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Commuter value perceptions in peak avoidance behavior: An empirical study in the Beijing subway system

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ABSTRACT

Peak-avoidance has been suggested as a strategy to ease congestion and improve the travel experience in the road traffic system. However, commuters' trade-offs when choosing whether to avoid the peak in the context of subway use have not yet been explored. In highly concentrated megacities, high demand during peak hours in the subway leads to long queues waiting to enter stations or platforms, as well as crowded trains, which yields highly negative externalities. This paper contextualizes and incorporates commuters' perceived value as a theoretical basis to explain how perceived benefits and perceived sacrifices affect commuters' intentions to avoid the peak in subway systems. A hybrid model was constructed to incorporate the perceived benefits and perceived sacrifices as latent variables to understand peak-avoidance behavior. Social norms, previous habits, and personal subjective feelings have significant impacts on subway commuters' peak-avoidance decisions. In addition, our combined model improved the explanatory power compared to a traditional ordered logit model. The framework can be used as a theoretical basis for further development of behavioral research into commuters' decision-making. Finally, these findings provide meaningful guidance for the government and subway companies to encourage travelers to avoid rush hours effectively.

1. Introduction

One of the most serious problems in megacities is traffic congestion, which affects daily commuting both above and below ground. Massive demand during peak hours leads to crowded subway carriages, unstable operations and exhausting passenger experiences (Tirachini et al., 2013). In metropolitan areas, such as Bogota, Sao Paulo, Beijing, Tokyo, and Singapore, as many as nine or ten passengers can be crowded into one square meter of standing space during the morning peak hours. Due to the upper limit on the supply of subway transportation services, and the difficulty of increasing the limit, many transit authorities have adopted demand management policies to encourage commuters to engage in peak-avoidance, i.e. travelling during off-peak hours to reduce travel demand during peak hours. Examples of peak-avoidance initiatives include Singapore's "Travel Early, Travel Free" campaign and the "Free Tempura and Soba" challenge in Tokyo, in addition to peak and off-peak differential pricing systems that exist in many cities (Yang and Lim, 2018). As with other megacities in the world, Beijing too has a highly congested subway system. The average

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occupancy rates of the Beijing subway system during peak hours are as high as 135% (Zhang et al., 2014). To reduce congestion, Beijing has implemented a variable pricing strategy that includes a 30% reduction in fares for 16 stations on the Batong and Changping Lines for commuters departing before 7:00 a.m. in 2015 and the discount increased to a 50% reduction in 2016. Despite these fare discounts, no obvious reduction in peak demand was observed (Zou et al., 2018).

Traditionally, researchers have used modal attributes to explain commuters' behavior (Peer et al., 2016). Individual-specific variables can also be included to reflect individual differences and unobservable latent attributes. For example, Peer et al. (2016) developed departure time choice models (MNL and panel latent class) to study the trip scheduling preferences of train commuters. Similarly, based on a questionnaire survey on the Beijing subway system, Zhang et al. (2014) constructed four Probit models to examine the impact of incentives and personal characteristics on passenger travel behavior. Bianchi et al. (1998) tested the impact of different price levels on patronage by period, focusing on three aspects: change in time of travel, price differences and comfort improvements. While contributing useful insights, these studies have not addressed how travellers' perceptions of benefits and costs associated with the behavior change influence the peak avoidance decision.

To fill this gap, this study proposed a theoretical framework based on perceived value to explore commuters' internal process weighing benefits and costs. In commercial field, perceived value has been proven to be one of the best predictors of consumption intentions, as consumers will prefer the product or service with the highest level of perceived value after trading off benefits and sacrifices (Zeithaml, 2000; Zeithaml, 1988). Perceived value and behavioral intentions have significant relationships across a range of research scenarios (Chang and Wildt, 1994; Cronin et al., 2000; Kuo et al., 2009). Similar to other forms of consumption, peak-avoidance has both benefits (e.g. money savings, better commuting environments) and sacrifices (e.g. changing habits) for subway commuters (Tillema et al., 2013, Zhang et al. 2014).

The purposes of this study were to investigate which individual attributes influence commuters' perceived value of peak-avoidance and analyze the extent to which they influence peak-avoidance intentions. For this purpose, this study used a combined approach of integrated choice and latent variable (ICLV) model with an ordered logit model, making it possible to integrate both observable characteristics and latent variables into a psychologically and economically robust hybrid model. We represented commuters' internal trade-off processes by incorporating latent variables, which were able to improve the explanatory power compared to a traditional ordered logit model.

2. Literature review and theoretical framework

2.1. Commuters' peak-avoidance behaviour

Encouraging off-peak commuting can be considered a modification of commuting time and behavior for a commuter (Zhang et al., 2014). As mentioned in the Introduction, there have been several transport demand management policies using price discrimination to influence people's daily commuting routines (Cervero, 1990). These policies include the free pre-peak fare programs in Singapore and Melbourne (Pluntke and Prabhakar, 2013; Currie, 2009), and the route-based incentives for the Hong Kong MTR system (Li and Wong, 1994). Similar discounts or peak surcharges have also been implemented in cities such as Beijing, Washington, D.C., London, Tokyo, and Sydney. Other options include working with employers to encourage them to implement a Flexible-Work-System (LTA[1]), coming up with lottery/rebate rewards schemes (Pluntke and Prabhakar 2013), or providing public crowding information (BART[2] and JR East[3]). Despite these efforts, commuters' responses to policies do not always meet the expectations of authorities.

Empirical studies on commuters' peak-avoidance report that the willingness of commuters to change their behavior varies according to the incentives. Ben-Elia and Ettema (2011a, 2011b) explored different levels and types of rewards applied to encourage peak-avoidance in the Netherlands, and their results indicated that rewards can be an effective tool for commuting behavior change. In Beijing, Zhang et al. (2014) found that snack discount coupons, flexible work schedules, and fare concessions were more effective in encouraging peak-avoidance behavior than fare discounts. Wang et al. (2018) found that four hypothetical incentives (mark-up in peak, mark-down in off-peak, extra service, and credits for gifts) could result in more than 40% of commuters participating in peak avoidance behaviour.

Commuters' peak-avoidance appears to be governed by many external factors, including flexibility, displacement time, trip length, fare and discount level, and socio-demographic attributes (Peer et al., 2016; Halvorsen et al. 2016). For example, Ben-Elia and Ettema (2011a) found that male drivers are more likely to avoid rush hour than female drivers. Zou et al. (2018) identified considerable differences in the retiming elasticities of different passenger groups, concluding that low-frequency passengers are more sensitive to discounted fares than high-frequency passengers. In addition, previous researchers have found that experience with other transport modes plays an important role in travelers' peak-avoidance behavior (Ben-Elia and Ettema, 2011a; Wang et al., 2018). In these studies, however, "experience" was included as an indicator, and the authors discussed its significance in simple terms. It is essential to further explore its in-depth influence in the weighing process.

