Travel preferences of multimodal transport systems in emerging markets

Travel Preferences of Multimodal Transport Systems in Emerging Markets: The Case of Beijing

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Abstract Metropolises in emerging markets are facing serious urban transport challenges. Understanding people's travel preferences is crucial for designing effective sustainable urban policies. Little attention has been paid to studying travel preferences in multimodal transport systems in these markets. This study estimates the travel preferences in the metropolitan area of Beijing, which is notoriously plagued with high degrees of congestion. We administered a series of interwoven stated preference experiments on travel behavior. A semi-random sample of 2652 respondents participated in the experiments. The data were pooled and a scaled mixed logit model was used for estimation. The results provide rich information on how trade-offs are made among the manipulated attributes regarding travel time, cost, convenience, and reliability. Many findings deviate from results obtained in developed countries. A contrast standing out is that travelers in Beijing place much less weight on possible delays caused by traffic congestion.

Keywords choice experiment; multimodal transport; congestion; travel preference.

1. Introduction

The rise of so-called emerging markets is accompanied by grand urbanization processes. It results in a dramatic increase in urban population and changes in social and economic activities (Florida et al., 2008). The mismatch between the ever-increasing mobility demand and lagging supply induces serious urban issues such as congestion, air pollution, and excessive energy dependency (Wang, 2010; Çolak et al., 2016). Contrary to large-scale capacity expansion, better integration of the existing infrastructure and understanding people's travel behavior are crucial for developing sustainable transport systems (Farr, 2008). Multimodality, the use of more than one transport mode during a trip or a specified period in a broad sense, has been considered as an essential mechanism for improving the accessibility of locations, reducing fossil fuel-based car-dependency, and accomplishing a fundamental shift to environmental-friendly modes (Nobis, 2007; van Wee et al. 2014).

Multimodal transport constitutes a complex system (Zhang et al., 2011; Domenico et al., 2015) in that diverse mode options are involved and the modes differ in various ways, including availability, speed, cost, density, and the most appropriate use. Modeling traveler behavior in multimodal transport systems has received increasing attention in behavioral research. The concept of supernetwork was introduced for

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modeling multimodal routing at the trip level (Sheffi, 1985). The seminal concept was extended to formulate mode and facility choice and further to complete multimodal multi-activity trip chains (Liao et al., 2010, 2011, 2012, 2013, 2014, 2017; Liao, 2016, 2019). However, those studies concentrated on modeling feasibility. The incorporation of travel preferences is a crucial step needed for applications.

A number of studies investigated to what extent socio-demographics, travel habits and attitudes, and the built environment have effects on the adoption of multimodality during a specified period (Diana and Pirra, 2016). For example, Molin et al. (2016) applied a latent class cluster analysis to identify multimodal travelers as a function of attitudinal variables and found that solo car drivers have more negative attitudes to public transport and bicycle. Scheiner et al. (2016) studied the changes in multimodality over time and found that certain life course events are associated with changes in multimodality. Klinger (2017) analyzed the dependences between modal variability as a part of everyday mobility and found that people in a public transport or cycling-friendly city are more likely to become multimodal. Groth (2019) discussed the transition from unimodal to multimodal in relation to emerging mobility services and transport poverty in western society and suggested a change of perspective for mode choice shift.

Other studies applied discrete choice modeling to estimate individuals' travel preferences using revealed observations in reality or stated preferences (SP) in hypothetic situations. As reviewed in Kato et al., (2010) and Wardman et al., (2016), existing studies have mainly addressed particular aspects of travel behavior and only covered a subset of travel preferences. Few studies explicitly represented different trip stages and mode combinations (Bos et al., 2004; Bekhor and Shiftan, 2010). Schakenbos et al. (2016) quantified the experienced transfer disutility in multimodal public transport trips and found that the total disutility during the interchange depends on the total time, the distribution of the time expenditure, and headway. Likewise, Garcia-Martinez et al. (2018), Lois et al. (2018), and Cascajo et al. (2019), etc. have examined the preferences regarding transfer in mode chains. To explicitly capture the stage-wise intermodal choice in a trip chain (for this reason, intermodal is used instead of multimodal), de Freitas et al. (2019) developed a recursive logit model for estimation. Still, the level of detail of multimodal transport choice is rather limited. Comprehensive analysis of multimodal travel preferences across all relevant attributes is scarce. The first endeavor of modeling a large range of travel options in a multimodal system was conducted in the Dutch context (Arentze and Molin, 2013), in which extensive attributes of various trip stages were considered in a coherent set of SP experiments.

Recently, there has been a growing interest in studying travel behavior in emerging markets and, particularly, the BRICS group (Kates, 2011). For example, Beijing (Wang et al., 2015, 2017; Viard and Fu, 2015; Anderson et al., 2016; Mao et al., 2016; Zhan et al., 2016; Guo et al., 2018; Qin et al., 2019) and New Delhi (e.g., Menon and Mahanty, 2016) have been considered the study areas. These studies solely paid attention to certain transport modes or travel groups. Little is known to date about residents' full spectrum of travel preferences in the commonly congested multimodal systems. Fragmentary analyses tend to bring inconsistent outcomes that do not facilitate mobility-related analyses in relation to sustainability. In fact, driven by the rapid economic growth and penetration of new technologies, mobility services are diverse and multimodal travel becomes a common phenomenon in those megacities. After the rapid expansion of the cities, limits are being reached for a substantial capacity increment of the infrastructure. Taking Beijing for example, it is afflicted with high degrees of crowdedness both on roads and in public transport (PT) vehicles. Half of the commuting time (approximately one hour on average) is accredited to traffic congestion (Beijing Transport Annual Report, 2015). It is high on the local government's policy agenda to design and implement effective strategies to ease congestion but still vitalize the urban regions.

To investigate multimodal travel behavior in megacities of emerging markets, we conduct a large-scale stated choice experiment to estimate multi-faceted travel preferences in Beijing. We further developed the SP experiment decomposition method (Arentze and Molin, 2013) to reduce task complexity. Mode alternatives were grouped by trip distance depending on suitability. A group is further decomposed if there are more than three mode alternatives; a mode may appear in two subgroups serving as the reference. In total, six interrelated SP sub-experiments with respective efficient designs were created to include nine mode alternatives at three travel distance levels. The estimation results do not only provide information on how tradeoffs are made between various attributes, but also generate new knowledge on how people assess travel time, cost, convenience, and reliability. It is found that much of the travel behavior commonly recognized in developed countries appears to be different in this context.

The remainder of this paper is organized as follows. Section 2 introduces the representative multimodal trips in Beijing. Section 3 explains the experimental designs and descriptions of the online survey. Section 4 and 5 respectively discuss the data and the model specification. Section 6 presents the estimation results. Finally, the paper is completed with discussions and plans for future work.

2. Representative multimodal trips

Fig. 1 shows a map of the Beijing metropolitan area encircled by the 6th ring road (the outer ring), where more than 75% of the total population of Beijing is located. The highlighted route in red is the 4th ring road (approximately 20 km in length and width), inside which the population and facilities of services are un-proportionally amassed, accommodating around 35% of the total population but more than 65% of the trip origins and/or destinations (Wang et al., 2015). This is one of the main reasons why severe road congestion and crowding in public transport (PT) vehicles are long-standing issues. Based on the Beijing Transport Annual Report (2015), the average trip distances of car and PT across all purposes are around 10 km and 15 km respectively. In the experiments, we distinguish three trip distance levels in the Beijing metropolitan area, i.e., short: 5 km, medium: 20 km, and long: 45 km.

Fig. 2 displays five representative trip categories, which cover a large range of mode varieties in Beijing according to the municipal report mentioned above. As shown, most trip categories include three stages labeled as access, main and egress. The main stage may consist of a combination of modes (e.g., car and metro). The access and egress stages represent accessing the main mode from an origin and egressing the main mode to the destination. In the figure, the trip stages are separated by filled dots, while the main mode combinations are divided by unfilled dots. The relevant attributes of a trip stage are listed below the stage label. As for the mode combinations in C4 and C5, the values of the attributes represent an aggregated value. Intentionally, the attributes are chosen to capture the most important dimensions of travel preferences without the necessity of enumerating the trip stages and attributes. The dimensions consist of travel time and cost, travel convenience (access, egress, transfer, and seat availability) and reliability (possible delay). Several points are noteworthy in Fig. 2.

