Impacts of congestion pricing and reward strategies on automobile travelers' morning commute mode shift decisions

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ABSTRACT

This paper studies the impacts of congestion pricing and reward strategies on automobile travelers' morning commute mode shift decisions using stated preference travel mode choice data of over 1,000 automobile travelers collected in Beijing inner districts. To address the complex impacts of these strategies on automobile travelers, a stage-based model framework is developed to analyze their mode shift decision-making process (whether they will shift from using automobile to public transit, biking or walking or continue using automobile) under these strategies. Four multilevel structural equation models are created for participants using automobile (personal vehicle and/or taxi) as the most common mode of transportation (hereafter referred to as "more habitual automobile travelers") and those using automobile as second most common mode (hereafter referred to as "less habitual automobile travelers") under each strategy. Model estimation results show that the impacts of latent psychological factors on mode shift decisions under congestion pricing and reward strategies are significantly different between more and less habitual automobile travelers. The results also show that congestion pricing strategies are more effective than reward strategies in promoting mode shifts among more habitual automobile travelers, while the opposite is observed for less habitual automobile travelers. This study provides insights for designing congestion pricing and reward strategies and illustrates the importance of developing complementary modules that target numerous factors in different stages of the mode shift decision-making process to effectively promote mode shifts from automobile to sustainable travel modes in China.

1. Introduction

With rapid economic growth, vehicle ownership has increased drastically in China over the past decade. From 2012 to 2016, private vehicle stock has increased from 72.2 to 146.4 million and this growth trend is expected to continue in the future (Motor Vehicle Pollution Prevention Report of China, 2016). Growing vehicle ownership has created many challenges in metropolitan regions such as growing traffic congestion, environmental pollution and energy consumption which have negative impacts on human health and environment (Zhang and Crooks, 2012; Tommy and Friman, 2015; Guo et al., 2018). There is a critical need to develop effective strategies to promote mode shifts from automobile to sustainable travel modes such as public transit, bike and walk (hereafter referred to as "mode shifts to sustainability").

Various pricing strategies, such congestion pricing and reward strategies, have been considered to promote such mode shifts in China. Megacities such as Beijing, Shanghai, Shenzhen and Guangzhou have evaluated the feasibility of implementing congestion pricing strategies to promote mode shifts by increasing automobile travel cost (Sun et al., 2016).

However, these strategies were not implemented in these cities after evaluation because of various social concerns such as equity and public acceptance (Link, 2015). As an alternative to congestion pricing strategies, reward strategies, are considered as innovative and effective pricing strategies to promote mode shifts to sustainability by providing monetary incentives to travelers for using sustainable travel modes (Khademi, 2016). Empirical evidence has shown that both strategies can potentially promote mode shifts to sustainability (Harbeck, et al., 2017; Ettema and Verhorf, 2006). However, none of the previous studies has evaluated the potential for implementing reward strategies in China, analyzed their impacts on mode shift decisions, compared these impacts with those of congestion pricing strategies on mode shift decisions or understood the potential similarities and dissimilarities of these impacts on travel mode shift decisions of more and less habitual automobile travelers.

Apart from using congestion pricing and reward strategies to promote mode shifts to sustainability, previous studies also show that providing personalized, trip- and mode-specific information such as pollution emission information (e.g., amount of CO_2 emissions) and physical activity information (e.g., calories burnt) associated with each mode can also encourage such mode shifts (Jariyasunant, et al., 2015; Börjesson, et al., 2016; Guo and Peeta, 2017; Guo et al., 2017; Sunio and Schmöcker, 2017). For example, "Quantified Traveler" is a Web-based app that provides feedback in terms of cost, calories, time and emissions based on a given origin-destination trip to promote mode shifts to sustainability (Jariyasunant, et al., 2015). These results illustrate that integrating personalized, trip- and mode-specified information with congestion pricing and reward strategies can potentially increase their effectiveness.

This study aims at evaluating the effectiveness of congestion pricing and reward strategies on morning commute mode shift decisions (whether they will shift from using automobile to public transit, biking or walking or continue using automobile) of more and less habitual automobile travelers in China. A stage-based modeling framework is developed to capture the impacts of psychological factors on travelers' mode choice behavioral changes. To achieve these objectives, a web-based stated preference survey for Beijing inner districts in China is designed. Participants were asked to select their travel mode choice before and after the implementation of congestion pricing and reward strategies for their morning commute. Eight modes of transportation were considered, including personal vehicle, taxi (including traditional taxi and ridesharing such as DiDi taxi[1]), bus transit, subway transit, electric bike, shared bike (including docked bike and dockless bike such as Mobike[2]), personal bike and walk. Both shared and personal bikes are manually operated. Personal vehicle and taxi are considered as automobile modes and the rest as sustainable travel modes. An interactive mode choice information map is designed for the survey to provide participants with travel-related information, including travel time, travel cost/reward, amount of CO_2 emissions, amount of particulate matter emissions, walk steps and calories burnt associated with using each mode for a given origin and destination, once they have entered home and work addresses. By providing these types of information, we can also ensure that all participants can have similar levels of familiarity with the modes available. Four multilevel structural equation models using the

[1] DiDi taxi is one type of taxi hailing service via a smartphone application in China. This taxi-hailing app (like Uber) uses GPS technology to allow users to locate taxicabs that are nearby on their handheld device, and then users can send the required information to book a taxi.

[2] Mobike is one type of bike sharing service via a smartphone application in China. This bike-sharing app allows users to pick up and leave a bike at their convenience.

stage-based modeling framework are estimated based on both more and less habitual automobile travelers' stated preference mode shift decisions under each strategy while capture the potential correlations among these responses. This study provides a comprehensive and in-depth understanding of the impacts of congestion pricing and reward strategies on morning commute mode shift decisions. These results and insights can assist decision-makers to develop intervention strategies to complement pricing strategies that target automobile travelers' various stages of mode shift decision-making process to increase public acceptance and improve the effectiveness of various pricing strategies to promote mode shifts to sustainability in China.

The remainder of this paper is organized as follows. The next section outlines the relevant theoretical background and proposes a conceptual model for mode shift decisions under pricing strategies. After that, the survey design and descriptive statistics are analyzed. The model estimation results are then presented and discussed. The paper concludes with some comments and insights.

2. Literature review

The theoretical background of the decision-making process can be categorized into three main clusters: (1) the theory of planned behavior (TPB), which characterizes the decision-making process as a process of forming the intention to adopt certain behavior (Ajzen, 1985), (2) norm activation model (NAM), which explains the decision-making process as a motivational basis for the realization of altruistic behavior (Hunecke et al., 2001), and (3) self-regulation model, which describes the decision-making process as a transition through a sequence of volitional phases (Schwarzer, 2008; Fu et al, 2012).

The TPB and NAM have been widely used to model the travel mode shift decision-making process in the literature (Bamberg et al, 2007; De Groot et al, 2008; Klöckner and Matthies, 2009; Hsiao and Yang, 2010; Eriksson and Forward, 2011; Mann and Abraham, 2012; Onwezen et al, 2013; Nordfjærn et al, 2014; Lois, Moriano, & Rondinella, 2015; Guo and Peeta, 2015). A key assumption in these studies is that a person's choices are governed by his/her behavioral intention or pro-social motives. However, empirical evidence (e.g. Armitage and Conner, 2001; Bamberg and Möser, 2007; Susan, et.al, 2009) has shown that there is a gap between intention and behavior (referred to as "intention-behavior gap"). It implies that behavioral changes such as mode shifts to sustainability requires travelers to not only form strong behavioral intentions or pro-social motives but also develop skills and strategies to control the temptation of reverting back to old behavior (such as using automobile) and break down barriers to implement a set of behaviors (such as using sustainable travel modes).

To bridge such gaps, some recent studies (e.g., Bekkum and Elizabeth, 2011; Fu, et.al. 2012) introduced conceptual self-regulation models based on the assumption that implementation intention is the foundation of the volitional phase which can bridge the intention-behavior gap. Bamberg (2013a, 2013b) proposed a more cumulative theoretical framework which integrates the stage concept with TPB and NAM. This model describes the behavioral change process as a series of four stages: (a) pre-decisional stage, (b) pre-actional stage, (c) actional stage and (d) post-actional stage. Goal intention, behavioral intention and implement intention are three transition points between stages. The process can be described as follows:

- In the pre-decisional stage, an individual becomes aware of the problems and re-evaluates his/her habitual behavior. This can create the goal intention (i.e. the intention to act) that transitions to the pre-actional stage. Such intention can be captured by personal norm (i.e. personal value system) which is correlated with a traveler's awareness of consequences (i.e., the consequences of shifting or not shifting to sustainable travel modes), sense of responsibility to making such shift, and social norms (i.e. perceived social pressure to engage/not engage in shifting from automobile to sustainable travel modes).

- Once the goal intention is established, the individual transitions to the pre-actional stage and starts to select a new behavioral alternative and prepare for change. This leads to behavioral intention (i.e. self-commitment to change to a new alternative). Attitude (i.e. favorable/unfavorable view of using each travel mode.) and perceived behavioral control (i.e. perceived ability to shift to sustainable travel modes) are the two main social-cognitive factors that promote the formation of behavioral intention.
- In the actional stage, the individual initiates and implements necessary actions to make the behavioral change. The enactment of such change is facilitated by implementation intention. Concrete planning abilities and the ability to remove psychological barriers (action/coping planning) are essential factors to implementation intention. Then, the decision-making process transitions to the post-actional stage.
- In the post-actional stage, the individual will evaluate what he/she has achieved and decide whether to maintain the new behavior. The individual's confidence can influence his/her ability to maintain the new behavior and resume the new behavior after a relapse (so-called self-efficacy). This is critical to maintaining the new behavior.

