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Accounting for the effects of travel demand management on metro commuters' behavioural loyalty using hybrid choice models

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Abstract

As part of efforts to promote sustainable mobility, many cities are currently experiencing the rapid expansion of their metro network. The consequent growth in ridership motivates a broad range of travel demand management (TDM) policies, both in terms of passenger flow control and dynamic pricing strategies. This work aims to reveal the impact of TDM on metro commuters' behavioural loyalty using stated preference data collected in Guangzhou, China. Commuters' behavioural response to TDM strategies is investigated in terms of the possible shift in departure time and travel mode. A hybrid choice model framework is used to incorporate four latent variables of interest, i.e., service quality, overall impression, external attractiveness and switching cost, into the discrete choice model and thereby capture the relationships between the attitudinal factors and observed variables. The model estimation results indicate that the four latent variables all prove useful in interpreting commuters' behavioural loyalty. Commuters' perceived service quality and overall impression both show a positive effect on their willingness to continue travelling by metro and are thus instructive for ridership retention. External attractiveness is found to be significant only in the case of the tendency to shift to a private car. Switching costs reveal commuters' emotional attachment to their already developed commuting habit. These insights into commuters' behavioural change intention enable metro operators to enhance commuters' loyalty to their service and develop more effective TDM strategies in future practice.

Keywords behavioural change · nested logit model · attitude · factor analysis · SP-off-RP survey · urban rail transit

Introduction

Travel demand management (TDM) refers to a variety of strategies that aim to alleviate the impacts of recurrent congestion by redistributing travel demand spatially and temporally (Roby 2014). In recent decades, TDM has made excellent contributions to a broad range of areas, delivering beneficial environmental outcomes, improved public safety and health, and prosperous communities and cities (Bao et al. 2020; Holguín-Veras et al. 2020; Nesset and Helgesen 2014; Saleh 2007). In the context of growing interest in the application of TDM strategies to mass transit systems, transport operators face the challenge of declining service and the accompanying task of ridership retention. In Guangzhou, China, metro network has experienced unprecedented expansion in the past decade. There were 14 metro lines and 271 stations in operation in December 2019. The evolution of mileage and ridership is presented in Fig. 1.

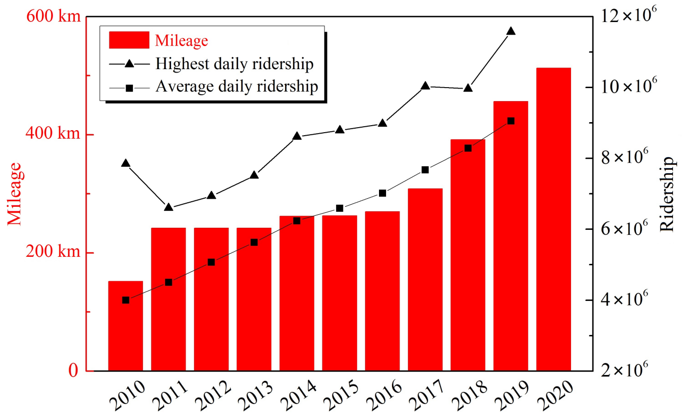


Fig. 1 Evolution of mileage and ridership of the Guangzhou Metro network

The expansion of the metro network has radically increased ridership, with the highest daily ridership reaching over 11 million in 2019. Nearly 4 million commuters use the network during the morning rush hour, and this number tends to rise over time. As a consequence, the severe mismatch between supply and demand leads to unexpected operational risks and impedes the sustainable development of the metro system. In this context, TDM provides solutions for reshaping demand patterns to adapt to the current supply capacity in both mandatory and incentivised ways. The two most commonly used strategies, i.e., passenger flow control and dynamic pricing, are discussed in the present paper.

The passenger flow control strategy is a typical mandatory measure implemented during commuting peaks (Jiang et al. 2017; Yang et al. 2017). To avoid overcrowding inside the station, batch release plays a vital role in slowing the movement of crowds, helping relieve the pressure on platforms and carriages, as shown in Fig. 2. In the Guangzhou Metro network, passenger flow control is currently used at 41 stations during the morning peak and 16 stations during the evening peak. In recent years, the passenger flow control strategy has also been widely adopted in many other cities in China, such as Beijing, Shanghai and Shenzhen. Although this mandatory measure immediately mitigates crowding and reduces operational risks, large numbers of commuters who arrive during the control periods are severely delayed. A decline in travel experience and extended commuting time is thus inevitable for many metro commuters.

(a) Station entrance (b) Security checkpoint (c) Automated fare gate (d) Transfer channel

Fig. 2 Common control points for batch release

In contrast to the flow control strategy, dynamic pricing has a long history and a wide range of applications. The use of dynamic pricing is well established across industries, such as hospitality, entertainment and retailing, allowing flexible pricing rules for products or services tied to current market demands (Abrate et al. 2019; Chen et al. 2020; Jørgensen and Zaccour 2019). The literature also details extensive applications of dynamic pricing to public transport systems (Kamandanipour et al. 2020; Saharan et al. 2020; Zhang et al. 2019). In regard to metro systems, off-peak discounts and extra peak charges are the two most common approaches in operation management (Zhao and Yang 2013). For instance, the London Underground provides off-peak fares for commuters travelling outside the peak hours of 6:30 am-9:30 am and 4:00 pm-7:00 pm. The discount is up to 2 pounds on a single trip and depends on the distance travelled. In Beijing, the first dynamic pricing scheme took effect in December 2015, awarding those tapping in before 7:00 am 30% off of the whole trip. Shortly afterwards, the off-peak discount was raised to 50% for a larger effect. However, even in this case, the daily ridership continued to grow sharply, and disputes over the implementation details of future dynamic pricing are ongoing.

TDM has direct impacts on metro commuters' daily travel experience, likely leading to changes in current ridership patterns and thus, in turn, having irreplaceable importance in the development of appropriate strategies. To better understand metro commuters' responses, this paper focuses on understanding the effects of TDM on metro commuters' behavioural loyalty. More specifically, metro commuters' behavioural change intention in the context of passenger flow control and dynamic pricing strategies is modelled in terms of departure time and mode choice. By combining the revealed-preference (RP) survey's advantage in collecting actual choice information with the stated-preference (SP) survey's superiority in understanding trade-offs in hypothetical (future) scenarios, an SP-off-RP-like survey is conducted in Guangzhou, China, to capture metro commuters' SP choices and attitudinal responses in terms of service quality (SQ), overall impression (OI), external attractiveness (EA), and switching cost (SC). As much previous research has suggested (Ashok et al. 2002; Hoyos et al. 2015; Kim et al. 2014), directly incorporating attitudinal responses into discrete choice models as explanatory variables results in measurement error and endogeneity bias. As a way to address this issue, the integrated choice and latent variable (ICLV) model, also commonly called the hybrid choice model (HCM), has received growing attention since it was proposed by (Ben-Akiva et al. 2002a; Ben-Akiva et al. 2002b). Following the hybrid choice modelling approach (Abou-Zeid and Ben-Akiva 2014; Ashok et al. 2002; Bolduc et al. 2005), the unobservable factors of SQ, OI, EA and SC are used to account for metro commuters' behavioural loyalty in the form of latent variables in the discrete choice model.

The remainder of this paper is organised as follows. Section 2 reviews related studies on modelling commuting behaviour. Section 3 describes the survey work carried out for this study. Section 4 presents the model specification.

Section 5 reports the model estimation results and discusses the policy implications. In the last section, the conclusions drawn from the above content are summarised, and directions for future work are discussed.

Literature Review

Loyalty is a common concept that has been extensively studied in relation to marketing in recent decades. Berkowitz et al. (1978) defined customer loyalty towards a specific product as repetitive purchase behaviour that reflects the choice to buy the same product. Customer loyalty can be categorised as behavioural loyalty or attitudinal loyalty (Bandyopadhyay and Martell 2007; Webb 2010). In the purchase decision-making process, behavioural loyalty is manifested in a customer's repeated selection of a certain brand over the competition (Odin et al. 2001). In contrast, attitudinal loyalty emphasises emotional commitment to a brand, which exists before the actual choice is made(Izogo 2015). Nevertheless, loyalty is not specific to the purchase of products but also applies to transport services. Many studies have used loyalty to explain travellers' attachment to a transport mode. A widely accepted definition is that given by the Transportation Research Board (1999): "A user's intention to continue using the service". Additional components include the willingness to recommend the service to others, service quality and a user's image or involvement with the transport mode (van Lierop et al. 2018). Other studies (Li et al. 2018; Sun and Duan 2019) suggest four determinants of loyalty: service experience, switching cost, the attractiveness of cars and other attitudinal factors (e.g., environmental concerns). In addition to applying structural equation modelling (SEM), utilising long-term panel data is a more realistic way to reveal users' behavioural loyalty (Tao et al. 2017; Wang et al. 2020). Despite intensive research efforts, there is no unique, established methodology to measure users' loyalty to transport services (Losada-Rojas et al. 2019). In this paper, we employ a narrower definition of loyalty, i.e., the intention of continuing to use the current commuting plan, in the TDM context. More precisely, metro commuters' behavioural loyalty is measured indirectly by the intention to adjust the current commuting plan by shifting to either other modes or other departure times when passenger flow control and dynamic pricing strategies become operative.

The most relevant research on TDM in metro systems has focused on how to develop appropriate passenger flow control strategies (Li et al. 2017; Liu et al. 2020; Shi et al. 2019) and various pricing strategies (Huang et al. 2016; Liu and Wang 2017; Peng et al. 2016; Rantzien and Rude 2014) in light of current demand. However, the existing methodologies develop strategies based on the already known travel demand, namely, on-demand or demand-oriented approaches. A common assumption in the above studies is that travel demand remains unchanged due to the stability of commuting needs. Precisely under such a premise, some studies use current ridership as a reference to evaluate the performance of the proposed strategies. These studies have focused on these methodologies for the purpose of policy development instead of on understanding the effects of TDM on commuters. In this regard, a better grasp of commuters' behavioural loyalty in the TDM context is crucial to make these studies more applicable than they already are. That is what the present work intends to achieve.

Discrete choice models have been applied extensively in the literature to interpret commuters' behaviour, and most were based on RP data. For instance, Zaman and Habib (2011) investigated commuting mode choice behaviour using survey data collected over the course of a week to understand how TDM strategies (i.e., flexible office hours and compressed workweeks) discourage car use and propel commuters towards sustainable transportation modes. Nurul (2012) studied travel mode, work start time and duration choice behaviour as two-stage continuous choices with an econometric model. Additionally, the impact of TDM strategies (i.e., congestion pricing, P&R incentives, flexible office hours) on behaviour was further discussed. Sasic and Habib (2013) used trip diary data to explain commuters' departure time choice for a home-based commuting trip using a generalised extreme value (GEV) model. Ding et al. (2015) modelled commuters' travel mode and departure time choice with a cross-nested logit (CNL) model based on household survey data. Heinen et al. (2017) observed the impacts of a newly built guided busway with both walking and cycling paths on commuters' mode choice behaviour, supported by week-long commuting records. Keyes and Crawford-Brown (2018) explored the reasons for the decline in car use in urban areas, developing a multinomial logistic regression model using national travel survey data.

