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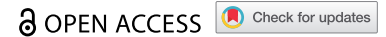
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ARTICLE

How does interchange affect passengers' route choices in urban rail transit? – a case study of the Shanghai Metro

Yan Cheng [a], Xiafei Ye[b,c] and Taku Fujiyama[a]

aCentre for Transport Studies, University College London, London, UK; bMOE Key Laboratory of Road and Traffic Engineering, Tongji University, Shanghai, China; cShanghai Key Laboratory of Rail Infrastructure Durability and System Safety, Tongji University, Shanghai, China

ABSTRACT

Interchange provides more flexibility in route choice, a key travel behaviour in urban rail transit, but its influence is usually simplified. This paper investigates how interchange affects route choice with passenger perception considered. At single-interchange level, perceived interchange time was proposed and modelled under three resolutions to capture passenger perception and its sensitivity. At route level, the influence of interchange was modeled by first comparing eight quantifications of interchange. Mixed logit models with the best interchange proxy were further developed to address the correlation among alternative routes and reveal the potential taste variations among passengers. Results based on Shanghai Metro data showed perceived interchange time, including passenger perception and interchange environment, better represents the influence of interchange in route choice, meanwhile the weights of interchanges on one route rise sequentially and non-linearly. The results can improve route choice prediction in demand modelling and route recommendation in advanced traveller information systems.

Introduction

In urban rail transit, route choice is one of the key behaviors that influences passenger flows over the entire network, affecting service performance measurement, operation strategies analysis, and infrastructure development evaluation. Choosing one route out of multiple alternatives is quite common for passengers traveling in a complex urban rail transit network. According to the latest survey for the London Underground (Transport for London 2017), 34.42% of the investigated 33,289 Origin–Destination (OD) station pairs had more than one used route, and 1420 had more than three. The survey also showed for each tube journey in London, the average number of interchanges is 1.44, while in the Shanghai Metro, it was 1.73 in 2017 (China Urban Rail Transit Association 2017).

Route choice is a comprehensive decision-making process based on each passenger's subjective perceptions of many factors, including journey time, in-vehicle crowdedness, the ease of interchange (s), etc. Interchange becomes an indispensable factor of route choice in urban rail transit as its topological structure only allows travelers to change between lines at a set of specific stations, also called interchange stations. This is quite distinctive from road and bus transit traffic, where travelers can change from one road/route to others more easily through crossings or multi-line bus stops and thus interchange does not play a significant role. The limited number of interchange options in urban rail networks makes interchange a key factor when passengers face several alternative routes between their origin and destination stations, especially when the numbers and attributes of interchange processes involved in each route are different.

Thanks to the rapid advancement of information and communication technology, Advanced Traveler Information System (ATIS) can now make use of more real-time data from both the operator side (e.g. Automatic Vehicle Location (AVL), Automated Fare Collection (AFC), Automatic Passenger Counters (APCs),

etc.), and passenger side (e.g. smart card data, mobile phone data, social media data, GPS data, etc.) (Welch and Widita 2019) to give advice to travelers for trip planning, such as route recommendation in urban rail transit. However, most ATISs do not provide 'soft' characteristics such as convenience, comfort and privacy, about which travelers often wish to be informed (Chorus, Molin, and Van Wee 2006); unfortunately, information about interchange processes is one of them. Furthermore, most ATISs have two drawbacks, which are insufficiently personalized services and carelessness of traveler diversity. Although improvements are made to overcome them by considering traveler's preferences and variety (Arentze 2013; Ceder and Jiang 2020; Kem, Balbo, and Zimmermann 2017; Nuzzolo et al. 2014, 2013), passenger perception of route attributes has not been given enough emphasis to date. Thus, the alternative routes recommended by ATISs may not suit all passengers.

Interchange provides more flexibility as passengers potentially have more feasible routes to choose from. For some OD station pairs having direct routes, routes with interchange are also competitive thanks to less time and/or crowdedness. However, it cannot be denied that interchange itself still causes inconvenience, which may lessen the appetite of passengers to use such routes (Lam and Xie 2002). The influence of interchange is mainly quantified at single-interchange and route levels. Weighted walking time between services, weighted waiting time for the connection and pure penalty, i.e. the inconvenience and risks involved in interchange, are commonly distinguished as three components of interchange disutility (Wardman and Hine 2000). Two major issues with this conception are its simplification of the pure penalty and neglect of the influence of passenger perception.

