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Exploring the role of individuals' attitudes in the use of on-demand mobility services for commuting – A case study in eight Chinese cities

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ABSTRACT

The use of on-demand mobility (ODM) services has increased in Chinese cities and is used by people for various purposes, such as leisure activities or commuting. The aim of this study is to identify and analyze factors that play a role in the use of ODM services for commuting of high-income earners in China. In previous studies, this group of people was identified as extremely relevant for ODM use as they can afford the services in principle. A specific focus of this study is on the influence of travel mode attitudes as well as sociodemographic characteristics. The data set used in this study was collected with the innovative travel skeleton approach based on information given by high-income individuals. The survey took place in eight different Chinese cities with 5,192 respondents. They have provided insights on their everyday travel (e.g., commuting) and attitudes towards car and public transit. To investigate the role of psychological factors behind the use frequency of ODM services, we applied a factor analysis to identify latent factors from psychological item sets used. Next, we integrated them into an ordered hybrid choice model (OHCM). The results show that people's perceived public transit experience increase the probability to use ODM more often for commuting. We suggest a strong interrelation between public transit and such services, even among people with high incomes.

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1. Introduction

In addition to public transit and private individual transport, an increasing mixture of these two mobility options can be observed in urban areas. Services have emerged that combine the characteristics of public transit with the flexibility of individual transport options. A growing demand for these individual mobility options beyond the private car can be observed. This also leads to an increasing variability of new mobility offers in urban areas. An example for these new services is on-demand mobility (ODM) such as car sharing or ride hailing services. In urban areas in China these services are gaining popularity and are increasingly utilized as additional transport modes for commuting either substituting other modes or utilized in combination. In cities with poor public transit, these services are the only motorized alternative to the private car. This may mitigate the sharp increase in private car ownership in these cities.

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Both in the context of transportation research and to derive appropriate practical recommendations, the investigation of the role of psychological factors in the use of these ODM services on the commuting trip is crucial. Besides sociodemographic characteristics, psychological factors such as travel mode attitudes can deliver further insights into the decision-making process to use such services more often. This helps to better understand what latent factors are behind the behavior and whether there is an interrelation. Examining attitudes can also provide information if the use of a certain mode would be assessed favorably, even if it is not available yet. Other than already existing demands, attitudes towards transport modes can give hints to future market potentials and provide more detailed information on individuals' travel behavior. To measure the role of attitudes, in hybrid choice model these latent factors are integrated in the choice component. These models are able to consider attitudes when describing decision-making behavior. However, we believe these models have not yet been sufficiently employed to determine psychological factors in ODM use for habitual trips such as commuting. While most research focuses on the entire population, little consideration has been given to the study of people from high-income households. However, they have the financial resources to use ODM regularly for commuting. This study thus aims to close that research gap and broaden the scope in existing literature. Due to the importance and increasing development of ODM services in urban cores, this research focuses on determining influencing sociodemographic characteristics in combination with psychological factors and aims to find answers to the following questions:

- Which factors play a significant role in ODM use of people from high-income households on commuting trips?
- How large is the interrelation of travel mode attitudes on ODM use frequency?

In order to interpret and analyze relevant information on sociodemographic characteristics and psychological factors, a large dataset with 5192 participants was used. To collect the data, we applied an innovative survey approach to interview high-income individuals in eight different Chinese cities on their travel behavior and their attitudes towards transport modes. The focus of this study lies on high-income individuals and households, as these have the financial scope to own a car and to use ODM services frequently. As a result of growing welfare, this stratum of the population is continuously becoming larger in China. With this work we would like to gain a better understanding of people with high incomes and their decision to use car sharing or ride hailing for routine trips. Besides the public transit these services make people more independent of their own car and helps to reduce the enormous growth in car ownership in Chinese cities. To determine the influencing factors for this research, we used the methodology of hybrid choice modeling in form of an ordered hybrid choice model (OHCM), which is known in a more general version as an integrated choice and latent variable model (ICLV).

The paper is structured as follows: First, we show a brief literature review on hybrid choice models and the investigation of ODM. Second, we describe the data and the methodology used for our analysis. Third, we use a factor analysis to identify latent factors. Fourth, we create a discrete choice model (DCM) in the form of an ordered probit model to determine sociodemographic characteristics derived from the data set we prepared. Next, the model is extended to an OHCM to suitably calculate and visualize the role of latent factors behind behavior. Finally, we draw a conclusion, discuss the limits of our approach and refer to further work.

2. Literature review

In the existing literature, a variety of studies focus mainly on the influence of sociodemographic characteristics on ODM use. Dias et al. (2017) examined the sociodemographic influence on car sharing and ride sourcing services and were able to determine that individuals prone to use such services are usually well educated, higher income earners living in dense urban areas. Rayle et al. (2016) examined the use of ride sourcing services in San Francisco and also showed that the average user of such services is generally younger and better educated. Krueger et al. (2016b) investigated the willing to use shared autonomous vehicles (AVs) with an Australian online panel. The results indicated that young people with lower income and people with multimodal travel behavior are more willing to use shared AVs.

Besides the influence of sociodemographic characteristics, there are also studies on the trip purpose of ODM use. In general, most existing studies showed a higher probability of ODM use for non-routine trips like for leisure activities (Alemi et al., 2018; Clewlow and Mishra, 2017; Dawes and Zhao, 2017; Kooti et al., 2017). ODM services are rather less used for commuting trips. In the survey of Lavieri and Bhat (2019) in Dallas, 10% of ride-hailing trips are made for the purpose "work". In the study from Rayle et al. (2016), only 16% of the respondents use ODM for commuting trips. Henao (2017) found that work was an origin or destination for 30% of the respondents in Denver. However, the presented studies do not consider psychological factors as influencing factors on the decision to use ODM services.

2.1. Psychological factors in discrete choice models

To explain decision-making behavior of individuals, discrete choice models (DCM) are have been widely used in transportation research by examining observable factors such as sociodemographic characteristics (Ben-Akiva and Lerman, 1985). In addition to socio-demographic characteristics, research conducted in the 1970s already showed significant statistical correlations between psychological factors such as attitudes, perceptions, beliefs, values etc. of individuals and their travel behavior (Dumas and Dobson, 1979; Recker and Golob, 1976). Extensive further studies support these observations.

It could be shown that psychological factors influence decision-making behavior, and conversely, that decision-making behavior also influences psychological factors. Attitudes thus influence behavior and vice versa, both being interdependent (Kroesen et al., 2017).