With TDM strategies becoming increasingly common in public transport systems, the literature also provides analyses of mode shift behaviour when the external environment changes. Although both mode choice and mode shift behaviour reflect the decision-making process of choosing a travel mode, there are subtle differences in the situations that lead commuters to make a choice. Indeed, commuters need to overcome both physical and mental reluctance when departing from their regular commuting habit. To better simulate environmental changes, SP surveys have been widely used to understand commuters' behaviour. For instance, Hensher et al. (2011) used SP and developed an error components model to explain commuters' mode choice between currently available travel modes and a forthcoming metro service. Resdiansyah (2018) studied the binary choice between existing bus vehicles and recently upgraded bus vehicles using SP data.

With an eye towards attitudinal factors, a growing number of researchers have sought to provide in-depth explorations of the roles of various attitudes in commuting behaviour. SEM is widely used to explore the linear relationships between endogenous and exogenous variables in relevant studies (Gao et al. 2020; Jia et al. 2018; Mijares et al. 2016). Alongside numerous applications of SEM, HCM has been employed to account for a variety of attitudes in research on key decisions in the public transport context, such as mode choice (Atasoy et al. 2013; Hess et al. 2018; Kamargianni et al. 2014; Roberts et al. 2018; Song et al. 2018; Tran et al. 2020) and departure time choice (Thorhauge et al. 2016). Additionally, substantial effort has been devoted to further refinement of the HCM framework in studies exploring the proper way to accommodate latent variables in choice models (Bahamonde-Birke et al. 2017), testing non-linearity and distributional assumptions (Kim et al. 2016), and seeking to improve estimation techniques (Bhat and Dubey 2014; Daziano 2015; Raveau et al. 2012). To reveal the roles of SQ, OI, EA and SC in our research context, a detailed factor analysis is conducted in the data section to seek rational structures for these four attitudinal variables, as well as an HCM-based analytical framework for interpreting commuters' behavioural responses to metro TDM strategies.

It is also worth noting that most of the previous work analysing commuters' behavioural responses to TDM measures, such as the study presented by Zaman and Habib (2011), sought to reduce commuters' car dependency by making public transport more appealing. The motivation of the present work differentiates it from previous efforts: the priority here is retaining existing users rather than attracting potential users, given that the TDM strategies studied in this paper make metro service less attractive. Indeed, as TDM strategies become increasingly essential in a growing number of oversaturated metro systems worldwide, understanding metro commuters' behavioural loyalty is becoming increasingly important.

Data

This section presents an overview of the survey work carried out for this study. In reality, commuters' behavioural loyalty largely depends on individual circumstances, e.g., whether the commuter can freely postpone his or her arrival time at the workplace and whether the metro is more competitive than the other modes in a specific O-D pair. We thus use an SP-off-RP-like survey to obtain respondents' RP data and then construct SP scenarios for each of them. Each respondent was asked to complete four parts, namely, the instructions for filling out the questionnaire (including a brief introduction to the goal of the survey and the relevant technical terms), the SP-off-RP-like survey, attitudinal statements and a socio-demographics section.

Respondent sampling

The survey implementation was delegated to a professional online survey agency, Changsha Ranxing Information Technology Co., Ltd. Since only regular metro commuters who are familiar with the metro peak service are qualified to complete the questionnaire, the questionnaires were disseminated to those who registered as residents of Guangzhou and had metro commuting experience.

In the RP part, respondents were asked to specify their everyday commuting activity, with further details available in Fig. 4. Based on the RP data, we used the following logical and consistent tests to remove ineligible respondents, as we believe that regular metro commuters are clear about the name of the metro line, the ticker price and the travel time.

(a) Respondents' self-reported origin and destination for the commuting trip should be consistent with the self-reported metro lines that they usually took, which ruled out 18 respondents.

(b) The respondents' self-reported ticket fare should be consistent with the officially released price, which ruled out 42 respondents.

(c) Respondents' self-reported travel time should not deviate more than 40% from the standard travel time derived from the actual train timetable during the survey period (provided by the operator of Guangzhou Metro), which ruled out 75 respondents.

(d) Respondents' employment should not be freelancer, undergraduate (mostly living in a student dormitory near the campus in Guangzhou, China) or retiree, as these respondents do not have a need to commute, which ruled out 28 respondents.

We obtained a final sample of 852 out of 1,015 collected questionnaires. Each respondent answered three SP choice tasks, for a total of 2,556 choice observations. Fig. 3 presents several statistical indicators of the RP data.

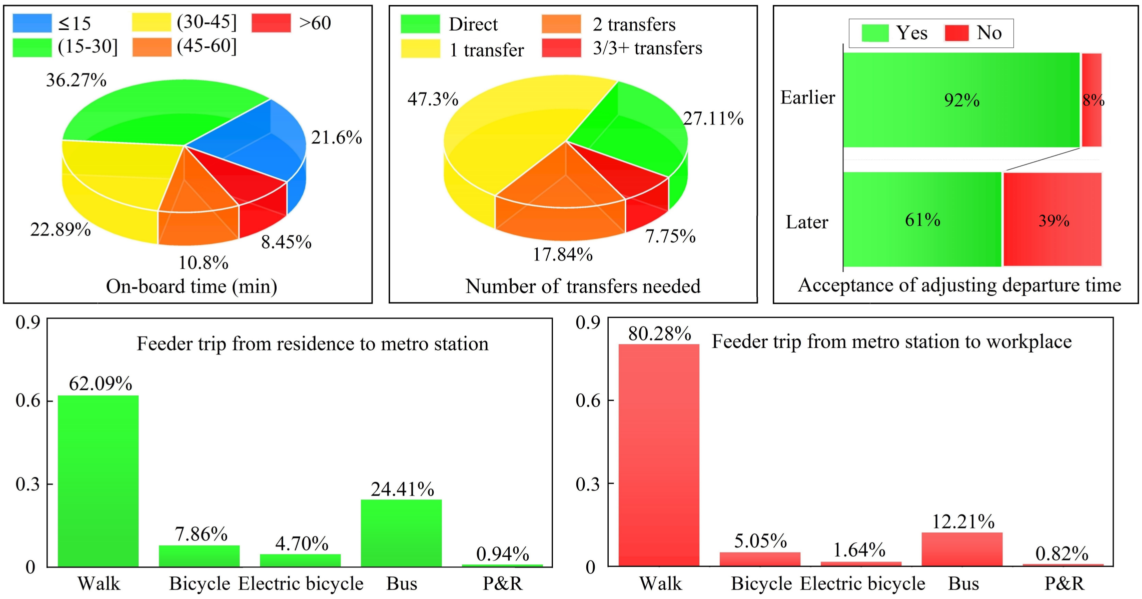


Fig. 3 Statistical results for the commuting characteristics

It can be observed that 59.16% of commuters spend 15-45 min on the metro trip, suggesting that metro service is targeted towards medium or long-distance trips of 14 km on average. More than three-quarters of commuters do not need to transfer or only make one transfer on the metro trip. Additionally, there are usually two feeder trips, one on either end of the major trip. As seen from the histograms in Fig. 3, walking is the most common way to bridge a metro trip, with an overwhelming 62.09% of respondents using this method on the start side and 80.28% on the end side. A total of 24.41% of commuters have a bus bridging trip before taking the metro, and the percentage decreases to 12.21% on the end-side feeder trip, which means that commuters tend to arrange to take the bus earlier in the trip. It should be noted that we allowed for the P&R option on the end-side because CBD workers who often drive for business purposes in the daytime may park the car at a nearby metro station and then take the metro back home. Therefore, the next morning, there is a possibility of using the end-side P&R to get from the metro station to the workplace. However, generally, the start-side P&R and the end-side P&R are not used in the same trip. Additionally, the respondents were asked two questions to preliminarily test their willingness to adjust their regular departure time in the context of TDM strategies. Ninety-two percent of commuters were willing to depart earlier. However, in regard to departing later, the percentage decreased to 61%, which is in line with a desire to not arrive late for work.

Survey design

In the SP-off-RP survey, a respondent's alternatives and choices in a real-world setting are first observed to support the SP task design. Based on the RP choice results, the respondents are asked whether they would make the same choice or switch to another alternative if the attributes of the chosen alternative become less desirable or the attributes of the non-chosen alternatives become more desirable (Guevara and Hess 2019; Train and Wilson 2009). In this way, the RP survey's advantage in collecting actual choice results and the SP survey's superiority in soliciting choice results in hypothetical scenarios can be optimally combined.

Given that the implementation of TDM strategies can be considered to represent changes in the attributes of a chosen alternative, commuters' behavioural loyalty is equivalent to whether they would make the same choice or switch to another mode or departure time. We thus used an SP-off-RP-like survey to obtain commuters' possible response to the upcoming TDM strategies. In the actual survey, the respondents were asked a series of questions to collect RP commuting information such as routine details (i.e., origin and destination metro stations, transfer stations, ticket price and the mode choices for the feeder trips) and timescale details (i.e., departure time from residence, arrival time at workplace, travel time of both the major trip and feeder trips). Based on the above information, three SP scenarios were tailored for each respondent, as illustrated in Fig. 4.

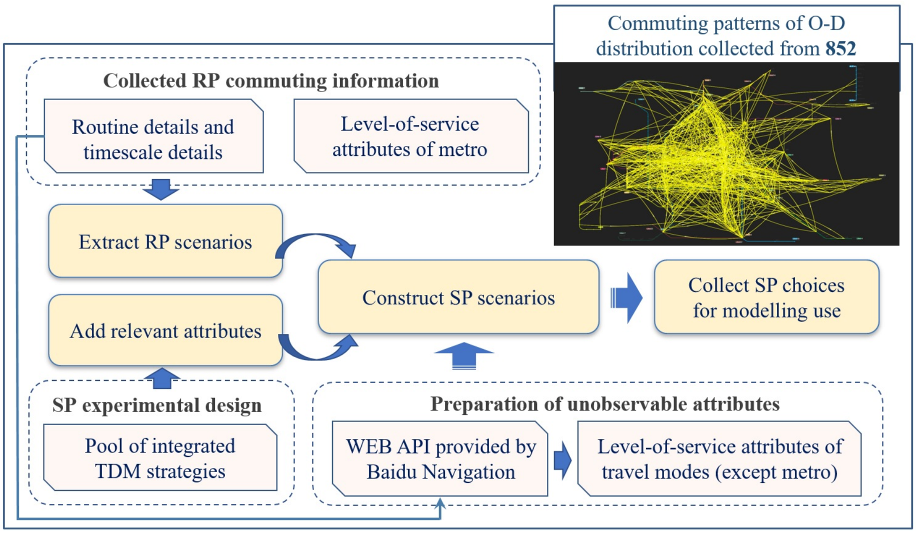


Fig. 4 Illustration of the construction of the SP scenarios based on the collected RP data

For each respondent, the hypothetical scenarios are created based on his/her own O-D (Origin-Destination) pair and departure time. The level-of-service attributes of the metro (e.g., travel time, ticket price and the number of transfers) are extracted from the respondent's self-reported information. On this basis, the impact of TDM strategies is accounted for by introducing five relevant attributes, i.e., extra waiting time at the control point (*WT*, indicating the time that the commuters have to spend waiting for batch release if they continue travelling by metro under enforcement of passenger flow control), off-peak discount (*OP*, part of the dynamic pricing strategy for incentivising peak-avoidance behaviour), extra peak charge (*EP*, another part of dynamic pricing strategy for achieving more potent incentivising effects), ahead of departure time (*AT*) and delay of departure time (*DT*, compared to the respondents' regular departure time), into the obtained RP scenario. The values of the above five TDM strategy-related attributes are determined through the D-efficient experimental design.