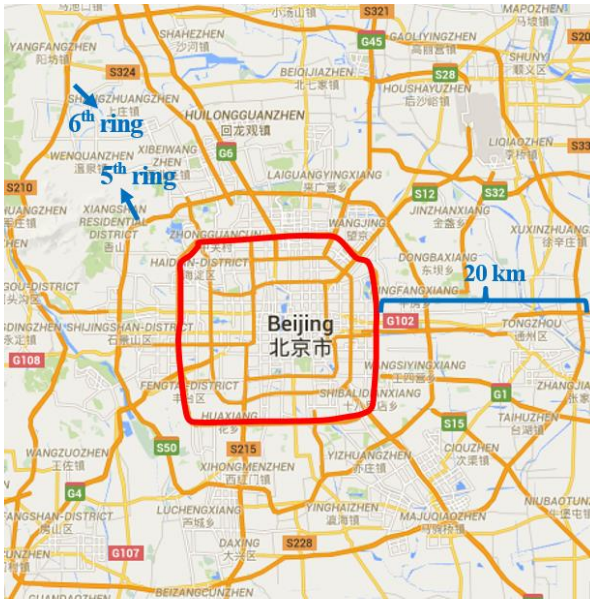

Fig. 1 Metropolitan area of Beijing (the 4th ring road is highlighted in red).

First, if the main mode is a private vehicle (PV), an access stage is not taken into account (C1). This is based on the assumption that individuals usually have quick access to where the PV is parked (e.g., from home to garage) so that variation in access time has no significant influence on an individual's preference. Although the range of PVs (e.g., ordinary bike and motorcycle) is broader, only car and e-bike (pedal-assisted electric bike) are considered because they are the most frequently chosen PVs with distinctive characteristics. Especially, the e-bike is uniquely popular in China due to its affordability, easiness to use, and longer travel range compared to the ordinary bike (Cherry et al., 2009). E-bike is considered an emerged disruptive transportation mode in China (Ling et al., 2015). In the past decades, e-bike ownership in China has increased rapidly. For example, it is shown in Hurst and Wheelock (2010) and the National Bureau of Statistics (2016) that the number of electric bikes in China has increased from 58,000 to 466,000,000 from 1998 to 2010, with an average increasing rate of 64.8% per year. In terms of travel range, speed, and cost, e-bike and car are primarily complementary transport modes, but they are also competing for a variety of trips. It was found in Campbell et al. (2016) that the capacity of an e-bike to travel relatively long distances makes it an alternative to public transport and private car in Chinese cities.

Second, the egress stage of taking a taxi (C2) is not considered because in common situations taxi passengers are directly dropped at the destinations. Conventional taxi passengers may need to wander on the streets searching for vacant taxis in the access stage. Such a need has become unnecessary with the recent widely-used mobile applications for e-hailing, with which taxies nearby approach the departure points on-demand. Hence, only waiting time is the major factor in the access stage. Currently, the share of taxi is only around 5~7% of the trips (Beijing Transport Institute, 2018), but this share is expected to increase dramatically owing to the pervasive availability and quick adoption of the mobile applications, such as Didi and Uber.

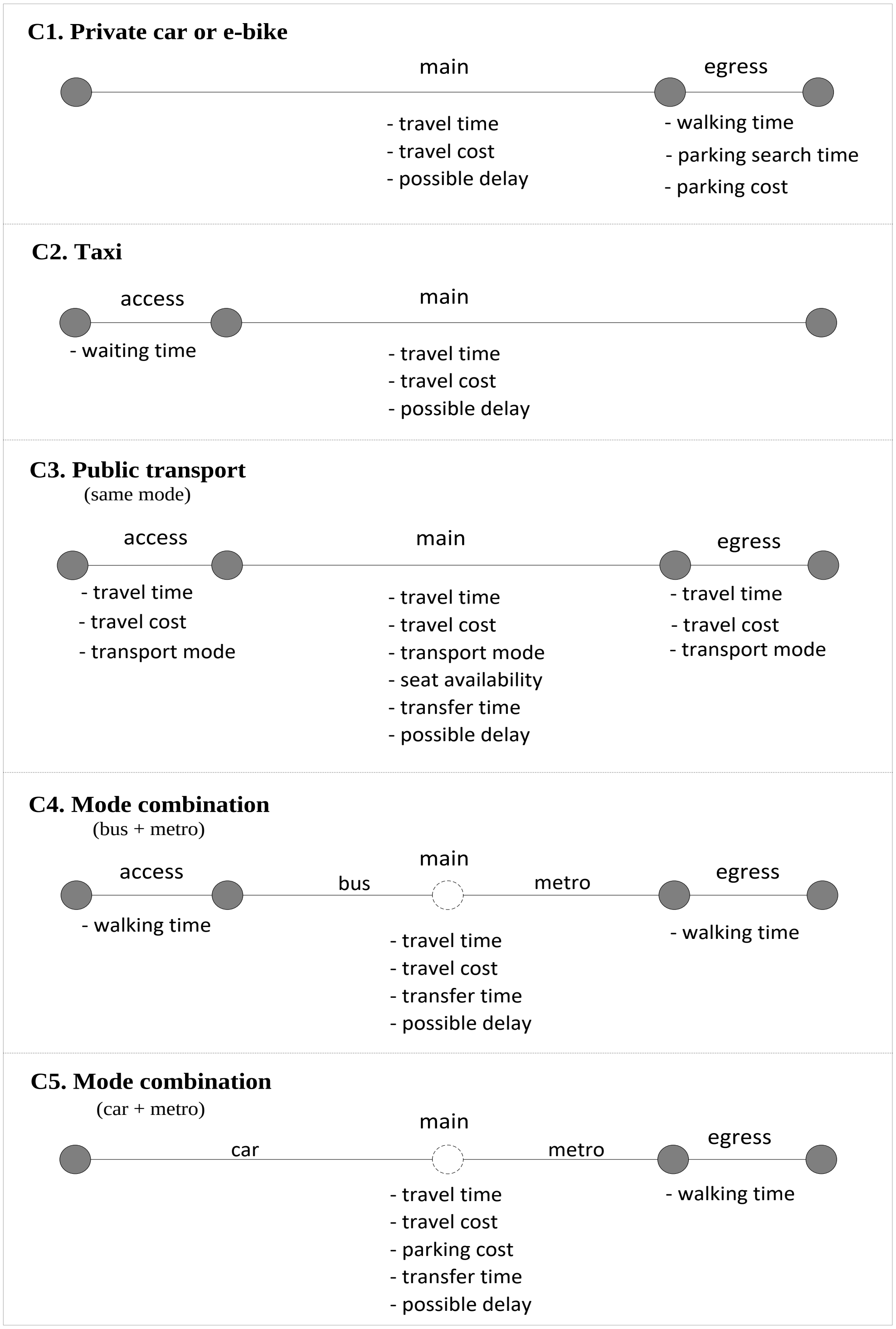

Fig. 2 Representative multimodal trips.

Third, both access and egress stages are considered for taking PT (C3). Relevant PT modes are bus, metro, coach (mainly for long distance trips), and inner-city train (with limited coverage currently). Individuals need to access and egress PT stations/stops, and it is found that people generally have different travel preferences for these two stages compared to the main stage (Abrantes and Wardman, 2011). In this trip category, the transfer is confined to change of vehicle within the same mode i.e., transfer to different PT lines. In the case of long distance travel, individuals may need to access and egress a few sparsely scattered transport hubs rather than neighboring PT stops. Thus, faster access and egress modes other than walking will be involved, such as shared ordinary bike or e-bike.

Fourth, for medium distance trips, it is also common that people first take the bus for a relatively long distance and then transfer to metro at transport hubs (C4). The transfer is aimed at avoiding road congestion in busy commercial districts. This is a typical phenomenon in Beijing and other large cities in China because it is usually more expensive to take metro than bus, and it takes a longer time for accessing a metro station than a bus stop. This mode combination takes the merits of the bus for access convenience and the metro for reliability. In that sense, bus is not considered as the access mode but as a parallel mode. Thus, C4 is supplementary to C3.