The pure penalty should theoretically consider the factors specific to each interchange process and its environment, including safety and security, ease of way-finding during interchange, availability of escalators, etc. (Guo and Wilson 2011). However, it is

usually held constant, with identical values for the same types of interchange situations regardless of interchange environments (Cheng et al. 2019; Douglas and Karpouzis 2006; Jung and Casello 2019; Ministry of Land, Infrastructure, Transport and Tourism, 2012; Transport for London 2013; Wallis, Lawrence, and Douglas 2013). There is scant literature on how environment variables influence pure penalty. Douglas and Jones (2013) have indicated that 'cross-platform transfers' at rail stations have a lower pure penalty than an 'up/down interchange', but the limited dimensionality of choice situations in stated preference surveys also restricts how interchange disutility can be directly integrated into route choice models. The influence of passenger perception has been gradually catching more attention. Hua et al. (2020) investigated metro transfer perception time (MTPT), but the limited number of transfer stations and categorized values of MTPT did not provide a clear, overall picture of how passenger perception may be affected.

For route-level modeling, the simplest way to interpret interchange is to include a dummy or nominal variable denoting how many interchanges are included in a route, along with in-vehicle time or overall journey time in the utility of a route (Wardman 2001; Wardman and Hine 2000). Although this straightforward method considers the premium cost of interchanges, it punishes all the interchanges indiscriminately without considering different interchange environments. Furthermore, interchange time is either ignored or given the same weight as other components of the overall journey time. Inspired by the study of single interchange disutility, some researchers have extracted interchange time from overall journey time and assigned it different weights from other time components (Guo and Wilson 2011; Jia et al. 2020; Liu 2013). Jin et al. (2017) introduced a perceived transfer threshold to further differentiate the weight of each interchange's time. When the number of interchanges exceeds a threshold, the weight of interchange time will increase to reflect how the attitudes of passengers change, but within one segment, each interchange's time shares the same weight.

The influence of interchange environment has been explored in other studies. Stations layout (ascending, even and descending levels) and stations infrastructure (assisted, semi-assisted, and non-assisted) attributes were introduced into route utility and were shown to have significant effects on route choice (Raveau et al. 2014; Raveau, Muñoz, and de Grange 2011). However, due to the diversity and complexity of interchange processes, whether these characteristics can sufficiently represent the effect of interchange environments remains questionable. One counterexample is for a descending level interchange, the interchange process may involve going-up in part, such as changing from Victoria line to Piccadilly line at King's Cross and St. Pancras station (Godwin 2012). Also, the semi-assisted option in station infrastructure characteristic is very ambiguous.

Guo and Wilson (2011) considered more interchange environment variables, studying the 303 interchange processes involved in the London Underground. Escalator availability, the number of stairs, horizontal distance, ramp length, and whether the two transfer platforms were at the same level were five significant influencing factors for route choice. Interchange cost was found to be unevenly distributed across stations and platforms at a station, and interchange stations are perceived very differently by passengers. However, the dummy variables that represented the involvement of specific interchange stations are not transferable for cases other than London as there was no way to externally determine the coefficients of station-based dummy variables.

No matter how interchange is quantified at the route level, its influence on route choice is usually investigated using discrete choice models based on random utility theory (Ben-Akiva, Lerman, and Lerman 1985). The multinomial logit model (MNL) is the most popular model because of its closed-form formula and ease of interpretation, however, the independence from irrelevant alternatives (IIA) property derived from the assumption of independent distributions largely limits the model's applicability and fidelity. Nested logit and other variations were then developed to overcome these problems, followed by great progress in the new Generalized Extreme Value (GEV) family of models and mixed logit models (McFadden 2001), which provide more flexibility. Particularly, mixed logit models can approximate any random utility model (McFadden and Train 2000). A more advanced version, the hybrid choice model has now been developed based on the discrete choice model to enhance the predictability of choice models (Ben-Akiva et al. 2002).