The aforementioned behavioral change model provides a framework to quantify the impacts of psychological factors on the behavioral change by breaking from habitual travel behavior and/or forming new ones. However, to the best of authors' knowledge, none of the existing studies have applied this model to understand the impacts of monetary incentives/disincentives (i.e., rewarding mode shift to sustainability or penalizing the usage of automobile through pricing strategies) on travel mode shift decision-making process in China. In this study, a stage-based mode shift decision-making model under pricing strategies is proposed, as shown in Fig. 1. The model structure is adopted from Bamberg (2013a) with two major differences highlighted in green. First, the post-actional stage is substituted by an adaptive stage without further predictors. This is because pricing strategies have yet to be implemented in Beijing and only stated preferences are available. Second, in the pre-actional stage, perception of pricing strategies (i.e. individual's cognitive capacity to evaluate the strategies) has been added as an additional predictor. As shown in previous studies (Sun et al, 2016), a traveler's willingness to adopt an alternative travel mode under pricing strategies is associated with his/her perception of these strategies (such as perceived effectiveness, freedom, fairness and acceptability).

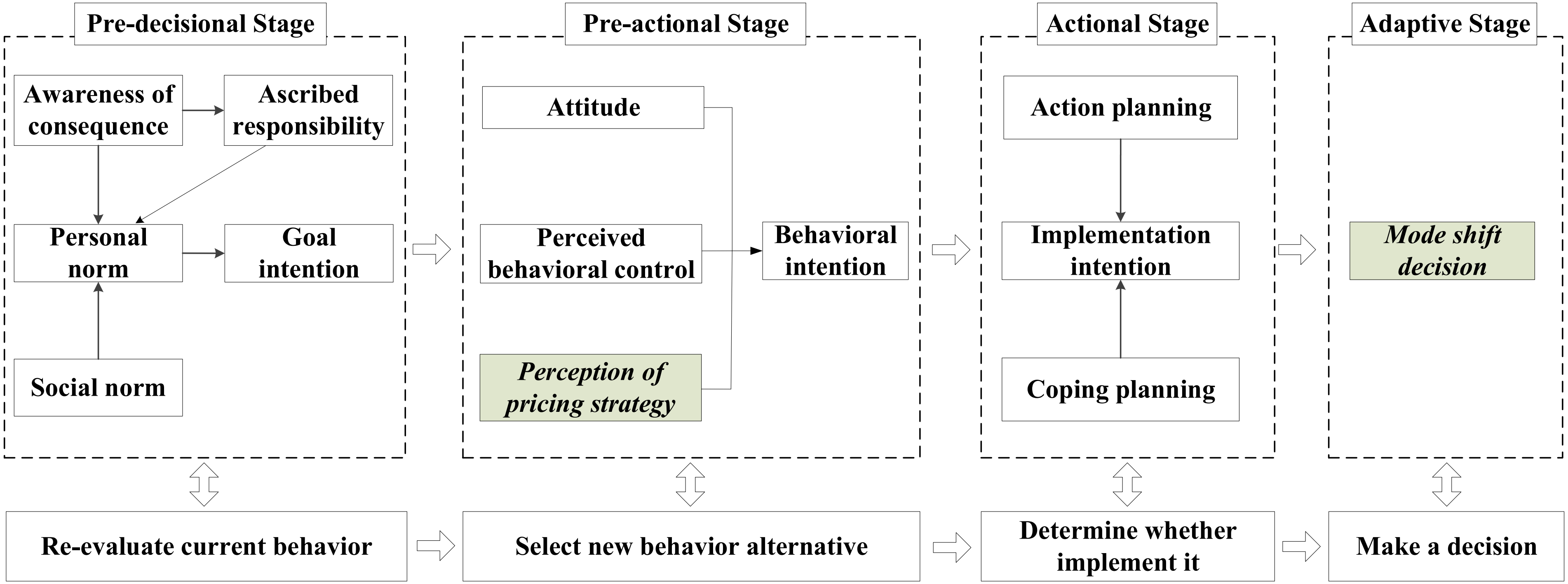


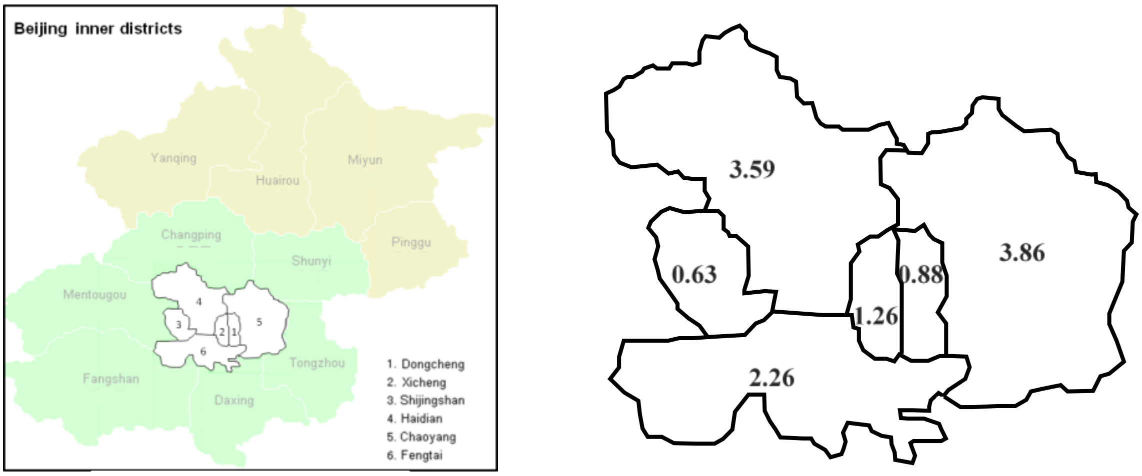
Fig. 1. Proposed conceptual model.

3. Methods

To understand travelers' mode shift decision-making process and evaluate the proposed model, an experiment is designed using stated preference survey method. In the survey, participants who live and/or work in Beijing inner districts (Fig. 2) were asked to answer a wide range of questions (Fig. 3) related to each component of the proposed conceptual model. Participants were expected to choose between "continue to travel by car/taxi" and "switch to sustainable travel mode" under three congestion pricing strategies and three reward strategies. The following subsections include more details related to the description of the study area (section 3.1), survey design (section 3.2), how the survey was implemented and some of the descriptive statistics (section 3.3), and structural equation modeling method (section 3.4).

3.1 Study area

As shown in Fig. 2, the Beijing inner districts, which include Xicheng, Dongcheng, Haidian, Chaoyang, Shunyi, and Shijingshan, were selected as the study area. In these districts, travelers often experience high congestion during morning peak hours due to increasing automobile ownership. According to the Annual Report on Traffic Development in Beijing (2016), the commute mode shares of automobile, bus and subway are around 31.9%, 25% and 25%, respectively. The average vehicle speed during the morning peak hour in the study area is about 14.7 km/h (or 9.1 mph), and the travel time during peak hour is twice as much as the travel time under free-flow conditions. There is an urgent need to reduce automobile usage and promote mode shifts to sustainability. Participants are recruited based on the inclusion criteria that they must live or work in Beijing inner districts, and the most or second common mode of morning commute (go to work/school) is automobile (include car or taxi).



(a) Beijing inner districts **(b) Residential population of each district (in millions)**

Fig. 2. Survey area.

3.2 Survey design

The structure of the questionnaire is presented in Fig. 3. It consists of three main parts: participants' sociodemographic characteristics, current morning commute mode choice and morning commute mode choice preference under six pricing strategies and psychological factors related to the morning commute mode shift decision-making process. Six pricing strategies include three congestion pricing strategies and three reward strategies. In the first part, questions related to personal and household information, and household mobility resources were asked.

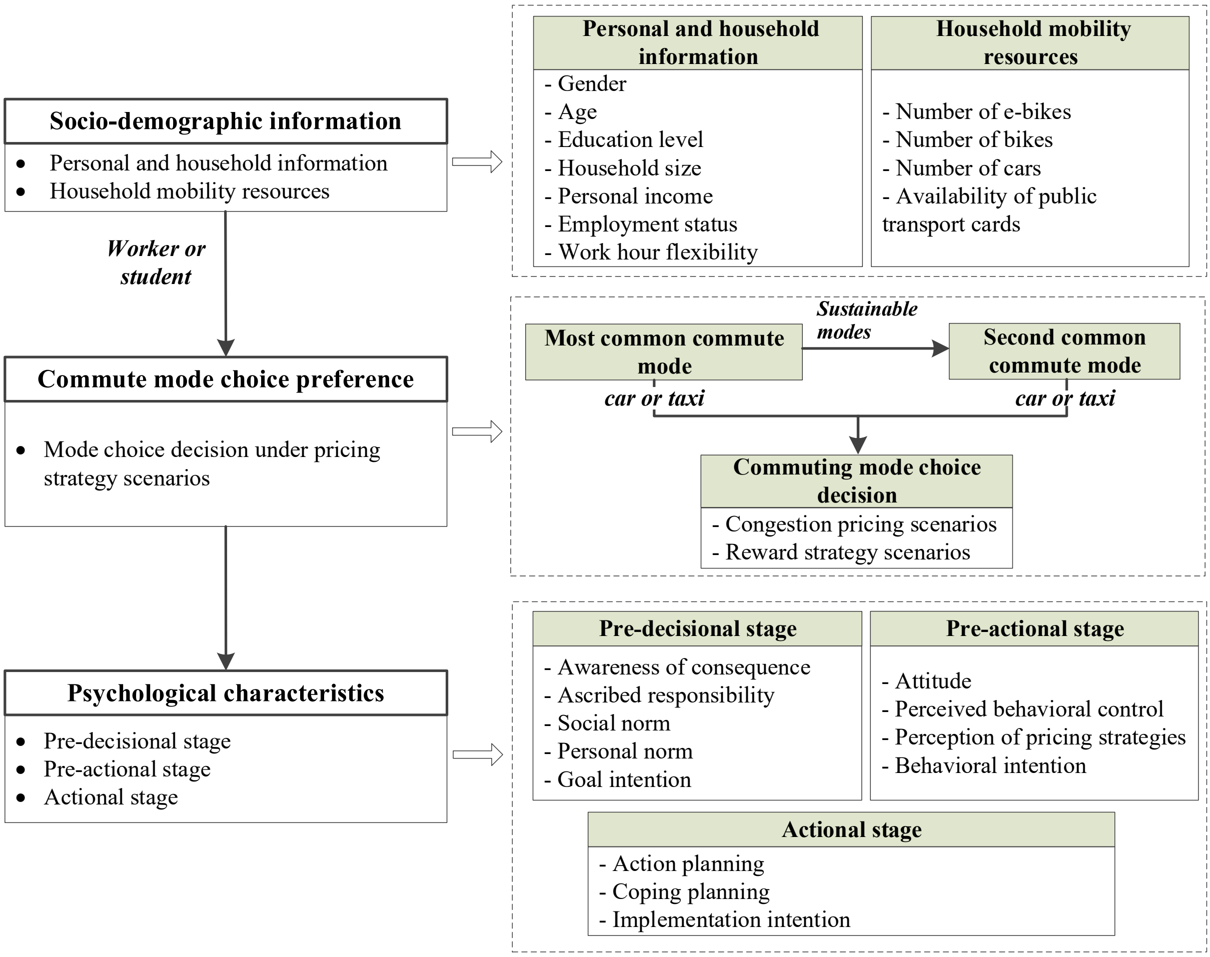


Fig. 3. Structure of questionnaire.