In addition to the metro-related alternatives, the respondents were provided with three mode alternatives (i.e., bus, private car, taxi or e-hailing) in the SP scenarios. The actual level-of-service attributes of these modes were accessed with the aid of the Baidu Map API (Application Programming Interface) in light of their own O-D pair because this information was not recorded in the RP data. We assume that if a commuter gives up metro service and switches to another mode, he/she maintains his/her regular departure time. Specifically, a shift in departure time occurs only if the commuter decides to continue travelling by metro. Thus, there are a total of six alternatives (I1, I2,…, I6) in each SP scenario. For those who do not have a car or cannot drive a car, we set the availability of I5 to 0 when calibrating the choice model. Beyond that, I1, I2, I3, I4 and I6 apply to each choice observation. More explicitly, Fig. 5 presents the overall design of the questionnaire.

Attitudinal statements

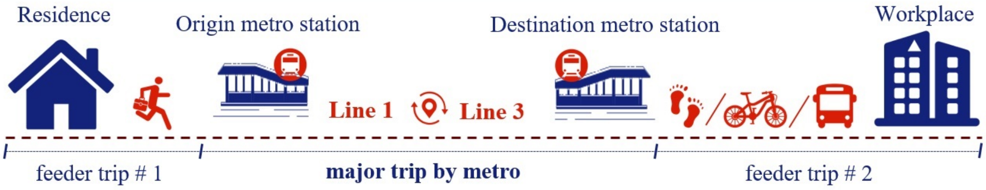
To capture respondents' attitudes, a set of attitudinal statements are used to measure the respondents' attitudes in terms of service quality (SQ), overall impression (OI), external attractiveness (EA) and switching cost (SC). In the actual survey, each respondent is asked to score these statements after completing the SP survey using a five-point Likert scale ranging from 'strongly disagree' to 'strongly agree.' The elaboration of SQ, OI, EA and SC is outlined below.

The SQ reflects customers' evaluation of the actual service (Zeithaml et al. 1996). A widely accepted interpretation was proposed by (Parasuraman et al. 1988), who used five dimensions (i.e., tangibility, reliability, responsiveness, assurance and empathy) to measure SC from a general perspective. To make our study realistic and helpful to practitioners, we designed the measurement indices with the purpose of fully reflecting the metro service's features. By referring to the passenger satisfaction survey periodically conducted by the operator of Guangzhou Metro, we identified the operator's major concerns, which can be summarised as passengers' perceived performance with respect to a variety of aspects of the service provided. These concerns are reflected in the attitudinal statements (see *SQ1~SQ5* in Table 1). In this regard, the sequential structure of SQ herein is in line with the opinion of (Kittelson & Associates Inc 1999), i.e., that the SQ of public transport reflects the overall perceived performance from the perspective of a passenger.

Survey introduction

- The name of the organisation
- The goal of the survey
- How the response will be used
- Relevant instructions that aren't explained in the survey questions (e.g., technical terms)

RP Commuting information



The daily commuting activity was collected with a fill-in-the-blank template, including

- Routine details (i.e., O-D metro stations, transfer stations, ticket price, bridging modes)
- Timescale details (i.e., depart from residence, arrive at workplace, travel time of three trips)

Example of SP scenario

If the **origin metro station** on your commuting trip is about to be affected by the upcoming flow control and dynamic pricing scheme, your **metro trip** will be influenced as below, whereas **other modes** maintain the status quo. Please tick the box in front of the option that you prefer.

Origin: *cited from the RP answer   Destination: *cited from the RP answer

Current departure time: *cited from the RP answer

Alternative	Metro			Shift to Bus	Shift to private car	Shift to taxi/e-hailing
	Depart earlier	Depart as usual	Depart later	Depart as usual		
Travel time	47 min*			58 min*	28 min*	
Pick-up time	-			-	-	11 min*
Ticket price	¥ 5*			¥ 4*	-	¥ 51*
Fuel & parking fees	-			-	¥ 40*	-
Number of transfers	1*			2*	-	-
Ahead of departure time (*AT*)	11 min	-	-	-		
Delay of departure time (*DT*)	-	-	14 min	-		
Extra waiting time at the control point (*WT1*, *WT2*, *WT3*)	10 min	17 min	6 min	-		
Off-peak discount (*OP1*, *OP2*, *OP3*)	45 %	/	20 %	-		
Extra peak charge (*EP1*, *EP2*, *EP3*)	/	20 %	/	-		
Select one:	☐ (I1)	☐ (I2)	☐ (I3)	☐ (I4)	☐ (I5)	☐ (I6)

Note: 28 hypothetical integrated strategies were prepared using the D-efficient experimental design and formed the pool of the SP tasks. Each respondent was required to complete three SP tasks randomly. Three sets of values of the relevant attributes are given as examples.

- Scenario 1: $AT = 6$; $DT = 9$; $WT1 = 4$; $WT2 = 8$; $WT3 = 2$; $OP1 = 10$; $OP2 = 0$; $EP3 = 30$
- Scenario 2: $AT = 14$; $DT = 13$; $WT1 = 9$; $WT2 = 14$; $WT3 = 6$; $OP1 = 20$; $EP2 = 20$; $EP3 = 10$
- Scenario 3: $AT = 12$; $DT = 15$; $WT1 = 8$; $WT2 = 16$; $WT3 = 12$; $EP1 = 15$; $EP2 = 0$; $OP3 = 40$

… …

Attitudinal statements

In the form of a five-point Likert scale

Socio-demographics

With a series of multiple choice quizzes

Fig. 5 Overall design of the questionnaire

Note: '-' indicates that the attribute does not apply to the alternative; '*' indicates an RP-based attribute that only varies with the respondents' O-D pairs and therefore remains unchanged in the three scenarios for one respondent; and '/' indicates a binary choice between *OP* and *EP*.

The OI represents commuters' overall feeling about the current metro service based on their experience, differing from SQ, which puts more focus on specific aspects (e.g., cleanliness, punctuality). On the basis of consumers' overall impression of the product (Yancey et al. 2010), we use the OI to represent the metro's general image from the point of view of the commuter (see *OI1~OI4* in Table 1), and we speculate that metro commuters' OI relates positively to their behavioural loyalty. From the metro operator standpoint, exploring the role of the OI in commuters' behaviour is of great value in improving user satisfaction, and thereby helps retain as much ridership as possible (Rosell and Allen 2020).

The EA indicates the attractiveness of the travel modes (i.e., bus, car, taxi and e-hailing), excluding the current choice (i.e., the metro). The inclusion of EA was inspired by the retailing research of Jones et al. (2000), which indicated that customers' repurchase intention increases when the attractiveness of an alternative is weak. Additionally, the application of attractiveness to public transport by Li et al. (2018) suggests that car attractiveness is significantly related to public transport users' loyalty. Further, referring to insights from the studies of Ping (1993) and Yan (2004), we measure EA in terms of typical service quality indices and willingness to shift to a specific mode (see *EA1~EA6* in Table 1).

The SC refers to the cost that a customer might incur as a result of switching products or service providers (Aydin et al. 2005; Ibáñez et al. 2006; Mohammadoghli et al. 2013). As Oliver (1999) suggested, SC is recognised as a solution to improve customer loyalty. Although the most prevalent SC is monetary in nature, there are also psychological, time-based or effort-based definitions of SC (Dick and Basu 1994). Following a recent transport study by Li et al. (2018), we use SC to capture commuters' emotional attachment to the current commuting choice, which is believed to be instructive for ridership retention in the TDM context. Four statements are designed to measure SC (see *SC1~SC4* in Table 1).

The statistical results of the collected responses to the attitudinal statements are reported in Table 1.

Table 1 Statistical results of responses to the attitudinal statements

Notion	Statements	Mean	S.D.	CITC
Indicators of SQ (Cronbach α = 0.630)				
SQ1	Metro platforms and carriages are clean and tidy	4.099	.828	.338
SQ2	The metro is least likely to be affected by weather conditions	4.603	.710	.410
SQ3	The Passenger Information System (PIS) for the metro is convenient	4.221	.867	.436
SQ4	The metro responds well to emergencies and passenger complaints	3.926	.941	.405
SQ5	The punctuality of the metro service is irreplaceable	4.383	.837	.337
Indicators of OI (Cronbach α = 0.737)				
OI1	I enjoy commuting by metro	4.294	.826	.429
OI2	I am satisfied with the metro commuting service so far	4.258	.804	.556
OI3	I would like to keep commuting by metro	4.272	.765	.546
OI4	I would like to recommend others to choose the metro for commuting	4.232	.854	.591
Indicators of EA (Original Cronbach α = 0.499, revised Cronbach α = 0.580 after deleting *EA4*, *EA5* and *EA6*)				
EA1	Driving would give me a better commuting experience than public transport	3.501	1.026	.393
EA2	Driving would be my ideal choice if there were no traffic jams and parking concerns	3.617	1.141	.417
EA3	I love the feeling of driving	3.015	1.184	.361
EA4	Taxi or e-hailing would provide me with comfortable lounge space during commuting	3.523	.990	.224
EA5	The price advantage of bus travel is an important factor to consider	3.614	1.123	.173
EA6	Bus stops are widely distributed over the city and have great flexibility	3.175	1.112	.189
Indicators of SC (Cronbach α = 0.651)				
SC1	I prefer keeping a regular commuting habit rather than trying different ways	3.401	1.115	.311
SC2	Changing my commuting habit would make me feel uncomfortable	3.015	1.142	.569
SC3	It may take me some time to get used to a new commuting plan	3.155	1.207	.567
SC4	A shift in my regular commuting plan may get me in unexpected trouble	3.853	.927	.315

In addition to the mean value and standard deviation, CITC (corrected item-total correlation) for each indicator and Cronbach's alpha for the four explanatory factors are presented. Generally, the variable should be reserved if the value of CITC is greater than 0.3. Additionally, Cronbach's alpha is commonly used to measure the internal consistency among each group of indicators. A higher value of Cronbach's alpha indicates a more rational structure of the assumed factors. As expected, the performance of EA improved when the underperforming indicator in terms of the CITC values (i.e., *EA4*, *EA5* and *EA6*) were dropped.

To further verify the rationality of the present selection of indicators, a confirmatory factor analysis (CFA) was conducted on the expected four explanatory factors. Based on the factor loading results, an indicator with a loading value less than 0.4, i.e., *SC1*, was removed from the present model due to a weak correlation between *SC1* and its explanatory factor. As the modification indices suggest, there is a high correlation between *OI1* and *SQ1*. We thus removed *SQ1* from from the present structure due to a relative low value of factor loading. In addition, an indicator that is not sufficiently representative for the explanatory factor, i.e., *OI4*, was dropped to ensure conceptual consistency. The compositions of the explanatory factors were thus determined and were used to measure the latent variables in the HCMs. Table 2 presents the final list of the analytic indicators, as well as the factor loadings.

Table 2 STDYX standardisation results for the analytic indicators

Service quality		Overall impression		External attractiveness		Switching cost	
Indicator	Est.	Indicator	Est.	Indicator	Est.	Indicator	Est.
SQ2	0.526	*OI1*	0.552	*EA1*	0.572	*SC2*	0.635
SQ3	0.613	*OI2*	0.756	*EA2*	0.492	*SC3*	0.896
SQ4	0.519	*OI3*	0.567	*EA3*	0.627	*SC4*	0.573
SQ5	0.494	-	-	-	-	-	-

Model Specifications

A nested logit (NL)-based HCM framework is used to characterise commuters' behavioural loyalty in terms of the shift in departure time and mode choice. As illustrated in Fig. 6, the HCM model structure consists of three components, namely, the structural model, the measurement model and the choice model. In particular, we consider two three-level nesting structures for the NL model, i.e., nesting by mode shift (Model 1) or departure time shift (Model 2) from the top, to explore correlations across different combinations of the alternatives and find a more rational structure for interpreting the behaviour of interest.