Hence, the concept of discrete choice modeling was extended by unobservable latent variables, in order to add psychological factors to the observable variables when examining travel behavior. Factors describing travel behavior can thereby be defined more clearly and described in more detail, thus adding validity to the model (Ashok et al., 2002; Ben-Akiva et al., 2002, 1999). The hybrid choice model (HCM), as an example, extends common DCMs by merging different models and at the same time calculating all models simultaneously within one frame (Ben-Akiva et al., 2002, 1999). The HCM contains a latent variable model, which determines psychological factors such as attitudes and perceptions and adds them to the decision-making components (Ben-Akiva et al., 2002). This model approach has repeatedly been used in transportation research and specifically in studies examining travel behavior and mode choice. As an example for many studies, Atasoy et al. (2013) investigated with a HCM the influence of "pro-car attitudes" and "environmental concern" on mode choice in Switzerland. Results showed that pro-car-attitude decrease the use of public transit. There is a large amount of research work that cannot fully be mentioned here. We focus on commuting and the application of HCMs in this context.

2.2. Applying hybrid choice model to explain commuting behavior

Studies also exist in the transportation literature that use an HCM to examine travel behavior and mode choice for commuter trips. Johansson et al. (2006) used the model to examine impacts of attitudes and personality traits on the mode choice of individuals commuting between Stockholm and Uppsala. Ding et al. (2017) examined the influence of attitudes towards cycling and walking on the decision-making behavior on commuting trips. Sarkar (2018) studied the influence of attitudes and perceptions on travel mode decisions of commuters in India and was able to determine significant influence of the variables "comfort" and "flexibility". A study conducted by Paulssen et al. (2014) examined the influence of values on travel mode choices on commuting trips. Ababio-Donkor et al. (2020) investigated the influence of "affect" and "salience" on mode choice on the way to work. Private motorized users were found to be more sensitive to overcrowding and antisocial behavior in public transport. The described selection of studies on transport mode choice using HCM models already shows an increasing use of HCM models, also as they present a better insight into decision-making behavior than other simple common discrete choice models.

2.3. Explaining on-demand mobility use

To explain the ODM use, there are also studies in the existing literature available in which psychological factors have been considered. Alemi et al. (2018) examined which factors influence acceptance and use of ODM. Among the latent variables considered, attitudes such as "strong ecological conscience" or "affinity to technology" were identified, which encourage individuals to use services such as Uber and Lyft. Although this last study indeed examined latent variables, its focus was on sociodemographic characteristics. Moore et al. (2020) investigated the potential effects of AV on commuting time. Results showed that especially younger people under 34 years have a great interest to use AV to be productive when commuting. Lavieri et al. (2017) analyzed the role is played by lifestyle and attitudinal factors for using shared AVs. Findings from their research indicated that younger, urban residents with a high level of education and lower income are more likely to be early adopters. In addition, males are more inclined in shared AVs. The authors mentioned also the need for more research on psychological factors to target those who may be positively disposed toward specific new mobility technologies. Krueger et al. (2016a) used a HCM to investigate the adaption of shared AVs. This ODM service is more likely to be chosen by young people, and there is a strong relationship between the transport modes a person uses frequently and the tendency to choose shared AVs. Xie et al. (2019) presented in their study a general framework for modeling the behavior of ODM with a HCM. They integrated two latent variables "app-lover" and "environmentalist" in their model. A study with a focus on the ODM use for commuting using a HCM is from von Behren et al. (2020a). A representative survey was used to analyze the influence of attitudes on ODM use for commuting in Shanghai. Results show that individuals with a positive "attitude towards public transit" use ODM more often, whereby the "pro-car attitude" has no influence considering all strata of the population. In addition, this study has shown that income plays an important role in the use of ODM for commuting in Shanghai. People with a high income are more likely to use these services for routine trips in everyday travel.

Existing studies on ODM use generally consider the entire population. There is a lack of knowledge about the influence of psychological factors on the ODM use of people from high-income households. Especially, as high-income earners had been identified as highly relevant (von Behren et al., 2020a) for routine trips, we look on this specific group in eight different cities in China to give further insights into the decision-making process. To our knowledge, it is also one of the largest surveys with more than 5000 high-income earners in which psychological factors in ODM use for commuting are collected and analyzed.

3. Survey design, data and descriptive results

In the following, we start with the introduction of the applied survey design. We then describe how the survey was conducted in eight Chinese cities and finally show descriptive analyses of the survey data used in this study.

3.1. Survey design

The research presented in this paper is based on a survey, which collects information on activities and mode choices using the concept of a travel skeleton (von Behren et al., 2020a, 2018b, 2018c).

3.1.1. Concept of a travel skeleton

The idea is based on the longitudinally-oriented trip diary survey of the German Mobility Panel (MOP). However, instead of asking the people about every single trip in a random week, we ask the people about relevant activities and mode choice in a typical week. We describe the concept of the travel skeleton as a "pseudo-longitudinal" approach (see Fig. 1). Thus this concept focuses on the collection of typical travel behavior elements. In the questionnaire, the most important activities in a week: commuting (red ellipse), chauffeuring, leisure, shopping and errands (grey or green ellipse) are asked. The questioning of typical behavior – in our research referring to the frequent, daily repetition of activities across many weeks – reduces the error rate of short-term snapshots like diary-oriented surveys (von Behren et al., 2020b). With our approach we create a cost-effective survey alternative to longitudinal trip diaries. In our survey, we asked respondents for the current study in detail about their typical commuting behavior considering ODM as a mode option. Besides everyday travel, this approach is also able to capture long-distance traveling (outside of the grey ellipse), tech savviness and psychological factors of respondents. The skeleton provides a reasonable compromise between the level of detail needed and the required effort to survey travel behavior. The idea of using a skeleton to identify routines and typical behavior is common in travel behavior research; for an overview of applications and a detailed description of our approach see von Behren et al. (2018b). The concept of a travel skeleton was originally designed and tested for a study in Hamburg and Berlin (Germany) by von Behren et al. (2018c).

3.1.2. Psychological items

In order to investigate respondents' attitudes towards different modes of transport we used two standardized and well-tested psychological item sets by Hunecke et al. (2010) and Steg (2005). The items are rated on a Likert scale from 1 to 5 ("does not apply" to "apply"). In our study, we focus on ten psychological items (indicators) that record attitudes towards public transit and the car. With these items, we want to analyze how the attitudes towards these two main modes affect ODM use on the way to work. Table 1 shows the items used. In selecting the items on attitudes towards public transit, we have attempted to reflect different aspects of public transit. For example, the autonomy to travel which can be achieved by public transit or the possibility of relaxing instead of driving a car. The selection of items relating to the car is more concerned with affective motives for use, i.e. the emotional affinity to the car.