Fifth, C5 refers to the combination of car and PT, i.e., park and ride (P+R). The use of P+R at dedicated P+R facilities has not been as high as expected since the introduction of these facilities. To make good use of the metro system, which is known for the high coverage and travel time reliability, it has recently been the transport authorities' intention to create more car parking spaces at metro stations near the 4th and 5th rings so that car drivers from the suburban area can transfer to metro for entering the city center. The modal share of C5 is expected to grow due to the license plate rationing policy inside the 5th ring and the prospective congestion charging policy inside the 3rd ring (Linn et al., 2016). C5 is supplementary to C1 and C4.

Taken together, the five trip categories cover a large spectrum of multimodal travel patterns in Beijing.

3. Experiment specification

The experiment specification is largely in line with (Arentze and Molin, 2013), but we further developed the experiment decomposition technique for handling a large number of mode alternatives. Including all the mode alternatives in a single choice experiment causes a problem of excessive task complexity, despite using the decomposition technique. Evidence on choice experimental research shows that alternative quantities have strong effects on respondents' ability to choose, reflected in the estimated scale of error variance (Chung et al., 2011). There are also specific challenges in conducting SP experiments for developing countries where the surveyed population may not be accustomed to market research and cultural settings may interfere with responses (Mangham et al., 2009). To keep task complexity manageable, we decomposed a "one-includes-all" SP experiment into six interrelated sub-experiments (Table 1). Pooling together the choice data from the sub-experiments allows us to estimate all the travel preferences consistently. An implicit assumption is that one can deduce the preference to an un-included factor from the analysis outcomes. For example, car as a mode alternative is considered in the trip distances of 5 km and 20 km, but not of 45 km. The underlying consideration is that the preferences to car use for 5 km is expected to be significantly different from those for 20 km, while those for 20 km are not expected to be significantly different from those for 45 km.

Table 1 Setup of six interrelated sub-experiments

Distance	*Exp.*	*Main mode alternatives*								
		e-bike	car	taxi	bus	metro	coach	train	BM	CM
Short	1	√	√	-	-	√	-	-	-	-
	2	√	-	√	√	-	-	-	-	-
Medium	3	√	√	-	√	-	-	-	-	-
	4	√	-	√	-	√	-	-	-	-
	5	-	√	-	-	-	-	-	√	√
Long	6	-	-	-	-	√	√	√	-	-

(Exp.: experiment; √: the mode (combination) is included in the corresponding experiment; -: not relevant. BM: bus plus metro, CM: car plus metro)

The design of the trip stages and attributes follows the principle of capturing the most salient preferences. Attributes of choice alternatives are related to time, cost, convenience, and reliability. The attributes and levels of the mode alternatives are all set realistically with the annual reports issued by the Beijing Transport Institute (2015) as the major references. D-optimal designs (Kessels et al., 2006; Bliemer and Rose, 2010) were developed for the experiments based on priors that were estimated from a sample of 300 respondents in a pilot study. To include variation in trip contexts, each respondent is confronted with three different trip contexts, so that he or she makes three choice tasks under one trip context. The attributes of the travel contexts were varied based on an orthogonal fractional factorial design involving 40 profiles. The contextual attributes include trip purpose, flexibility in arrival time, travel party, weather conditions, traffic conditions, and weight of carrying bags. Focusing on behavioral analysis, this study does not take control of the matching between socio-demographic background and travel contexts. Independent fractional factorial designs are used to create trip contexts and choice sets. Each respondent was randomly assigned to a trip distance level and three construed trip contexts. If they encountered an unfamiliar scenario, the respondents can quit and regenerate the trip contexts and choice sets, which had been stated in the remarks before the survey. For each context, the respondent was presented with three choice tasks and asked to choose the first and second best travel options. Hence, we obtain 18 (or 3×3×2) observations for each respondent.

3.1. Experimental designs

The specifications of the six sub-experiments are described below. The attributes and attribute levels of the choice alternatives are shown in Tables 2-4. In the tables, time attributes are measured in minutes and monetary attributes in the Chinese currency, i.e., CNY (Chinese Yuan, 1 CNY ≈ 0.155 US dollar in 2015). If the numbers are not followed by “CNY”, the unit of measurement refers to time in minutes. A zero level for an attribute means either “free of charge” or “not relevant” (e.g., zero for possible delay means no delay and for transfer time means no transfer). Unless stated otherwise, the access/egress stages to/from main modes are traveled by foot. To generate efficient designs (Bliemer and Rose, 2010), prior estimates of the effects of the attributes are used to increase the efficiency of the designs. The priors are based on a pilot study where orthogonal designs were used.

Exp. 1 (*short distance trips*). The choice alternatives of Exp. 1 are e-bike (C1), car (C1) and metro (C3). The first section of Table 2 displays the attributes and attribute levels. Similar to an ordinary bike, e-bike is assumed to be easily accessed at the origins and egressed at the destinations, and thus no walking is involved in the access and egress stages. As electricity-charging and parking an e-bike may incur costs, the travel cost attribute is taken as the total of the two types of costs. No cost represents a possible situation where the government would provide free quick-charging facilities to promote e-bike use. On the other hand, the egress stage of a car trip possibly involves parking search time, walking to the destination and parking costs. Free car parking is viewed as an option in the case of short parking duration or parking in non-busy areas. Even for short distance trips, car may face a delay. In total, Exp. 1 includes twelve 3-level attributes. An efficient design of 27 choice situations is created.

Exp. 2 (*short distance trips*). The choice alternatives of Exp. 2 are e-bike (C1), taxi (C2) and bus (C3). The second section of Table 2 shows the attributes and attribute levels. The settings of e-bike in Exp. 1 and Exp. 2 are the same; thus, e-bike is the reference mode for Exp. 1 and Exp. 2. The settings of the attribute levels of bus and metro reflect the fact that it usually takes less time to access or egress bus stops than metro stations and that the bus speed is in general slower than that of metro. Walking for access or egress is not a forced component for taking taxi, but the taxi fare is substantially higher than other modes. Bus and taxi may also encounter delays. For that reason, waiting time for taxi is included. In total, Exp. 2 includes twelve 3-level attributes. An efficient design of 36 choice situations is created.

Exp. 3 (*medium distance trips*). The choice alternatives of Exp. 3 include e-bike (C1), car (C1) and bus (C3). To enable comparisons among the modes, we switch bus with metro compared to Exp. 1. The first section of Table 3 displays the attributes and attribute levels. For medium distance trips, e-bike is still a relevant option. Moreover, an explanation to the respondents is added, rephrased as “the e-bike is pedal-assisted in case of electricity exhaustion”. Compared to short distance trips, the attribute levels for travel times, travel costs, and possible delays are scaled up. Also, the level of parking cost is enlarged to take into account the fact that people travel further to pursue activities of longer durations. In addition, it is more likely that accessing and egressing PT stops take a longer time because it is more demanding to find the PT stops in case of longer distance connections. In this trip category, seat availability (including three levels: no seat, a chance of no seat, or seat always available) and transfer time are considered as factors representing the quality of service. Parking search time and egress time after using car are set as at an average of 5 minutes. In sum, *Exp.* 3 includes thirteen 3-level attributes. An efficient design of 36 choice sets is created.

Exp. 4 (*medium distance trips*). The fourth sub-experiment includes the choice alternatives of e-bike (C1), taxi (C2) and metro (C3), by switching metro with bus in Exp. 2. The second section of Table 3 displays the attributes and attribute levels. The settings of e-bike in Exp. 3 and Exp. 4 are the same; thus, e-bike is a reference mode for Exp. 3 and Exp. 4. Likewise, the levels of travel time and costs attributes are scaled up to reflect the longer distance compared to Exp. 1 and Exp. 2. The waiting time for taking taxi is also increased because there is a possibility that some taxi drivers may not respond to passengers for trips of such a distance level. The possible delay levels for taxi and bus are set the same as car. Even though metro vehicles guarantee punctuality, metro passengers may still suffer delays resulting from the difficulty of boarding. It is because the frequency and number of direct metro lines between two locations on such a distance level are relatively less for economic considerations. Nevertheless, the delays are smaller compared to other modes due to the high frequency and large vehicle capacity. In total, the choice sets include thirteen 3-level attributes. An efficient design of 36 choice sets is created.