Further, passengers' peak-avoidance behaviors are complex and are related to both external factors and various internal psychological factors. Because these internal factors are not directly observable they can be difficult to analyse, they can provide rich representations in structural equation models (SEM) as latent variables (Witte et al., 2013). To incorporate latent variables such as

[1] https://www.lta.gov.sg/content/ltaweb/en.html. Accessed May 19, 2019.
[2] https://www.bart.gov/. Accessed May 16, 2019.
[3] http://www.jreast.co.jp/. Accessed May 27, 2019.

perceptions, value orientation and attitudes into behavioral models, one solution is to construct an ICLV model, which allows models to benefit from the economic and behavioral foundations of both approaches (Ben-Akiva et al., 2002). ICLV models are primarily developed to provide a better understanding of how behaviors are formed and to uncover the "black box" of decision processes (Walker and Ben-Akiva, 2004; Ben-Akiva et al., 2002; Ashok et al., 2002; Link, 2015). Based on ICLV, several latent variables can be selected to reflect the richness and extent of the commuters' behavior, such as, value orientation (Paulssen et al., 2014), comfort degree (Glerum et al., 2014), convenience and accessibility (Yanez et al., 2010), environmental consideration (Kamargianni et al., 2014), safety (Raveau et al., 2010), reliability (Raveau et al., 2010), habitual attributes (Idris et al., 2015), and mood (Kamargianni et al., 2014). However, to the best of our knowledge, the internal process of subway commuters' peak-avoidance has not yet been properly studied with these techniques.

2.2. Perceived value

The concept of perceived value emerged as a business definition in the 1990s and continues to be widely studied in this century (Sanchez-Fernandez and Iniesta-Bonillo, 2007). Researchers increasingly acknowledge perceived value as a key factor in marketing strategies (Mizik and Jacobson, 2003; Spiteri and Dion, 2004) and is an important concept for understanding behavioral intentions (Vantrappen, 1992; Woodruff, 1997; Chen, 2008). Many studies have used the idea of perceived value to analyze various aspects of consumption behavior. For example, Pura (2005) analyzed the direct effect of the dimensions of perceived value on the attitudinal and behavioral components of loyalty in mobile phone services. Wu et al. (2014) found that consumers' perceived value and each cost component are positively related to repurchase intention in the context of online shopping. To date, however, only a handful of studies have used perceived value to study commuter behavior intentions (Sumaedi et al. 2012). Wang et al. (2018) found that travelers' intentions to adopt shared bicycles are significantly influenced by their perceived conditional, environmental, functional, and social values. Sumaedi et al. (2012) explored the relationship between passengers' behavioral intentions and other latent factors, including satisfaction, perceived sacrifice, and perceived service quality. The empirical results revealed that perceived value and service quality significantly affect passengers' intentions.

Despite these wide areas of potential relevance, the concept of perceived value still lacks clear definition. Both unidimensional and multidimensional concepts of value are considered in providing simplified (unidimensional, such as benefits) and complex (multidimensional, such as perceived quality and price) understandings of it (Holbrook, 1999; Woodruff, 1997; Zeithaml, 1988). One of the most commonly cited definitions (Zeithaml, 1988, page 14) defined perceived value as "the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given." This view proposes perceived value as an internal trade-off between benefits and sacrifices. And, the intrinsic attributes of products themselves are not always directly linked to value, but instead filter through other personal benefits that are themselves abstract, making it difficult to use them in as measures in traditional multi-attribute or utility models (Zeithaml, 1988).

Since different people may have different perceptions of the different entities in different contexts, commuters' perceived benefits and sacrifices must be considered situation-dependent (Swait and Sweeney, 2000). Based on the above, a theoretical framework was developed which is shown in Fig. 1.

2.2.1. Perceived benefits

Perceived benefits refer to the sum of gains perceived by customers in the consumption process (Zeithaml, 1988; Woodruff, 1997). A positive link has been established between perceived benefits and purchase intention (Chen and Tsai, 2008; Ryu et al., 2012;

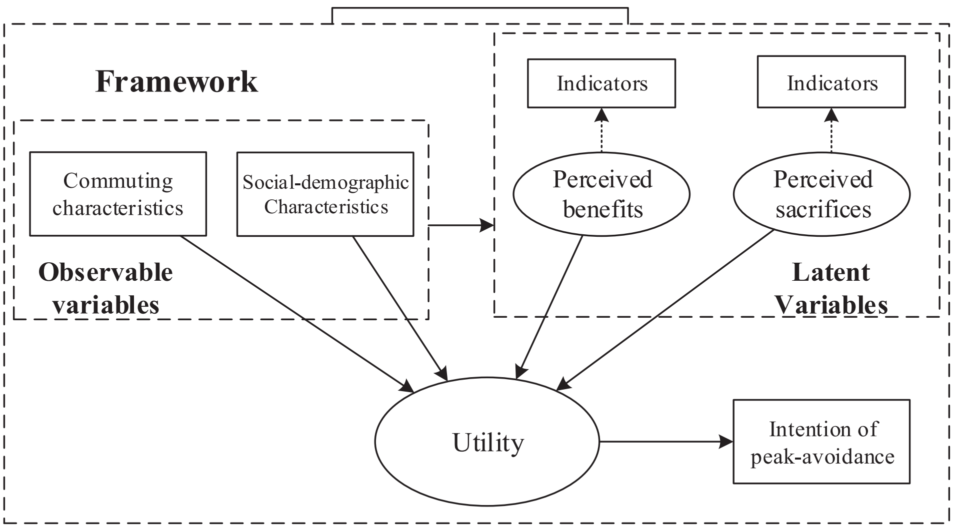

Fig. 1. Theoretical framework for the understanding of commuters' intention of peak-avoidance.

Zeithaml, 1988). Based on the literature and the specific context of peak-avoidance, commuters may perceive the following benefits:

First, peak-avoidance will result in commuters saving in both monetary and non-monetary terms. From 2014, the fare of Beijing Metro increased from ¥2 (around USD 0.32) to ¥3 (around USD 0.48), and the fare increased by mileage. On the one hand, passengers can participate peak-avoidance to pay discounted fares or switch to another travel mode (e.g. buses or shared bicycles), thus perceiving money saving (Zhang et al., 2014). On the other hand, commuters at stations with limited traffic flow must wait a long time to board the trains and commuters travelling at off-peak times will perceive both time and effort savings in waiting for trains (Zhang et al., 2014).

Second, the perception of external incentives by commuters, such as the subjective perception of increased travel quality, convenience, and comfort may encourage them to avoid peaks when commuting (De Grange et al., 2015). Previous literature has presented the influence of various monetary (e.g. discount fare) and non-monetary incentives (e.g. free breakfast and credits for smartphones) on peak-avoidance (Leblanc and Walker, 2013; Ben-Elia and Ettema, 2011a, 2011b). In addition to these external incentives, internal incentives such as comfort and increased safety during off-peak periods are equally important (Zhang et al., 2014).

Finally, social and personal behaviors are guided by norms and rules (March 1954; Schultz et al., 2007) and people learn how to behave and what is appropriate to do by observing and copying the behavior of others. Norms can be viewed as the basic knowledge of individuals about what others do and think that they should do (Schultz et al., 2007). The effect of norms in the transportation context has been widely researched. Biel and Thøgersen (2007) argued that what others do may influence personal travel decisions based on environmental consideration (Garcia-Sierra et al., 2015). Schuitema et al. (2010) found that people are sensitive about others acceptability of congestion charging and experiencing the benefits of congestion charging during trial periods increases their acceptability. As a behavior that reduces congestion, peak-avoidance is considered to be in line with social norms. In an experiment of peak-avoidance with car commuters by Ben-Elia and Ettema (2009), 48% of respondents mentioned “helping to solve the congestion problem” as the reason for engagement. The Beijing government and various social groups have been urging commuters to avoid peaks to help alleviate congestion[4]. On the one hand, participating peak-avoidance will help commuters feel that they are responding to the authorities’ call and are doing their part to ease congestion. On the other hand, they can get approval from others by doing so.