3.2. Data

In our study, we use data collected through a survey in eight Chinese cities between May 2017 and July 2017. The surveyed cities were selected according to the categorization of cities into first-, second- and third-tier cities (The World Bank and Development Research Center of the State Council, 2014) in order to represent exemplary cities for each category in China. Cities in different tiers reflect differences in consumer behavior, income level, population size, infrastructure and business opportunity. Categorization by tiers is also a suitable proxy for the volume of ODM service supply. Based on the

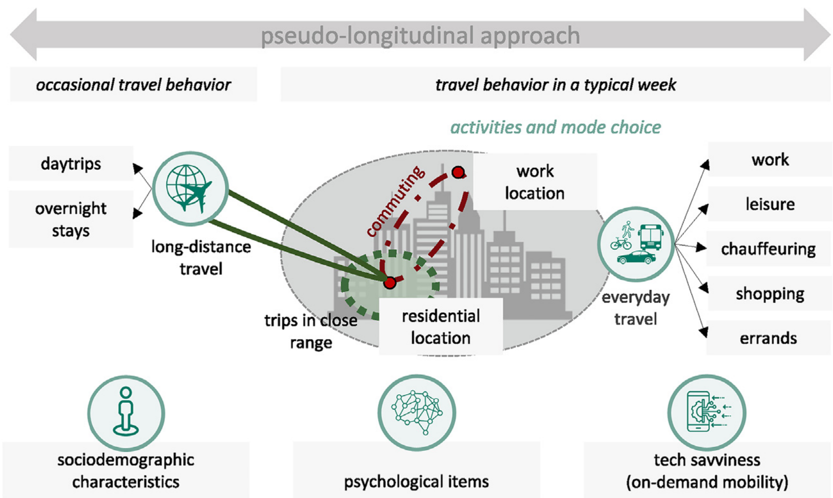

Fig. 1. Concept of the travel skeleton – Everyday and long-distance travel as a pseudo-longitudinal approach.

Table 1
Psychological items (indicators) used in the study.

Items	Questions
I_1^{PT}	I can relax well in public transportation.
I_2^{PT}	I can easily use the traveling time on the bus or train for other things.
I_3^{PT}	I appreciate public transportation, because there is usually something interesting to see there.
I_4^{PT}	I have resolved to travel the ways I need to go in everyday life using buses and trains.
I_5^{PT}	I can take care of what I want to with public transportation.
I_1^{CAR}	Driving a car means fun and passion for me.
I_2^{CAR}	Driving a car means freedom to me.
I_3^{CAR}	Being able to use my driving skill when driving a car is fun for me.
I_4^{CAR}	I feel free and independent when I drive a car.
I_5^{CAR}	I like to drive a car.

selection of cities from different categories, the survey took place in Shanghai and Beijing (tier 1); Chongqing, Shenyang and Wuhan (tier 2); Kunming, Urumqi and Zhuhai (tier 3). The survey primarily focused on capturing travel behavior and psychological factors of people in higher income classes in urban and high density areas. The selected respondents have a monthly income of more than 10,000 RMB and represent nearly the top 5% earners in China (Li et al., 2018). Therefore, the survey does not claim to be representative for the selected cities or for the Chinese population. To generate a comparable dataset from each city, we used a standardized survey approach based on a computer assisted personal interview (CAPI). The survey was carried out by a professional Chinese market research firm. The full sample size was 5192 individuals with more than 550 respondents from each city. Prior to the analysis, we prepared the data and performed different data plausibility checks. In particular, we analyzed the psychological questions on the basis of the Likert scale with regards to a possible response bias using an algorithmic measure method as presented by Magdolen et al. (2019). Based on the data preparation, we selected 4158 respondents for the following analyses.

3.3. Descriptive results

Based on our survey design, we were able to analyze the typical commuting behavior and the related ODM use. In our study we focus on car-related ODM services such as ride sourcing (e.g., Didi Chuxing) or car sharing (e.g., EVCard). Access to this form of mobility is generally flexible, individualized and spontaneous ("on-demand"). For this research ODM also includes taxi services. In our study, 10.8% of respondents use ODM in some way for commuting. Out of all commuting trips, 2.9% are performed with ODM. For our model and in order to obtain a sufficiently large sample size for all alternatives, respondent's choices were divided into three categories, according to the use of ODM:

- *no use*, corresponding to zero commuting trips with the use of ODM services in a typical week (89.2%, 3709 respondents),
- *occasional use*, corresponding to one commuting trip with the use of ODM services in a typical week (7.3%, 305 respondents)
- *regular use*, corresponding to at least two trips with the use of ODM services in a typical week (3.5%, 144 respondents).

3.3.1. Working, person and household characteristics

In addition to the answers given on ODM use we also recorded sociodemographic data. These are shown in Table 2. 60.1% of the respondents are male. As to the monthly income, the sample, as shown above, consists of predominantly high-income households. Income classification was chosen in a manner to reflect very high-income households separately, so that their significance could be examined separately within the model. We distinguished households by household types. 30.1% were households with 1 or 2 adults, 42.8% were households with children and 27.1% were household with at least 3 adults and no children. The variable *mode choice stability* describes whether an individual behaves multimodally in his or her everyday travel, i.e. varies different modes. This variable is based on the Herfindahl-Hirschman-Index (HHI) on a scale from 0 to 1 (von Behren et al., 2018b, 2018a). The value 1 implies that a person uses only one single mode for their everyday travel, displaying monomodal behavior of this person. In contrast, a lower value implies a higher multimodal behavior. For reasons of simplification, a dummy variable (mode choice stability) was created for which a stable mode choice in everyday travel starts from a value above 0.8. The descriptive analysis shows also that about 65% of all respondents have a commuting distance of maximum 10 km to their work place. 7.5% of the respondents cover more than 20 km to work (see Table 2). People with higher incomes have more options in their residential choices and have not to choose cheap residential areas, which can results in a longer commute to work.

3.3.2. Psychological characteristics

Fig. 2 summarizes the responses to the psychological indicators. About a quarter of the participants rated the indicators for public transit (I_{1-5}^{PT}) positively. The larger proportion (up to 40%) of respondents does not agree with the statements and has rather poor experiences in the context of public transit. This is also shown in the figure by the fact that the center of the

Table 2
Person, working and household characteristics.