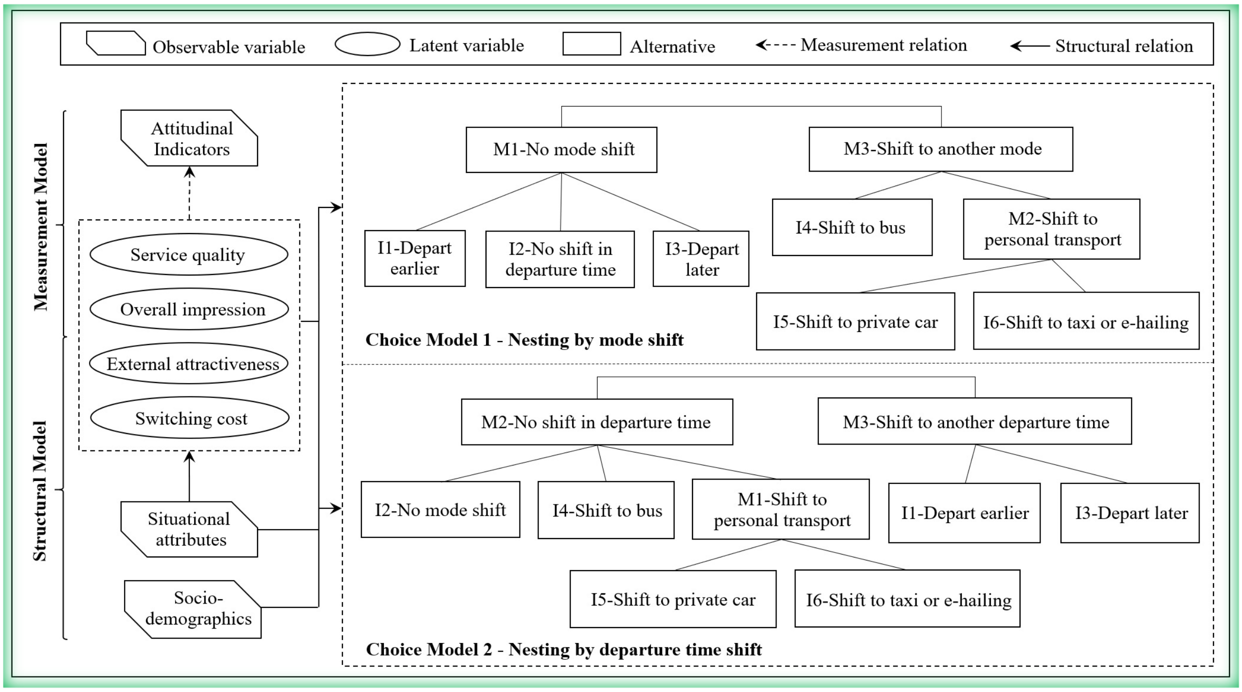


Fig. 6 Illustration of the HCM-NL model structures

The structural model represents the relationship between the socio-demographic variables and latent variables, and the measurement model further links the latent variables with the attitudinal indicators. In the choice model, two NL structures are used to explain commuters' behavioural loyalty in terms of the shift in departure time and mode choice, formed by the combinations among the three departure time-related alternatives (i.e., no shift, depart earlier, and depart later) and four mode related alternatives (i.e., no shift, shift to bus, shift to private car, and shift to taxi or e-hailing). Please note that we use a unique concept for the alternative in the two models, i.e., I1~I6, which is in line with the indices used in Fig. 5.

Structural model

Our model uses four latent variables, *SQ*, *OI*, *EA* and *SC*. Each has a structural equation to link the value to the observed socio-demographic variables. We use α_l^n to denote the latent variable l of commuter n, which we specify in a linear formulation as

$$\alpha_l^n = \zeta_l + \beta_l Z_n + \varphi_l^n,\ \varphi_l^n \sim N(0, \sigma_{\varphi_l}) \tag{1}$$

where β_l and ζ_l are the coefficient vector and intercept of latent variable l to be estimated and Z_n is the socio-demographics vector of commuter n. φ_l^n is the assumed stochastic error term of latent variable l. It follows a standard normal distribution across commuters, with a mean value of zero and standard deviation of σ_{φ_l}.

Measurement model

A total of 13 attitudinal statements are selected to help calibrate the choice model. The response to each statement is defined as an attitudinal indicator and requires a measurement equation representing its relationship with the corresponding latent variable. Many previous studies have thoroughly discussed the specification of measurement models under the HCM framework. Based on the five-level response scale for the attitudinal statements, an ordered specification was used to represent the ordinal characteristics of the indicators (cf. Daly et al. 2012 and Hess and Stathopoulos 2013). We thus used an ordered probit model to explain the value of indicator $I_{l,s}^{n*}$, linked with the *s*-th attitudinal statement of commuter n and using latent variable l as an explanator such that:

$$I_{l,s}^{n*} = \gamma_{l,s} + \beta_{l,s}\alpha_l^n + \eta_{l,s}^n,\ \eta_{l,s}^n \sim N(0,\ \sigma_{\eta_{l,s}}) \tag{2}$$

$$I_{l,s}^n = \begin{cases} \upsilon_{l,s}^1, & I_{l,s}^{n*} < \tau_{l,s}^1 \\ \upsilon_{l,s}^2, & \tau_{l,s}^1 \le I_{l,s}^{n*} < \tau_{l,s}^2 \\ \quad\vdots & \\ \upsilon_{l,s}^x, & \tau_{l,s}^{x-1} \le I_{l,s}^{n*} < \tau_{l,s}^x \\ \quad\vdots & \\ \upsilon_{l,s}^X, & \tau_{l,s}^{X-1} \le I_{l,s}^{n*} < \tau_{l,s}^X \end{cases} \tag{3}$$

where $\beta_{l,s}$ and $\gamma_{l,s}$ are the coefficient and intercept of α_l^n to be estimated for the *s*-th attitudinal statement; $\eta_{l,s}^n$ is the assumed stochastic error term of $I_{l,s}^{n*}$, which is normally distributed and has a mean value of zero and standard deviation of $\sigma_{\eta_{l,s}}$; $I_{l,s}^n$ is the response to the *s*-th attitudinal statement from commuter n; $\upsilon_{l,s}^x$ is the *x*-th ordinal scale of the *s*-th attitudinal statement; and $\tau_{l.s}^{x\text{-}1}$ and $\tau_{l,s}^x$ are the lower and upper thresholds of $I_{l,s}^{n*}$.

We set the first threshold $\tau_{l,s}^0$ as 0; therefore, in our case of a five-level response scale, four threshold values are required in the measurement model. Namely, we estimate three difference values of the threshold as follows.

$$\tau_{l,s}^x = \tau_{l,s}^{x-1} + \delta_l^{x-1} \tag{4}$$

The probability of commuter n responding $\mu_{l,s}^x$ to the *s*-th attitudinal statement can be written as

$$P_s^n\ (I_{l,s}^n = \upsilon_{l,s}^x) = P(\tau_{l,s}^{x-1} \le I_{l,s}^{n*} < \tau_{l,s}^x) \tag{5}$$

$$P_s^n\ (I_{l,s}^n = \upsilon_{l,s}^x) = \Gamma\left(\frac{\tau_{l,s}^x - \gamma_{l,s} - \beta_{l,s}\alpha_l^n}{\sigma_{\eta_{l,s}}}\right) - \Gamma\left(\frac{\tau_{l,s}^{x-1} - \gamma_{l,s} - \beta_{l,s}\alpha_l^n}{\sigma_{\eta_{l,s}}}\right) \tag{6}$$

where $\Gamma(\cdot)$ is the cumulative distribution function of the standard normal distribution.

Choice model

In the NL model, we use P_{im}^n to denote the probability of commuter n choosing alternative i, where $i \in m$, with m being one of the nests $R = 1,\ 2,\ \ldots,\ R$. This can be expressed as

$$P_{im}^n = P_{i|m}^n \times P_m^n \tag{7}$$

where $P_{i|m}^n$ is the conditional probability of commuter n choosing alternative i in nest m, and P_m^n is the marginal probability of commuter n choosing nest m.

The general derivative formulae for calculating $P_{i|m}^n$ and P_m^n are given by

$$P_{i|m}^{n} = \frac{e^{\mu_m V_{i|m}^{n}}}{\sum_{j \in S_m} e^{\mu_m V_{j|m}^{n}}} \tag{8}$$

$$P_{m}^{n} = \frac{e^{\mu (V_m^n + V_m^{n*})}}{\sum_{r \in R} e^{\mu (V_r^n + V_r^{n*})}} \tag{9}$$

$$V_m^{n*} = \frac{1}{\mu_m} \ln \sum_{j \in S_m} e^{\mu_m V_{j|m}^{n}} \tag{10}$$

where V_m^{n*} is the logsum term reflecting the lower-level effects on the upper level; μ is the upper-level scale parameter; μ_m is the lower-level scale parameter of nest m. As the normalisation of the NL model is done from the top, we estimate μ_m for each nest containing at least two alternatives, where $\mu = 1$ and $\mu_m \geq 1$; $V_{i|m}^{n}$ is the lower-level utility perceived by commuter n when choosing alternative i in nest m; V_m^n is the upper-level utility perceived by commuter n when choosing nest m; and S_m is the set of alternatives in nest m.

There are five specific parts of the utility function, i.e., situational attributes, latent variables, socio-demographic variables, constants and model parameters. A detailed specification is outlined below (an explicit illustration of the indices for the alternatives used below is available in Fig. 6).

The situational attributes can be categorised into the level-of-service attributes and the TDM strategy-relevant attributes, as illustrated in Fig. 4. Specifically, the considered level-of-service attributes include travel time (*TT*, applied to I1~I6, with coefficients varying with travel mode), travel cost (*TC*, applied to I1~I6, reflecting the total monetary cost of, for example, the ticket, fuel and parking fees, with the same expected coefficient across alternatives), no transfer required on the bus trip (*BT*, indicating that the commuter does not need to transfer if he/she switches to the bus; in other words, there is a direct bus connecting the O-D of this respondent, which is expected to increase the probability that I4 will be chosen), taking the bus on either side of the major trip (*FB*, applied to I4, as we expect that commuters who initially take the bus to bridge their metro trip are more likely to shift to bus), and pick-up time (*PT*, applied to I6, indicating the extra time cost of waiting for the taxi or e-hailing service compared to the cost of I5, which is automatically collected through Baidu Map API). Additionally, five dedicated situational attributes are used to capture the impact of TDM strategies on commuters' metro trips: *WT* (applied to metro-related alternatives I1, I2 and I3), *OP* (applied to I1~I3), *EP* (applied to I1~I3), *AT* (applied to I1) and *DT* (applied to I3), as concretely specified in the survey design subsection. In particular, *OP* and *EP* are included in the utility function independently rather than being incorporated into *TC*. The reason for this is to isolate the impact of the dynamic pricing strategy, thereby capturing commuters' price sensitivity in the TDM context separately.