Exp. 5 (*medium distance trips*). The choice alternatives consist of car (C1), the combination of bus and metro (BM, C4) and the combination of car and metro (CM, C5). The third section of Table 3 displays the attributes and attribute levels. The settings of car in Exp. 3 and Exp. 5 are the same; thus, car is a reference mode for Exp. 3 and Exp. 5. As mentioned above, metro stations facilitating parking are generally distributed near the 4-5th rings; thus, we assume that search time for parking is not involved for taking CM. Also, both CM and BM logically involve a transfer. Search time for parking, the access time for BM, and egress time for both BM and CM are set to fixed values. In this sub-experiment, the choice sets include thirteen 3-level attributes. An efficient design of 36 choice sets is created.

Exp. 6 (*long distance trips*). The last sub-experiment considers long distance trips. The choice alternatives include coach (C3), inner-city train (TR, C3) and metro (C3). E-bike is no longer a relevant mode option. Table 4 shows the attributes and attribute levels. Coach and TR mainly connect transport hubs in the urban area and district centers in the suburban areas. They use the same vehicles as bus and metro respectively, but seat availability is assumed to be guaranteed. While taking metro for such a distance involves many stops and several transfers, coach and TR only pick-up and drop-off passengers at limited stops. As these three modes follow given time schedules, we set fixed main travel times to avoid the choice tasks becoming too complex. Furthermore, we assume that travelers' preferences for in-vehicle time of coach and TR are the same as those of bus and metro in Exp. 3 and Exp. 4. It is assumed that preferences of using car for long distance trips are similar to those for medium distance trips (negligible effect difference). Unlike metro stations, stations for coach and TR are sparsely scattered. Thus, faster access and egress modes rather than walking are involved in taking coach and TR. Relevant modes are e-bike, taxi, bus, and shared public bike (PT-bike hereafter). To maintain the manageability of the experiment, we alternately included them in either access or egress modes. The costs of taking bus, PT-bike, and taxi are not included in the main travel costs to avoid high task complexity. Instead, we add notes, phrased as "2 CNY for taking bus; 2 CNY for using PT-bike for 2 hours; 14 CNY for taking taxi". An implicit assumption is that the access and egress (monetary) costs are not significantly different from those in the main stage. In sum, the choice sets include eleven 3-level attributes and five 2-level attributes. An efficient design of 36 choice sets is created.

3.2. Online survey description

Based on the experimental designs, an online survey accommodating the six sub-experiments was developed in Chinese. A respondent is requested to participate in only one sub-experiment with a randomly assigned trip distance. The three contexts and nine choice sets are randomly drawn without replacement from the respective designs and then randomly paired. Fig. 3 shows an example of a choice task of Exp. 3 where the choice set consists of e-bike, car, and bus for a trip around 20 km (the contents are translated from Chinese). The upper part of the display specifies the trip context and the lower part displays the choice alternatives. To enlarge the number of observations, we asked the respondents to indicate also the second-best travel option (e.g., car and bus are the first and second choices respectively). For the other sub-experiments, the same method of presentation was used.

To instruct the respondent sufficiently, special attention has been paid to rephrasing the descriptions of two attributes. First, door-to-door travel time is represented as the total deterministic travel time. The time components include all the time attributes of a choice alternative excluding possible delay. The travel time of the main stage is not shown since that time can be calculated as the difference between the door-to-door travel time and the shown components. Note that this is a matter of presentation of the trip but not the experimental design. This way of presenting the information allows respondents in an intuitive way to trade-off the total travel time against those elements that cause inconveniences, such as walking time, parking time, and transfer time. Second, "possible delay" is explained to the respondents as extra travel time that occurs with 30% probability, rephrased as "if you travel 10 times on the same trip, you will encounter delay 3 times". The length of the delay is varied, where the value of zero means no delay.

Table 2 Short distance trips (around 5 km)

Attribute	*Attribute level*		
***Exp.* 1**			
Main mode	E-bike	Car	Metro
Main mode travel time	(16, 23, 30)	(5, 10, 15)	(6,10,14)
Access time			(5, 10, 15)
Egress time (W)		(0, 5, 10)	(5, 10, 15)
Parking search time		(0, 5, 10)	
Parking cost		(0, 10, 20) CNY	
Travel cost	(0, 1, 2) CNY	(2, 6, 10) CNY	(1, 4, 7) CNY
Possible delay		(0, 10, 20)	
***Exp.* 2**			
Main mode	*E-bike*	*Bus*	*Taxi*
Main mode travel time	(16, 23, 30)	(6, 11, 16)	(5, 10, 15)
Access time (W)		(1, 6, 11)	
Egress time (W)		(1, 6, 11)	
Waiting time		(1, 6, 11)	(0, 5, 10)
Parking cost			
Travel cost	(0, 1, 2) CNY	(1, 3, 5) CNY	(14, 22, 30) CNY
Possible delay		(0, 10, 20)	(0, 10, 20)

(Time attributes are measured in minutes; cost attributes are measured using Chinese currency.)

Table 3 Medium distance trips (around 20 km)

Attribute	*Attribute level*		
***Exp.* 3**			
Main mode	E-bike	Car	Bus
Main mode travel time	(50, 70, 90)	(20, 30, 40)	(20, 35, 50)
Access time (W)			(5, 10, 15)
Egress time (W)		(5)	(5, 10, 15)
Parking search time		(5)	
Parking cost		(0, 15, 30) CNY	
Travel cost	(1, 2, 3) CNY	(10, 20, 30) CNY	(2, 6, 10) CNY
Seat availability			(never, unsure, always)
Transfer time			(0, 10, 20)
Possible delay		(0, 30, 60)	(0, 30, 60)
***Exp.* 4**			
Main mode	E-bike	Taxi	Metro
Main mode travel time	(50, 70, 90)	(20, 30, 40)	(20, 30, 40)
Access time (W)			(5, 12, 19)
Egress time (W)			(5, 12, 19)
Waiting time		(0, 15, 30)	
Travel cost	(1, 2, 3) Y	(40, 60, 80) CNY	(2, 7, 12) CNY
Seat availability			(never, unsure, always)
Transfer time			(0, 10, 20)
Possible delay		(0, 30, 60)	(0, 10, 20)
***Exp.* 5**			
Main mode	Car	Bus + metro (BM)	Car + metro (CM)
Travel time	(20, 30, 40)	(20, 35, 50)	(20, 30, 40)
Access time (W)		(5)	
Egress time (W)	(5)	(10)	(10)
Parking search time	(5)		
Parking cost	(0, 15, 30) CNY		(0, 10, 20)
Travel cost	(10, 20, 30) CNY	(2, 7, 12) CNY	(5, 10, 15) CNY
Transfer time		(4, 12, 20)	(4, 12, 20)
Possible delay	(0, 30, 60)	(0, 15, 30)	(0, 15, 30)

Table 4 Long distance trip (around 45 km)

Attribute	*Attribute level*		
***Exp.* 6**			
Main mode	Coach	Inner-city train (TR)	Metro
Main mode travel time	45	30	65
Travel cost (main)	(5, 20, 35) CNY	(5, 20, 35) CNY	(2, 10, 18) CNY
Access mode	(bus, e-bike)	(taxi, e-bike)	(e-bike, walk)
Access time	(10, 20, 30)	(10 or 20) [a]	(5 or 15)[a]
Waiting time for PT	(5, 15, 25)	(5, 15, 25)	(0, 5,10)
Transfer time			(0, 10, 20)
Egress mode	(bus, PT-bike)	(bus, PT-bike)	(walking)
Egress time	(10)	(10)	(10)
Possible delay	(0, 30 ,60)	(0, 15, 30)	(0, 15, 30)

([a]: access times correspond to the above access modes respectively.)

Imagine you are going to make a medium distance trip around **20 km** in the following context:

- You are on a business trip
- You have to arrive on time
- You are carrying a small bag
- You travel alone
- You are traveling in non-peak time
- It is raining

Please make choices on your **first** and **second** travel options.