Person characteristics				
	Yes	no		
Female	39.9%	60.1%		
Driver's license	79.2%	20.8%		
Age (<37 years)	49.0%	51.0%		
High educated	12.5%	87.5%		
Mode choice stability	11.2%	88.8%		
Usage of mobility-related apps less than once a week	62.2%	37.8%		
Net income	<10 k RMB	10 k – 60 k RMB	> 60 k RMB	
	2.0%	93.4%	4.6%	
Working characteristics				
	yes	**no**		
Side job	5.4%	94.6%		
Home office	5.5%	94.5%		
Workdays per week	<5 days	=5 days	>5 days	
	2.4%	71.4%	26.2%	
Business trips per month	0	1–3	>3	
	77.5%	16.3%	6.2%	
Working time model	fixed	partially fixed	flexible	
	77.5%	16.3%	6.2%	
Commuting distance (in kilometers)	<5km	5–10 km	10–20 km	>20 km
	34.4%	31.3%	26.8%	7.5%
Household characteristics				
Household type (HH-Type)	1–2 adults	Household with children	3 + adults	
	30.1%	42.8%	27.1%	
Tier ranking city	tier 1	tier 2	tier 3	
	25.8%	40.9%	33.3%	
Cars per household	0	1	>1	
	34.9%	60.7%	4.4%	
Parking satisfaction	yes	no		
	66.9%	33.1%		
				N = 4,158

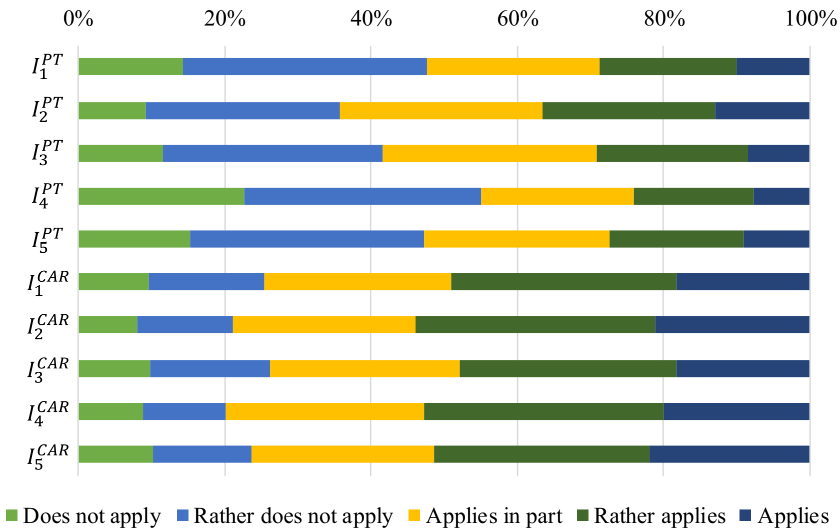

Fig. 2. Attitudes towards public transit and car. 1–5 Likert scaled questions as described in Table 1.

neutral area (yellow bar) is above the 50% mark. This applies to all indicators except I_2^{PT}. Consent to this indicator is higher than for the other indicators, as people confirm that they can use their time on the bus or train for other things. As to questions about cars (I_{1-5}^{CAR}), people tend to agree more with the statements made (see Fig. 2). The middle point of the neutral range for all indicators is not only below the 50% mark, it is also below the 40% mark, which indicates a high agreement with the statements. The highest agreement is to be observed with I_2^{CAR}. For these people driving a car means freedom. This characteristic cannot be provided by conventional (mass) public transit services.

As a preliminary analysis for our ordered hybrid choice model (OHCM) and to identify latent variables, we conducted an explorative factor analysis based on the attitudinal indicators as presented. Table 3 shows the results of the principal factor analysis (PFA). Based on the scree plot (elbow criterion), Kaisers criterion and parallel analysis, two factors can be extracted: one describing the experience with public transit (factor 1) and one describing the emotional attitude to cars (factor 2). Factor 1 characterizes whether people can handle their everyday life with public transit and what their experience with public transit is like, whereby high values imply positive experience with public transit usage. Factor 2, emotional car attitude, describes whether people like to use a car and if they are emotionally bound to cars, regardless of whether respondents own a car or not. Both factors were found to have excellent internal reliability with a Cronbach's alpha of 0.88 and 0.91, respectively

4. Methodology

To investigate the influence of psychological factors on on-demand mobility (ODM) use in the selected Chinese cities, we used an ordered hybrid choice model (OHCM). The use of an OHCM is inspired by the work of Belgiawan et al. (2017). A more general version of this model is also known as integrated choice and latent variable model (ICLV). In our study, we do not calculate a separate OHCM for each city, as the results are rather complicated to compare between cities. In addition, the complexity and the optimization effort for eight individual models prevent a meaningful implementation. Instead, we attempt to identify influences across cities in order to make generally valid statements for high-income earners in China.

In this section, we first describe our model specification in Section 4.1. Then, we explain the OHCM of our study in more detail (Section 4.2). Before we address the choice model component, we look at the latent variables (LVs) and their structural model. We then consider the joint estimation of the different model components.

4.1. Model specification

Before the OHCM, we calculated an ordered probit model as a "base" model. The objective of the "base" model is to select the relevant independent variables for our final model. The sample of 4158 observations was split into a training and a test data set to validate the predictive power of the model. The 3210 observations constituting 77% of the sample was randomly selected and used to estimate the model. The estimated model was then applied to the remaing test data to validate the predicition power of the model.

Table 3
Principal factor analysis (PFA) - Varimax rotated factor pattern.