The first and second latent variables, *SQ* and *OI*, measure commuters' perceived metro service quality and their overall feeling about the current metro service, respectively, which are both expected to be positively related to commuters' behavioural loyalty, i.e., to have a positive impact on retaining metro ridership. Based on this speculation, *SQ* and *OI* are included in the utility functions of I1~I3. The third latent variable, *EA*, reflects the attractiveness of all the travel modes except the metro, especially for the private car, according to the results of CFA. We thus expect that a higher *EA* results in lower behavioural loyalty to the metro service and positively contributes to the perceived utility of I5. The fourth latent variable, *SC*, focuses on capturing the psychological cost of overcoming the aversion to adjusting one's commuting habits, which is expected to have a positive effect on maintaining loyalty in the TDM context. *SC* is thus applied to the reference alternative with neither a mode shift nor a departure time shift, i.e., I2.

The socio-demographics are used in both the measurement model and choice model and include gender, age, income, education and employment, as clearly presented in the following estimation results. Additionally, there are four alternative-specific constants (*ASCs*) in each model to help capture the impact of unobserved factors. For a nest containing *n* alternatives, we chose one alternative as the reference and added ASCs to the utility functions of the other $n-1$ alternatives. For instance, in M1 of Model 1, ASCs are used in the utility functions of I1 and I3 since I2 is chosen as the reference alternative.

Regarding the panel effect in the sample set, special care is required in relation to identification and normalisation, which is discussed in detail by Walker et al. (2007). To capture potential individual-specific effects, an error component (*EC*) is included in each alternative, with the same variance but different draws for each alternative.

Results and implications

This section presents the model estimation results based on the model specification described above, as well as the implications of the results.

Model estimation results

With the model specification described above, two HCM-NL models are calibrated with Monte Carlo integration (500 MHLS draws) using Python Biogeme, an open-source software developed for estimating discrete choice models (Bierlaire 2015; 2016a; 2016b). The results of the choice model component are displayed in Table 3, together with the interpretation of the variables used.

Table 3 Results for the choice model component

Variable	Interpretation	Apply to[1]	Model 1		Model 2	
			Est.	t-rat.	Est.	t-rat.
Situational variables						
	Travel time for metro (hours)	I1~I3	-0.479	-2.84	-0.682	-3.12
TT	Travel time for bus (hours)	I4	-0.604	-3.97	-0.729	-4.03
	Travel time for private car, taxi or e-hailing (hours)	I5, I6	-0.855	-2.10	-1.22	-2.23
TC	Travel cost (CNY)	I1~I6	-0.00945	-2.93	-0.0137	-2.49
WT	Extra waiting time at control point (hours)	I1~I3	-2.81	-11.25	-3.89	-10.75
AT	Ahead of departure time (hours)	I1	-0.187	-8.19	-0.234	-8.14
DT	Delay of departure time (hours)	I3	-0.151	-5.32	-0.158	-4.24
OP	Off-peak discount (%)	I1~I3	0.746	4.46	0.994	5.21
EP	Extra peak charge (%)	I1~I3	-0.635	-2.71	-1.07	-2.33
BT	No transfer required on the bus trip (1 yes; 0 no)	I4	0.0634	2.07	0.0279	1.80
FB	Taking bus on either side of the major trip (1 yes; 0 no)	I4	0.305	3.01	0.367	3.21
PT	Pick-up time for taxi or e-hailing (hours)	I6	-2.03	-2.20	-2.59	-1.87
		I1	1.47	5.21	0.595	3.84
		I2	-[2]	-	-1.07	-2.22
ASC	Alternative-specific constants	I3	0.373	2.78	-	-
		I4	0.497	2.17	1.13	2.29
		I5	-1.67	-3.28	-1.90	-3.07
		M1	1.29	7.98	2.88	4.96
μ_m	Scale parameter	M2	1.86	4.81	1.66	9.34
		M3	1.10	5.82	1.19	7.29
EC	S.d. for error component	I1~I6	0.0292	0.251	0.0458	0.124
Latent variables						
SQ	Service quality	I1~I3	0.0731	2.35	0.0844	2.16
OI	Overall impression	I1~I3	0.163	5.25	0.152	4.95
EA	External attractiveness	I5	0.513	3.55	0.447	3.64
SC	Switching cost	I2	1.18	2.93	1.24	3.07
Socio-demographics						
GEN	Male	I2	0.184	3.04	0.327	2.88
EDU1	Master degree or above	I5	0.913	2.33	0.917	2.08
		I6	1.41	5.49	1.52	5.35
INC1	Monthly income < 6k	I4	0.122	2.01	0.134	1.92
INC2	Monthly income >10k	I5	0.521	2.86	0.504	2.60
		I6	0.946	4.59	1.05	4.54
EMP	Work for government departments or institutions	I5	1.04	3.63	1.30	3.98
Model summary						
	Number of parameters		31		31	
	Sample size		2556		2556	
	Log-likelihood		-3046.752		-3037.427	
	Rho-squared value		0.266		0.268	
	Adjusted rho-squared value		0.258		0.261	
	Non-nested Hyp. Test to reject Model 1		NA		<0.001	

[1] The column 'apply to' indicates where the variable is used in utility functions. For the indices for the alternative and nests, see Fig. 6. [2] The hyphen '-' implies the variable not modelled in the model specification.

For the situational variables, the two most commonly discussed variables of *TT* and *TC* present significant negative estimates, as expected. We observe a higher value-of-time for the bus, private car, and taxi or e-hailing than for the metro, indicating that mode shift decisions are usually driven by a strong time sensitivity. *WT* reflects the perceived utility of queuing for batch release under passenger flow control. The estimated coefficients of -2.81 and -3.89 in the two models indicate a negative impact on commuters' willingness to continue travelling by metro. The estimated coefficients of *AT* and *DT* are negative in both models, with a high level of confidence; this result suggests a positive sensitivity to commuters' behavioural loyalty, especially in terms of maintaining the current choice of departure time. In addition, *OP* and *EP* have the opposite effect of incentivising commuters' peak-avoidance choice, implying the important role of the price factor in TDM practices.

To further compare the effects of *OP*, *EP* and *TC*, we assume that the average metro fare is 5 CNY in light of the RP responses collected in this study. The units of *OP* and *EP* can be converted from % into CNY by dividing by the average metro fare. Taking Model 1 as an example, the coefficients of *OP* and *EP* are thus estimated at 0.149 and -0.127 in CNY, with higher absolute values than that of *TC*, implying that commuters are more sensitive to the fare rate variations than to the base price. We thus speculate that the current ticket price is at a slightly higher level; thus, a small fare reduction or extra charge can incentivise a shift in departure time choice.

TT and *TC* aside, further explanation is provided by the other level-of-service attributes. The bus is often considered the natural second choice for metro commuters. The positive coefficient of *BT* indicates that commuters are more liable to shift to the bus if no transfer is required. We also explore the potential relationship between bridging mode choice and commuters' behavioural loyalty. The positive coefficients of *FB* demonstrate that commuters who originally take the bus to bridge metro trips tend to shift to the bus completely in the TDM context. Additionally, the coefficient of *PT* indicates a negative perception of choosing to switch to a taxi or e-hailing, reflecting commuters' aversion to the extra waiting time.

In terms of the latent variables, the estimates for *SQ* are 0.0731 and 0.0844 in the two models, implying that commuters' perceived service quality positively contributes to behavioural loyalty, thus leading to a high dependence on the metro service. The signs of *OI* are also significant and indicate a positive effect on commuters' willingness to continue travelling by metro. The third latent variable, *EA*, captures the external factors that potentially attract commuters to shift to using a private car, with estimated coefficients of 0.513 and 0.447 in the two models, creating a negative impact on commuters' loyalty to the metro. Additionally, we put *SC* in I2, which eventually leads to a positive coefficient. The inclusion of *SC* further explains commuters' preference for their original commuting plan.

Four ASCs are used to capture the impacts of unconsidered factors. In Model 1, the positive ASCs for I1 and I3 indicate that commuters tend to adjust regular departure time under the condition of continuing to travel by metro (i.e., in M1). Regarding M3 (the nest of shifting to another mode), commuters have a preference for shifting to a bus (I4) compared to personal transport (M2). Furthermore, there are unobserved factors that make I6 more desirable than I5 in M2. In Model 2, the positive estimates for I1 in M3 imply that commuters dislike departing later (I3) if they decide to shift their departure time. In M2—namely, on the premise of intending to stay with the current departure time—the negative estimate for I2 suggests that continuing to travel by metro (I2) is less desirable than shifting to personal transport (M1). The positive ASC for I4 has the opposite meaning. With respect to M1, the negative ASC for I5 is in line with that of M2 in Model 1.

Additionally, a series of socio-demographic variables help explain commuter behaviour and improve the model fit. Men rely more on the previous choice and express more preference for I2 than women. The influence of income level varies by the position in the utility function. The lower-income group is more likely to shift to the bus due to the considerable price advantage. On the other hand, those with a monthly income higher than 10,000 CNY are more in favour of personal transport. Specifically, we allow different coefficients of *INC2* to capture the unobserved factors in I5 and I6 separately for a better model fit. Similarly, the signs of *EDU* indicate that the group with higher education is also inclined to shift to personal transport. In addition, commuters who work for government departments or institutions prefer shifting to private cars. The most likely cause is that most of these commuters have easy access to a parking space at their workplace.

The pseudo-panel effect in the two models is examined using the error component terms, and the estimated coefficients of the standard deviation for *EC* are not significant. Both absolute t-values are less than 1.0, indicating no significant individual-specific effects in the sample set except for the correlation across choices captured by the latent variable.

Overall, both models have the correct signs and are statistically significant. We then turn our attention to the scaled parameters μ/μ_m in the two nesting structures. The decreasing value of the scaled parameters indicates an increased correlation across the alternatives contained in nest m (Bierlaire 2009; Hess et al. 2012). The base value of

1 indicates an absence of correlation, which is equivalent to the MNL model. According to the estimates of μ_m presented in Table 3, in Model 1, the scaled parameters for M1 (containing I1, I2 and I3), M2 (containing I5 and I6) and M3 (containing I4 and M2) are 0.775, 0.591 and 0.909, respectively. In Model 2, the scaled parameters for M1 (containing I5 and I6), M2 (containing I2, I4 and M1) and M3 (containing I4 and M2) are 0.576, 0.602 and 0.840, respectively.

A relatively high correlation is observed in M2 of Model 1 and M3 of Model 2, i.e., shifting to personal transport. In contrast, the scaled parameter for M3 of Model 1 has a comparatively high value, indicating that only low levels of correlation arise in this nest. By comparing it with M2 of Model 2, the inclusion of I2 strengthens the correlation across the alternatives in the nest. Furthermore, based on the specification of Model 2, we tested another specification in which I2 and I4 were put in an additional nest within M2, given that both of these alternatives are associated with public transport. However, the scaled parameter for this additional nest almost collapsed to a value of 1, which indicates that this specification was rejected.

In terms of the adjusted rho-squared value, both Models 1 and 2 have acceptable goodness-of-fit, suggesting that it is reasonable to choose to use either specification. Model 2 has a higher adjusted rho-squared value, and performs better in light of the scaled parameters. Additionally, considering that Model 1 is not a restricted version of Model 2, we used the non-nested hypothesis test to compare the base Model 2 and the alternative specification (Model 1). This test is based on the hypothesis that the model with the lower rho-squared value is the true model. Following the approach proposed in (Horiwitz et al. 1986) and further illustrated in (Koppelman and Bhat 2006), in this test, the null hypothesis that Model 1 is the true model is rejected at the significance level determined by Eq. (11).

$$\kappa = \Phi\left[-(-2(\bar{\rho}_{\mathrm{H}}^2 - \bar{\rho}_{\mathrm{L}}^2) \times LL(0) + (K_{\mathrm{H}} - K_{\mathrm{L}}))^{1/2}\right] \tag{11}$$

Where κ is the significance level that the null hypothesis is rejected; $\bar{\rho}_{\mathrm{H}}$ and $\bar{\rho}_{\mathrm{L}}$ are the adjusted rho-squared values for the models with the higher and lower value, respectively; $LL(0)$ is the log-likelihood at zero, $LL(0) = -4149.847$; K_{H} and K_{L} are the numbers of parameters in models H and L, respectively; and $\Phi[\cdot]$ is the standard normal cumulative distribution function.

