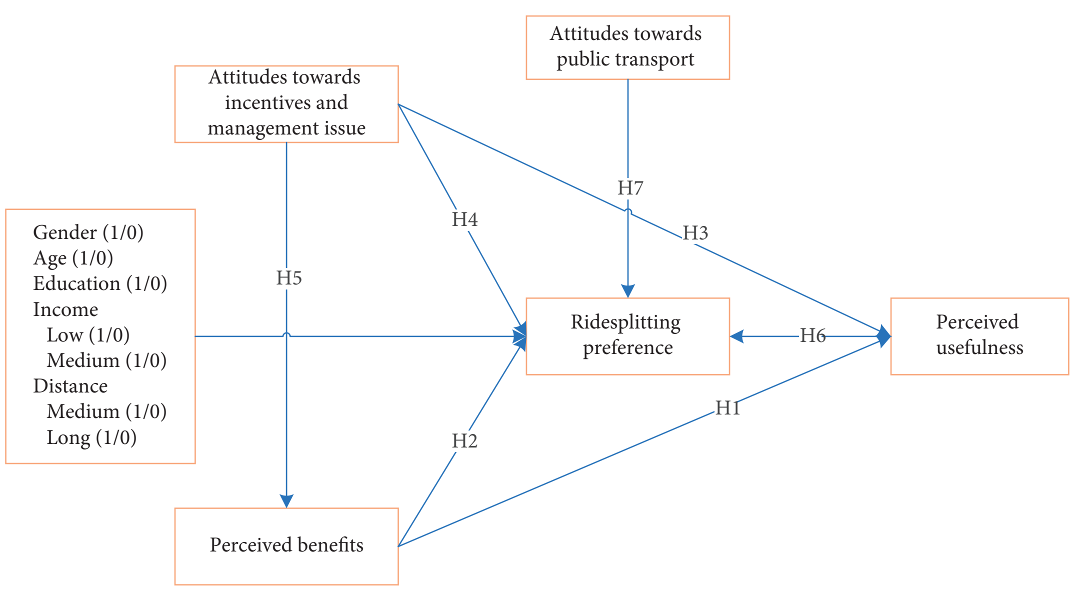

Figure 1: Theoretical model.

significant impact on ridesplitting preference. The larger value of the path coefficients indicates the greater influence, and the negative path coefficient represents a negative influence. From the results of path coefficients, cognitive factors including perceived usefulness ($\alpha = 0.39$), perceived benefit ($\alpha = 0.36$), and attitude towards incentives and management issues ($\alpha = 0.3$) exert a significant impact on the ridesplitting preference. Additionally, perceived benefit significantly influence the perceived usefulness of ridesplitting ($\alpha = 0.41$), indicating that the indirect effect of perceived benefit will be imposed on ridesplitting preference. Similarly, the results demonstrate that attitude towards

Table 5: Confirmatory factor analysis results.

Latent variable	Code	Loading	SMC	CR	AVE
Perceived usefulness	PU1	0.837	0.701	0.879	0.709
	PU2	0.83	0.689		
	PU4	0.858	0.736		
Perceived benefits	PB1	0.736	0.542	0.821	0.605
	PB2	0.847	0.717		
	PB3	0.746	0.557		
Attitude towards incentives and management issues	AIM1	0.819	0.671	0.858	0.669
	AIM2	0.887	0.787		
	AIM4	0.742	0.551		
Attitudes towards pubic transport	APT2	0.78	0.608	0.859	0.67
	APT3	0.816	0.666		
	APT4	0.857	0.734		
Ridesplitting preference	RP2	0.813	0.661	0.869	0.689
	RP3	0.847	0.717		
	RP5	0.829	0.687		