2.2.2. *Perceived sacrifices*

Perceived sacrifices refer to the sum of time, money, physical energy, and psychological costs involved in the entire process of obtaining a product or service (Zeithaml, 1988). Customers may face sacrifices involving monetary and non-monetary costs to obtain a product or service. Negative factors, such as higher price (Calabuig et al., 2014) or lower convenience (Berry et al., 2002), lead consumers to reduce consumption or obtain services from other providers. Similarly, when switching their previous commuting habits to commute in off-peak hours, commuters may perceive the following costs that reduce their behavioral intentions:

First, commuters may perceive costs (monetary and non-monetary) of switching to peak-hour avoidance (e.g. to avoid peaks, commuters will have to take a private car or taxi to work). Most daily travel modes are habitual and automatic, involving low information processing (Verplanken, 1997) and these habits lead to misperceptions about non-habitual modes (e.g., systematic underestimation of performance attributes, such as reliability) (Gärling et al., 2001, Anable and Gatersleben, 2005). Strong habits of daily travel moderate and even reduce the effect of deliberated intentions to change behavior (Aarts and Dijksterhuis, 2000). From a bounded rationality perspective, commuters are reluctant to change their habits. For example, some commuters prefer to sleep another half an hour instead of get up early to avoid crowded subway cars.

In addition, perceived risks, including an individual’s perceptions of uncertainties and possible adverse consequences, need to be considered (Mitchell, 1999; Ellsberg, 1961). Since commuters are highly familiar with their daily travel modes, which are already optimal or at least satisfactory, they are reluctant to change commuting behavior under uncertainty (Kim et al., 2017; Palma and Picard, 2005). Loss aversion can also help to explain non-optimal commuting decisions (Senbil and Kitamura, 2004; Jou et al., 2008). Individuals have asymmetric preferences for gains and losses (Kahneman and Tversky, 1979) and people are not comfortable with bearing even small risks. In this context, several studies have confirmed the importance of the availability of travel information to reduce uncertainty and influence travel mode decisions (Srinivasan and Mahmassani, 2003; Ben-Elia and Ettema, 2011a). Changing one’s commute causes uncertainty in travel time, travel cost, and commuters may not be sure of whether or not peak-avoidance can relieve congestion effectively. Therefore, when commuters do not receive enough information to help them develop an accurate peak-avoidance plan, they will perceive more risks of ambiguity in traveling.

From the literature reviewed above, one can conclude that various factors, including external incentives, social demographics, and commuting attributes, can influence commuters’ peak-avoidance intentions. However, peak-avoidance behavior is also affected by a number of perception factors that have rarely been discussed in previous studies. Therefore, it is worthwhile investigating these trade-offs between the benefits and sacrifices of peak-avoidance in this study.

3. Method

3.1. *Data collection and participants*

The target population for this study was Beijing’s frequent subway commuters. Screening questions were used to filter out

[4] https://www.bjsubway.com/news/qyxw/yyzd/2015–12-22/38344.html. Accessed May 19, 2019.

travelers and tourists who only use the subway occasionally. We selected respondents who were currently living in Beijing; (2) had a full-time or part-time job in Beijing; and (3) were commuting mainly by subway (Wang et al., 2018). Both web-based and face-to-face methods were used to recruit respondents.

The web-based survey was conducted through a Chinese professional survey website[5]. In total, 486 Beijing residents were recruited via e-mail, or WeChat (messaging APP). Of the 486 finished questionnaires, 376 (77.37% response rate) were valid. Regarding the offline survey, greater attention was given to the typical stations with the most congestion. The four busiest subway stations in the Beijing metropolitan area, namely Xizhimen, Dongzhimen, Xidan, and Zhongguancun, were selected (Report of the 5th Beijing Comprehensive Transportation Survey, 2015) and students from Beijing Jiaotong University recruited respondents face-to-face at malls near subway terminals and stations. Of 145 participants recruited in this way, 116 (80.00% response rate) provided usable questionnaires.

In total, 631 individuals participated in the survey (online or face-to-face) and 492 participants successfully completed the questionnaires, corresponding to an overall response rate of 77.97%. The descriptive statistics of the 492 respondents in the final sample are presented in Table 1. Among the respondents, 53.86% were male and 51.01% were young commuters (under 30 years old) and are representative of typical subway commuters (Report of the 5th Beijing Comprehensive Transportation Survey, 2015). Most respondents were highly educated (80% declared having a bachelor's degree), which is due to the fact that the Beijing is one of the most developed areas in China and the education threshold is high to find a job. Moreover, 56.1% of the respondents had annual income between ¥30,000 and ¥120,000, while 29.88% had annual income above ¥120,000 (the 2016 mean per capita annual income for Beijing is about ¥119,928[6]). Finally, 61.38% of the respondents had at least one private car in their household as compared to the 2014 average private car ownership in the city of 0.55 per household (Report of the 5th Beijing Comprehensive Transportation Survey, 2015).

The commuting attributes of participants are presented in Table 2. More than 50% commuters in our sample normally commute between 7.00 a.m. and 8.30 a.m., which is the most crowded period of the day in Beijing. About 70% of our commuters travelled through 3–8 stations, which indicates that the total travel time is not more than 40 min for most commuters. Moreover, more than 79% of commuters in our sample travelled at least four times a week by subway. In addition, 80% of commuters spend less than ¥5 on every commute. These statistics match well with the official city-wide data (Report of the 5th Beijing Comprehensive Transportation Survey, 2015). Finally, as to their previous peak-avoidance experience, 84.1% of commuters had experience of avoiding peaks. Most commuters (64.4%) have already had the experience of commuting earlier to avoid the peak hours, while 10.2% have tried later departures and 9.5% have experienced switching to other modes of transport, such as private cars.

3.2. Measurement

The measurement of variables was divided into three parts: explanatory variables, indicators of perceived benefits/sacrifices, and commuters' willingness to participate in peak-avoidance.

The explanatory variables are shown in Table 3, note that some are represented as dummy variables in the estimation model. The variable "education" was divided into three categories: "level 1" (below bachelor's degree), "level 2" (bachelor's degree), and "level 3" (above bachelor's degree), and "level 1" was set as the reference group. The variable "job" was divided into six categories: "students," "private enterprise workers," "enterprises and institutions workers," "enterprises and institutions managers," "national civil servants," and "retirees," and "students" was set as the reference group. The variable "peak-avoidance experience" was divided into 4 categories: "departure earlier," "departure later," "switch to other modes," and "never," and "never" was set as the reference group. The variable "normal departure time" was divided into 3 categories: "before 7:00 a.m.," "between 7:00 and 8:30 a.m.," and "after 8:30 a.m.," and "before 7:00 a.m." was set as the reference group. The variable "commute frequency" was divided into 4 categories: "less than 4 times/week," "4 times/week," "5 times/week" and "more than 5 times/week, and "less than 4 times/week" was set as the reference group.

To measure perceived benefits and sacrifices, respondents were required to indicate to what extent they agreed with the following statements on a five-point scale (1 = strongly disagree; 5 = strongly agree), as shown in Table 4.