Since the two models have the same number of parameters, the term $(K_{\mathrm{H}} - K_{\mathrm{L}})$ drops out, and Eq. (11) for the test of Model 1 being true is:

$$\kappa = \Phi\left[-(-2(0.260 - 0.258) \times (-4149.847))^{1/2}\right] = \Phi\left[-4.074\right] < 0.001 \tag{12}$$

The above result implies that the null hypothesis is rejected. We thus consider Model 2 to be more conceptually appropriate than Model 1, suggesting that nesting by the departure time shift is more suitable for interpreting commuters' behavioural loyalty.

Results for the structural and measurement model components in Table 4, with a few exceptions, presents very similar estimates of parameter in the two models. The structural model specifies linear relationships where *SQ*, *OI*, *EA* and *SC* are represented by different combinations of socio-demographic variables and random disturbance terms. The measurement model builds the equations between the latent variables and attitudinal indicators in an ordered probit specification. The signs of all the involved parameters are significant and are in line with expectations.

Implications

This study provides insights into the factors influencing metro commuters' behavioural loyalty as these factors directly determine the performance of TDM strategies and can thus offer indispensable references for both researchers and practitioners.

For researchers who focus on optimising either passenger flow control strategies (Li et al. 2017; Liu et al. 2020; Shi et al. 2019) or dynamic pricing strategies (Huang et al. 2016; Liu and Wang 2017; Peng et al. 2016; Rantzien and Rude 2014), our findings are helpful in correcting the biases in the base demand patterns by including commuters' responses to the target strategy, and thereby lead to more desirable strategy outcomes. Additionally, the inclusion of *SQ*, *OI*, *EA* and *SC* provides a new point of view for interpreting commuters' behaviour mechanisms, which is particularly beneficial in extending the existing conceptual models (Gao et al. 2020; Jia et al. 2018; Mijares et al. 2016) from a more practical standpoint.

Practitioners in the field of public transport, especially metro operators, will also find this study helpful in preventing commuters from shifting to other travel modes, given that retaining existing customers is considerably less costly than attracting new customers (Hart et al. 1990; Reichheld and Schefter 2000). Specifically, public transport operators need to reflect on the service provided, e.g., whether trains arrive at the scheduled time during the morning rush hour, whether the PIS displays useful and accurate information, and whether emergency services are broadly available; all these points prove to be significant for commuters' perceived service quality and behavioural intention to continue travelling by metro. Commuters' overall impression of the current service is an important reflection of loyalty, implying that more effort is needed to understand commuters' feedback, e.g., by conducting online or face-to-face satisfaction surveys. Additionally, it is crucial for metro operators to identify the commuters who are most dependent on their service using insights into the latent variables of external attractiveness and switching costs. On the other hand, for commuters who currently commute by metro but for whom a direct bus service is unavailable (either due to an inconvenient location or a long commuting distance), more attention to maintaining their regular metro service is sorely needed in the development of TDM strategies. This can easily lead to high returns of commuter loyalty compared to those commuters who have more appealing alternatives for their commuting trips.

The statistical results of two typical level-of-service attributes of a metro and its alternative commuting modes are presented in Fig. 7, which include O-Ds departing from the top 5 busiest stations (during the morning peak, from 7:00 am to 9:00 am) in the Guangzhou Metro network.

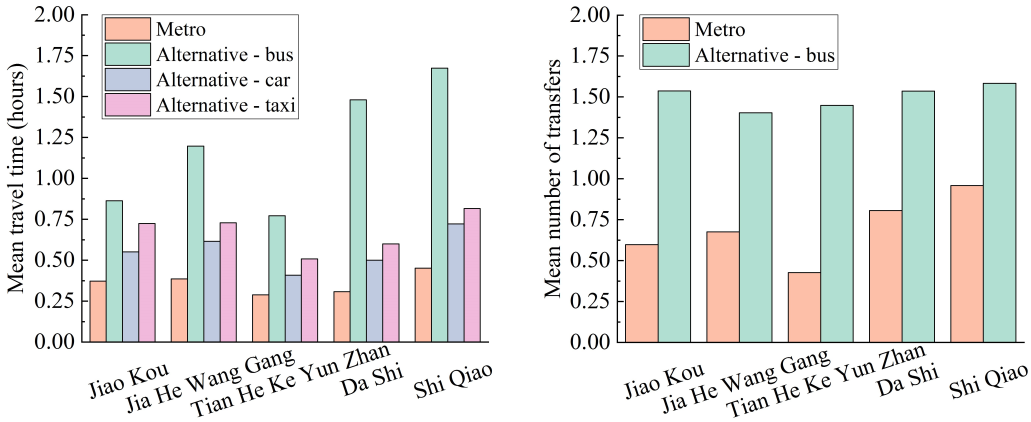


Fig. 7 Statistical results for the level-of-service attributes of different modes

The O-Ds used in the statistics were collected from the smart card data on a working day in December 2019. The level-of-service attributes of different modes were then obtained from the Baidu Map API. These five stations are all located in residential areas of Guangzhou city. The bus travel times for Da Shi (DS) and Shi Qiao (SQ) are comparatively longer than those of the other three stations, indicating that commuters who depart from DS and SQ are less likely to shift to the bus; however, they undergo more transfers on the metro trip. In this context, if passenger flow control measures are implemented at SQ, a supporting strategy of dynamic pricing may be effective in preventing these commuters from shifting to personal transport. In summary, the findings of this study enable metro operators to clearly understand the competitiveness of different modes in their circumstances, which is of great importance for staying competitive in the TDM context.

Conclusions

The present work focuses on the increasingly common demand management practices in metro systems. We conducted an SP-off-RP-like survey of regular metro commuters to reveal their behavioural loyalty in the TDM context. The HCM framework was used to model commuters' departure time and mode shift behaviour and provides insights into how attitudinal factors affect commuters' behavioural loyalty. In particular, two nesting structures are examined to seek a better model specification for the behaviour of interest. Several conclusions can be drawn from this study.

According to the five dedicated situational variables for characterising the impact of TDM strategies, we found that commuters are highly sensitive to any form of delay caused by passenger flow control extends their normal travel time on their daily commuting trip. They tend to change their departure time only if the shift helps reduce the extra delay considerably. Regarding the perception of the dynamic pricing strategy, commuters show different responses to the base fare and the differential fare rates, which indicates commuters' dissatisfaction with the current pricing rules. In regard to the newly adopted off-peak discount or extra peak charge, they tend to make a shift in their regular departure time, which is unfavourable for retaining ridership. We also observed a connection between the mode choice on the feeder trip and the mode shift preference on the major trip. Those who originally take the bus to bridge the metro trip have a higher probability of shifting to the bus completely in the TDM context.

Insights into attitudinal factors were provided in the following four areas. First, commuters' perceived metro service quality has a positive effect on retaining commuters, which suggests that the metro operator should take additional steps to deal with the declining transport service and prevent the loss of ridership due to TDM strategies. Second, the overall impression reveals commuters' overall opinion of the current service and their satisfaction to some extent, showing benefits in reducing commuters' behavioural changes. Third, the external attractiveness of private cars influences commuters' loyalty to metros the most significantly in contrast to other alternative modes. Thoughtful attention should be paid to the policymaking process to avoid creating increased car dependence. Fourth, the switching cost reflects the potential psychological cost of breaking already developed commuting habits and has a positive correlation with behavioural loyalty, illustrating commuters' aversion to rescheduling their commuting trips.

Overall, the present work helps better understand commuters' response to TDM strategies, which is essential for a metro operator to know what commuters think about their work and to find ways to guarantee the commuting service in challenging situations. Additionally, the finding regarding commuters' behavioural loyalty serves as the basis to forecast demand patterns in the context of policy intervention, which can in turn guide policymaking. Undoubtedly, there is still room for improvement in choice modelling, which can be achieved by investigating different types of decision heuristics in commuting behaviour, examining cross-nested model specification, and further exploring heterogeneity across respondents.

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Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Table 4 Results for structural and measurement model components

Variable	Interpretation	Service quality				Overall impression			External attractiveness			Switching cost		
		SQ2	*SQ3*	*SQ4*	*SQ5*	*OI1*	*OI2*	*OI3*	*EA1*	*EA2*	*EA3*	*SC2*	*SC3*	*SC4*
Model 1:														
Measurement model component														
$\beta_{l,s}$	Coefficient for the attitudinal indicator	1.0	0.466 (2.78)	0.107 (2.42)	0.722 (3.11)	1.0	0.176 (2.17)	0.188 (2.05)	1.0	1.97 (2.52)	10.2 (2.71)	1.0	2.35 (3.87)	2.37 (3.74)
$\gamma_{l,s}$	Intercept for the attitudinal indicator	0.0	0.954 (3.25)	1.62 (6.92)	0.465 (2.19)	0.0	2.61 (7.55)	1.84 (5.87)	0.0	-1.57 (-2.10)	-16.6 (-2.58)	0.0	-1.46 (-2.48)	-0.835 (-1.85)
δ_l^1, δ_l^2, δ_l^3	Interval for the ordinal scales	0.630(18.94), 0.756(37.38), 1.03(66.83)				0.543(13.47), 0.869(32.92), 1.11(63.10)			0.830(37.91), 0.965(58.33),0.733(48.70)			0.737(37.50), 0.808(51.89), 1.05(58.41)		
Structural model component														
β_l *GEN*	Male	-				-0.0174(2.45)			0.0618(2.40)			-0.0250(-2.75)		
*AGE*1	Age 25-50	-				-			0.00561 (1.87)			-0.103(-4.00)		
*AGE*2	Age > 50	3.41(2.84)				0.559(3.96)			-			-		
*INC*1	Monthly income < 6k	-				-0.236(-5.51)			-			0.0407(3.11)		
*INC*2	Monthly income >10k	-				-			0.00947(2.09)			-		
EDU2	Technical school or below	-0.0672(-2.68)				-			-			-		
EDU1	Mater degree or above	0.263(3.52)				0.262(3.20)			-0.0202(-2.39)			-		
EMP	Government employee	-				-			-			-0.0319(-3.07)		
ζ_l	Intercept for the latent variable	2.90(62.15)				2.58(44.15)			1.73(50.89)			1.26(38.02)		
σ_{φ_l}	S.d. for the latent variable	0.510(15.24)				0.489(18.11)			0.391(15.97)			0.694(14.21)		
Model 2:														
Measurement model component														
$\beta_{l,s}$	Coefficient for the attitudinal indicator	1.0	0.408 (2.71)	0.0917 (2.34)	0.603 (2.94)	1.0	0.171 (2.35)	0.223 (2.66)	1.0	2.10 (2.41)	10.7 (2.58)	1.0	2.42 (3.73)	2.44 (3.71)
$\gamma_{l,s}$	Intercept for the attitudinal indicator	0.0	1.12 (3.10)	1.65 (8.51)	0.812 (1.92)	0.0	2.42 (7.41)	1.70 (5.72)	0.0	-1.81 (-1.89)	-17.5 (-2.47)	0.0	-1.55 (-2.45)	-0.926 (-1.89)
δ_l^1, δ_l^2, δ_l^3	Interval of the ordinal scales	0.629(18.94), 0.757(37.38), 1.03(66.82)				0.544(13.48), 0.868(32.90), 1.11(63.10)			0.830(37.93), 0.965(58.33),0.733(48.70)			0.737(37.50), 0.807(51.89), 1.05(58.41)		
Structural model component												-		
β_l *GEN*	Male	-				-0.0122(2.33)			0.0587(2.37)			-0.0243(-2.73)		
*AGE*1	Age 25-50	-				-			0.00531(1.94)			-0.0997(-3.85)		
*AGE*2	Age > 50	3.69(2.76)				0.475(3.26)			-			-		
*INC*1	Monthly income < 6k	-				-0.214(-5.40)			-			0.0395(3.05)		
*INC*2	Monthly income >10k	-				-			0.00894(2.05)			-		
EDU2	Technical school or below	-0.0709(-2.65)				-			-			-		
EDU1	Mater degree or above	0.227(3.44)				0.242(3.45)			-0.0190(-2.32)			-		
EMP	Government employee	-				-			-			-0.0312(-3.04)		
ζ_l	Intercept for the latent variable	2.88(63.62)				2.54(44.68)			1.75(51.56)			1.28(37.82)		
σ_{φ_l}	S.d. for the latent variable	0.507(14.87)				0.495(18.40)			0.380(16.11)			0.686(14.36)		