Although the above-mentioned literature has contributed to a deepened understanding of the influence of interchange on route choice, the difference between the facts of interchange and passenger perception, and their potential influence on route choice demand more attention. Passenger taste variations about interchange also need to be discussed. This research explores the influencing factors on passenger perception of interchange and integrates the perception into route choice modeling using 'perceived interchange time' to investigate how this affects passengers' route choices. The three main questions to be addressed are listed below.

a)Whether interchange environment variables have an impact on passengers' perceived interchange time? If so, how do they impact?

b)What is the best quantification of interchange in route choice modeling?

c)How do passengers weigh the different interchanges within their routes?

The remaining parts of this paper are structured as follows. Section 2 models passenger perception of single interchanges by introducing perceived interchange time and identifies the resolution of passenger perception of interchange. Section 3 specifies eight different models to investigate the best quantification of interchange in route choice models, and adopts mixed logit models to understand passenger taste variation. Section 4 introduces how the surveys were designed and carried out with a brief description of the data collected. Section 5 analyses the results of perceived interchange time prediction models and route choice models considering the influence of interchange. Lastly, Section 6 summarizes the main findings of this paper.

Passenger perception of single interchanges

Perceived interchange time

In this paper, an interchange is defined as a movement process from a passenger alighting from the train of a starting line to arrival at the platform of an ending line. Actual interchange time is defined as the difference between these two time points, with waiting time on the platform of the ending line excluded as it only depends on the operation of the line so there is no difference between interchanging passengers and other passengers waiting on the platform. The definition indicates that each interchange has a certain direction depending on its starting and ending lines, that is, an interchange station of n lines involves at least $n!$ interchanges. One special case is when a line's platforms in different directions are asymmetrically located; in this case, the interchange process needs a further split. Each interchange process is composed of several stages, which can be categorized into two types of movements, horizontal or vertical, as shown in Figure 1. Horizontal movement refers to the movement
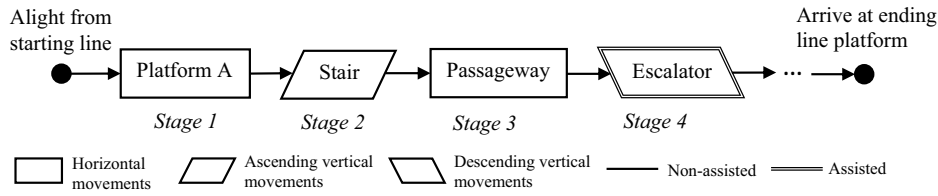
Figure 1. An example of the interchange process.

where passengers move in an open space (e.g. platform or concourse) or along a passageway or an upward/downward ramp with very little level change, while vertical movement refers to the movement where passengers move up or down mainly to change levels. Moving directions (ascending or descending) is a property specific to vertical movements. Assistance situations (non-assisted or assisted) are applicable for both. Movement with the help of moving walkway, escalator or lift is categorized as assisted movement. A continuous movement with the same movement type, moving direction and assistance situation is defined as a stage.

Perceived interchange time is proposed to quantify passenger perception of a single interchange, referring to their mental perception of the time spent for an interchange, which is the sum of a) the mean perceived interchange time, representing passengers' collective perceptions, mainly influenced by the mean of actual interchange time, interchange environment and mean perception difference and b) the random error representing individual perception deviations caused by other unobserved factors as shown in Equation (1). Perception coefficients can then be calculated as the ratio of mean perceived and actual interchange time.

$$PIT_i = \overline{PIT}_i + \varepsilon_i = \alpha + \boldsymbol{\beta}'_{\mathbf{t}}\mathbf{x_t} + \boldsymbol{\beta}'_{\mathbf{e}}\mathbf{x_e} + \varepsilon_i \quad (i \in I) \qquad (1)$$

where I is the number of interchanges; PIT_i is the perceived interchange time for interchange process I; $\overline{PIT}_i$ is the mean perceived interchange time; α is the mean difference between perceived and actual interchange time, which is identical for all interchanges; $\mathbf{x_t}$ and $\mathbf{x_e}$ are the vectors of interchange time variables and interchange environment variables, respectively; $\boldsymbol{\beta}_{\mathbf{t}}$ and $\boldsymbol{\beta}_{\mathbf{e}}$ are the vectors of coefficients; and ε_i is the random error of interchange i, which is assumed to be normally distributed with zero as its mean, $\varepsilon_i \sim N(0, \sigma_i^2)$. The perceived interchange time can be predicted using regression techniques, with the parameters α and βs estimated by the ordinary least square method.