The second part aims to capture participants' current morning commute behavior and stated mode shift decisions under six pricing strategies. The eight available modes are car, taxi, bus transit, subway transit, electric bike, personal bike, shared bike and walk. Participants were asked to select their most and second most common travel modes for morning commute. Only those who use automobile (i.e., car/taxi) as their most or second most common commute mode are included in the study. Based on their answers to these two questions, participants are divided into two groups: more and less habitual automobile travelers. By doing so, the potential similarities and dissimilarities of stated mode choice preference under various pricing strategies between travelers with different automobile usage habit strengths can be analyzed. These results will facilitate the designs of complementary strategies to pricing strategies for different sub-populations to promote mode shifts to sustainability. To understand their stated preference of mode choice under various pricing strategies, an interactive online mode choice information tool is designed, as shown in Appendix A. After participants enter their residential location and work/school location on the map, it provides mode choice options and information related to travel distance, travel time, travel cost, amount of CO_2 emissions, amount of particulate matter emissions, number of steps walked, the amount of activity calories burned and possible rewards/penalties for each mode under each proposed pricing strategy. The estimation of pollution emission information (amount of CO_2 emissions and amount of particulate matter emissions) and physical activity information (number of steps walked and the amount of activity calories burned) are based on previous studies (Table 1). The estimated amount of CO_2

emissions includes both exhaust emissions and indirect emissions of fuel consumed (Ma et al, 2011; Grazi et al, 2008) and the particulate matter emission factor is calculated based on an empirical study on emission factors of vehicle exhausts in Beijing (Fan et al, 2015). The number of steps walked is based on the stride length and average height of Beijing residents (Kanchan et al, 2015), and calories burnt are estimated based on a diet calculator (Golan, Y., 1998).

Table 1 Data used to calculate pollution emission information and physical activity information

	Car	Taxi	Bus	Subway	Electric bike	Personal bike	Shared bike	Walk
CO_2 emission factor (g/km)	178.6	178.6	73.8	9.1	69.6	0	0	0
Particulate matter emission factor (mg/km)	1	1	0.4	0.05	0.3	0	0	0
Walk steps (steps/km)	0	0	0	0	0	0	0	2000
Activity calories (Kcal/km)	0	0	0	0	0	27	27	38

Participants were asked to select their preferred morning commute travel mode under three congestion pricing strategies (penalized with 5-yuan, 15-yuan and 25-yuan for using automobile). Similarly, under the three reward strategies, participants were asked to select their preferred travel mode if they are rewarded with 1-yuan, 1.5-yuan and 2-yuan for using sustainable travel modes. The amount of monetary award given to travelers is designed to cover part or all of the travel costs if the participants want to use bus or subway. If a traveler has the bus pass (it only costs a 20-yuan deposit to obtain, and most travelers have it), the ticket costs 1-yuan. The starting price for subway ticket is 3-yuan, and a 50% discount is received if monthly cost of subway tickets is over 150-yuan. The estimated subway ticket cost per traveler per trip is 4.3-yuan. The reward amount and congestion cost are not created equal because congestion pricing strategies require a large amount of initial investment, but can generate revenue for government to cover the cost in the long run, while reward strategies can only increase government spending. It is not financially feasible for the government to set lower congestion price or higher reward values.

The third part of the survey is designed to capture psychological factors related to mode shifts. The details of these questions are presented in Table 2. Most of these questions are developed based on Bamberg (2013a), including participants' awareness of consequence (2 questions), ascribed responsibility (1 question), social norm (2 questions), personal norm (2 questions), goal intention (1 questions), attitude (3 questions) and perceived behavioral control (2 questions), using 5-point Likert scales between strongly disagree and strongly agree. Additional ones adapted from the literature (Sun et al., 2016; Bamberg, 2013b) were also asked related to participants' perception of pricing strategies (4 questions), behavioral intention (1 question) and implementation intention (1 question) under each pricing strategy. In addition, to capture action planning and coping planning, the method developed by Hsieh et.al (2017) is used. For action planning, participants were asked about when, where and how to act if they shift from automobile to sustainable travel modes, which includes how to search schedule and how to check required travel time information. For coping planning, the ability to overcome specific barriers and perception of different potential barriers are included. The ratio of the perceived level of barriers to the perceived ease of overcoming barriers is used to weigh coping planning.

Table 2 Survey questions for psychological variables

Category	Latent variable	Item	Observed variable
Pre-decisional stage	Awareness of consequence	AC1 [a]	Traffic congestion and pollution will become more serious with increasing automobile usage.
		AC2 [a]	There is no benefit to personal health if we use automobile to travel more.
	Ascribed responsibility	AR[a]	I feel personally responsible for the problems related to automobile usage.
	Social norm	SN1 [a]	People who are important to me think that it is good to commute using sustainable travel modes.
		SN2 [a]	Most people who are important to me expect me to reduce automobile usage.
	Personal norm	PN1 [a]	I feel personally obliged to reduce automobile usage as much as possible.
		PN2 [a]	Regardless of what other people do, I have a moral obligation to reduce automobile usage.
	Goal intention	GI [a]	I intend to think over how to reduce automobile usage in the future.
Pre-actional stage	Perceived behavioral control	PBC1 [b]	How much control do you have over whether you commute by automobile or not?
		PBC2 [a]	For me, it is easy to use sustainable travel modes more frequently to commute.
	Attitude	ATT1 [a]	I like to travel by sustainable travel modes.
		ATT2 [a]	Using sustainable travel modes more make me feel good.
		ATT3 [a]	If I reduce automobile usage, I will have positive influence on alleviating the problems caused by automobile usage.
	Perception of pricing strategy	PP1-C [c]	Do you perceive that each of the three the proposed congestion pricing strategies would alleviate traffic congestion and pollution?
		PP1-R [c]	Do you perceive that each of the three proposed reward strategies would alleviate traffic congestion and pollution?
		PP2-C [d]	Do you perceive that each of the three proposed congestion pricing strategies would be fair to you?
		PP2-R [d]	Do you perceive that each of the three proposed reward strategies would be fair to you?
		PP3-C [e]	Do you perceive that each of the three proposed congestion pricing strategies would affect your freedom to choose travel modes?
		PP3-R [e]	Do you perceive that each of the three proposed reward strategies would affect your freedom to choose any travel mode?
		PP4-C [f]	Do you perceive that each of the three proposed congestion pricing strategies would be acceptable?
		PP4-R [f]	Do you perceive that each of the three proposed reward strategies would be acceptable?

	Behavioral Intention	BI1-C [a]	I intend to use more sustainable travel modes frequently for everyday trips under each of the three proposed congestion pricing strategies.
		BI1-R [a]	I intend to use more sustainable travel modes frequently for everyday trips under each of the three proposed reward strategies.
Actional stage	Action planning	AP1 [a]	I know how to search the schedule if I change to public transit.
		AP2 [a]	I know how to check the travel time if I change to sustainable travel modes.
	Coping planning	CP1 [g, h]	Could inflexibility of departure time be a barrier to shift from automobile to public transit? [f] and, Is it easy for you to overcome it? [g]
		CP2 [g, h]	Could large travel time be a barrier to shift from automobile to sustainable travel modes? [f] and, Is it easy for you to overcome it? [g]
		CP3 [g, h]	Could difficulty of reaching places not near a transit station be a barrier to shift from automobile to public transit? [f] and, Is it easy for you to overcome it? [g]
		CP4 [g, h]	Could lack of freedom to travel be a barrier to shift from automobile to sustainable travel modes? [f] and, Is it easy for you to overcome it? [g]
		CP5 [g, h]	Could the possibility of harsh weather be a barrier to shift from automobile to sustainable travel modes? [f] and, Is it easy for you to overcome it? [g]
		CP6 [g, h]	Could inconvenience of carrying luggage be a barrier to shift from automobile to sustainable travel modes? [f] and, Is it easy for you to overcome it? [g]
	Implementation intention	II-C [a]	I will travel by sustainable travel modes on my next morning commute under each of the three proposed congestion pricing strategies.
		II-R [a]	I will travel by sustainable travel modes on my next morning commute under each of the three proposed reward strategies.

[a] Scales 1-5: from "strongly disagree" (1) to "strongly agree" (5).
[b] Scales 1-5: from "not at all" (1) to "complete control" (5).
[c] Scales 1-5: from "not at all" (1) to "very effective" (5).
[d] Scales 1-5: from "very unfair" (1) to "very fair" (5).
[e] Scales 1-5: from "not at all" (1) to "very freedom" (5).
[f] Scales 1-5: from "not at all" (1) to "very acceptable" (5).
[g] Scales 1-5: from "no, not at all" (1) to "yes, largely" (5)
[h] Scales 1-5: from "not at all" (1) to "very easy" (5).

3.3 Survey implemented and descriptive statistics

The questionnaire is distributed online by Sojump Survey Company (http://www.sojump.com) which possesses more than 2.6 million sample resources with diverse sociodemographic characteristics. Potential participants who meet the selection criteria in the respondent pool maintained by Sojump received an email invitation to join the study. Out of the 2500 questionnaire distributed, 1135 completed questionnaires were returned between mid-June and mid-July of 2017.