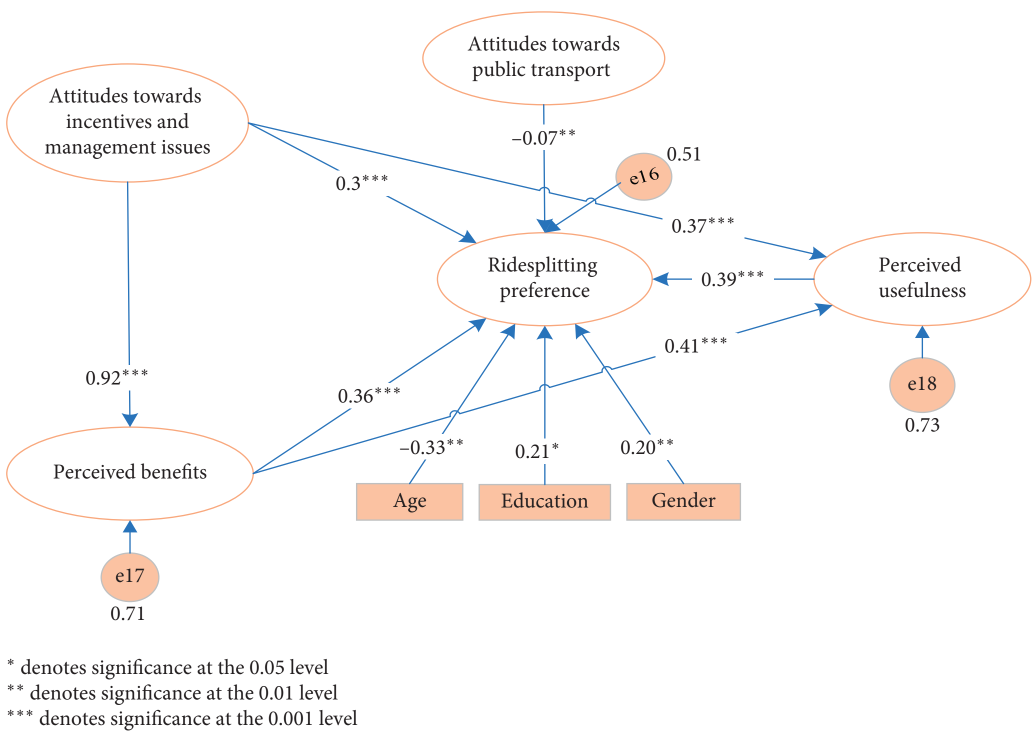

Figure 2: Estimate results of the structural equation model. *denotes significance at the 0.05 level, **denotes significance at the 0.01 level, ***denotes significance at the 0.001 level.

incentives and management issues significantly affect the perceived usefulness of ridesplitting ($\alpha = 0.37$) as well as the perceived benefit ($\alpha = 0.92$), which then indirectly affects ridesplitting preference. The attitudes towards public transport appear not to be a strong negative driving force ($\alpha = -0.07$) to discourage the desire to adopt ridesplitting.

4.4. Discussion of Model Result. According to the preliminary analysis discussed above, cognitive factors, such as PU, PB, and AIM, appear to be a positive driving force encouraging ridesplitting usage. To clarify the determinants, total effects of the factors on ridesplitting preference are further estimated using bootstrapping of AMOS [26]. The results are presented in Table 6.

As shown in Table 6, sociodemographic variables including education ($\beta = 0.044$), gender ($\beta = -0.065$), and age ($\beta = -0.088$) indicate that young female travellers with better education would prefer to adopt the ridesplitting, although the impact of such factors is relatively low. AIM, PB, and PU appear to be key determinants influencing ridesplitting preference. AIM can be regarded as the most influential determinant with β equalling to 0.772. This result indicates that incentives and management measurements, including

Table 6: Standardized effects on ridesplitting preference.

Effect analysis	PB ⟶ RP	AIM ⟶ RP	APT ⟶ RP	PU ⟶ RP	Education ⟶ RP	Gender ⟶ RP	Age ⟶ RP
Indirect effect	0.155	0.521	—	—	—	—	—
Direct effect	0.343	0.251	−0.065	0.346	0.044	−0.065	−0.088
Total effect	0.498	0.772	−0.065	0.346	0.044	−0.065	−0.088

ridesplitting discounts, ridesourcing surge pricing, and implementing HOV, would lead to the increase of ridesplitting preference and usage. The estimated effect of PB on ridesplitting preference is 0.498, suggesting that reasonable pricing for ridesplitting is necessary to stimulate ridesplitting adoption. According to the result, the influence level of PU is 0.346, which also has a positive impact on ridesplitting preference. Meanwhile, APT (β = -0.065) is the only latent variable leading to the negative impact on ridesplitting adoption. It means that travellers may have less preference on ridesplitting in areas with sufficient public transportation supply [27].

5. Conclusions

Ridesplitting is a new form of for-hire service that provides real-time share travel via the Internet. Although this service increases the sharing travel efficiency with less negative externalities, the market share of ridesplitting still maintains at a low level. Identifying determinants affecting ridesplitting preference would provide useful information for further ridesplitting service design and management. This paper identifies the cognitive determinants to affect ridesplitting preference and their inner relationships by the structural equation model. The model has been calibrated by the online survey data collected in Shanghai. The modal fitness results are reasonable and the path coefficients are significant, exhibiting that the proposed hypothesis cannot be rejected. The result demonstrates that attitude towards incentives and management issues, perceived benefit, and perceived usefulness are calibrated as cognitive determinants, which appear to be strong active driving forces encouraging the ridesplitting preference.

Similar to other experimental studies, this study has its own limitations. Firstly, the investigation was only conducted in Shanghai, China, and the results may not be suitable for other areas. Secondly, other potentially influential factors, such as impacts from friends and family [28], personal technology acceptance, environmental awareness [29], the attitude towards share travel with strangers [10], and other latent variables are not considered in this paper and should be further discussed.

Data Availability

The data were obtained from the online survey for travelers at Shanghai, China. The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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