	Factors		
	Public transit experience	*Emotional car attitude*	
Cronbach's Alpha	*α = 0.88*	*α = 0.91*	
Indicators in PFA			
I_1^{PT}	0.810		
I_5^{PT}	0.809		
I_3^{PT}	0.780		
I_2^{PT}	0.754		
I_4^{PT}	0.716		
I_2^{CAR}		0.828	
I_4^{CAR}		0.813	
I_1^{CAR}		0.812	
I_3^{CAR}		0.800	
I_5^{CAR}		0.792	
Printed is the maximum loading of each item			
Criteria of extraction and quality for PFA			
Criteria of extraction	*# Factors*		
Kaiser's criterion	2		
Parallel Analysis	2		
Scree Test	2		
Criteria of quality		*Value*	*Pr > Chi-Square*
Kaisers Measure of Sampling Adequacy (MSA)		0.888 > 0.8 (meritorious)	
Bartlett's test of Sphericity		χ^2 (9) = 66.754	<0.001
			N = 4,158

4.1.1. Explanatory variables in the model

After extensive specification testing, 13 observable variables X_n (respondent characteristics) were used in the model: gender (female used as the base), age (people under 37 used as the base, since they were born after the two-child policy in China), driver's license (no license as the base), car ownership (using those with no car as the base), mode choice stability (people with no stable mode choice behavior as the base), tier cities (using tier 2 city as the base), household type (split into three categories, taking household type 3 as the base), the distance to work (split into 3 categories, with more than 10 km as the base), use of mobility-related apps (usage of mobility-related apps less than once a week used as a base) and business trips (3 or less business trips used as the base). In our model, we did not use time and costs for transport alternatives, as we focus on the typical use frequency of ODM for commuting and not on classical mode choice. In this case, such information cannot be calculated either, since we did not have single trip information. Furthermore, ODM services often have a dynamic pricing system. Exact costs are difficult to determine. In addition, the other observable variables from Table 2 were not taken into account because they had no influence in the "base" ordered probit model.

The final ordered probit model with 13 observable variables (X_n) predicts the choice with an accuracy of 88.2% (log-likelihood = −1324.28), which gives a high reliance in the model and estimated parameters. These 13 explanatory variables are integrated in the subsequent OHCM (see Fig. 3). In general, one would expect more complex models, such as the later described OHCM, to fit the data better than less complex models, such as the "base" ordered probit model. However, as Vij and Walker (2015) showed, an "ICLV model can be reduced to a choice model without latent variables that fits the choice data at least as well as the original ICLV model framework from which it was obtained". Moreover, as Hess et al. (2018) mentioned, "it is well known that a model which is estimated only on the choice data alone will fit that data at least as well as the choice component of a hybrid structure". After careful consideration, we decided against showing the "base" ordered probit model alongside the hybrid structure in the present paper. But results of the "base" model are later used for comparison with the parameters of the OHCM as an important quality criterion of the OHCM (see Table 5). The focus of the study is to gain insights into the role that attitudinal constructs play in the use of ODM and what proportion of heterogeneity in the hybrid model can actually be associated with the attitudinal constructs.

4.1.2. Hybrid structure of the model

Consequently, we focus on the hybrid structure in this paper. In a "base" ordered probit model, only observable variables are considered to describe the choices of the individuals. The OHCM provides a framework to integrate unobservable, latent attitudes into our model of the decision-making process. As those psychological factors cannot be observed directly,

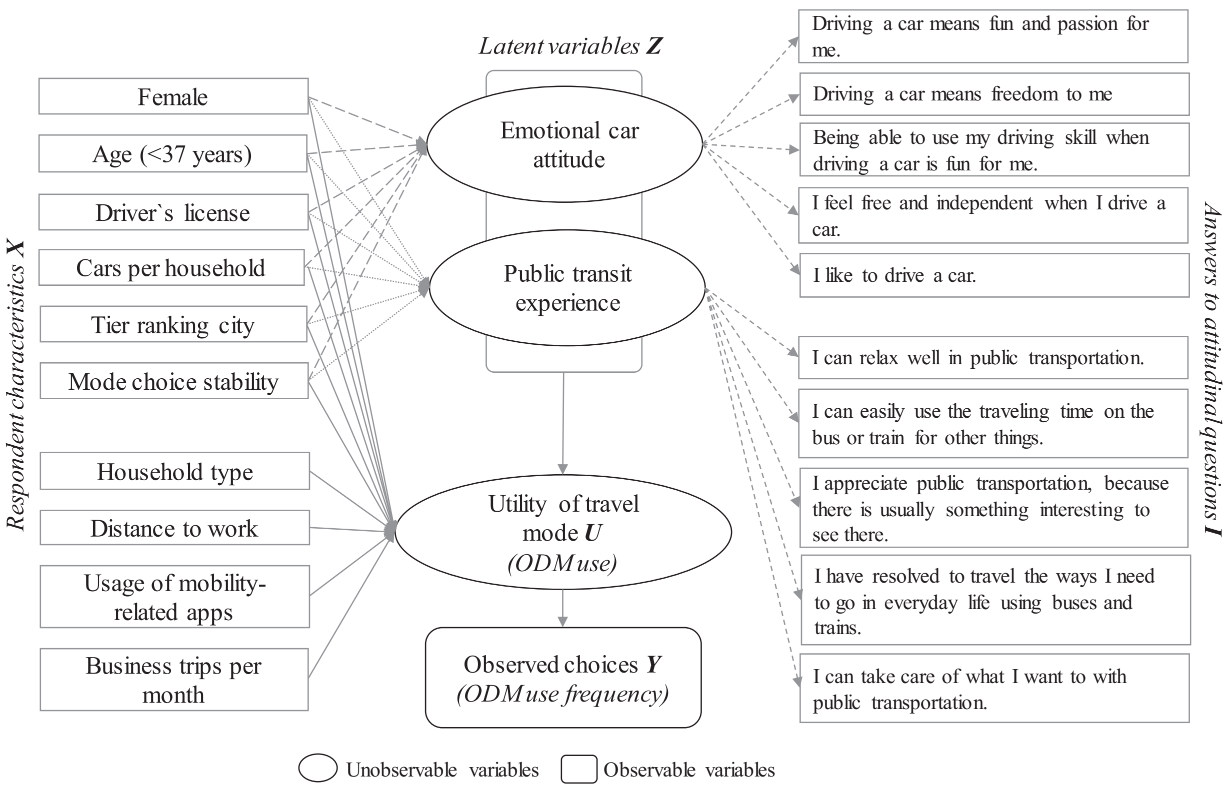

Fig. 3. Ordered hybrid choice model (OHCM) framework and model specification.

responses to a set of indicators on an ordered scale are asked in the survey (see Table 1). Those indicators are used to gain information on the LVs describing respondents' travel mode attitudes towards car and public transit. For this purpose, we performed the factor analysis described in the previous chapter.

In the resulting OHCM, two LVs from the factor analysis are integrated: public transit experience and emotional car attitude. Fig. 3 illustrates the structure of our model.

4.2. Ordered hybrid choice model (OHCM)

The OHCM with the ordered probit kernel consists of three relevant components (structural model, measurement model, choice model), which we describe in the following in more detail.