Reference

Abou-Zeid, M., Ben-Akiva, M.: Hybrid choice models. In: Hess, S., Daly, A. (Eds.), Handbook of Choice Modelling. Edward Elgar, Cheltenham. (2014)

Abrate, G., Nicolau, J.L., Viglia, G.: The impact of dynamic price variability on revenue maximization. Tour. Manag. 74, 224–233 (2019). https://doi.org/10.1016/j.tourman.2019.03.013

Ashok, K., Dillon, W.R., Yuan, S.: Extending discrete choice models to incorporate attitudinal and other latent variables. J. Mark. Res. 39, 31–46 (2002). https://doi.org/10.1509/jmkr.39.1.31.18937

Atasoy, B., Glerum, A., Bierlaire, M.: Attitudes towards mode choice in Switzerland. Disp. 49, 101–117 (2013). https://doi.org/10.1080/02513625.2013.827518

Aydin, S., Özer, G., Arasil, Ö.: Customer loyalty and the effect of switching costs as a moderator variable. A case in the Turkish mobile phone market. Mark. Intell. Plan. 23, 89–103 (2005). https://doi.org/10.1108/02634500510577492

Bahamonde-Birke, F.J., Kunert, U., Link, H., Ortúzar, J. de D.: About attitudes and perceptions: finding the proper way to consider latent variables in discrete choice models. Transportation (Amst). 44, 475–493 (2017). https://doi.org/10.1007/s11116-015-9663-5

Bandyopadhyay, S., Martell, M.: Does attitudinal loyalty influence behavioral loyalty? A theoretical and empirical study. J. Retail. Consum. Serv. 14, 35–44 (2007). https://doi.org/10.1016/j.jretconser.2006.03.002

Bao, Y., Xu, M., Dogterom, N., Ettema, D.: Effectiveness investigation of travel demand management measures in Beijing: Existing measures and a potential measure–tradable driving credit. Transp. Res. Part F Traffic Psychol. Behav. 72, 47–61 (2020). https://doi.org/10.1016/j.trf.2020.05.010

Ben-Akiva, M., Mcfadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D.S., Daly, A., De Palma, A., Gopinath, D., Karlstrom, A., Munizaga, M.A.: Hybrid Choice Models: Progress and Challenges. Mark. Lett. 13, 163–175 (2002)(a). https://doi.org/10.1023/A:1020254301302

Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T., Polydoropoulou, A.: Integration of Choice and Latent Variable Models. In Perpetual Motion. 431–470 (2002)(b). https://doi.org/10.1016/b978-008044044-6/50022-x

Berkowitz, E.N., Jacoby, J., Chestnut, R.: Brand Loyalty: Measurement and Management. John Wiley and Sons, New York. (1978)

Bhat, C.R., Dubey, S.K.: A new estimation approach to integrate latent psychological constructs in choice modeling. Transp. Res. Part B Methodol. 67, 68–85 (2014). https://doi.org/10.1016/j.trb.2014.04.011

Bierlaire, M.: Estimation of discrete choice models with BIOGEME 1.8. Transport. 111 (2009)

Bierlaire, M.: Monte-Carlo integration with PythonBiogeme. (2015)

Bierlaire, M.: Pythonbiogeme: a short Introduction. Report TRANSP-OR 160706. Series on Biogeme, Transport and Mobility Laboratory. (2016)(a)

Bierlaire, M.: Estimating Choice Models with Latent Variables with PythonBiogeme. (2016)(b)

Bolduc, D., Ben-Akiva, M., Walker, J., Michaud, A.: Hybrid Choice Models with Logit Kernel: Applicability to Large Scale Models. Integr. Land-Use Transp. Model. 275–302 (2005). https://doi.org/10.1108/9781786359520-012

Chen, S., Sun, G., Wei, Z., Wang, D.: Dynamic pricing in electricity and natural gas distribution networks: An EPEC model. Energy. 207, 118138 (2020). https://doi.org/10.1016/j.energy.2020.118138

Daly, A., Hess, S., Patruni, B., Potoglou, D., Rohr, C.: Using ordered attitudinal indicators in a latent variable choice model: A study of the impact of security on rail travel behaviour. Transportation (Amst). 39, 267–297 (2012). https://doi.org/10.1007/s11116-011-9351-z

Daziano, R.A.: Inference on mode preferences, vehicle purchases, and the energy paradox using a Bayesian structural choice model. Transp. Res. Part B Methodol. 76, 1–26 (2015). https://doi.org/10.1016/j.trb.2015.02.012

Dick, A.S., Basu, K.: Customer loyalty: Toward an integrated conceptual framework. J. Acad. Mark. Sci. 22, 99–113 (1994). https://doi.org/10.1177/0092070394222001

Ding, C., Mishra, S., Lin, Y., Xie, B.: Cross-Nested Joint Model of Travel Mode and Departure Time Choice for Urban Commuting Trips: Case Study in Maryland–Washington, DC Region. J. Urban Plan. Dev. 141, 04014036 (2015). https://doi.org/10.1061/(asce)up.1943-5444.0000238

Gao, K., Yang, Y., Sun, L., Qu, X.: Revealing psychological inertia in mode shift behavior and its quantitative influences on commuting trips. Transp. Res. Part F Traffic Psychol. Behav. 71, 272–287 (2020). https://doi.org/10.1016/j.trf.2020.04.006

Guevara, C.A., Hess, S.: A control-function approach to correct for endogeneity in discrete choice models estimated on SP-off-RP data and contrasts with an earlier FIML approach by Train & Wilson. Transp. Res. Part B Methodol. 123, 224–239 (2019). https://doi.org/10.1016/j.trb.2019.03.022

Hart, C.W., Heskett, J.L., Sasser, W.E.: The profitable art of service recovery. Harv. Bus. Rev. 68, 148–156 (1990)

Heinen, E., Harshfield, A., Panter, J., Mackett, R., Ogilvie, D.: Does exposure to new transport infrastructure result in modal shifts? Patterns of change in commute mode choices in a four-year quasi-experimental cohort study. J. Transp. Heal. 6, 396–410 (2017). https://doi.org/10.1016/j.jth.2017.07.009

Hensher, D.A., Rose, J.M., Collins, A.T.: Identifying commuter preferences for existing modes and a proposed Metro in Sydney, Australia with special reference to crowding. Public Transp. 3, 109–147 (2011). https://doi.org/10.1007/s12469-010-0035-4

Hess, S., Fowler, M., Adler, T., Bahreinian, A.: A joint model for vehicle type and fuel type choice: Evidence from a cross-nested logit study. Transportation (Amst). 39, 593–625 (2012). https://doi.org/10.1007/s11116-011-9366-5

Hess, S., Spitz, G., Bradley, M., Coogan, M.: Analysis of mode choice for intercity travel: Application of a hybrid choice model to two distinct US corridors. Transp. Res. Part A Policy Pract. 116, 547–567 (2018). https://doi.org/10.1016/j.tra.2018.05.019

Hess, S., Stathopoulos, A.: Linking response quality to survey engagement: A combined random scale and latent variable approach. J. Choice Model. 7, 1–12 (2013). https://doi.org/10.1016/j.jocm.2013.03.005

Holguín-Veras, J., Amaya Leal, J., Sanchez-Diaz, I., Browne, M., Wojtowicz, J.: State of the art and practice of urban freight management Part II: Financial approaches, logistics, and demand management. Transp. Res. Part A Policy Pract. 137, 383–410 (2020). https://doi.org/10.1016/j.tra.2018.10.036

Horiwitz, J., Koppelman, F., Lerman, S.: A self-instructing course in disaggregate mode choice modeling. Dot-T-93-18. 193 (1986)

Hoyos, D., Mariel, P., Hess, S.: Incorporating environmental attitudes in discrete choice models: An exploration of the utility of the awareness of consequences scale. Sci. Total Environ. 505, 1100–1111 (2015). https://doi.org/10.1016/j.scitotenv.2014.10.066

Huang, H.S., Hu, S.C., Lee, P.H., Tseng, Y.C.: An adaptive Paris Metro Pricing scheme for mobile data networks. Int. J. Netw. Manag. 26, 422–434 (2016). https://doi.org/10.1002/nem.1941

Ibáñez, V.A., Hartmann, P., Calvo, P.Z.: Antecedents of customer loyalty in residential energy markets: Service quality, satisfaction, trust and switching costs. Serv. Ind. J. 26, 633–650 (2006). https://doi.org/10.1080/02642060600850717

Izogo, E.E.: Determinants of attitudinal loyalty in Nigerian telecom service sector: Does commitment play a mediating role? J. Retail. Consum. Serv. 23, 107–117 (2015). https://doi.org/10.1016/j.jretconser.2014.12.010

Jia, N., Li, L., Ling, S., Ma, S., Yao, W.: Influence of attitudinal and low-carbon factors on behavioral intention of commuting mode choice – A cross-city study in China. Transp. Res. Part A Policy Pract. 111, 108–118 (2018). https://doi.org/10.1016/j.tra.2018.03.010

Jiang, M., Li, H. ying, Xu, X. yue, Xu, S. peng, Miao, J. rui: Metro passenger flow control with station-to-station cooperation based on stop-skipping and boarding limiting. J. Cent. South Univ. 24, 236–244 (2017). https://doi.org/10.1007/s11771-017-3424-x

Jones, M.A., Mothersbaugh, D.L., Beatty, S.E.: Switching barriers and repurchase intentions in services. J. Retail.