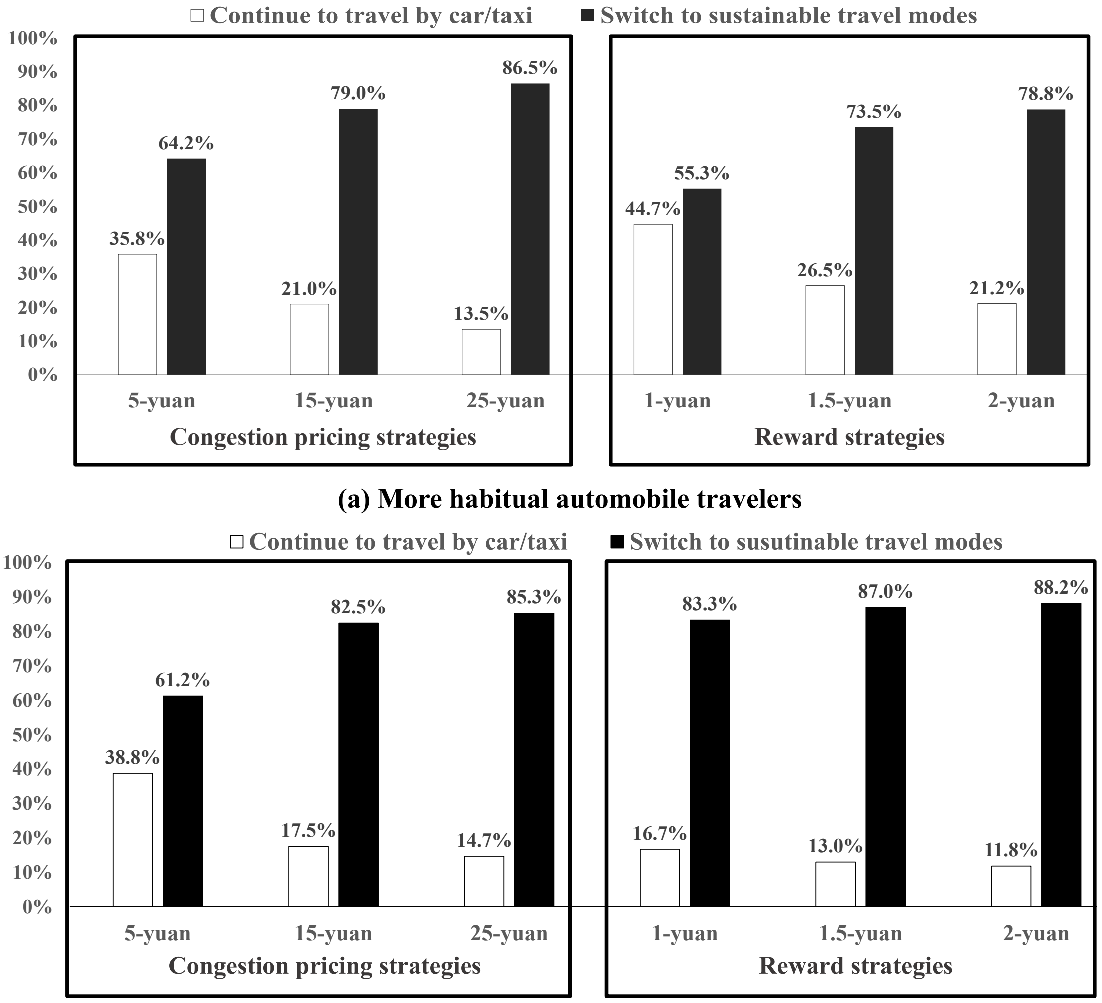
Table 3 Sociodemographic characteristics of the target population and participants

Characteristic	**Target Population**[1]	**All samples** (N=1135)	**More habitual automobile travelers** (N=557)	**Less habitual automobile travelers** (N=578)	***p*-value**[2]
Gender					
Male	50.9%	58.6%	64.8%	52.6%	0.000
Female	49.1%	41.4%	35.2%	47.4%	
Age					
18-24	12.5%	19.3%	18.7%	19.9%	0.000
25-34	26.2%	45.7%	46.5%	45.0%	
35-44	18.4%	27.0%	26.2%	27.7%	
45-54	16.4%	7.1%	7.2%	7.1%	
>55	26.5%	0.8%	1.4%	0.3%	
Education level					
High school diploma or lower	43.3%	7.5%	5.9%	9.0%	0.021
College degree	46.9%	74.3%	74.7%	74.0%	
Post-graduate degree or above	9.8%	18.2%	19.4%	17.0%	
Personal monthly income (Yuan)					
<4000	19.2%	21.8%	18.3%	25.1%	0.000
4000-6000	22.8%	18.5%	12.7%	24.0%	
6001-8000	18.5%	24.1%	28.7%	19.6%	
8001-10000	10.5%	9.7%	7.4%	11.9%	
>10000	26.0%	26.0%	32.9%	19.4%	
Household size					
1	22.7%	12.6%	11.8%	13.3%	0.008
2	30.7%	16.6%	14.2%	19.0%	
3	29.0%	41.0%	42.0%	40.1%	
≥4	17.6%	29.7%	32.0%	27.5%	
Employment status					
Public sector employee	22.0%	28.3%	25.5%	31.0%	0.001
Private sector employee	65.3%	56.7%	58.7%	54.7%	
Self-employment	8.1%	6.7%	6.8%	6.7%	
Students	-	8.3%	9.0%	7.6%	

[1]Data from Beijing Census Bureau 2015.

[2]Chi-square test result on demographic characteristics between more and less habitual automobile travelers.

The sociodemographic characteristics of the population in the target area, survey samples (N = 1135), and more (N = 557, 49.1%) and less (N = 578, 50.9%) habitual automobile travelers are shown in Table 3. Compared to the sociodemographic characteristics of the target population, our sample comprises a larger percentage of men, aged between 25 and 44, with college degree or above, with relatively high monthly income (the median monthly wage in Beijing Urban area was about 7086 yuan per month in 2015 based on the National Bureau of Statistics (2016)), or a household with more than 3 family members. In addition, more habitual automobile travelers are a larger percentage in the aforementioned categories compared to less habitual automobile travelers. These differences exist because all respondents use automobile as the first or second most common mode choice; so, they often belong to middle class or above households with a higher income and larger family size, especially for the more habitual automobile travelers.



(b) Less habitual automobile travelers

Fig.4. Mode shift decisions under congestion pricing and reward strategies.

Fig. 4 illustrates participants' stated mode shift decisions under six congestion pricing and reward strategies of more and less habitual automobile travelers. For participants who choose to shift to sustainable travel modes under congestion pricing and reward strategies, about 35.5%, 18.9% and 17.5% of them want to shift to subway, bus and biking, respectively. The results show that when the congestion fee is 5 yuan, over half of the participants want to shift from automobile to sustainable transportation modes, while in developed countries such as in Sweden (Karlström & P. Franklin, 2009) or Netherlands (Tillema et al, 2013), the congestion fee needs to be much higher to promote mode shifts. However, our results are consistent with one recent study (Linn et al, 2016) in Beijing which estimates that 95% automobile travelers will be gave up driving (or taking a taxi) if congestion fee is 8 Yuan. There are three main reasons for the differences observed between Beijing and cities in some developed countries. First, Beijing has relatively complete intra-city public transportation service, which consists of subway, bus, and bicycle sharing systems. For example, over 20 percent of participants who choose to shift to subway from automobile will experience a shorter travel time, and only about 20 percent of them will experience a 25 percent or higher increase in travel time. Second, rising concerns related to health risks and environmental pollution caused by intensifying city smog also contribute to a higher willingness to shift modes. Over 67 percent of the participants in our study have a strong perception that health risks and environmental pollution will become more serious with increased automobile usage. This is consistent with the literature (Sun et al, 2017) which shows that more than 63 percent of Beijing residents have strong awareness of smog and environmental pollution. Third, the estimated average subway and bus fares per traveler per morning commute trip are 4.3-yuan and 1.5-yuan, respectively, which are much lower than under automobile usage and the rewards provided are sufficient to cover most or all of the subway and bus fares.

Four additional observations can be made from Fig. 4. First, consistent with the literature, most participants are more likely to shift to sustainable travel modes as the penalty/reward increases. Second, the percentage difference between travelers making mode shifts under 15-yuan and 25-yuan congestion fees is not very significant, as also under 1.5-yuan and 2-yuan. One reason is that participants with higher income are more likely to be less sensitive to the amount of penalty/reward provided, but are more likely to value more other benefits associated with using automobile such as the sense of freedom and shorter travel times. Another reason is that some travelers with relatively longer morning commute times (sometimes over one hour using automobile) are captive automobile travelers and the commute times under sustainable travel modes are too long (sometimes double or triple that amount) for them to be viewed as credible alternatives. Third, a smaller percentage of more habitual automobile travelers is more likely to shift to sustainable travel modes under congestion pricing strategies compared to that under reward strategies, while the opposite is observed for less habitual automobile travelers. A possible reason is people who are more habitual automobile travelers are less sensitive to rewards associated with shifting to sustainable travel modes, while being more sensitive to penalties for using automobile. This is different from the findings of some past studies (e.g. Tillema et al, 2013) in which automobile travelers are more willing to reduce car usage under a reward strategy than that under a congestion pricing strategy. This is likely because the reward provided is relatively lower compared to other perceived benefits of using automobile. Fourth, congestion pricing and reward strategies are more effective in promoting less habitual automobile travelers to shift to sustainable travel modes, especially reward strategies. This is because less habitual automobile travelers are using sustainable travel modes as their most common morning commute mode choice and it is easier for them to shift to modes that they are more familiar with. Considering that in developing countries such as China, travelers have only just started becoming habitual automobile travelers unlike most developed countries with high automobile ownership, it may be more beneficial to implement pricing strategies in these countries to impede the habit of using automobile and promote the usage of sustainable travel modes when the automobile habit is not very strong.