4.2.1. Latent attitudes: structural model

In the OHCM, we describe the vector of L different LVs of individual n by Z_n. Each LV Z_{nl} is characterized by a linear combination of the individual's observable variables X_n and a random component ξ_{nl}. In Fig. 3 the observable variables used in the structural model are shown. In the structural Eq. (1) the vector α_l are the weights and the error component ξ_{nl} is assumed to be normally distributed with mean zero and variance σ_l^2:

$$Z_{nl} = \alpha_l X_n + \xi_{nl}, \xi_{nl}\ N\left(0, \sigma_l^2\right). \tag{1}$$

In our hybrid model, we will assume independency of the LVs given the observable variables and the weights α_l. In short: ξ_{nl} is assumed to be independent for all $l \in \{1, \cdots, L\}$ and $n \in \{1, \cdots, N\}$. As scale and spread of the LVs are arbitrary, no constant is needed in the specification of the LVs and the variance can be set to one.

4.2.2. Latent variables: measurement model

The LVs (in our model: public transit experience and emotional car attitude) are used in the measurement model component of our OHCM to explain the answers to attitudinal questions. We used 10 indicators based on a 5-level Likert-scale (see Fig. 2). The indicators, the responses to which are given on an ordered scale represented by the values 1 to S, are manifestations of the LV. We denote the set of indicators of individual n by the vector I_n, containing the K single indicators I_{nk}, $k \in \{1, \cdots, K\}$. We model each indicator by a continuous representation I_{nk}, which is composed of a linear combination of the LVs with weights given by the vector ζ_k and an error component ψ_{nk} with mean zero:

$$I_{nk} = \zeta_k Z_n + \psi_{nk}. \tag{2}$$

The distribution of the indicators I_{nk} is then defined by allocating the variables I_{nk} to intervals given by the thresholds $\rho_k^{(0)}, \cdots, \rho_k^{(S)}$:

$$\begin{aligned}
I_{nk} = 1 &\iff \rho_k^{(0)} < I_{nk} \le \rho_k^{(1)}, \\
I_{nk} = 2 &\iff \rho_k^{(1)} < I_{nk} \le \rho_k^{(2)}, \\
&\vdots \\
I_{nk} = S &\iff \rho_k^{(S-1)} < I_{nk} \le \rho_k^{(S)},
\end{aligned} \tag{3}$$

where $\rho_k^{(0)} = -\infty$ and$\rho_k^{(S)} = \infty$ for all $k \in \{1, \cdots, K\}$. Assuming the error components ψ_{nk} are i.i.d. and follow a Gumbel distribution for all n and k and to take into account the ordered nature of the indicators, we apply an ordered logit model to explain the likelihood of the observed values of I_{nk} of individual n as:

$$P(I_{nk} = s|Z_n, \zeta_k) = P\left(\rho_k^{(s-1)} < I_{nk} \le \rho_k^{(s)}|Z_n, \zeta_k\right) = \frac{\exp\left(\rho_k^{(s)} - \zeta_k Z_n\right)}{1 + \exp\left(\rho_k^{(s)} - \zeta_k Z_n\right)} - \frac{\exp\left(\rho_k^{(s-1)} - \zeta_k Z_n\right)}{1 + \exp\left(\rho_k^{(s-1)} - \zeta_k Z_n\right)}, \tag{4}$$

4.2.3. Choice model component

Finally, in the choice component of our model, we include the LVs to explain their influence on ODM use. The utility is now composed of the observable variables, the LVs and an error component ϵ. The error component is assumed to be normally distributed with mean 0 and variance σ_{choice}^2. The utility function is defined as

$$U_n = \beta X_n + \gamma Z_n + \epsilon_n \tag{5}$$

where β and γ are the vectors of weights of the observable variables and the LVs in the utility function respectively. The choice probabilities, given all variables X_n and Z_n, is then:

$$P(Y_n = j|X_n, Z_n, \beta, \gamma, \tau) = \Phi\left(\frac{\tau^{(j)} - (\beta X_n + \gamma Z_n)}{\sigma_{choice}}\right) - \Phi\left(\frac{\tau^{(j-1)} - (\beta X_n + \gamma Z_n)}{\sigma_{choice}}\right). \tag{6}$$

where $\tau^{(j)}$ are the threshold parameters in the ordered probit model. The random components ϵ_n include all unobserved heterogeneity among individuals. By including the LVs as in Eq. (5) and considering that they are random variables themselves, we hope to reduce the role of the purely random terms ϵ_n and to explain some of the heterogeneity through the LVs instead.

Since the OHCM specification has been clarified, the likelihood can now be calculated for a given data set (consisting of observable variables and indicators) and for given parameters (consisting of β, γ, τ, σ, ζ, ρ, α). For the estimation of the parameters the approximation of distributions, e.g. by Halton draws, is necessary, resulting in the maximum simulated likelihood estimation method in the OHCM. In our final model we used 500 Halton draws for each latent variable. The estimation is based on the CMC choice modelling code for R (CMC, 2017). For the application with the ordered probit in the choice component we adapted and accelerated the given basis code.

5. Results

The ordered hybrid choice model (OHCM) helps to illustrate how various sociodemographic characteristics as well as attitudes towards modes play a role in the use of on-demand mobility (ODM) services on commuting trips. We cannot discover improvement in the log-likelihood of the choice component of the OHCM against the "base" ordered probit model (see Table 4). But this is in line with the existing literature as the overall log-likelihood can never be better than that of the corresponding reduced form model (Hess et al., 2018; Song, 2019; Vij and Walker, 2015).

5.1. Direct effects on on-demand mobility use for commuting

First, we look at the direct effects of the respondents' characteristics (β) in the utility function (see Table 4 (column A)). It is not surprising that younger people are more likely to use such services for commuting. Likewise, private car availability (CarAV) has a negative influence. These results are in line with existing research studies. However, the influence in our model is not significant. Contrary to the influence in existing studies, the educational level in high-income classes has no influence

Table 4

Main parameter estimates. (A) Parameters of the structural equation of the choice model. (B) Parameters of the structural equations of the latent variables.