Route attributes	Option 1	Option 2	Option 3
You are traveling by the main mode	**E-bike**	**Car**	**Bus**
Door-to-door travel time	70 min	40 min	50 min
including:			
Access to main mode	-	-	10 min
Transfer time	-	-	5 min
Parking time	-	5 min	-
Egress to the destination	-	5 min	5 min
Possible delay	-	60 min	30 min
Seat availability	-	-	unsure
Travel cost	2 CNY	15 CNY	6 CNY
Parking cost	-	10 CNY	-
Your first choice	○	◉	○
Your second choice	○	○	◉

Fig. 3 An example of a choice task of Exp. 3.

4. Data

Respondents were recruited from an existing large panel from an online survey service in Beijing. A pilot study involving a sample of 300 respondents has been conducted to establish the priors for generating efficient experimental designs. The main survey was administered in the form of an online questionnaire. A random sample was drawn from this panel except that controls on the characteristics of the respondents were implemented to obtain a representative sample. The following controls were implemented. First, the characteristics of the respondents are constrained to be more or less in line with the basic socio-demographics regarding gender, age, and education level. Second, since Exp. 1, Exp. 3, and Exp. 5 include car as a choice alternative of the main mode, we only allow those respondents who own cars and have driving licenses to enter these three sub-experiments. This is to ensure that the respondents have experience with using a car. For other background information, for example, whether the respondents have long distance travel experiences, we could not verify it due to the lack of personal information. Therefore, we assume that the respondents continue with the choice tasks only if they are familiar with the contexts, otherwise they would quit the choice tasks. Third, all respondents are allowed to enter Exp. 2, Exp. 4, and Exp. 6, whereby the ratio of car and driving license owners against the rest is kept at around 1:2, approximating the current situation in Beijing. Fig. 4 depicts the flow of respondents in the survey.

These control measures were taken due to poor internet penetration in China. People aged over 50 have limited access to the internet and are also inactive in participating in online surveys. To implement these controls, respondents owning car and driving license are first randomly assigned to one of the six sub-experiments. The other respondents are randomly assigned to one of the experiments that do not involve a car (Exp. 2, Exp. 4, and Exp. 6). As the experimentation progressed, respondents with certain characteristics were not qualified for some of the sub-experiments. In total 2652 respondents participated in the main survey and were included in the analysis. The numbers per sub-experiment are 293 (Exp. 1), 602 (Exp. 2), 316 (Exp. 3), 557 (Exp. 4), 330 (Exp. 5) and 554 (Exp. 6) respectively. Due to these specific controls, we claim that the sample is semi-random. Table 5 shows the composition of the sample regarding several key socio-demographic variables. For comparison, the distributions of several characteristics from the Chinese National Bureau of Statistics (2016) are shown. Travelers in the age group of 30 to 50 years, working in state-owned enterprises, and with Bachelor degree were oversampled. It is because travelers owning car and driving license were intentionally recruited to participate in Exp. 1, Exp. 3 and Exp. 5, who generally belong to the oversampled categories. Overall, the sample is near-representative of the travelers in Beijing.

As specified above, each respondent was presented with three trip contexts and three choice tasks per trip context and asked to make two choices per choice task. Thus, the total number of observations is 47,736 (or 18 × 2652).

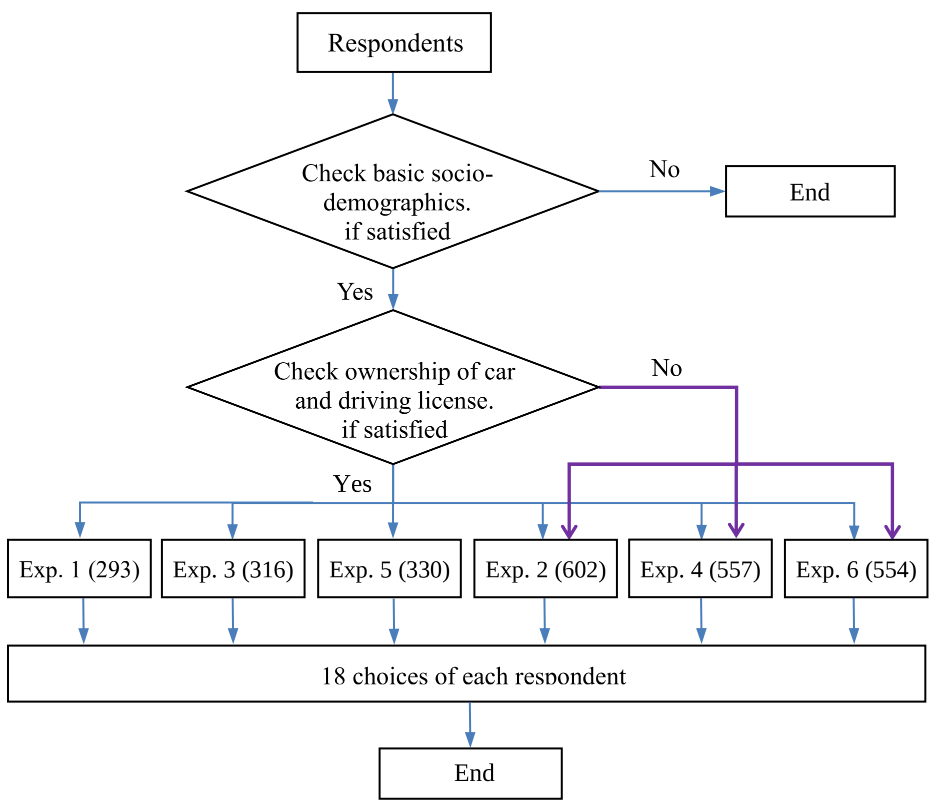

Fig. 4 Flow of respondents in the survey.

Table 5 Characteristics of the respondents

Attribute	*Level*	*Percentage* (%)	*Beijing municipal statistics (2016)* (%)
Gender	Male	52.2	51.6
	Female	47.8	48.4
Age	[18, 30]	34.4	35.3
	[30, 50]	50.6	39.0
	>= 51	15.0	25.7
Education level	No higher education	32.0	62
	Bachelor level	49.8	31.5
	Master or higher	18.2	6.5
Driving license & car ownership	None	33.4	-
	One of two	14.3	-
	Both	52.2	-
Work status & employer type	State-owned enterprise	28.3	8.5
	Foreign or private company, self-employed	62.2	73.5
	Students	5.7	5.5
	Part-time, unemployed, retired	3.8	12.5
Family income (monthly)	<= 10,000 CNY	26.7	-
	[10,000, 20,000] CNY	46.9	-
	>= 20,000 CNY	26.4	-
Possibility of reimbursement	Never	24.6	-
	Only for business trips	64.3	-
	Always	11.1	-

5. Model specification

The data collected through the online survey allow the estimation of travelers' preferences related to the manipulated attributes of different stages of multimodal trips. The data of all sub-experiments are pooled. Data from the sub-experiments with the same trip distance levels are assumed to have the same scales of error term because of the existence of reference modes and thus are put in the same assortment. Moreover, the data contain repeated choice observations of the same respondents and hence have a panel structure. To account for these properties, we use a scaled mixed-logit model framework to estimate the parameters. All parameters (i.e., travel preferences to all trip attributes covered in the experiments) are estimated in an integrated model. Interaction effects with contextual and socio-demographic characteristics were not included in the current study, and thus the estimated effects of manipulated attributes hold for the average background. The utility $U_{ani\tau}$ that traveler n associates with alternative i on choice occasion τ in data assortment a (distance category) is specified as:

$$U_{ani\tau} = \mu_a \cdot \left(\beta'_{ai0} + \sum_k \beta_{aik} \cdot X_{anik\tau} \right) + \sum_j \varphi_{ij} \cdot \eta_{anij} + \varepsilon_{ani\tau} \quad (1)$$

where the notations are defined as follows,

a — a data assortment $a \in \{S, M, L\}$, corresponding to distance level {short, medium, long}

n — a traveler

i, j an alternative
τ a choice occasion
k an attribute, $k = 1,2, \ldots$
μ_a scaling factor for assortment a
β'_{ai0} coefficient for constant assumed to be normally distributed, $\beta'_{ani0} \sim N(\beta_{ai0}, \sigma^2_{ai0})$
β_{aik} coefficient for attribute k
$X_{anik\tau}$ value of attribute k
η_{anij} shared error term by i and j, assumed to be normally distributed with a mean of zero
φ_{ij} indicator of the existence of shared error term, $\varphi_{ij} \in \{0,1\}$
$\varepsilon_{ani\tau}$ i.i.d. extreme value