Finally, respondents answered their willingness to avoid peak-hours according to a five-point Likert scale ranging from "very unlikely" to "very likely" In our analysis, individuals' intentions of peak-avoidance was regarded as a dependent variable.

3.3. Model construction

The analysis used an ICLV model that merges the ordered logit (OL) model with the structural equation model (SEM). The ICLV model consisted mainly of two sub-models: the latent variable model and ordered logit model. Each sub model consisted of one or more structural equations and measurement equations (Ben-Akiva et al., 2002). In the context of peak-avoidance, the model specification is described in Fig. 2, which provides a full path diagram of the model.

The impact of perceived value on commuters' peak-avoidance willingness is specified by the Eqs. (1) to (6) below, while Eqs. (1) and (3) describe the latent variable model and Eqs. (2) and (4) describe the ordered logit part.

[5] https://www.wjx.cn/. The earliest and largest online survey platform in China. Users have covered more than 90% of universities and research institutes in China.

[6] http://www.bjstats.gov.cn/nj/main/2016-tjnj/zk/indexch.htm. Accessed May 14, 2019.

Table 1
Description of sampled commuters.

Socio-demographic attributes		No.	Pct. (%)
Gender	Women	227	46.14
	Men	265	53.86
Age	< =20	38	7.72
	21–30	213	43.29
	31–40	140	28.46
	41–50	63	12.80
	> 50	38	7.72
Education level	High school and under	33	6.71
	Associate degree	62	12.60
	Bachelor's degree	201	40.85
	Master's degree	149	30.28
	Doctoral degree or above	47	9.55
Personal annual income	Less than ¥30,000	71	14.43
	¥30,000-¥80,000	110	22.36
	¥80,000-¥120,000	166	33.74
	¥120,000-¥200,000	78	15.85
	¥200,000-¥300,000	52	10.57
	More than ¥300000	17	3.46
Job type	Student	94	19.11
	Private enterprise worker/self-employed/freelancer	100	20.33
	Enterprises and institutions workers	157	31.91
	Enterprises and institutions managers	81	16.46
	National civil servants	44	8.94
	Retirees	17	3.46
Household car number	0	190	38.62
	1	215	43.70
	> 1	87	17.68

Table 2
Commute attributes of sampled commuters.

Commute attributes		No.	Pct. (%)
Normal departure time	Earlier than 6:00 a.m.	9	1.8
	6:00–6:30 am	57	11.6
	6:30–7:00 a.m.	68	13.8
	7:00–7:30 a.m.	98	19.9
	7:30–8:00 a.m.	89	18.1
	8:00–8:30 a.m.	61	12.4
	8:30–9:00 a.m.	42	8.5
	Later than 9:00 a.m.	68	13.8
Number of subway stations travelled	1–2	8	1.6
	3–4	47	9.6
	5–6	134	27.2
	7–8	107	21.7
	9–10	69	14.0
	10 and more	127	25.8
Weekly commute frequency	Less than four times a week	102	20.7
	Four times a week	179	36.4
	Five times a week	162	32.9
	More than five times a week	49	10.0
Commute cost	¥3	60	12.2
	¥4	142	28.9
	¥5	191	38.8
	¥6	55	11.2
	¥7 and more	44	8.9
Previous peak-avoidance experience	Departure earlier	317	64.4
	Departure later	50	10.2
	Switch to other modes	39	9.5
	Never	86	17.5

In the equations, y represents commuters' willingness of peak-avoidance; X is the vector of explanatory variables; P^* represents the vector of latent variables, where P_1^* is the perceived benefit and P_2^* is the perceived sacrifice; U represents the utility of commuters' willingness; I is the vector of indicators that reflect the latent variables; α indicates which share of variance of indicator I is explained by the latent variable; β_1, β_2, γ presents the regression coefficient; η, ε, υ are random error terms; i represents decision makers, and q represents one of the survey responses.

Table 3
List of explanatory variables.

Variable	Data format	Variable	Data format
Gender (X_1)	Dummy	Peak-avoidance experience: Commute earlier (X_{12})	Dummy
Age (X_2)	Dummy	Peak-avoidance experience: Commute later (X_{13})	Dummy
Education: level 2 (X_3)	Dummy	Peak-avoidance experience: Switch to other modes (X_{14})	Dummy
Education: level 3 (X_4)	Dummy	Normal departure time: between 7:00–8:30 a.m. (X_{15})	Dummy
Income (X_5)	Discrete	Normal departure time: after 8:30 a.m. (X_{16})	Dummy
Number of private cars (X_6)	Discrete	Number of stations (X_{17})	Continuous
Job: Private enterprise workers (X_7)	Dummy	Commute frequency: 4 times/week (X_{18})	Dummy
Job: Enterprises and institutions workers (X_8)	Dummy	Commute frequency: 5 times/week (X_{19})	Dummy
Job: Enterprises and institutions managers (X_9)	Dummy	Commute frequency: more than 5 times/week (X_{20})	Dummy
Job: National civil servants (X_{10})	Dummy	Ticket price (X_{21})	Continuous
Job: Retirees (X_{11})	Dummy		

Table 4
Scale items of perceived value.

Latent variables$P*$	Indicators$I$	Measurement items
Perceived benefits (P_1*)	Perceived money saving (I_1)	Avoiding the peak-hours can help me save money. (e.g. discount fares)
	Perceived time saving (I_2)	Avoiding the peak-hours can help me save time. (e.g. less waiting time)
	Perceived energy saving (I_3)	Avoiding the peak-hours can help me save energy. (e.g. less queuing)
	Discount (I_4)	Discount fare is important to encourage me to avoid the peak-hours.
	Other forms of incentive (I_5)	Other forms of incentives are important to encourage me to avoid the peak hours. (e.g. gifts in kind, free breakfast, credits for gifts)
	Service (I_6)	Better services in off-peak hours are important to encourage me to avoid the peak-hours. (e.g. free Wi-Fi)
	Subjective feeling (I_7)	Feeling better during off-peak hours is important to encourage me to avoid the peak-hours. (e.g. feeling more comfortable)
	Security (I_8)	A safer commuting environment during off-peak hours is important to encourage me to avoid the peak-hours. (e.g. less stampede)
	Social standards (I_9)	Avoiding the peak-hours will help me feel accepted by others.
	Life standards (I_{10})	Commuting during off-peak hours is a good lifestyle.
	Responsibilities and standards (I_{11})	I have the responsibility to help relieve the congestion during peak hours by avoiding the peak-hours.
Perceived sacrifices (P_2*)	Changes in habits (I_{12})	If I avoid the peak-hours, I will have to change my habits (e.g. sacrifice morning exercise time).
	Monetary cost (I_{13})	If I avoid the peak-hours, my commuting monetary cost will increase.
	Social risk (I_{14})	I am not sure whether peak-avoidance can relieve congestion effectively.
	Information risk (I_{15})	I am not sure about what the travel conditions would be if I avoid the peak-hours.
	Financial risk (I_{16})	I am not sure about how much my travel fee would cost if I avoid the peak-hours.
	Time risk (I_{17})	I am not sure about how long my travel time would last if I avoid the peak-hours.