Log-likelihood		−40,427.68					
Log-likelihood of choice component		−1,324.32					
Log-likelihood of null model (choice component)		−3,526.56					
Log-likelihood of the base ordered probit model		−1,324.28					
McFadden Pseudo-R^2 (choice component)		0.62					
N	3,210						
Thresholds of the choice component							
$\tau^{(1)}$	6.059						
$\tau^{(2)}$	8.834						
(A)				(B)			
Parameter	**Value**		**Parameter α from variable**	**on latent variable Emotional car attitude**		**PT experience**	
	Parameter estimates	**t-statistics**		**Parameter estimates**	**t-statistics**	**Parameter estimates**	**t-statistics**
β_{Female}	0.866	6.31	Female	−0.263	−6.97	0.240	6.30
$\beta_{Age<37}$	0.212	1.42	Age < 37	0.096	2.62	0.052	1.44
$\beta_{Driver's license}$	0.995	7.28	Driver's license	1.022	21.51	−0.277	−5.83
β_{CarAV}	−0.198	−0.63	CarAV	0.961	19.78	−0.626	−13.22
$\beta_{Tier1city}$	−1.640	−5.77	Tier 1 city	−0.035	−0.82	0.345	8.19
$\beta_{Tier3city}$	−2.346	−9.02	Tier 3 city	−0.273	−5.18	−0.394	−7.70
$\beta_{HH-1,2adults}$	1.000						
$\beta_{HHwithchildren}$	−0.834	−3.50					
$\beta_{ModeChoiceStability}$	1.522	7.50	ModeChoice Stability	0.159	2.71	0.424	7.25
$\beta_{Appusage}$	0.598	1.75					
$\beta_{Distancework<5km}$	−0.479	−1.73					
$\beta_{Distancework5-10km}$	1.177	7.73					
$\beta_{Businesstrips}$	1.073	2.83					
γ_{PT-Exp}	0.265	1.92					
γ_{Car}	−0.212	−1.55					
σ_{choice}	4.441	26.43					

on the probability and was not considered in the improvement of the model quality. The high income itself is a more relevant aspect than education as the repeated use for commuting becomes expensive in the time of demand peaks. This implies that ODM is no mode option for all commuters. The results of von Behren et al. (2020a) in Shanghai confirmed this conclusion. Noticeable, and in contrast to previous studies, is the fact that women are more likely to use ODM in high-income groups. High earners who are less multimodal (mode choice stability) use ODM more often for commuting. This contrasts with the study by Krueger et al. (2016b), in which people with multimodal behavior tend to use ODM more frequently for various trip purposes.

The results show also differences between the city tiers. People in tier 2 cities are more likely to use these services on their way to work than in tier 1 or tier 3 cities. In general, ODM has big potential in tier 2 cities. It is a good alternative solution for tier 2 cities with less-developed public transit infrastructure to meet the increasing demands of mobility. This motivates people to use ODM for routine trips like commuting. It can be assumed that more people would use car-related ODM services in tier 1 cities as a result of a greater availability. One explanation for the results could be that it is more difficult to use ODM due to congestion and that tier 1 cities offer better alternatives in the form of well-developed public transit services. Therefore car sharing and car hailing are maybe less accepted in tier 1 cities, due to the safety consideration. And thus in tier 1 cities the private car still is a preferred mode of transport in the stressful and crowded environment. If we look at the commuting distance, we find the highest probability at a distance between 5 and 10 km. Distances under 5 km are most unlikely.

We next look at the impact of the latent variables (LVs) in the utility function (see Table 4 (A)). We see a significant influence of the LV public transit experience (γ_{PT-Exp}). Respondents with a higher value for this LV have a greater utility for ODM. The second LV describing the emotional car attitude has a negative high significant influence in the utility function. This result shows that people with a high emotional car affinity use less ODM services. They prefer to drive themselves or already have their own chauffeur.

Table 4 (column B) presents the findings for the structural model for the two latent variables. We see female respondents have a lower value for emotional car attitude and a higher value for public transit experience. People from tier 1 cities obtain a higher value for public transit experience than people from tier 3 cities. In tier 3 cities the public transit is not yet well developed, thus private means are mostly used. Beijing and Shanghai already have a well-developed public transit system in contrast to the tier 3 city like Urumqi. People from tier 2 cities have the highest value for emotional car attitude.

5.2. Direct effects vs. effects through the latent variables

The OHCM has the advantage that, in addition to the overall effects of the respondents' characteristics, it allows us to also consider the split into direct effects and effects through the LVs, given by the vectors β, $\gamma_{Car}\alpha_{Car}$ and $\gamma_{PT-Exp}\alpha_{PT-Exp}$ respectively. For validation of the parameter estimates, we followed the procedure of Vij and Walker (2016) and additionally constructed a reduced form model of the HCM. The direct influences and the influences through the LVs on the choice are summarized in Table 5. The effects of age and gender on ODM use are almost entirely direct effects. The effect over age has nothing to do with a higher car affinity. We can therefore assume that younger people use car-related ODM services for other reasons. The direct positive effect via the driver's license is strongly reduced by the two LVs. Car availability reduces the probability of using ODM. This effect is strongly amplified by the LVs. The results show clearly that car owners with emotional car attitudes tend to use less ODM for routine trips such as commuting. People without a private car have a higher probability. They use these services presumably to avoid the crowded and stressful environment in the public transit. Tier 3 cities have the lowest probability of using ODM for commuting. The effect is amplified slightly by the public transit experience.

Comparing the two last columns in Table 5 we see that the overall effects on utility in the OHCM are, as expected, similar to the effects in the "base" ordered probit model using the same observable variables. Also, the overall variance in the OHCM,

Table 5
Direct effects vs. effects through the LVs on ODM use.

Variable	*Direct effect*	*Effect via LV Emotional car attitude*	*Effect via LV PT Exp*	*Effect via LVs combined*	*Overall effect OHCM*	*Overall effect "base" ordered probit*
Female	0.866	0.056	0.064	0.119	**0.985**	**0.932**
Age < 37	0.212	−0.020	0.014	−0.006	**0.205**	**0.179**
Driver's license	0.995	−0.216	−0.073	−0.290	**0.705**	**0.661**
Car availability	−0.198	−0.203	−0.166	−0.369	**−0.567**	**−0.534**
Tier 1 city	−1.640	0.007	0.091	0.099	**−1.541**	**−1.478**
Tier 3 city	−2.346	0.058	−0.104	−0.047	**−2.393**	**−2.288**
Household type 1	1.000				**1.000**	**1.000**
Household type 2	−0.834				**−0.834**	**−0.789**
ModeChoiceStability	1.522	−0.034	0.112	0.079	**1.601**	**1.524**
App usage	0.598				**0.598**	**0.604**
Distance work < 5 km	−0.479				**−0.479**	**−0.421**
Distance work 5 – 10 km	1.177				**1.177**	**1.120**
Business trips	1.073				**1.073**	**1.000**

Model comparison of OHCM with "base" ordered probit model in bold.

as discussed earlier, is almost identical to the variance in the pure "base" ordered probit model. This gives strong confidence into the parameter estimates with the maximum simulated likelihood estimation method in the OHCM. Such a comparison is often not done in the existing literature when hybrid choice modeling is applied. However, it is necessary to determine the deviation through simulation and to determine the quality of the results. Small deviations are to be expected due to simulation noise using the maximum simulated likelihood method. Thus, the share of the total variance linked to the LVs in the utility is 1%. Hence, we were able to explain 1% of the overall heterogeneity in a pure ordered probit model by including LVs. Although this may not sound like a lot, this is not to be disdained considering that the overall variance in the utility function is rather high.