This model specification allows all main effects to be estimated mode-specific at different trip distance levels. The effects of attributes of trip contexts and socio-demographics are not included in the present model. Thus, the effects estimated hold for average contextual situations and socio-demographic background. The main effects are estimated across different experiments and Eqn. (2) shows the used parameterization. b denotes another data assortment and $\Delta\beta_{bik}$ represents the coefficient value difference between the i-th and j-th choice alternative of assortment a and b respectively on the same attribute k. $i = j$ or $a = b$ may occur, but they are mutually exclusive. By setting $\Delta\beta_{bjk}$ equal to zero, we have $\beta_{bik} = \beta_{aik}$ and thus only a common parameter will be estimated; otherwise, $\Delta\beta_{bjk}$ will be estimated in addition to β_{bik}, with which we can find out whether β_{bik} is significantly different from β_{aik}. As the suggested model specification does not have a closed-form and cannot be solved analytically, the simulated maximum log-likelihood method with Halton draws (Train, 2009) is applied to estimate the model. For the estimation, we used 500 Halton draws for the random parameters. The simulated log-likelihood is calculated based on Eqn. (3-6).

$$\beta_{aik} = \beta_{bjk} + \Delta\beta_{aijk} \tag{2}$$

$$P_{an\tau}(i) = \frac{\exp(V_{ani\tau})}{\sum_j \exp(V_{anj\tau})} \tag{3}$$

$$S_{an}(\boldsymbol{\beta}_{an}) = \prod_i \prod_\tau \left(P_{an\tau}(i)\right)^{\delta_{ani\tau}} \tag{4}$$

$$L_a = \prod_n S_{an}(\boldsymbol{\beta}_{an}) \tag{5}$$

$$SLL = \sum_a \sum_n \ln\left\{\frac{1}{R}\sum_r S_{an}(\boldsymbol{\beta}^r_{an})\right\} \tag{6}$$

where the definitions of the notations are the following,
$V_{ani\tau}$ utility component of $U_{ani\tau}$ excluding the term $\varepsilon_{ani\tau}$
$P_{an\tau}(i)$ probability that i is chosen by n at τ in a
$S_{an}(\boldsymbol{\beta}_{an})$ likelihood of n in a in a function of coefficient vector $\boldsymbol{\beta}_{an}$

$\delta_{an\tau i}$	an indicator, being 1 if n chooses i at τ in a; otherwise, 0
L_a	likelihood of a
SLL	overall simulated log-likelihood
R	number of Halton draws
$\boldsymbol{\beta}_{an}^{r}$	the r-th Halton draw of $\boldsymbol{\beta}_{an}$

Error terms may be correlated due to similarities between the transport modes. The correlations are taken into account by an error-component specification (η_{anij}). For sake of parsimony, only the most important sources of correlation are of interest. Table 6 shows the shared error components (causing mode correlations) included in the present study (the φ_{ij} terms).

Table 6 Specification of φ_{ij} (symmetrical)

	e-bike	car	metro	bus	taxi	BM	CM	coach	TR
e-bike	-								
Car	1	-							
metro	0	0	-						
Bus	0	0	1	-					
Taxi	0	1	0	0	-				
BM	0	0	1	1	0	-			
CM	0	1	1	0	0	1	-		
coach	0	0	0	0	0	0	0	-	
TR	0	0	1	0	0	0	0	1	-

(BM: bus + metro, CM: car + metro, TR: inner-city train)

6. Results

100 parameters, including 26 random parameters, were estimated in a scaled mixed logit framework (see *Section 5*). Most estimates show significant effects. An adjusted rho-square of 0.208 was obtained, indicating a satisfactory goodness-of-fit of the model. Travel time valuations were estimated for different distance levels to account for possible non-linearity. Travel time and cost were expressed respectively in minutes and CNY. Effect coding was used for categorical attributes. For convenience of expression, the nine main modes (combinations) are abbreviated and used at appropriate places as e-bike (EB, pedal-assisted electric bike), car (CA), taxi (TX), bus (BU), metro (ME), coach (CO, for long-distance trips), inner-city train (TR), bus plus metro (BM), and car plus metro (CM). Although this study adopts a similar (not the same) experiment design and estimation framework with Arentze and Molin (2013), it is advisable to compare the estimates only based on relative differences rather than absolute values.

Table 7 shows the estimates of scaling parameters that are used to convert all experiments to the same scale of error variance. Observations related to the same distance levels were put in the same data assortments. The medium distance was arbitrarily considered as the scale reference, i.e., μ_M=1. Scale parameters for the other assortments (μ_S and μ_L) are significant and larger than 1, implying that the observations have smaller error variances than the reference. μ_L has the highest value, indicating that error variance is the smallest for long distance trips. This may be caused by the fact that fewer choice alternatives are involved in the long distance assortment. All results reported below concern values after re-scaling.

Table 7 Scale parameters of scaled mixed-logit model

Coefficient	Note	Estimate	t-value	Sig.
μ_S	scale of level short distance	1.417	5.41	***
μ_M	scale reference	1	n/a	n/a
μ_L	scale of level long distance	1.699	2.40	**

(Sig.: significance level; **: Significance at 5% level; ***: Significance at 1% level)

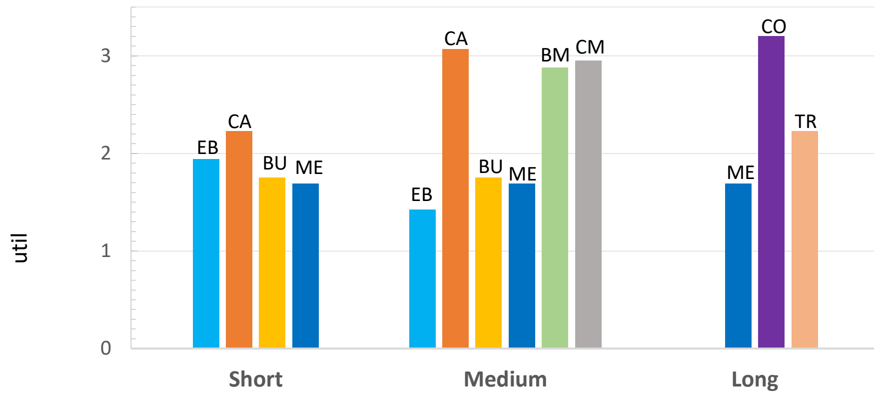

Fig. 5. Base preferences for different transport modes in the cases of short, medium and long distance trips (all estimates are significant at 1% level).

Base preference. Fig.5 shows the estimates of the base preferences, i.e., the intrinsic utilities assigned to mode alternatives. The modes of different trip distance categories are directly linked with specific designs discussed in section 3.1. All estimated values are significant at 1% level. The constants are dummy-coded arbitrarily considering taxi as the base for travel in the main stage for short and medium distance trips. It appears that for short and medium distance, car has the highest base preference, despite being vulnerable to congestion in Beijing. For short distance, e-bike has a higher base preference compared to bus and metro probably due to its convenience; furthermore, the base preference for bus is slightly higher than that for metro. For medium distance, the base preference for e-bike drops considerably. This may be caused by the travel range limitation of the e-bike. It also appears that combinations (bus plus metro and car plus metro) are favored more than bus or metro as a single mode possibly because they remedy the disadvantages of a single PT mode (Section 2), which is contrary to the findings in the Dutch context. It should be noted that this finding only refers to the base preference in the context of medium-distance trips. It does not necessarily mean that "people don′t see transfers as sufficiently negative". In fact, according to the results in Table 9 below, it is found that people see transfers sufficiently negative, indicated by the coefficient of "ED: transfer time in a BM trip". For long-distance trips, metro has the lowest and coach has the highest base preference, suggesting that coach is predominantly perceived as a mode for long trips. These findings indicate that the base preferences vary across trip distances. Moreover, estimates of the standard deviation of random components show that significant differences exist among travelers in the base preferences for e-bike and metro.