Structural Equations

For the latent variable model, this equation represents the effect of observable variables on people's perceived benefit and perceived sacrifice:

$$P^*_{ilq} = \sum_k \gamma_{ilk} X_{ikq} + \eta_{ilq} \tag{1}$$

For the odered logit model, the utility for commuters' response to "willingness to avoid peak-hour commute" is:

$$U_{iq} = \sum_k \beta_{1ik} X_{ikq} + \sum_l \beta_{2il} P^*_{ilq} + \varepsilon_{iq} \tag{2}$$

Measurement Equations

For the latent variable model, commuters' perceptions of peak-avoidance are included as indicators to express the perceived benefits and sacrifices. This results in one equation for each indicator:

$$I_{ipq} = \sum_l \alpha_{ilp} P^*_{ilq} + \upsilon_{ipq} \tag{3}$$

For the ordered logit model, we need to express the commuters' willingness to avoid peak-hour commuting as a function of the utilities:

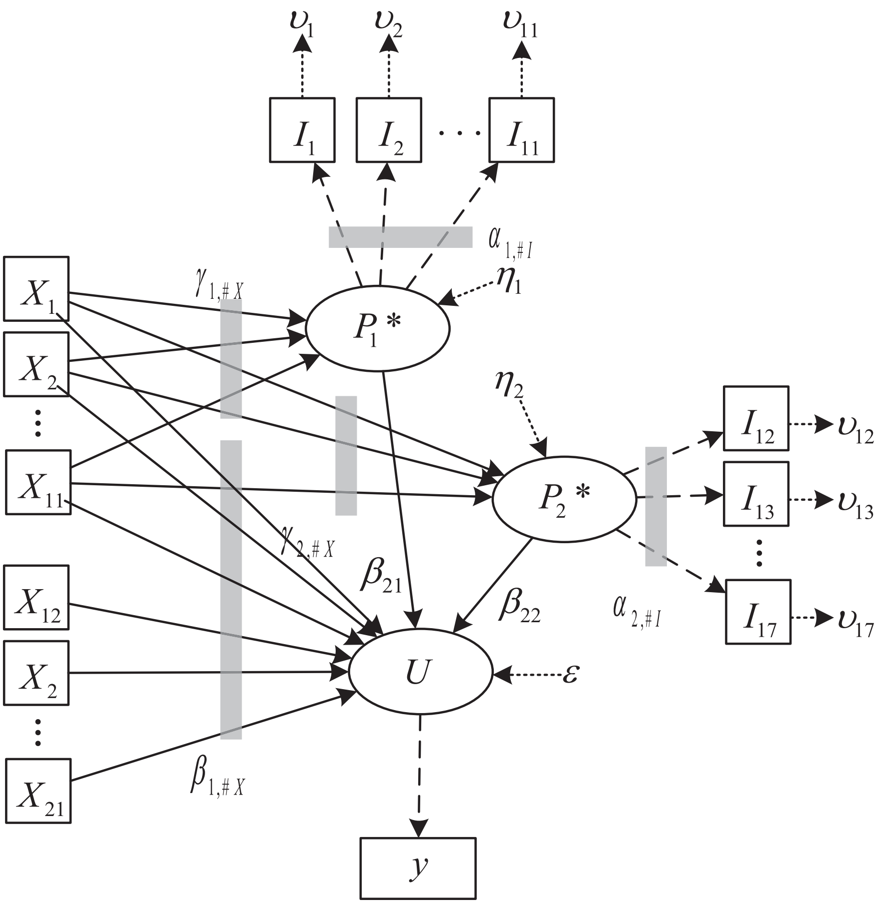

Fig. 2. Full path diagram for the ICLV model.

$$y_{iq} = \begin{cases} 1, 0 < U_{iq} \leqslant \mu_1 \\ 2, \mu_1 < U_{iq} \leqslant \mu_2 \\ 3, \mu_2 < U_{iq} \leqslant \mu_3 \\ 4, \mu_3 < U_{iq} \leqslant \mu_4 \\ 5, \mu_4 < U_{iq} \leqslant \infty \end{cases} \tag{4}$$

Suppose ε_{iq} is distributed logistic, then the familiar ordered logit model can be obtained, whereμvaries from situation to situation:

$$P_{iq} = \frac{\exp(\mu_n - \sum_k \beta_{1ik} X_{ikq} - \sum_l \beta_{2il} P^*_{ilq} + \varepsilon_{iq})}{1 + \exp(\mu_n - \sum_k \beta_{1ik} X_{ikq} - \sum_l \beta_{2il} P^*_{ilq} + \varepsilon_{iq})} - \frac{\exp(\mu_{n+1} - \sum_k \beta_{1ik} X_{ikq} - \sum_l \beta_{2il} P^*_{ilq} + \varepsilon_{iq})}{1 + \exp(\mu_{n+1} - \sum_k \beta_{1ik} X_{ikq} - \sum_l \beta_{2il} P^*_{ilq} + \varepsilon_{iq})} \tag{5}$$

The maximum likelihood estimation method is adopted to estimate the parameters in the model. The likelihood function can be expressed as (Raveau et al., 2010):

$$P(y_{iq}, I_{ipq}|\bullet) = \int_{P^*_{ilq}} P(y_i|X_{ikq}, P^*_{ilq}; \beta_{1ik}, \beta_{2ik}) \bullet f_I(I_{ipq}|P^*_{ilq}, \alpha) \bullet f_{P^*}(P^*_{ilq}|X_{ikq}; \gamma_{ilq}) \tag{6}$$

where $f_{P^*}(P^*_{ilq}|X_{ikq}; \gamma_{ilq})$ is the probability density function of the indicators for the latent variables. $P(y_i|X_{ikq}, P^*_{ilq}; \beta_{1ik}, \beta_{2ik})$ is the conditional probability function. $f_I(I_{ipq}|P^*_{ilq}, \alpha)$ is the measurement equation where latent variables P^* are measured by a set of indicators I by linear factor models.

In order to reduce the error of parameter estimation, this paper selected the simultaneous method to estimate the model parameters (Raveau et al., 2010). The model presented in this paper was estimated using the SEM software package Mplus (Muthén and Muthén, 2007). The MLR was used for the joint estimation of the hybrid models, and the Monte Carlo simulation was used for integration (Link, 2015).

Table 5
Parameter estimates for the measurement model.

	Items	Perceived benefits		Perceived sacrifice	
		loading	t Value	loading	t Value
Perceived benefits	Perceived money saving	0.668	8.637		
	Perceived time saving	0.581	10.857		
	Perceived energy saving	0.572	10.300		
	Discount	0.703	15.140		
	Other forms of incentive	0.649	12.717		
	Service	0.589	10.783		
	Subjective feeling	0.659	8.817		
	Security	0.650	9.812		
	Social standards	0.858	12.427		
	Life standards	0.799	11.206		
	Responsibilities and standards	0.663	12.526		
Perceived sacrifices	Changes in habits			0.601	6.382
	Monetary cost			0.524	7.327
	Social risk			0.597	6.098
	Information risk			0.718	6.008
	Financial risk			0.694	6.511
	Time risk			0.668	6.045

4. Results

4.1. Results of the latent variable model

As shown in Table 5, all the indicators show significant effects in measuring individuals' perceived values, which are the standardized model results.

The perceived benefits are mainly explained by the indicators "perceived money saving," "discount," "subjective feeling," "social standards" and "life standards." This implies that both the monetary incentives (e.g. discount) and internal incentives caused by the behavior itself, such as having a seat or a comfortable travel environment, are important for commuters' perceptions of gains. Then, commuters' perceptions are influenced by others. Commuters can perceive that they contribute to relieving congestion when participating peak-avoidance.