3.4 Multilevel Structural equation modeling (ML-SEM)

As each participant responded to each of the three congestion pricing strategies and reward strategies, it is important to factor the potential correlation among these three responses. Multilevel structural equation modeling framework Rabe-Hesketh et al, 2004a; Rabe-Hesketh et al, 2004b; Rabe-Hesketh et al, 2007) is used in this study to capture such potential correlations. A multilevel structural equation model is a statistical technique to model the relationships of multiple independent and dependent variables varying at different levels. Within this framework, multilevel structural equation models combine both measurement models and structural models. The measurement models are used to study the possible interrelationships among a set of observed variables (response to survey questions) of one latent variable, which can be written as follows:

$$v = \beta x + \sum_{l=2}^{L} \sum_{m=1}^{M_l} \eta_m^{(l)} \lambda_m^{(l)\prime} z_m^{(l)} \tag{1}$$

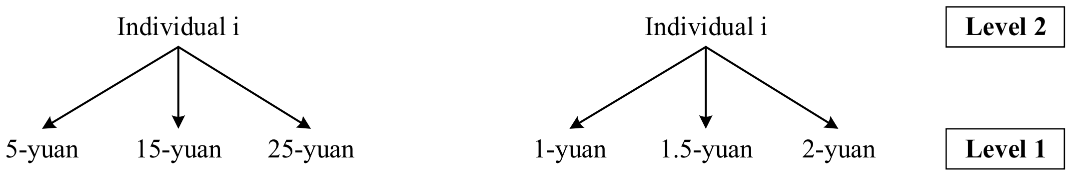
where v represents the log odds for observed indicators, x is explanatory variable associated with fixed effect β. The *m*th latent variable at level *l*, $\eta_m^{(l)}$, is multiplied by a linear combination of explanatory variable $\lambda_m^{(l)\prime} z_m^{(l)}$. Note that the variables of a multivariate response are treated as level 1 units in a multilevel dataset (the original units become level 2 units).

The structural model is used to capture relationships between different latent variables, which can be represented as:

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\zeta} \tag{2}$$

where $\mathbf{B}$ is a regression parameter matrix for the relations among the latent variables $\boldsymbol{\eta}$, and $\boldsymbol{\zeta}$ is a vector of errors. Details of ML-SEM theory, model identification issues, estimation procedures, and model evaluation can be found in Rabe-Hesketh et al (2004b).

In this study, the survey data is modeled as a two-level structural equation model where individual's choices of pricing strategies scenarios are considered as a lower level (level 1) which are nested in individual at level 2, as shown in Fig.5.



（a）Congestion pricing strategies （b）Reward strategies

Fig.5. Survey data structure

Four separate ML-SEM models for more and less habitual automobile travelers' mode shift decision-making process under congestion pricing and reward strategies are estimated using STATA. The latent variables used in level 1 includes perception of pricing strategies, behavioral intention, implementation intention and mode choice decision. The mode choice decision is a binary choice between “continue to travel by car/taxi” and “switch to sustainable travel mode” for each strategy. The model optimization processes utilize modification indices to improve the model fit. Model fitness is evaluated using $\chi2$/df, The Tucker-Lewis index (TLI), Comparative Fit Index (CFI), and Root Means Square Error of Approximation (RMSEA) (Schreiber et al, 2006). Based on the model fitness of each estimation iteration, modification indices are used to adjust the originally hypothesized model until the goodness-of-fit indices indicate a reasonable fit.

4. Results and discussion

4.1 Reliability analysis

Before conducting SEM analysis, we first examined the reliability of the latent variables expected to be used in SEM. Cronbach's α is calculated to assess scale reliabilities and the internal consistency of different questions within a latent variable in the conceptual model. The means and Cronbach's α of all latent variables are shown in Table 4. Note that the mode shift decision in the proposed conceptual model is whether a participant will continue using automobile or shift to sustainable travel modes. The mode shift decision is modeled as a binary variable, with choosing automobile as 1 and choosing sustainable travel modes as 0. All Cronbach's α levels of the variables, which have more than one observed variable, are greater than the acceptable level (α>0.70) in practice (Nunnally, 1978), indicating a high level of reliability and internal consistency. Moreover, the composite reliability of all measures in each model is also greater than the acceptable level (i.e. 0.70). Overall, these results show that the measurement questions in this study possess adequate reliability.

4.2 ML-SEM analysis of mode shift decision-making process under pricing strategies

The estimation results of the measurement models are shown in Table 5. Standardized coefficients of measurement model paths illustrate the relationship between observed variables and latent variables and only statistically significant paths (p<0.05) are presented. The final model structures for more and less habitual automobile travelers’ mode shift decision-making process under congestion pricing and reward strategies are shown in Fig. 6(a) and Fig. 6(b), respectively. The first number on each path represents the variable under congestion pricing strategies and the second one represents the variable under reward strategies. The results of $\chi2$/df, TLI, CFI and RMSEA of each model are found to be acceptable (1 <$\chi2$/df <3, TLI>0.9, CFI>0.9 and RMSEA < 0.1) (Schreiber et al, 2006; Hooper et al, 2008).

The relationships among psychological variables in each stage are illustrated by the estimated coefficients of the paths (Fig. 6). For example, in pre-decisional stage, personal norms depend on social norms, awareness of consequence and ascribed responsibility. External social pressure plays a more important role in strengthening more habitual automobile travelers’ obligation to shift to sustainable travel modes decision compared to that for less habitual automobile travelers.

Table 4(a) Mean and reliability analysis of latent variables (For more habitual automobile travelers)

Latent variables		Congestion pricing strategy						Reward strategy					
		5-yuan		15-yuan		25-yuan		1-yuan		1.5-yuan		2-yuan	
		Mean (SD)	α	Mean (SD)	α	Mean (SD)	α	Mean (SD)	α	Mean (SD)	α	Mean (SD)	α
Awareness of consequence	AC1	3.70 (1.15)	0.79	3.76 (1.15)	0.79	3.76 (1.15)	0.79	3.76 (1.15)	0.79	3.76 (1.15)	0.79	3.76 (1.15)	0.79
	AC2	3.76 (1.20)		3.70 (1.20)		3.70 (1.20)		3.70 (1.20)		3.70 (1.20)		3.70 (1.20)	
Ascribed responsibility	AR	3.42 (1.27)	-	3.42 (1.27)	-	3.42 (1.27)	-	3.42 (1.27)	-	3.42 (1.27)	-	3.42 (1.27)	-
Social norm	SN1	3.42 (1.20)	0.81	3.42 (1.20)	0.81	3.42 (1.20)	0.81	3.42 (1.20)	0.81	3.42 (1.20)	0.81	3.42 (1.20)	0.81
	SN2	3.16 (1.22)		3.16 (1.22)		3.16 (1.22)		3.16 (1.22)		3.16 (1.22)		3.16 (1.22)	
Personal norm	PN1	3.50 (1.16)	0.79	3.50 (1.16)	0.79	3.50 (1.16)	0.79	3.50 (1.16)	0.79	3.50 (1.16)	0.79	3.50 (1.16)	0.79
	PN2	3.28 (1.06)		3.28 (1.06)		3.28 (1.06)		3.28 (1.06)		3.28 (1.06)		3.28 (1.06)	
Goal intention	GI	3.56 (1.15)	-	3.56 (1.15)	-	3.56 (1.15)	-	3.56 (1.15)	-	3.56 (1.15)	-	3.56 (1.15)	-
Attitude	ATT1	3.03 (1.17)	0.72	3.03 (1.17)	0.72	3.03 (1.17)	0.72	3.53 (1.10)	0.72	3.53 (1.10)	0.72	3.53 (1.10)	0.72
	ATT2	3.67 (1.05)		3.67 (1.05)		3.67 (1.05)		2.20 (1.84)		2.20 (1.84)		2.20 (1.84)	
	ATT3	3.09 (1.50)		3.09 (1.50)		3.09 (1.50)		3.65 (1.05)		3.65 (1.05)		3.65 (1.05)	
Perceived behavioral control	PBC1	3.66 (1.05)	0.73	3.66 (1.05)	0.73	3.66 (1.05)	0.73	3.66 (1.05)	0.73	3.66 (1.05)	0.73	3.66 (1.05)	0.73
	PBC2	3.41 (1.14)		3.41 (1.14)		3.41 (1.14)		3.41 (1.14)		3.41 (1.14)		3.41 (1.14)	
Perception of pricing strategy	PP1	3.31 (1.43)	0.73	3.31 (1.43)	0.73	3.31 (1.43)	0.73	3.01 (1.23)	0.79	3.01 (1.23)	0.79	3.01 (1.23)	0.79
	PP2	2.92 (1.25)		2.92 (1.25)		2.92 (1.25)		3.20 (1.15)		3.20 (1.15)		3.20 (1.15)	
	PP3	2.96 (1.28)		2.96 (1.28)		2.96 (1.28)		3.42 (1.06)		3.42 (1.06)		3.42 (1.06)	
	PP4	2.95 (1.30)		2.95 (1.30)		2.95 (1.30)		3.41 (1.20)		3.41 (1.20)		3.41 (1.20)	
Behavioral intention	BI	3.12 (1.10)	-	3.44 (1.10)	-	3.54 (1.07)	-	2.96 (0.68)	-	3.11 (0.86)	-	3.25 (1.37)	-
Action Planning	AP1	3.54 (1.09)	0.91	3.54 (1.09)	0.91	3.54 (1.09)	0.91	3.54 (1.09)	0.91	3.54 (1.09)	0.91	3.54 (1.09)	0.91
	AP2	3.56 (1.10)		3.56 (1.10)		3.56 (1.10)		3.56 (1.10)		3.56 (1.10)		3.56 (1.10)	
Coping Planning	CP1	1.88 (0.72)	0.76	1.88 (0.72)	0.76	1.88 (0.72)	0.76	1.88 (0.72)	0.76	1.88 (0.72)	0.76	1.88 (0.72)	0.76
	CP2	2.40 (1.55)		2.40 (1.55)		2.40 (1.55)		2.40 (1.55)		2.40 (1.55)		2.40 (1.55)	
	CP3	1.84 (1.34)		1.84 (1.34)		1.84 (1.34)		1.84 (1.34)		1.84 (1.34)		1.84 (1.34)	
	CP4	1.84 (0.75)		1.84 (0.75)		1.84 (0.75)		1.84 (0.75)		1.84 (0.75)		1.84 (0.75)	
	CP5	1.59 (1.05)		1.59 (1.05)		1.59 (1.05)		1.59 (1.05)		1.59 (1.05)		1.59 (1.05)	
	CP6	1.47 (0.86)		1.88 (0.72)		1.88 (0.72)		1.88 (0.72)		1.88 (0.72)		1.88 (0.72)	
Implementation intention	II	3.05 (1.34)	-	3.23 (1.08)	-	3.43 (1.53)	-	2.98 (0.69)	-	3.12 (1.06)	-	3.34 (1.25)	-
Automobile decision	AD	0.36 (0.65)	-	0.21 (0.44)	-	0.14 (0.45)	-	0.45 (0.48)	-	0.27 (0.45)	-	0.21 (0.56)	-
Sustainable travel modes decision	STMD	0.64 (0.54)	-	0.79 (0.44)	-	0.86 (0.42)	-	0.55 (0.36)	-	0.74 (0.25)	-	0.79 (0.42)	-
Composite reliability		0.86		0.87		0.87		0.88		0.88		0.89	