In-vehicle time. The effects of in-vehicle time (IVT) for travel preference are estimated for short and medium distance trips under uncongested conditions (Fig. 6). It is assumed that the values of IVT for long distance are not significantly different from those for medium distance, i.e., linear effects. IVT of e-bike and bus have stronger negative effects than those of car or metro in short distance trips. Furthermore, non-linear effects of IVT appear to exist in the cases of e-bike and taxi where the marginal value of time is lower for medium distance trips. However, the diminishing effect does not occur in the case of car, bus or metro. This results in an unforeseen effect that the marginal values of IVT of e-bike (−0.024, or −0.058+0.034) and taxi (−0.018, or −0.033+0.015) are less negative than that of car (−0.026) for medium distance. A possible explanation is that the e-bike is not affected by traffic congestion and taxi passengers may make use of the time while traveling. Finally, we find that the marginal values of IVT do not differ significantly between metro, bus plus metro, and car plus metro.

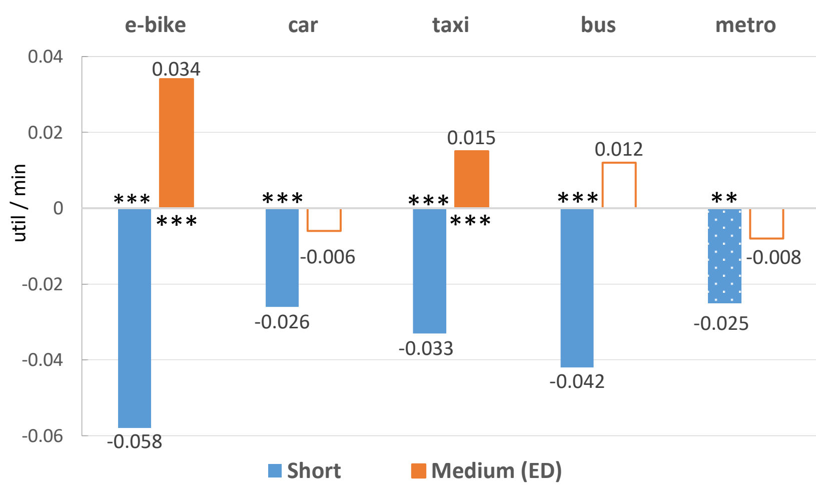

Fig. 6. Effects of IVT on preferences for modes in short and medium trip distance. ED stands for effect difference based on effects of short distance. (**: Significance at 5% level; ***: Significance at 1% level; non-filled bars indicate no significance.)

Access and egress time. It is commonly found that access and egress times by walking are weighed more negatively than IVT in the main stage of a trip (Kato et al., 2011; Arentze and Molin, 2013; Wardman et al., 2016). As seen in Fig. 7, we find this as well for short trips by car and metro. In the case of car, the effect of egress time is more than two times that of IVT. As for metro, the effect of access time is much stronger than that of egress time. This can be explained by the fact that the access stage often involves traveling on the road, whereas the egress stage often takes place inside buildings (facilities of services are usually agglomerated at the metro stations in China). Surprisingly, we find that bus egress time has a little higher marginal value than IVT and the effect of access time is even weaker. This finding may reflect a general public impression that in-bus service is poor. As in the case of IVT, the effect of distance on the marginal values of access and egress time for car, bus and metro trips are insignificant. In addition, we find that no significant differences in base preferences for bus, e-bike and PT-bike (or shared-bike) as access mode. The base preference for taxi as the access mode, however, is lower. Meanwhile, travelers prefer e-bike and PT-bike over walking to access and egress stations.

Travel cost. Table 8 shows the estimated effects of travel costs of different types. Travelers are not sensitive to the electricity costs of e-bikes. The marginal values of ticket costs for parking car and taking bus or metro are less negative compared to car fuel costs. This is opposite to common findings in developed countries. A reason may be that the PT fare and parking costs are undercharged in Beijing due to the intensive subsidies from the government and ill parking management. As the fares for long distance modes (coach and train) are more market-driven and higher, the negative effect is much stronger. The marginal value of taxi costs is relatively small. A possible explanation is that the costs can be shared by other taxi passengers or paid by third parties since more than 70% of the respondents reported that travel costs could somehow be reimbursed (Table 5).

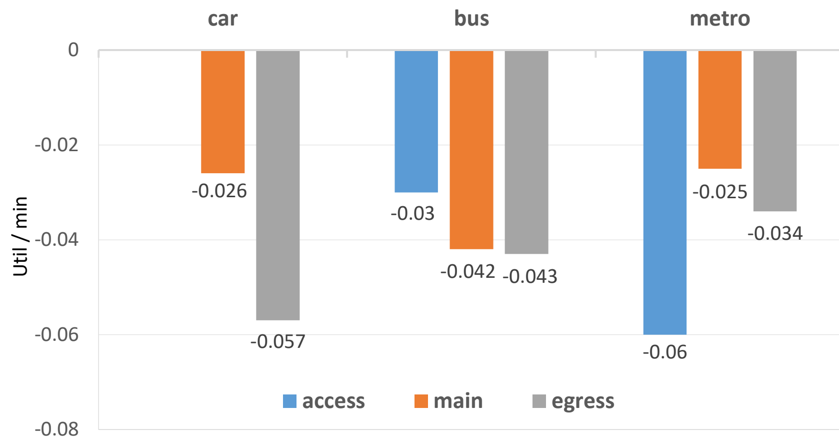

Fig. 7. Effects of access and egress time by walking for short distance trips (all estimates are significant at 1% level).

Table 8 Marginal effects of travel costs

Coefficient	Estimate	t-value	Sig.
Electricity cost for charging e-bike	-0.030	-1.63	
Fuel cost for car	-0.026	-17.15	***
Parking cost for car	-0.021	-20.86	***
Ticket cost for taking taxi	-0.009	-5.09	***
Ticket cost for taking bus and metro	-0.020	-5.06	***
Ticket cost for taking coach and train	-0.038	-4.04	***

Convenience. Table 9 shows the preference values related to parking, waiting, transfer, and seat availability. Nearly all the coefficients are significant, indicating that travelers are sensitive to these factors. In accordance with common findings, car parking search time is valued more negatively than IVT of car (Fig. 2). Waiting time for bus is weighed less negatively than IVT in the case of short trips, and slightly more negatively than access time by walking. Waiting times for taxi and metro (only for long trips) are weighed approximately the same as IVT. As expected, transfer times during the main stages have strong negative effects. Transfer time in-between buses has the least effect (−0.021), and transfer time between bus and metro has the strongest effect (−0.047, or −0.027−0.02). A possible explanation is that walking stairs underground are often involved. The effect is smaller for long trips by metro (−0.017, or −0.027+0.01).

Lastly, having a seat has positive effects on the value of bus or metro. The effect is stronger for bus, implying that travelers attach larger value to find a seat in bus than in metro. Other levels of seat availability do not show significant effects.

Table 9 Estimates related to travel convenience

Coefficient	Estimate	t-value	Sig.
Search time for car parking	-0.054	-6.80	***
Waiting time for bus	-0.034	-6.15	***
Waiting time for taxi	-0.026	-3.98	***
Waiting time in a long metro trip	-0.026	-7.73	***
Transfer time in a bus trip	-0.021	-4.61	***
Transfer time in a metro trip	-0.027	-6.65	***
ED: transfer time in a BM trip	-0.020	-3.02	***
ED: transfer time in a CM trip	-0.018	-2.70	***
ED: transfer time in a long metro trip	0.010	2.00	**
SA in bus = always	0.332	5.30	***
SA in bus = unsure	-0.037	-0.64	
SA in bus = never (base)	-0.295		n/a
SA in metro = always	0.151	5.51	***
SA in metro = unsure	0.105	1.93	
SA in metro = never (base)	-0.256		n/a

(ED: effect difference from the above last coefficient without ED; SA: seat availability)

Table 10 Estimates related to possible delay time

Coefficient	Estimate	t-value	Sig.
Possible delay by car in S trip	-0.029	-8.55	***
ED: possible delay by car in M trip	0.018	3.49	***
Possible delay by taxi in S trip	-0.009	-2.73	***
ED: possible delay by taxi in M trip	0.006	0.83	
Possible delay by bus in S trip	-0.008	-2.55	**
ED: possible delay by bus in M trip	0.002	0.49	
Possible delay by metro in M trip	-0.008	-1.98	**
ED: possible delay by BM in M trip	-0.008	-1.54	
ED: possible delay by CM in M trip	-0.009	-1.90	
ED: possible delay by metro in L trip	-0.002	-0.44	
Possible delay by coach in L trip	-0.008	-4.68	***
Possible delay by train in L trip	-0.002	-0.77	

(Coefficients ending with S, M and L refer to short, medium and long distance trips respectively. If a coefficient with “ED” in its note is not significant, the effect is taken as the same as the above last coefficient without “ED”.)