6. Discussion and conclusion

In China, cities have seen a sharp increase in on-demand mobility (ODM) services in recent years going simultaneous with income rises at least for a proportion of the population. These services are also increasingly used for mandatory activities such as work. Therefore, the aim of our study was to determine factors that influence ODM usage of high-income earners for commuting. To this end, we not only focused on sociodemographic characteristics, we also took psychological factors into account. First, a discrete choice model in the form of an ordered probit model was applied, which was subsequently extended to an ordered hybrid choice model (OHCM), taking into account two latent travel mode attitudes in order to adequately map the role of psychological factors. Through the OHCM it was possible to analyze the direct effects as well as the indirect effects via the latent variables (LV).

People living in tier 2 cities such as Chongqing, Shenyang and Wuhan are most likely to use ODM. These services have great potential in Tier 2 cities, as the public transit infrastructure cannot handle the high travel demand. In these cities there are fewer alternatives to the private car. Hence, car-based services are more interesting for everyday travel. ODM can offer another good alternative solution even for commuting. In contrast, in tier 1 cities there is a higher attractive availability of public transit. In tier 3 cities the public transit system is even less developed than in tier 2 cities. In addition, the supply of ODM services in tier 3 cities is not sufficient to provide reliability for routine trips such as commuting. An important point when considering the sustainability of such ODM services is the distance classes in which the services are used. If short commuting distances by foot or bicycle (less than 5 km) were increasingly substituted, this would have a very negative effect on the environment. However, the results show an increased probability for medium distances (5–10 km) and a lower probability for short distances. Longer distances over 10 km become expensive and are therefore less suitable. Among the sociodemographic characteristics, gender in particular is the most notable. In contrast to existing literature, women in high-income groups are more likely to use ODM than men.

6.1. Effects of emotional car attitude and public transit experience

The two latent variables have a significant direct influence on the use frequency of ODM on the way to work. The public transit experience has a positive effect. The emotional car attitude has the reverse effect. This is in contrast to the existing study of von Behren et al. (2020a). They analyzed influences across all income groups and affinity to the car had no effect on the ODM use. As a result, we can assume that there is a significant difference between people from high income household and the general population with regard to ODM use for commuting. This negative effect of the emotional car attitude is similar to the findings of Atasoy et al. (2013) regarding the use of public transit. People with a higher emotional car attitude use public transit less. It can be assumed that ODM is maybe for people from high-income household with a high emotional car attitude a more similar mode to public transit. While for other population groups ODM is a more similar option to the private car (von Behren et al., 2020a). In addition to the direct effects, the OHCM offers the possibility to show the effects of the latent variables on the utility function. This gives additional insights which would not be obtained in a "base" ordered probit model.

6.2. Implications for transport policies and on-demand mobility provider

But what do the results mean for a sustainable transport policy in the cities? In the case of car availability, we can see a large part of the overall effect in the OHCM comes from the latent variables. The emotional car attitude reinforces the effect of car ownership. This is an important aspect, as these people tend to abstain from ODM services for routine trips like commuting. These people like to drive their private cars instead of using an ODM service. This population stratum with car ownership will further grow in many Chinese cities, and ODM services can only curtail this development to a limited extent if there are strong emotional connections to private cars. This issue is even more prevalent in Tier 3 cities (see Table 4 (A)), as people from such cities are less likely to use ODM for commuting. Punitive push measures for private car use, such as road pricing, show the strongest impact in terms of affective motives for car use (Stradling et al., 2000). The use of the tier categories helps to transfer the findings to other cities in the same categories in China.

In the presented study ODM is more likely to be used by young high-earners. This is particularly important for policy makers to ensure that access to ODM also becomes attractive for older people. It can be assumed that older people also have more comfort requirements. The ODM services should therefore also be designed more for older people in order to increase demand.

The results show that there is already a group of people who use ODM more regularly for routine trips such as commuting. The young women from high-income households do not like to drive a car (see Table 4 (B)). Women are positively disposed toward these new mobility technologies. The large offer of ODM services makes it attractive for young women to use ODM in Chinese cities. This insight is also interesting as a transfer to other cities that still have a lower ODM supply, such as in Europe. This group of young women could also benefit from shared autonomous vehicles in the future. The results are also helpful for ODM providers, as they can tailor their services more to women. In other income classes we cannot observe this difference in gender (von Behren et al., 2020a).

An important finding is the positive influence of public transit experience. The influence of the LV is not so strong for high-income earners than in the findings of von Behren et al. (2020a) in Shanghai. But it has still a positive effect. When high-income earners combine ODM with public transit multimodally than this can relieve the transport system. Therefore, a well-developed public transit is necessary. These findings can also be transferred to other cities. In order to use ODM for routine trips, such as commuting, people must be attracted by attractive public transit services. If they use public transit and have positive experiences, this also increases the likelihood of using ODM services for commuting and prevents them from using their private cars. Especially the group of high income earners have the purchasing power to buy a car or combine ODM with public transit.

However, the question arises whether the negative influences of emotional car attitude on ODM use remain the same if, for example, the parking situation worsens further in Chinese cities. It is also interesting to investigate how the attitudes and their influence change if the quality of public transit continues to decline due to excessive demand combined with longer waiting times, especially if the cities do not invest in public transit to satisfy the growing demand in cities.

In conclusion, the OHCM delivers significant added values, as important insights have been disclosed in the decision-making process. For further research, it will be necessary to investigate psychological influences on ODM use for other trip purposes in more detail, especially in Chinese tier 2 cities, which do not have a well-developed public transit yet. It would also be interesting to examine the role of psychological factors in the use of ridesharing services for long-distance events during Chinese holidays (cf. Jiang et al., 2018).

Declaration of Competing Interest

All the authors have no conflict of interest with the funding entity and any organization mentioned in this article in the past three years that may have influenced the conduct of this research and the findings.

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