76, 259–274 (2000). https://doi.org/10.1016/S0022-4359(00)00024-5

Jørgensen, S., Zaccour, G.: Optimal pricing and advertising policies for a one-time entertainment event. J. Econ. Dyn. Control. 100, 395–416 (2019). https://doi.org/10.1016/j.jedc.2019.01.007

Kamandanipour, K., Mahdi Nasiri, M., Konur, D., Haji Yakhchali, S.: Stochastic data-driven optimization for multi-class dynamic pricing and capacity allocation in the passenger railroad transportation. Expert Syst. Appl. 158, 113568 (2020). https://doi.org/10.1016/j.eswa.2020.113568

Kamargianni, M., Ben-Akiva, M., Polydoropoulou, A.: Incorporating social interaction into hybrid choice models. Transportation (Amst). 41, 1263–1285 (2014). https://doi.org/10.1007/s11116-014-9550-5

Keyes, A.K.M., Crawford-Brown, D.: The changing influences on commuting mode choice in urban England under Peak Car: A discrete choice modelling approach. Transp. Res. Part F Traffic Psychol. Behav. 58, 167–176 (2018). https://doi.org/10.1016/j.trf.2018.06.010

Kim, J., Rasouli, S., Timmermans, H.: Hybrid Choice Models: Principles and Recent Progress Incorporating Social Influence and Nonlinear Utility Functions. Procedia Environ. Sci. 22, 20–34 (2014). https://doi.org/10.1016/j.proenv.2014.11.003

Kim, J., Rasouli, S., Timmermans, H.: A hybrid choice model with a nonlinear utility function and bounded distribution for latent variables: application to purchase intention decisions of electric cars. Transp. A Transp. Sci. 12, 909–932 (2016). https://doi.org/10.1080/23249935.2016.1193567

Kittelson & Associates Inc: Transit capacity and quality of service manual. Transit Cooper. Res. Program Web Document 6, 1–35. (1999)

Koppelman, F.S., Bhat, C.: A Self Instructing Course in Mode Choice Modeling : Multinomial and Nested Logit Models. Elements. 28, 501–12 (2006)

Li, L., Bai, Y., Song, Z., Chen, A., Wu, B.: Public transportation competitiveness analysis based on current passenger loyalty. Transp. Res. Part A Policy Pract. 113, 213–226 (2018). https://doi.org/10.1016/j.tra.2018.04.016

Li, S., Dessouky, M.M., Yang, L., Gao, Z.: Joint optimal train regulation and passenger flow control strategy for high-frequency metro lines. Transp. Res. Part B Methodol. 99, 113–137 (2017). https://doi.org/10.1016/j.trb.2017.01.010

van Lierop, D., Badami, M.G., El-Geneidy, A.M.: What influences satisfaction and loyalty in public transport? A review of the literature. Transp. Rev. 38, 52–72 (2018). https://doi.org/10.1080/01441647.2017.1298683

Liu, M.Y., Wang, J.W.: Pricing Method of Urban Rail Transit Considering the Optimization of Passenger Transport Structure. Jiaotong Yunshu Xitong Gongcheng Yu Xinxi/Journal Transp. Syst. Eng. Inf. Technol. 17, 53–59 (2017). https://doi.org/10.16097/j.cnki.1009-6744.2017.03.009

Liu, R., Li, S., Yang, L.: Collaborative optimization for metro train scheduling and train connections combined with passenger flow control strategy. Omega (United Kingdom). 90, (2020). https://doi.org/10.1016/j.omega.2018.10.020

Losada-Rojas, L.L., Gkartzonikas, C., Pyrialakou, V.D., Gkritza, K.: Exploring intercity passengers' attitudes and loyalty to intercity passenger rail: Evidence from an on-board survey. Transp. Policy. 73, 71–83 (2019). https://doi.org/10.1016/j.tranpol.2018.10.011

Mijares, A.C.S., Suzuki, M., Yai, T.: An analysis of Metro Manila MRT-3 passengers' perception of their commuting experience and its effects using structural equation modeling (SEM). Asian Transp. Stud. 4, 1–18 (2016). https://doi.org/10.11175/eastsats.4.1

Mohammadoghli, N., Hassanzadeh, M., Esmaeli, E.: Key factors affecting customer loyalty in ISP (internet Service Provider) companies in Ardabil Province. Int. Res. J. Appl. Basic Sci. 4, 3411–3413 (2013)

Nesset, E., Helgesen, Ø.: Effects of switching costs on customer attitude loyalty to an airport in a multi-airport region. Transp. Res. Part A Policy Pract. 67, 240–253 (2014). https://doi.org/10.1016/j.tra.2014.07.003

Odin, Y., Odin, N., Valette-Florence, P.: Conceptual and operational aspects of brand loyalty: An empirical investigation. J. Bus. Res. 53, 75–84 (2001). https://doi.org/10.1016/S0148-2963(99)00076-4

Oliver, R.L.: Whence Consumer Loyalty. J. Mark. Vol. 63, 33–44 (1999)

Parasuraman, A., Berry, L.L., Zeithaml, V.A., Kelley, S.W., Turley, L..: SERVQUAL: A Multiple-Item Scale for Measuring Consumer Perceptions of Service Quality. J. Retail. 64, 5–6 (1988)

Peng, Y., Yang, J., Zhao, X.: Research on the urban rail transit's pricing with bi-level programming model based on particle swarm optimisation algorithm. J. Wuhan Univ. Tech. 40, 535–539 (2016)

Ping, R.A.: The effects of satisfaction and structural constraints on retailer exiting, voice, loyalty, opportunism, and neglect. J. Retail. 69, 320–352 (1993). https://doi.org/10.1016/0022-4359(93)90010-G

Rantzien, V.H. af, Rude, A.: Peak-load pricing in public transport: a case study of Stockholm. J. Transp. Lit. 8, 52–94 (2014). https://doi.org/10.1590/s2238-10312014000100004

Raveau, S., Yáñez, M.F., Ortúzar, J. de D.: Practical and empirical identifiability of hybrid discrete choice models. Transp. Res. Part B Methodol. 46, 1374–1383 (2012). https://doi.org/10.1016/j.trb.2012.06.006

Reichheld, F.F., Schefter, P.: E-loyalty: Your secret weapon on the web. Harv. Bus. Rev. 78, 105–113 (2000)

Resdiansyah: Travel mode choice preferences of urban commuters in Kuching City, Malaysia based on stated preference data. MATEC Web Conf. 181, 02007 (2018). https://doi.org/10.1051/matecconf/201818102007

Roberts, J., Popli, G., Harris, R.J.: Do environmental concerns affect commuting choices?: hybrid choice modelling with household survey data. J. R. Stat. Soc. Ser. A Stat. Soc. 181, 299–320 (2018). https://doi.org/10.1111/rssa.12274

Roby, H.: A Supplementary Dictionary of Transport Studies. In: A Supplementary Dictionary of Transport Studies. Oxford University Press (2014)

Rosell, J., Allen, J.: Test-riding the driverless bus: Determinants of satisfaction and reuse intention in eight test-track locations. Transp. Res. Part A Policy Pract. 140, 166–189 (2020). https://doi.org/10.1016/j.tra.2020.08.013

Saharan, S., Bawa, S., Kumar, N.: Dynamic pricing techniques for Intelligent Transportation System in smart cities: A systematic review. Comput. Commun. 150, 603–625 (2020). https://doi.org/10.1016/j.comcom.2019.12.003

Saleh, W.: Success and failure of travel demand management: Is congestion charging the way forward? Transp. Res. Part A Policy Pract. 41, 611–614 (2007). https://doi.org/10.1016/j.tra.2006.09.014

Sasic, A., Habib, K.N.: Modelling departure time choices by a Heteroskedastic Generalized Logit (Het-GenL) model: An investigation on home-based commuting trips in the Greater Toronto and Hamilton Area (GTHA). Transp. Res. Part A Policy Pract. 50, 15–32 (2013). https://doi.org/10.1016/j.tra.2013.01.028

Shi, J., Yang, L., Yang, J., Zhou, F., Gao, Z.: Cooperative passenger flow control in an oversaturated metro network with operational risk thresholds. Transp. Res. Part C Emerg. Technol. 107, 301–336 (2019). https://doi.org/10.1016/j.trc.2019.08.008

Song, F., Hess, S., Dekker, T.: Accounting for the impact of variety-seeking: Theory and application to HSR-air intermodality in China. J. Air Transp. Manag. 69, 99–111 (2018). https://doi.org/10.1016/j.jairtraman.2018.02.008

Sun, S., Duan, Z.: Modeling passengers' loyalty to public transit in a two-dimensional framework: A case study in Xiamen, China. Transp. Res. Part A Policy Pract. 124, 295–309 (2019). https://doi.org/10.1016/j.tra.2019.04.007

Tao, S., Corcoran, J., Mateo-Babiano, I.: Modelling loyalty and behavioural change intentions of busway passengers: A case study of Brisbane, Australia. IATSS Res. 41, 113–122 (2017). https://doi.org/10.1016/j.iatssr.2016.10.001

Thorhauge, M., Haustein, S., Cherchi, E.: Accounting for the Theory of Planned Behaviour in departure time choice. Transp. Res. Part F Traffic Psychol. Behav. 38, 94–105 (2016). https://doi.org/10.1016/j.trf.2016.01.009

Train, K.E., Wilson, W.W.: Monte Carlo analysis of SP-off-RP data. J. Choice Model. 2, 101–117 (2009). https://doi.org/10.1016/S1755-5345(13)70006-X

Transportation Research Board: A Handbook for Measuring Customer Satisfaction and Service Quality. (1999)

Walker, J.L., Ben-Akiva, M., Bolduc, D.: Identification of parameters in normal error component logit-mixture (NECLM) models. J. Appl. Econom. 22, 1095–1125 (2007). https://doi.org/10.1002/jae.971

Wang, J., Yamamoto, T., Liu, K.: Key determinants and heterogeneous frailties in passenger loyalty toward customized buses: An empirical investigation of the subscription termination hazard of users. Transp. Res. Part C Emerg. Technol. 115, 102636 (2020). https://doi.org/10.1016/j.trc.2020.102636

Webb, V.: Customer Loyalty in the Public Transportation Context. Massachusetts Institute of Technology. Dept. of Civil and Environmental Engineering., (2010)

Yan, H.Y.: The influence factors of customer loyalty and its mechanism of action. Zhejiang University, China Doctoral dissertation. (2004)

Yancey, J.W.S., Apple, J.K., Meullenet, J.F., Sawyer, J.T.: Consumer responses for tenderness and overall impression can be predicted by visible and near-infrared spectroscopy, Meullenet-Owens razor shear, and Warner-Bratzler shear force. Meat Sci. 85, 487–492 (2010). https://doi.org/10.1016/j.meatsci.2010.02.020

Yang, J., Jin, J.G., Wu, J., Jiang, X.: Optimizing Passenger Flow Control and Bus-Bridging Service for Commuting Metro Lines. Comput. Civ. Infrastruct. Eng. 32, 458–473 (2017). https://doi.org/10.1111/mice.12265

Zaman, H., Habib, K.M.N.: Commuting mode choice in the context of travel demand management (TDM) policies: An empirical investigation in Edmonton, Alberta. Can. J. Civ. Eng. 38, 433–443 (2011). https://doi.org/10.1139/l11-015

Zeithaml, V.A., Berry, L.L., Parasuraman, A.: The behavioral consequences of service quality. J. Mark. 60, 31–46 (1996). https://doi.org/10.2307/1251929

Zhang, J., Meng, M., Wang, D.Z.W.: A dynamic pricing scheme with negative prices in dockless bike sharing systems. Transp. Res. Part B Methodol. 127, 201–224 (2019). https://doi.org/10.1016/j.trb.2019.07.007

Zhao, X., Yang, J.: Research on the Bi-level Programming Model for Ticket Fare Pricing of Urban Rail Transit based on Particle Swarm Optimization Algorithm. Procedia - Soc. Behav. Sci. 96, 633–642 (2013). https://doi.org/10.1016/j.sbspro.2013.08.074