Possible delay time. Table 10 displays the preference values related to possible delay time on the basis of a probability of 30% that delay may occur on a trip. The estimates convey the evaluation of travel time reliability. Compared to the effect of IVT (−0.026) by car, the possible delay time has a strong negative impact (−0.029) in the case of short trips. However, for medium trips, the impact is considerably smaller (plus 0.018 units). Apart from a distance effect, a possible explanation is that travelers are more accustomed to delays for longer trips. The effects of possible delay time by taxi (for short distance), bus (short), metro (medium) or coach (long) are rather weak compared to the IVT by the same mode. In sum, the results suggest that travelers in Beijing place less weight on possible delays than those in western countries (Wardman et al., 2016).

Remarks on value of time. The ratios between the marginal values of time and cost provide estimates of the value of time (VOT), which indicates the willingness-to-pay for time-saving (Hensher, 2006). VOT analysis plays a central role in transport project appraisals and allows intuitive comparisons between different time periods and geographic areas. Since time and cost components are estimated stage and mode-specific (Fig. 5-7, Table 8-10), the ratios are also calculated stage and mode-specific. The ratios indicate that the mean VOT for IVT of car, bus, metro, and taxi for short distance are 0.16, 0.33, 0.19 and 0.57 USD/minute respectively. For medium distance trips, the same VOTs apply to car, bus, and metro, since there are no significant differences in estimated values from the short distance level. VOT for IVT of taxi decreases to 0.31 USD/minute in the case of medium distance trips. Several meaningful comparisons are as follows.

First, IVT of car is valued 1.5 times the average income rate in Beijing (1098 USD/month in 2015), which is in line with the result reported in another study (Anderson et al., 2016). However, this ratio is around 2 to 3 times the counterparts in developed countries (Small, 2012).

Second, the results confirm the common finding that VOT for IVT of car is less than those of other modes due to a general preference for car travel. Similar to the findings in (Arentze and Molin, 2013), VOT for walking (access and egress), waiting and transfer (except in long metro trips) is in the range of 1.2 to 2.2 times those for IVT. Remarkably, however, the IVT of bus is valued around 100% higher than that of car; parking search time is valued more than 150% higher than IVT of car; VOT for accessing bus is only 50% of VOT for IVT. These deviations also reflect inadequate in-bus and parking services.

Third, possible delay times (on a 30% possibility basis) are valued between 1/3 and 1/2 of the IVTs except for short car trips. In comparison, schedule delay for being late is generally valued twice the IVT in western countries (Wardman et al., 2016).

Lastly, it is interesting to compare VOT to findings in other countries. VOT for IVT of car is the most studied aspect in travel behavior research. The average VOT across trip purposes in Japan (Kato et al., 2011) (data of 2005), the Netherland (Arentze and Molin, 2013) (data of 2012), UK (Department for Transport of UK, 2014) (data of 2010 to 2012), and USA (USDOT, 2015) (data of 2015) are roughly 0.22, 0.19, 0.37, and 0.26 in USD/minute, respectively. In China, the number of studies reporting VOT of car travel is still limited but increasing. Compared to the value in Beijing (0.16 USD/minute) found in this study, we see that after three decades of rapid development, the VOT in Beijing, supposedly one of the highest in China, is still lower than the averages in developed countries.

7. Discussions and future work

The emerging markets have experienced profound social transformations during the globalization and urbanization process. The mobility sector is also experiencing enormous changes due to the influx of increasing mobility demand and new modality advancements, while daily travel has ceased to grow in developed countries because of saturation of demand (Metz, 2013). This study extended the SP experiment decomposition method to analyze travel preferences in the multimodal transport system in Beijing. The estimation results provide quantitative insights into travelers' choice behavior to attributes of mode alternatives. The effects of some attributes related to route/mode components turn out to be quite different from those in developed countries. Although the estimates may not be applied directly to metropolises in other emerging markets due to institutional differences, this study adds to the evidence base and benchmark for further comparisons.

The findings shed light on the transport regulations and policies that are currently under debate in Beijing. First, we find that e-bike has a high base preference for short distance trips and is considered preferable to walking to access metro stations. It implies that bike-sharing programs (Wang et al., 2017), which have received much attention in large cities in China since 2016, have the potential to address the "first/last mile" transport problem. In other words, bike-sharing potentially increases the use of metro and facilitates multimodality. As an ingredient of shared economy, bike-sharing should be encouraged by adapting the motorization-oriented infrastructure more bike-friendly.

Second, the marginal value of IVT of bus suggests a strong negative evaluation of in-bus services. One possible solution is to raise the bus ticket price to eliminate some flexible demand and reduce in-bus crowdedness. However, it may increase the crowdedness on the road and, moreover, it may cause an issue of social exclusion. Increasing the frequency of bus services, regardless of financial issues, may be a plausible solution; however, this may not immediately contribute to improvement with the presence of congestion on the road surface; conversely, it may result in the phenomenon of bus bunching. If road surface congestion is removed by, for example, bus priority strategies, we believe that increasing bus frequency will reduce in-vehicle crowding and improve seat availability. That is also why it is more often to see the frequency of metro services is increased from time to time. Thus, it is recommended that bus operators improve bus services by applying resilient bus scheduling timetables and strong priority enforcements to ensure seat availability and reliability.

Third, this study found that travelers in Beijing take into account parking costs at the destinations of car trips, despite not as strongly as in developed countries. We suggest implementing parking pricing policies in the city center since the alternative of free curbside parking is one of the main causes of congestion in Beijing. Although parking pricing alone still cannot prevent cars from entering the city center especially with the arrival of self-driving cars (Bonnefon et al., 2016), it does restrain the traffic and other externalities resulting from cruising for parking. On the other hand, it is likely to contribute to transforming the car ownership of residents living in the city center.

Finally, we find that travelers are not necessarily against multimodality as indicated by the high base preferences for BM and CM. The real obstacle lies in the transfer burden. Hence, seamless connections between different modes are crucial. If this is achieved, we are optimistic about the effects of introducing congestion charging and park & ride strategies in combination with the above interventions, which may, otherwise, not work alone. Under such policy combinations, multimodality is most strongly supported, and congestion is hopefully alleviated without the compromise of reducing travel satisfaction.

Several issues are worth future investigating. First, on the modeling side, heterogeneity caused by contextual conditions, social-demographic background, and other symbolic and attitudinal variables (e.g., privacy, status, and environmental concerns) were not taken into account in the current study. Including these effects will not only increase the model fit but also provide additional information for designing target-driven travel demand management policies. Second, as the city of Beijing is comparatively well-developed, the travel preferences may also be different from those in less-developed areas. It would be interesting to apply the comprehensive experiment system in different economic and geographical settings. Such extensions allow us to draw a complete picture of travel behavior by systematic comparison or meta-analysis of travel preferences across cities in emerging and developed markets. Third, due to poor internet penetration and low interest in survey research, the sample is not very representative of the population in Beijing and this may cause bias in the results. Special attention should be paid to the applications and comparisons of the reported results. Fourth, with the fast-paced technological developments, emerging modalities, such as car-sharing and autonomous vehicles, are assumed to enforce disruptions to the mobility industry. Therefore, incorporating them into the experiment system is a worthwhile extension. All in all, this study provides a starting point for future research along these lines.

Acknowledgements

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