The perceived sacrifices are mostly explained by the indicators "changes in habits," "information risk," and "financial risk." This implies that high switching costs contribute to the high perceived sacrifice of travelers when switching to commute off-peak. Commuters may have to change their previous habits, such as sacrificing their rest and spare time, which also yields other corresponding adverse consequences (e.g. reschedules). Then, perceived risks lead to perceived sacrifices. Due to the dynamic nature of the metro transportation system and information asymmetry, commuters are faced with uncertainties on travel conditions, travel cost, and other factors. Such uncertainties constitute important parts of the perceived risk, cost, and restraint.

Table 6 shows the results of the structural equations for the latent variables. Only age significantly affects the perceived benefits and sacrifices. As age increases, perceived benefits increase and perceived sacrifices go down when avoiding peak hours. A possible reason is that older commuters prefer a comfortable commuting environment and their work schedule may be more flexible. This is consistent with the finding that retirees have a higher perceived benefit. It is also worth mentioning that, although education does not significant influence perceived benefits or sacrifices, it has a direct and significant effect on behavior utility, which will be discussed

Table 6
Parameter estimates for the structural model.

Items	Perceived benefits		Perceived sacrifices	
	coefficient	P value	coefficient	P value
Gender	0.011	0.812	0.010	0.845
Age	0.086*	0.086	-0.120**	0.031
Education: level 2	−0.023	0.785	0.147	0.105
Education: level 3	−0.022	0.803	0.200	0.232
Income	−0.057	0.317	−0.066	0.285
Number of private cars	−0.027	0.606	−0.004	0.944
Job: Private enterprise workers (ref. = students)	0.031	0.618	0.107	0.193
Job: Enterprises and institutions workers	0.030	0.629	0.064	0.337
Job: Enterprises and institutions managers	0.061	0.304	0.063	0.331
Job: National civil servants	−0.046	0.488	0.051	0.427
Job: Retirees	0.053**	0.025	0.002	0.970

Note: ** indicates $P < 0.05$, and * indicates $P < 0.1$.

Table 7
Parameter estimates for the ordered logit model and for the ICLV.

	Ordered logit model		ICLV		
	coefficient	P Value	coefficient	P Value	Odds ratio
Socio-demographic characteristics					
Gender	0.006	0.912	0.022	0.595	1.134
Age	0.034	0.546	−0.017	0.741	0.931
Education: level 2	0.123	0.132	0.154*	0.068	2.397
Education: level 3	0.153	0.100	0.171*	053	2.764
Income	0.005	0.937	0.047	0.317	1.092
Number of private cars	0.117*	0.028	0.142***	0.001	1.754
Job: Private enterprise workers	0.019	0.758	0.022	0.655	1.162
Job: Enterprises and institutions workers	0.070	0.270	0.080	0.152	1.618
Job: Enterprises and institutions managers	0.072	0.229	0.075	0.143	1.766
Job: National civil servants	−0.058	0.257	−0.019	0.679	0.829
Job: Retirees	0.064	0.231	0.000	0.997	1.003
Commuting characteristics					
Peak-avoidance experience: Commute earlier	0.496***	0.002	0.285***	0.000	5.351
Peak-avoidance experience: Commute later	0.272***	0.004	0.162***	0.000	4.511
Peak-avoidance experience: Commute in other ways	0.184**	0.020	0.112**	0.012	3.222
Normal departure time: between 7:00–8:30 a.m.	−0.050	0.565	0.026	0.751	1.157
Normal departure time: after 8:30 a.m.	0.053	0.583	0.031	0.731	1.231
Number of stations	−0.032	0.601	0.074	0.192	1.160
Commute frequency: 4 times/week	−0.004	0.949	−0.028	0.642	0.808
Commute frequency: 5 times/week	−0.112	0.163	−0.075	0.291	0.639
Commute frequency: more than 5 times/week	−0.132	0.089	−0.150**	0.026	0.245
Ticket price	0.034	0.546	−0.032	0.572	0.921
Perceived value					
Perceived benefits			0.672***	0.000	30.832
Perceived sacrifice			−0.167***	0.002	0.215
Goodness of Fit	OL model		ICLV		
AIC	814.121		671.793		
BIC	910.686		831.885		
Rho-squared	0.210		0.585		
Brant test: Chi-square/P-value	42.818/0.202		26.584/0.874		

Note: *** indicates $P < 0.01$, ** indicates $P < 0.05$, and * indicates $P < 0.1$.

in Section 5.

4.2. Results of the ordered logit part

The standardized results are shown in Table 7. Brant test results as shown in table 7 provide evidence that the parallel regression assumption has not been violated (Peterson and Harrell, 1990). Commuters with higher perceived benefit ($\beta = 0.672$) have higher intentions to participate peak-avoidance, while higher perceived sacrifice ($\beta = -0.167$) has the opposite effect. Similar to customers' intentions to purchase goods and services, commuters would like to maximize their perceived value. Through comparison of coefficients, we discovered that perceived benefit plays a more important role in the process of trading off benefits and sacrifices.

Regarding social demographic attributes, the estimation results indicate that more highly educated commuters are more willing to avoid peaks. A possible explanation is that highly educated commuters are more likely to use a sustainable travel mode. Further, ownership of private cars positively influence the peak-avoidance intention, since it offers an alternative way to travel. In terms of commuting attributes, if commuters have the experience of commuting earlier/later or travel in other modes to avoid the peaks, they are more willing to avoid the peak. Furthermore, commuters are restricted by commuting habits, and therefore less willing to participate peak-avoidance if they use the subway to commute more frequently.

Coefficients from the ordered logit model provide insights into the significance and direction of the relationships, but they cannot be easily interpreted in the manner of OLS regression coefficients to understand the magnitude of the relationships. To facilitate comparison of different variables, odds ratios for the ICLV model are also provided, which compare the relative odds of the event in each group (Zhu and Fan, 2018; Greene and Hensher, 2010).

In addition, same as the results of Ben-Akiva et al. (2002), the ICLV model has a higher explanatory power than the conventional model. Rho-squared is improved from 0.210 to 0.585. According to the information criterion, AIC has been reduced from 814.121 to 671.793 and BIC has been reduced from 910.686 to 831.885.

4.3. Having former experience VS No former experience

To better explore how prior experience moderates the trading-off process between perceived benefits and perceived sacrifices, separate models for both groups, with/without the former experience of peak-avoidance, are estimated and these results are shown in

Table 8
Parameter estimates for models of Having/Not having prior experience.