Independent variables under hypotheses of perception resolution on interchange time

The influencing factors of perceived interchange time consist of two parts, actual interchange time and interchange environment. As the basis of passengers' perceived interchange time, actual interchange time is influenced by movement type and the assistance situation, which can be measured by surveyed time. Meanwhile, interchange environment factors mainly include:

a) interchange form, which is categorized into three types: cross-platform, in-station and out-of-station interchanges. Note that the interchange between two lines sharing the same track and platform only generates extra waiting time without additional walking time, so such cases are excluded from this study;

b) the number of shifts, representing the complexity of an interchange process, which may cause passenger mental fatigue;

c) the grade of interchange movement distance, to capture additional influences caused by long-distance movements aside from just movement time;

d) the level of assistance, reflecting the convenience of an interchange process, which is measured by the percentage of assisted distance for a specific part (process/movement/stage).

It is worth noting that the sensitivity of passenger perception of interchange time may lead to different selections of quantitative proxies for the abovementioned influencing factors. Three hypotheses of passenger perception resolution were thus put forward to explore how sensitive passengers are to perceptions of single interchanges as listed below according to resolution ascendingly.

Hypothesis I (Process-level resolution): Passengers perceive their interchange time without thinking about different types of movements or stages separately.

Hypothesis II (Movement-level resolution): Passengers perceive their interchange time with horizontal and vertical movements being separately considered. But for each type of movement, stages are not separately considered.

Hypothesis III (Stage-level resolution): Passengers perceive their interchange time with stages that have different moving directions and/or assistance situations being separately considered.

Depending on the hypotheses of perception resolution, alternative independent variables for the regression model were aggregated at different levels to represent the influencing factors (see Table 1), and then input into the regression models. After comparison, the best-performing regression model was adopted to predict the perceived interchange time for all interchanges, which is to be input in the route-level analysis. The corresponding hypothesized passenger's perception resolution, indicating the sensitivity level at which passengers perceive single interchanges, will be accepted.

The influence of interchange on route choice

The framework of route choice modeling

Based on the understanding of passenger perception of single interchanges, the influence of interchange at route level could then be investigated by modeling passengers' route choices using discrete choice methods based on random utility theory (Ben-Akiva, Lerman, and Lerman 1985). Random utility theory assumes that each passenger tries to choose a route from all alternative routes to obtain the maximum utility according to his/her perception. The utility of a route consists of two components: the representative utility influenced by explanatory factors that can be observed, such as interchange, in-vehicle time, waiting time, etc., and the random error, which captures the impact of factors that could not be observed, as shown in Equation (2).

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \boldsymbol{\theta}'_{\mathbf{n}}\mathbf{x_{nj}} + \varepsilon_{nj} \quad (n \in N; j \in J_n) \qquad (2)$$

where N is the number of passengers; J_n is the number of alternatives for passenger n depending on the specific OD pair he/she travels; U_{nj} is the utility of alternative route j for passenger n; V_{nj} is

Table 1. Alternative regressors under different hypotheses of perception resolution.

Hypothesis	Category[a]	Alternative variables	Type and value
All	Envr.	Cross-platform interchange	Nominal (0,1)
	Envr.	Out-of-station interchange	Nominal (0,1)
I: Process-level resolution	Time	Total actual interchange time (min)	Continuous
	Envr.	The grade of total interchange movement distance*	Nominal (1,2,3,4)
	Envr.	The percentage of assisted movement distance	Continuous
II: Movement-level resolution	Time	Horizontal movement time (min)	Continuous
	Time	Vertical movement time (min)	Continuous
	Envr.	The number of shifts between movements	Integer
	Envr.	The grade of horizontal movement distance*	Nominal (1,2,3,4)
	Envr.	The grade of vertical movement distance*	Nominal (1,2,3,4)
	Envr.	The percentage of assisted horizontal movement distance	Continuous
	Envr.	The percentage of assisted vertical movement distance	Continuous
III: Stage-level resolution	Time	Horizontal movement time (min)	Continuous
	Time	Ascending vertical movement time (min)	Continuous
	Time	Descending vertical movement time (min)	Continuous
	Envr.	The number of shifts between stages	Integer
	Envr.	The grade of the longest horizontal movement distance[b]	Nominal (1,2,3,4)
	Envr.	The grade of ascending vertical movement distance[b]	Nominal (1,2,3,4)
	Envr.	The grade of descending vertical movement distance[b]	Nominal (1,2,3,4)
	Envr.	The percentage of assisted horizontal movement distance	Continuous
	Envr.	The percentage of assisted ascending vertical movement distance	Continuous
	Envr.	The percentage of assisted descending vertical movement distance	Continuous