Table 4(b) Mean and reliability analysis of latent variables (For less habitual automobile travelers)

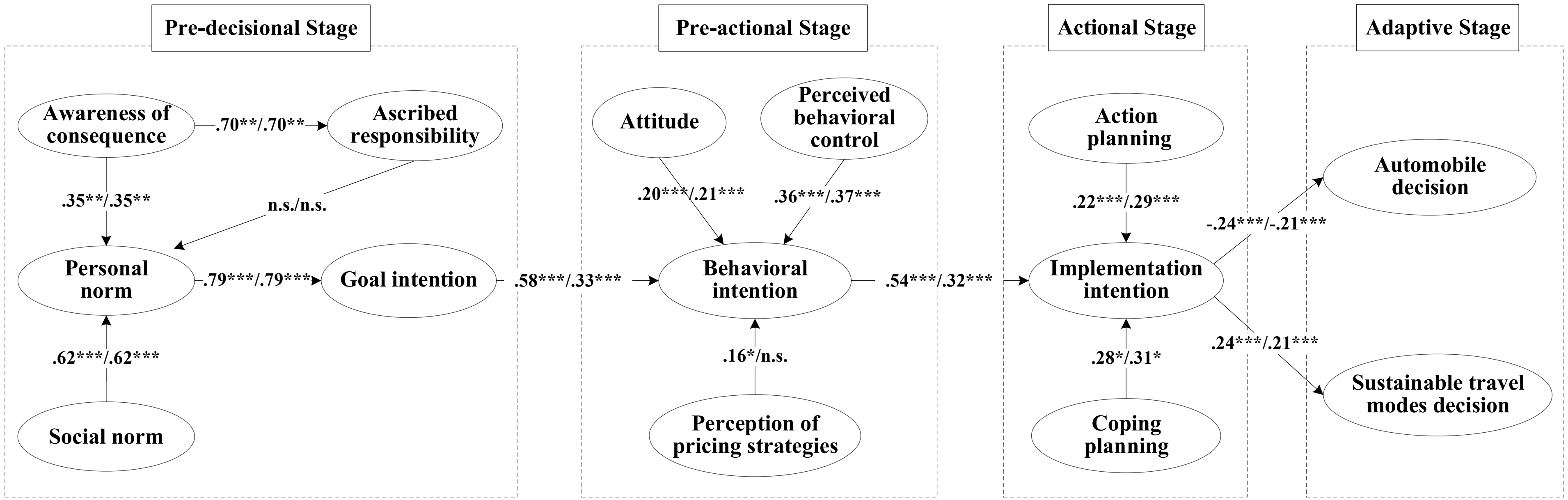
		Congestion pricing strategy						Reward strategy					
Latent variables		5-yuan		15-yuan		25-yuan		1-yuan		1.5-yuan		2-yuan	
		Mean (SD)	α	Mean (SD)	α	Mean (SD)	α	Mean (SD)	α	Mean (SD)	α	Mean (SD)	α
Awareness of consequence	AC1	3.83 (1.00)	0.74	3.83 (1.00)	0.74	3.83 (1.00)	0.74	3.83 (1.00)	0.74	3.83 (1.00)	0.74	3.83 (1.00)	0.74
	AC2	3.89 (1.02)		3.89 (1.02)		3.89 (1.02)		3.89 (1.02)		3.89 (1.02)		3.89 (1.02)	
Ascribed responsibility	AR	3.59 (1.15)	-	3.59 (1.15)	-	3.59 (1.15)	-	3.59 (1.15)	-	3.59 (1.15)	-	3.59 (1.15)	-
Social norm	SN1	3.70 (1.02)	0.79	3.70 (1.02)	0.79	3.70 (1.02)	0.79	3.70 (1.02)	0.79	3.70 (1.02)	0.79	3.70 (1.02)	0.79
	SN2	3.45 (1.04)		3.45 (1.04)		3.45 (1.04)		3.45 (1.04)		3.45 (1.04)		3.45 (1.04)	
Personal norm	PN1	3.93 (0.89)	0.78	3.93 (0.89)	0.78	3.93 (0.89)	0.78	3.93 (0.89)	0.78	3.93 (0.89)	0.78	3.93 (0.89)	0.78
	PN2	3.68 (1.01)		3.68 (1.01)		3.68 (1.01)		3.68 (1.01)		3.68 (1.01)		3.68 (1.01)	
Goal intention	GI	3.91 (0.87)	-	3.91 (0.87)	-	3.91 (0.87)	-	3.91 (0.87)	-	3.91 (0.87)		3.91 (0.87)	-
Attitude	ATT1	3.21 (1.12)	0.78	3.21 (1.12)	0.78	3.21 (1.12)	0.78	3.32 (1.11)	0.78	3.32 (1.11)	0.78	3.32 (1.11)	0.78
	ATT2	3.67 (1.01)		3.67 (1.01)		3.67 (1.01)		3.49 (0.87)		3.49 (0.87)		3.49 (0.87)	
	ATT3	3.93 (0.89)		3.93 (0.89)		3.93 (0.89)		2.75 (1.12)		2.75 (1.12)		2.75 (1.12)	
Perceived behavioral control	PBC1	3.95 (0.86)	0.76	3.95 (0.86)	0.76	3.95 (0.86)	0.76	3.95 (0.86)	0.76	3.95 (0.86)	0.76	3.95 (0.86)	0.76
	PBC2	3.92 (0.88)		3.92 (0.88)		3.92 (0.88)		3.92 (0.88)		3.92 (0.88)		3.92 (0.88)	
Perception of pricing strategy	PP1	3.48 (1.34)	0.73	3.48 (1.34)	0.73	3.48 (1.34)	0.73	3.17 (1.11)	0.78	3.17 (1.11)	0.78	3.17 (1.11)	0.78
	PP2	3.12 (1.12)		3.12 (1.12)		3.12 (1.12)		3.38 (1.01)		3.38 (1.01)		3.38 (1.01)	
	PP3	3.14 (1.11)		3.14 (1.11)		3.14 (1.11)		3.59 (1.12)		3.59 (1.12)		3.59 (1.12)	
	PP4	3.15 (1.18)		3.15 (1.18)		3.15 (1.18)		3.60 (1.00)		3.60 (1.00)		3.60 (1.00)	
Behavioral intention	BI	3.46 (1.13)	-	3.56 (0.95)	-	3.89(0.43)	-	3.82 (0.83)	-	3.90 (1.04)	-	3.97 (1.21)	-
Action Planning	AP1	3.85 (0.91)	0.88	3.85 (0.91)	0.88	3.85 (0.91)	0.88	3.85 (0.91)	0.88	3.85 (0.91)	0.88	3.85 (0.91)	0.88
	AP2	3.87 (0.85)		3.87 (0.85)		3.87 (0.85)		3.87 (0.85)		3.87 (0.85)		3.87 (0.85)	
Coping Planning	CP1	1.61 (0.99)	0.82	1.61 (0.99)	0.82	1.61 (0.99)	0.82	1.61 (0.99)	0.82	1.61 (0.99)	0.82	1.61 (0.99)	0.82
	CP2	1.72 (1.06)		1.72 (1.06)		1.72 (1.06)		1.72 (1.06)		1.72 (1.06)		1.72 (1.06)	
	CP3	1.58 (0.84)		1.58 (0.84)		1.58 (0.84)		1.58 (0.84)		1.58 (0.84)		1.58 (0.84)	
	CP4	1.59 (1.02)		1.59 (1.02)		1.59 (1.02)		1.59 (1.02)		1.59 (1.02)		1.59 (1.02)	
	CP5	1.53 (0.92)		1.53 (0.92)		1.53 (0.92)		1.53 (0.92)		1.53 (0.92)		1.53 (0.92)	
	CP6	1.53 (0.89)		1.53 (0.89)		1.53 (0.89)		1.53 (0.89)		1.53 (0.89)		1.53 (0.89)	
Implementation intention	II	3.29 (1.06)	-	3.46 (1.03)	-	3.52 (0.79)	-	3.51 (1.11)	-	3.62 (0.98)	-	3.76 (0.75)	-
Automobile decision	AD	0.39 (1.15)	-	0.18 (0.88)	-	0.15 (0.62)	-	0.17 (1.04)	-	0.13 (0.77)	-	0.12 (0.69)	-
Sustainable travel modes decision	STMD	0.61 (0.94)	-	0.72 (0.79)	-	0.85 (0.75)	-	0.83 (1.21)	-	0.87 (0.86)	-	0.88 (0.93)	-
Composite reliability		0.87		0.87		0.87		0.88		0.88		0.89	