	1. Having prior experience			2. No prior experience		
	coefficient	P Value	Odds ratio	coefficient	P Value	Odds ratio
Socio-demographic characteristics						
Gender	0.034	0.491	1.212	−0.135	0.216	0.433
Age	−0.023	0.709	0.912	0.133	0.458	1.746
Education: level 2	0.101	0.273	1.770	−0.198	0.247	0.300
Education: level 3	0.131	0.281	1.828	0.114	0.557	2.141
Income	0.132**	0.013	1.289	−0.294	0.247	0.578
Number of private cars	0.139*	0.007	1.720	0.121	0.238	1.698
Job: Private enterprise workers	0.038	0.501	1.302	0.150	−0.140	0.308
Job: Enterprises and institutions workers	0.095	0.139	1.772	0.080	−0.152	0.876
Job: Enterprises and institutions managers	0.062	0.308	1.591	0.020	−0.825	0.435
Job: National civil servants	0.008	0.877	1.085	−0.060	−0.481	0.531
Job: Retirees	−0.003	0.964	0.955	0.021	0.822	1.352
Commuting characteristics						
Normal departure time: between 7:00–8:30 a.m.	0.210**	0.040	3.261	−0.285	0.184	0.177
Normal departure time: after 8:30 a.m.	0.167	0.116	3.224	−0.339*	0.075	0.102
Number of stations	−0.011	0.872	0.977	0.204	0.184	1.534
Commute frequency: 4 times/week	−0.098	0.244	0.469	0.050	0.675	1.464
Commute frequency: 5 times/week	−0.166*	0.079	0.358	0.152	0.295	2.553
Commute frequency: more than 5 times/week	−0.243***	0.007	0.122	−0.161**	0.030	0.118
Ticket price	−0.005	0.743	0.987	−0.100	0.342	0.765
Perceived value						
Perceived benefits	0.685***	0.000	33.671	0.573***	0.000	50.933
Perceived sacrifice	−0.171***	0.004	0.169	−0.079	0.613	0.660
Number of observations	406			86		
Rho-squared	0.467			0.201		

Note: *** indicates P < 0.01, ** indicates P < 0.05, and * indicates P < 0.1.

Table 8.

Compared with the group having prior experience of peak-avoidance, the group without prior experience is not significantly affected by perceived sacrifices anymore. Meanwhile, the odds ratio of perceived benefits in the model 1 (with prior experience) is smaller than the odds ratio in model 2 (without prior experience). After separating the two groups, for commuters with prior experience, “normal departure time between 7:00–8:30 a.m.” has a significantly positive impact on willingness to participate peak-avoidance. For commuters without prior experience, “normal departure time after 8:30 a.m.” now has a negative impact.

5. Discussion and implications

The odds ratios and coefficients report similar results, so in the following we will only discuss in terms of coefficients. The results are summarized in table 9 to facilitate the discussion.

Perceived benefit appears to positively influence commuters’ intention for peak-avoidance. In line with existing studies (Zhang et al., 2014; Wang et al., 2018; Leblanc and Walker, 2013), we found that both external and internal incentives have a significant and positive effect on perceived benefits. The commuters’ perception of a less crowded and more comfortable commuting environment helps to encourage them internally. Compliance with social norms help them to achieve social value when they engage in peak-avoidance. In addition, we found that perceived sacrifices have a significant negative impact on intentions of peak-avoidance, although its influence is not as great as that of perceived benefits..

Previous research has shown that prior experience of peak-avoidance has a positive effect on commuter intentions. Moreover, by

Table 9
Summary of the results.

Variables	Impact
Age	As age increases, perceived benefits will increase and perceived sacrifices will go down when avoiding peaking hours.
Education: level	Higher educated commuters are more willing to avoid peaks.
Number of private cars	Private car ownership has a positive impact on the peak-avoidance intentions.
Peak-avoidance experience	Commuters with prior experience of peak-avoidance are more willing to avoid the peak.
Commute frequency	Commuters with higher frequency of commuting are less willing to avoid the peak.
Normal departure time	• For commuters with prior experience, “normal departure time: 7:00–8:30 a.m.” has a significantly positive impact on the willingness to participate peak-avoidance. • For commuters without prior experience, “normal departure time: after 8:30 a.m.” has a negative impact.
Perceived benefits	Perceived benefits have a positive effect.
Perceived sacrifices	Perceived sacrifices have a negative effect. However, for commuters without prior experience, it is not significant.

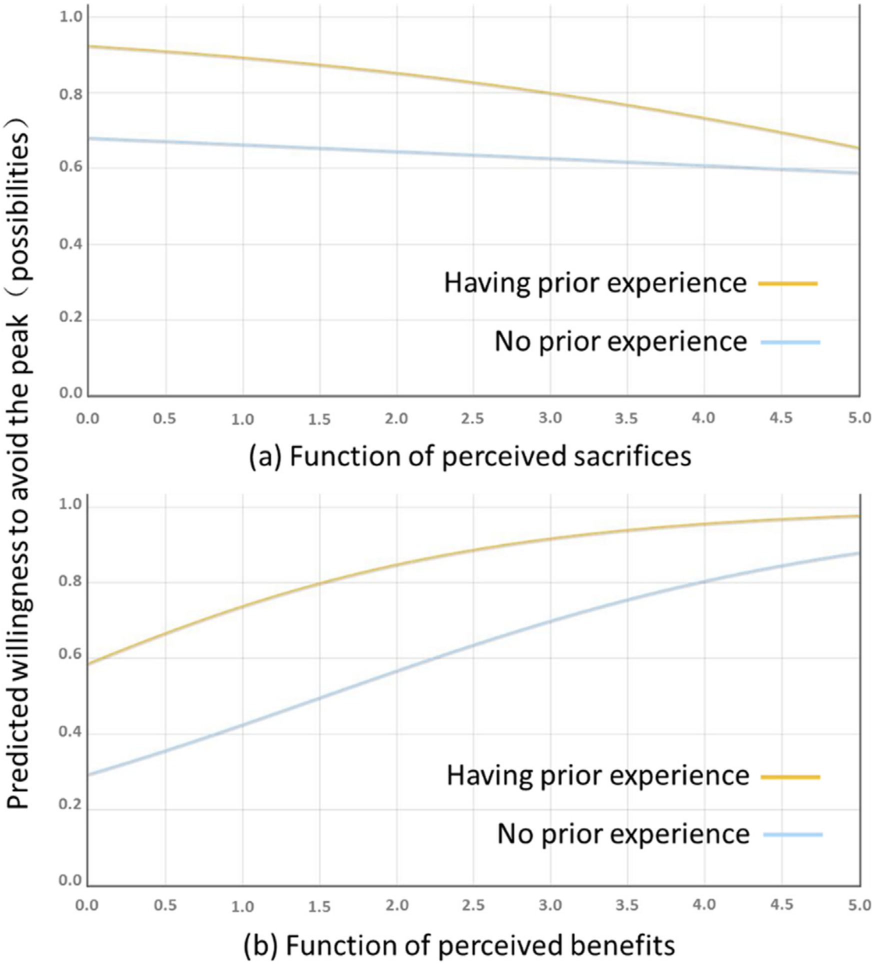

Fig. 3. Predicted willingness to avoid the peak for both groups.

estimating these two groups (with/without prior experience) separately, this paper further demonstrated how prior experience of peak-avoidance significantly influences commuters' tendency to change their behavior. Those who have experienced avoiding peak hours, because of the exposure to the real commuting environment, perceive the cost of changing the behavior differently than those who have not experienced avoiding the peak as shown in Table 8. They are capable of making a more comprehensive trade-off based on their experiences. In contrast, commuters without experience learn about the benefits of peak-avoidance only through indirect ways, such like government advertising, policies, or others' descriptions and it is difficult for them to fully understand the sacrifices of changing their commuting behavior, which may lead to perception bias. Meanwhile, familiarity with an alternative behavior seems to increase commuters' intrinsic motivation to change (Ben-Elia and Ettema, 2011a). It appears that the intention of behavior change is closely related to the perceived gap between the commuters' habitual behavior and changed behavior. The smaller the gap, the easier it will be to make the changes. Experience of peak-avoidance can help reduce the uncertainty of new mode of commuting. To provide a visual interpretation, referring to Zhu and Fan (2018), we plot the changes in willingness to avoid peak-hours against the level of perceived benefits and sacrifices in Fig. 3. The different tendencies of commuters with/without the priori peak-avoidance experience are also compared in the figure. Consistent with the analysis above, in the same scenario, commuters who have prior experience are more willing to avoid the peak. As perceived benefits increase, the willingness to avoid the peak also increases, and as perceived sacrifices increase, the willingness decreases, and vice versa.