Table 5 Measurement model estimate for testing construct of latent variables

Measurement model path	Standardized coefficient			
	More habitual automobile travelers		Less habitual automobile travelers	
	Congestion pricing strategy	Reward strategy	Congestion pricing strategy	Reward strategy
Awareness of consequence→AC1	0.73†	0.73†	0.67†	0.67†
Awareness of consequence→AC2	0.87***	0.87***	0.90***	0.90***
Ascribed responsibility→AS	1	1	1	1
Social norm→SN1	0.66†	0.66†	0.67†	0.67†
Social norm→SN2	0.70**	0.70**	0.71**	0.71**
Personal norm→PN1	0.63†	0.63†	0.65†	0.65†
Personal norm→PN2	0.73***	0.73***	0.76***	0.76***
Goal intention→GI	1	1	1	1
Perceived behavioral control→PBC1	0.70†	0.70†	0.72†	0.72†
Perceived behavioral control→PBC2	0.81*	0.81*	0.84*	0.84*
Attitude→ATT1	0.51†	0.51†	0.56†	0.56†
Attitude→ATT2	0.47**	0.47**	0.75***	0.75***
Attitude→ATT3	0.86***	0.88***	0.63**	0.63**
Perception of pricing strategy→PP1	0.41†	0.62†	0.35†	0.62†
Perception of pricing strategy→PP2	0.92***	0.93***	0.93***	0.88***
Perception of pricing strategy→PP3	0.86**	0.82**	0.89**	0.87**
Perception of pricing strategy→PP4	0.79**	0.72**	0.75**	0.75**
Behavioral Intention→BI	1	1	1	1
Action planning→AP1	0.92†	0.92†	0.91†	0.91†
Action planning→AP2	0.84***	0.84***	0.80***	0.80***
Coping planning→CP1	0.51†	0.51†	0.63†	0.63†
Coping planning→CP2	0.66***	0.66***	0.67***	0.67***
Coping planning→CP3	0.49*	0.49*	0.54**	0.54**
Coping planning→CP4	0.52**	0.52**	0.62**	0.62**
Coping planning→CP5	0.63**	0.63**	0.76**	0.76**
Coping planning→CP6	0.69**	0.69**	0.65**	0.65**
Implementation intention→II	1	1	1	1
Automobile decision→AD	1	1	1	1
Sustainable travel modes decision→STMD	1	1	1	1

† denotes a path for which the unstandardized coefficient is set to 1 as a reference item, and given this constraint, other paths of remaining questions within a latent variable can be then estimated.

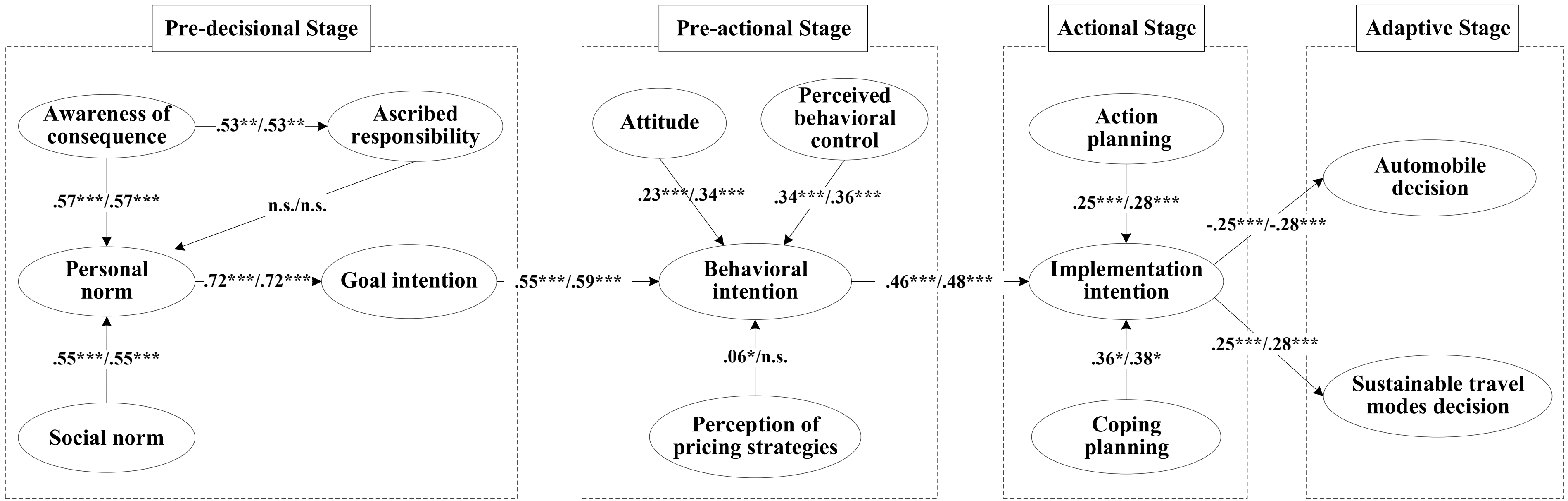
* denotes p<0.05 ** denotes p<0.01 ****denotes p<0.001



***p<0.05 **p<0.01 ***p<0.001 n.s. not significant**

<u>Model fit</u>: χ^2/df =2.44/2.07, TLI=0.92/0.93, CFI=0.95/0.93, RMSEA=0.07/0.08

(a) More habitual automobile travelers



***p<0.05 **p<0.01 ***p<0.001 n.s. not significant**

Model fit: χ^2/df =1.82/1.75, TLI=0.92/0.92, CFI=0.93/0.91, RMSEA=0.07/0.08

(b) Less habitual automobile travelers

Fig.6. Structural model of mode shift decision-making process under congestion pricing and reward strategies (standardized path coefficients, first number: congestion pricing, second number: reward strategy).

By contrast, the awareness of consequence plays a more important role in strengthening such obligation among less habitual automobile travelers compared to more habitual automobile travelers. A probable reason is that more habitual automobile travelers are less sensitive to the negative consequences caused by using automobile because using automobile is more like a habit to them and the potential consequences of using automobile are not in their decision-making process. Instead, guilt or other negative emotions induced by external social pressure can stimulate them to assess their current habit (i.e. using automobile for morning commute) and promote shift to sustainable travel modes. Compared to social norms and awareness of consequence, the impacts of ascribed responsibility on personal norm are not significant. A possible reason is that habitual travelers may believe that they should not be personally responsible to problems caused by automobile usage as they consider themselves not using automobile much. They may consider that these problems should be solved by government and people who use automobile more often than themselves.

In the pre-actional stage, a traveler's impulse from goal intention is translated into his or her more concrete behavioral intentions. Attitude and perceived behavior control have a positive impact on behavioral intention, and these impacts are slightly larger under reward strategies compared to that of congestion pricing strategies. This suggests that travelers who have a strong favorable evaluation of sustainable travel modes (i.e. attitude) and/or perceive shifting to sustainable travel modes is easy, are more likely to have a stronger behavioral intention to shift to sustainable travel modes under the reward strategy compared to that of congestion pricing. This is consistent with the results in previous studies (Khademi et al. 2014; Schall and Mohnen, 2017) that potential monetary gain for using sustainable travel modes can more effectively reinforce positive affection and attitude towards these modes which leads to the formation of behavioral intentions to shift to these modes. These results also suggest that attitude has a larger impact on behavioral intention of less habitual automobile travelers compared to that of more habitual automobile travelers, while the opposite is true for perceived behavior control. This suggests that improving the perceived degree of favorable evaluation may be more effective in promoting shifts to sustainable travel modes for less habitual automobile travelers compared to that for more habitual automobile travelers under pricing strategies. For more habitual automobile travelers, the perceived ease of shifting to sustainable travel modes are more effective in promoting shifts to sustainable travel modes compared to the perceived degree of favorable evaluation. Apart from attitude and perceived behavior control, perception of pricing strategies also has a positive impact on behavioral intention under congestion pricing, which implies that the behavioral intention is stronger under higher perceived effectiveness, fairness, freedom and acceptance of congestion pricing strategies. However, perception of pricing strategies under reward strategies are not statistically significantly correlated with behavioral intention. This suggests although some people have a strong positive perception of reward strategies, they have a relatively fixed arrival time and high penalties for late arrival for morning commute may discourage them from forming behavioral intention to shift to sustainable travel modes.

In the actional stage, behavioral intention and two types of planning ability (action planning and coping planning) have significant positive impacts on implementation intention. Action planning and coping planning have a larger direct impact on more habitual automobile travelers' implementation intention under the impacts of congestion pricing, while these impacts are slightly larger under reward strategies for less habitual automobile travelers. It indicates that the ability to plan and overcome barriers are more effective in promoting less habitual automobile travelers to form implementation intention to shift to sustainable travel modes under pricing strategies, especially under reward strategies. Additionally, the impacts of action planning on implementation intention are significantly larger than the impacts of coping planning on implementation intention. This implies that knowledge on how to overcome barriers is more strongly associated with implementation intention to shift to sustainable travel modes.

Moreover, the implementation intention has a significant negative impact on participants who continue to make the decision to use automobile, and a significant positive impact on those who plan to switch to sustainable travel modes. For more habitual automobile travelers, the impact of implementation intention on automobile usage decision or sustainable travel modes decision is larger under the congestion pricing strategy than under the reward strategy, while the opposite holds for less habitual automobile travelers. The relationship between goal intention, behavioral intention and implementation intention also follows a similar pattern. These results illustrate that more habitual automobile travelers are more sensitive to penalties associated with using automobile than the rewards associated with shifting to sustainable travel modes in their mode shift decision-making process under pricing strategies. For less habitual automobile travelers, the monetary gain may enhance their willingness to take the initiative to choose sustainable travel modes under congestion pricing and reward strategies.

The estimation results show that the impacts of latent psychological variables on promoting mode choice behavioral change intentions are different between more and less habitual automobile travelers under congestion pricing and reward strategies in different stages of the mode shift decision-making process. These differences illustrate the need for policymakers to design differential complementary intervention strategies to stimulate the intention to switch from automobile to more sustainable modes at different stages of their decision-making process for more and less habitual automobile travelers to improve the effectiveness of congestion pricing and reward strategies. For less habitual automobile travelers, intervention strategies that enhance awareness of consequence, positive attitude towards shifting to sustainable travel modes, perceived behavioral control, action planning and coping planning can potentially improve the effectiveness of both congestion pricing and reward strategies. For more habitual automobile travelers, complementary intervention strategies that focus on improving their perceived external social pressure can increase the effectiveness of both strategies. If reward strategies are implemented, complementary intervention strategies are needed to enhance positive attitudes towards shifting to sustainable travel modes, action planning and coping planning.

4.3 Identification of psychological determinants of mode shift decisions under pricing strategies

The direct impacts of different psychological variables revealed from the model structure were presented in Fig. 5. Further, the total impacts of each psychological factor on mode shift decision were also analyzed to explore which variables have larger impact on mode choice behavior under congestion pricing and reward strategies. For this purpose, the indirect impacts of each variable on the mode shift decision are calculated first. For example, for the mode shift decision-making process model under congestion pricing for more habitual automobile travelers, the direct impact of action planning on the sustainable travel modes decision is 0, while action planning through implementation intention had an indirect impact on the sustainable travel modes decision is 0.22 (0.22×0.24). The total impact is the sum of direct and indirect impacts (0.07), which implies that when action planning goes up by 1 standard deviation, sustainable travel modes decision goes up by 0.07 standard deviations.

Table 6 Total impacts of psychological variables on the sustainable travel modes decision (overall ranking in terms of their impacts on mode shift decisions)

	More habitual automobile travelers		Less habitual automobile travelers	
Psychological variables	Congestion pricing strategy	Reward strategy	Congestion pricing strategy	Reward strategy
Implementation intention	0.24(1)	0.21(1)	0.25(1)	0.28(1)
Action planning	0.05(6)	0.06(4)	0.06(5)	0.08(5)
Coping planning	0.07(4)	0.07(3)	0.10(3)	0.11(3)
Behavioral Intention	0.13(2)	0.07(2)	0.12(2)	0.13(2)
Perception of pricing strategies	0.02(11)	0.00(11)	0.01(11)	0.00(11)
Attitude	0.03(8)	0.01(8)	0.03(8)	0.05(8)
Perceived behavioral control	0.05(7)	0.02(7)	0.03(7)	0.04(7)
Goal intention	0.08(3)	0.02(5)	0.06(4)	0.08(4)
Personal norm	0.06(5)	0.02(6)	0.05(6)	0.06(6)
Social norm	0.04(9)	0.01(9)	0.03(9)	0.03(9)
Awareness of consequence	0.02(10)	0.01(10)	0.03(10)	0.03(10)
Ascribed responsibility	0.00(12)	0.00(12)	0.00(12)	0.00(12)

Table 6 summarizes the impacts of psychological factors on the sustainable travel modes decision under congestion pricing and reward strategies for both more and less habitual automobile travelers, and how they rank based on their impacts on mode shift decisions. Implementation intention and behavioral intention are the two most important factors that affect mode shift decision for both groups under congestion pricing and reward strategies. These results are consistent with the literature that an individual with a strong intention is more likely to make decisions such as mode shifts. In addition, these results show that there is a gap between intention and behavior, and other psychological factors also contribute to the mode shift decision. The estimation results also show that for more habitual automobile travelers, the impacts of all psychological factors on the mode shift decision under congestion pricing strategies are larger than those under reward strategies, while the opposite is true for less habitual automobile travelers. This illustrates the different levels of sensitivities to penalties and rewards between more and less habitual automobile travelers. More habitual automobile travelers are sensitive to the penalty associated with congestion pricing and are forced to use more sustainable transportation modes, while less habitual automobile travelers who only occasionally use automobile may not suffer much under congestion pricing strategies which makes them less likely to shift. Under the reward strategies, less habitual automobile travelers who are used to more sustainable transportation modes are encouraged by the benefits of the rewards strategies, reinforced by the rewards associated with using more sustainable transportation modes, and are willing to use more sustainable transportation modes. By contrast, reward amounts may not outweigh the perceived benefits of using automobiles among more habitual automobile travelers which makes them less likely to shift. These results also illustrate the potential of combining congestion pricing and reward strategies to target both more and less habitual automobile travelers.

5. Conclusions and policy implications

This study investigates the similarities and dissimilarities of behavioral response and psychological motivation of the mode shift decision-making process between more and less habitual automobile travelers under congestion pricing and reward strategies. A new stage-based conceptual modeling framework for the mode shift decision-making process under pricing strategies is proposed and evaluated using data from a web-based stated preference survey conducted in Beijing, China.

Model estimation results show that various types of psychological factors are found to be statistically significant to determine participants' mode shift decisions under congestion pricing and reward strategies. Further, latent psychological factors contribute differently to promoting intentions for more and less habitual automobile travelers' mode shift decision-making process under congestion pricing and reward strategies. More habitual automobile travelers are more likely to make mode shifts under congestion pricing strategies compared to less habitual automobile travelers, while the reverse is true under reward strategies. The model results also illustrate two key findings. First, the proposed stage-based conceptual modeling framework for mode shift decisions under congestion pricing and reward strategies is validated. Second, a traveler's perception of pricing strategies was found to have direct impact on his/her behavioral intention, though the impacts are not as strong as expected. These results suggest that the proposed stage-based model can also be applied to understand these pricing strategies' psychological impacts on the mode shift decision, while providing further support to Bamberg's model (2013a) at a theoretical level.

Intervention strategies complementary to pricing strategies can be developed to influence travelers' psychological factors in each stage of the mode shift decision-making process. For the pre-decisional stage, applications that provide specific positive and negative information under pricing strategies can be developed to promote and activate consequence awareness of different travel mode behavioral alternatives. Applications can also be extended to share or compare information with others to improve external social pressure. Moreover, educational programs which can strengthen a resident's perception of responsibility towards reducing traffic congestion and environmental problems may be necessary, especially for more habitual automobile travelers. For the pre-actional stage, behavioral intervention strategies should focus on improving perceived behavioral control of a sustainable travel modes decision such as the improvement of quality of service of different sustainable travel modes and the understanding of their ease of use. Communication of information on the usefulness of sustainable travel modes decision and the effectiveness and fairness of pricing strategies are also needed to improve attitude and perception of pricing strategies. For the actional stage, interventions providing concrete personalized action plans and implementation guidance recommendations are needed, especially for reward strategies.

A limitation of this study is that it uses statement preference survey data which cannot be used to explore how psychological factors influence people to form a new habitual mode choice behavior under pricing strategies. To address this, a potential future research direction is to conduct a pilot study by implementing pricing strategies on a group of travelers in China, collect revealed preference data, and study the long-term impact of these strategies on travelers' mode choice behavior. Another potential future research direction is to evaluate the applicability of the proposed model in other metropolitan regions in China. Another limitation of this study is that the information related to potential air pollution risk to travelers for biking and walking is not provided to them, which can potentially lead to underestimation of health risks associated with biking and walking. Additional studies are needed to capture potential air pollution risk to travelers for biking and walking in China.

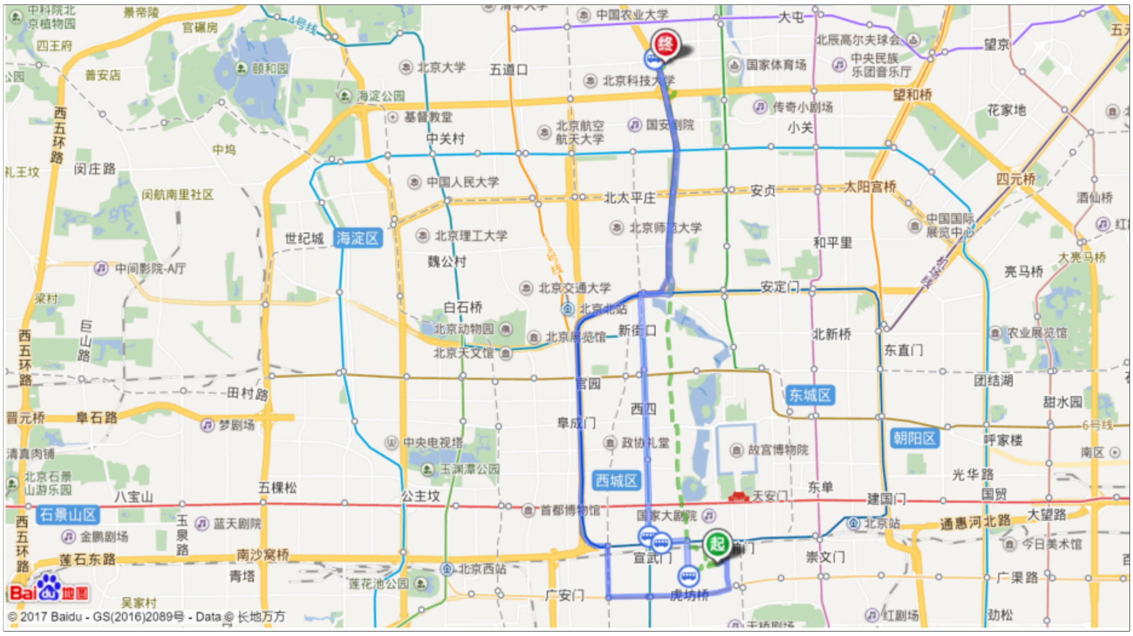
Appendix A: Interactive map

- **Please select your travel origin (Residential location) and destination (Work/School location) on the map.**

Origin: Yangmeizhuxie Street, Xicheng District, Beijing

Destination: Zhongguancun Science and Technology Park, Chaoyang District, Beijing

Search



- **Which morning commute mode will you select if you will be charged with 5-yuan, 15-yuan and 25-yuan penalties for using automobile, respectively?**

	Car	Taxi	Bus	Subway	E-bike	Personal Bike	Shared Bike	Walk
Travel time	25	25	70	65	29	48	53	150
Travel cost	14	49	3	5	0	0	2	0
Amount of CO_2 emission	3090	3090	1041	163	842	0	0	0
Amount of PM emission	17	17	6	1	4	0	0	0
Number of steps	600	600	3200	3360	400	400	1000	24200
Amount of activity calorie burned	11	11	61	64	334	334	346	460

	Car	Taxi	Bus	Subway	E-bike	Personal Bike	Shared Bike	Walk
5-yuan	○	○	○	○	○	○	○	○
15-yuan	○	○	○	○	○	○	○	○
25-yuan	○	○	○	○	○	○	○	○

Acknowledgments

This research is supported by the National Natural Science Foundation of China (No. 51478110), Jiangsu Science and Technology project (BY2016076-05) and the China Scholarship Council (CSC) Program sponsored by the Ministry of Education in China. This study is also based on research supported by the NEXTRANS Center, the USDOT Region 5 University Transportation Center at Purdue University.

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