In the case of observable variables, the results show that ownership of private cars has a positive influence on the likelihood of peak-avoidance, presumably because it offers an alternative way to travel. Previous literature have provided evidence that drivers may not always drive out of necessity, but also by choice (Handy et al., 2005). It is feasible to, however, provide service with sufficient appeal (for example: reliability, comfort, safe etc.) to attract car users to switch to public transport (Hensher, 1998; Gabriela and Sarsfield, 2007). In the context of peak-avoidance, it will be necessary to improve the apparent benefits of off-peak hours, and persuade drivers to commute at low peak instead of switching to driving. Further, it will be necessary to promote measures to reduce the attractiveness of car use (Gärling and Schuitema, 2007).

Interestingly, the higher the education lever of commuters, the larger the willingness to avoid the peak. One possible reason is that

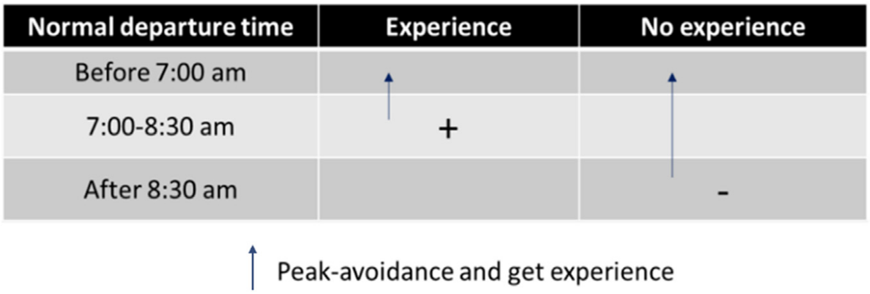

Fig. 4. Interaction of experience and departure time.

although flexible working schedule is not common in Beijing, people with higher education can find relatively more flexible jobs such as teachers, managers (Trend report of China Talent Recruitment 2018, by LinkedIn). Commuters with higher education levels may prefer socially desirable and environmentally sustainable travel modes (Knockaert et al., 2011; Zhang et al., 2014; Johansson et al., 2006).

According to the results of our stratified model, normal departure time variables become significant in Table 8. Since most commuters in Beijing lack flexible working schedules, for subway commuters, leaving earlier is the main option to avoid the peak (Zou et al., 2018). As shown in Fig. 4, compared to commuters who usually depart after 8:30, commuters who usually departure between 7:00–8:30 have lower switching costs and can advance their departure time to avoid peak hours (the sharpest peak in Beijing is 7:00–8:30). In fact, in our sample 68% of commuters who usually departure between 7:00–8:30 already have the experience of avoiding the peak hours, while that proportion in commuters who usually departure after 8:30 is only 32%. This result further explains what commuters are currently doing, intending to do or what they have done in the past. Likewise, since their departure time is too late, those who normally departure after 8:30 a.m. are less likely to participate in peak-avoidance and have no experience doing so.

These findings can promote policy-making in megacities through possible approaches that increase perceived benefits and reduce perceived sacrifices, thereby stimulating commuters' peak-avoidance behavior. In Beijing, the current 50% fare discount policy is not enough for commuters to feel the benefits of behavior change. Study shows that there is a maximum threshold of the influence time range of the discount fare policy (approximately 30 min) (Zou et al., 2018). Hence, dynamic time windows can be considered a feasible measure, as commuters traveling in different periods of time will be influenced and perceive the benefits caused by the policy. On the other hand, although the 50% fare discount is high, the actual discount amount is not considerably attractive because the subway fare amount itself is low (averagely ¥4.5 RMB\ $0.75 per trip). Greater discounts and more possible external incentives, including coupons, free drinks, free transfer tickets, lottery tickets, and credits, can be provided. However, revenue loss should be taken into account when providing external incentives. Moreover, since commuters' subjective feeling about off-peak commuting influences the perception of benefits, authorities should nudge commuters to experience off-peak commuting through public advertising or education. According to the estimation results in Section 4, experiencing peak-avoidance leads commuters to be more inclined to change their previous commuting habits because of the perceived internal incentives. The results also imply that if the commuters are provided with appropriate incentives, once these commuters have experienced peak-avoidance, they will have the internal motivation to continue their peak-avoidance.

Furthermore, appropriate policies should be adapted to reduce perceived sacrifices. To avoid risks associated with the lack of appropriate information, a better information distribution platform (e.g. Information APP) should be established to further assist commuters in the information inquiry process. In addition, experience in off-peak periods can also help reduce the uncertainties of commuting conditions, such as travel cost and travel time. When peak-avoidance becomes the newly formed habit, the perceived sacrifice of peak-avoidance will decrease and converge. Therefore, incentivizing commuters to experience peak-avoidance for a sufficiently long period of time (sufficient to form a new commuting habit) would still have a lasting impact on commuter behavior, even if the incentives subside.

6. Conclusion and further research

In this research, we proposed a framework to characterize subway commuters' perceived value of peak avoidance. Compared with previous studies, this framework extends the understanding of commuters' internal process of trade-offs between perceived benefits and sacrifices. Although previous studies have considered the influence of psychological variables on traveler behavior, there is a lack of theory to specifically explain the inner mechanism of trade-off between perceived benefits and sacrifices. The psychological trade-offs that we explained apply not only to peak-avoidance, but also to other scenarios. Further, this framework reveals the internal motivations that drive travelers to make changes, therefore helping us to be more targeted in encouraging people to change their behavior.

No research is without limitations. This paper pays more attention to private costs and benefits of the peak-avoidance behavior, but the discussion of the influence of peak-avoidance externality is insufficient. One of the limitations of this study is the lack of personal scheduling information. According to previous focus group interviews, we found that most Beijing commuters does not have flexible working hours. According to People's network (http://www.people.com.cn/, the most authoritative news release platform in China), due to the actual difficulties in Beijing, few companies implement flexible work schedules. Therefore, schedule flexibility is not yet included in the current analysis and should be further explored in our future research. In addition, this paper considered perceived benefits and sacrifices as latent variables, in which a more sophisticated multi-level model could be estimated (e.g., the possible impact of other important psychological factors, such as travel attitudes, can be explored in future studies). Finally, the stated preference survey only measured intentions rather than behavior and there was also a lack of more detailed information about means of accomplishing peak-avoidance. To test the actual impact on traveler behavior and examine the effectiveness of incentives in reducing peak congestion, it will be important to conduct field experiments to observe the real behavior of commuters.

CRediT authorship contribution statement

Yu Wang: Data curation, Writing - original draft. **Yacan Wang:** Conceptualization, Methodology, Supervision, Project administration. **Dick Ettema:** Software, Methodology. **Zidan Mao:** Visualization, Investigation. **Samuel G. Charlton:** Writing - review & editing, Resources. **Huiyu Zhou:** Formal analysis, Writing - review & editing, Validation.

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