[a]Time – interchange time variables, Envr.- interchange environment variables.
[b]The grades of movement distance were determined according to quartiles based on the investigation of all interchange processes in our case study.

the representative utility of alternative route j for passenger n; $\mathbf{x_{nj}}$ is the vector of explanatory variables of alternative route j for passenger n; $\boldsymbol{\theta_n}$ is the vector of coefficients representing the weights attached to explanatory factors by passenger n; and ε_{nj} is the random error of alternative route j for passenger n.

Depending on the assumptions of the distribution of random error, various discrete choice models can be used. The most widely used is the Multinomial Logit (MNL) model, assuming each ε_{nj} is an independently, identically Gumbel-distributed extreme value. The choice probability of passenger n to choose route j in MNL models is given by Equation (3).

$$P_{jn} = \frac{e^{V_{jn}}}{\sum_{k \in J_n} e^{V_{kn}}} \qquad (j, k \in J_n; n \in N) \tag{3}$$

The specification of the utility function, especially the representative utility, reflects how different factors influence passengers' choices and their importance. To better understand how interchange influences route choice, specifications with different quantifications of interchanges were developed (Section 3.2) and analyzed by comparing the predictive performances of MNL models using corresponding specifications of utility functions. Mixed logit models with the optimal specification were further developed

(Section 3.3) and estimated to reveal the potential passenger taste variations on interchange.

Note that for each OD pair, passengers may consider a set of alternative routes with the values of their key attributes within a reasonable range compared to the shortest route. A good alternative route set will also improve the predictive power of a route choice model, as it includes used routes and excludes un-used routes as far as possible. To generate alternative route sets of high quality, a two-step procedure was applied here. The first step is adopting a depth-first searching algorithm with qualitative and slightly relaxed quantitative constraints to create initial alternative routes to cover used routes as much as possible, without worrying about including some unreasonable routes due to identical thresholds for all OD pairs because they will be filtered out later on. Then, in the second step, the initial alternative routes for each OD pair are given two ranks within the whole set by sorting them in ascending order of travel time and the number of interchanges, respectively. When one is prioritized as the major ranking criteria, the other serves as auxiliary criteria in case of ties caused by using the main criteria only. Then, routes with both ranks less than a predetermined threshold were accepted as final alternative routes to be input into route choice models. This procedure avoids arbitrary adjustments of weight combinations of link costs in labeling approach (Ben-Akiva et al. 1984) and does not only pay attention to the shortest route.

Utility function specifications

In route choice modeling, the explanatory variables of utility function mainly include passengers' socio-economic characteristics and route features. Although researchers have tried adding variables like train and station usage, topological factors, etc., travel time is still the most traditional and important variable for explaining route-choice behavior, which can be further divided into in-vehicle time, waiting time and interchange time. Besides these, the number of interchanges is commonly used to reflect the influence of interchange. As this paper investigates the influence of interchange on route choice, variables were categorized into interchange-related and non-interchange-related, with interchange time and the number of interchanges in the former category whilst in-vehicle time and waiting time at the origin station and interchange stations in the latter. Ticket fare was not considered, as it is the same between a specific OD pair in the case of the Shanghai Metro, no matter which route was chosen, but this may be of concern for other networks. The key difference of this paper from existing studies is how it broadens the concept of interchange time by allowing it to be chosen from actual interchange time and perceived interchange time, as mentioned in Section 2, with the influence of interchange environment considered.

To understand how interchange affects passengers' route choices, eight specifications were developed and compared to examine a) whether actual or perceived interchange time better quantifies the influences of interchanges, b) whether the number of interchanges should be separately considered, and c) whether passengers consider interchange processes individually or holistically. As seen in the framework of specifications shown in Figure 2, Specification 1 and 5 shared a similar structure, and so forth. Specification 1 was taken as a benchmark as it is widely used in previous studies.

Mixed logit model

Although the MNL model is widely used, its assumptions usually contradict with reality, which leads to two major problems, i.e.
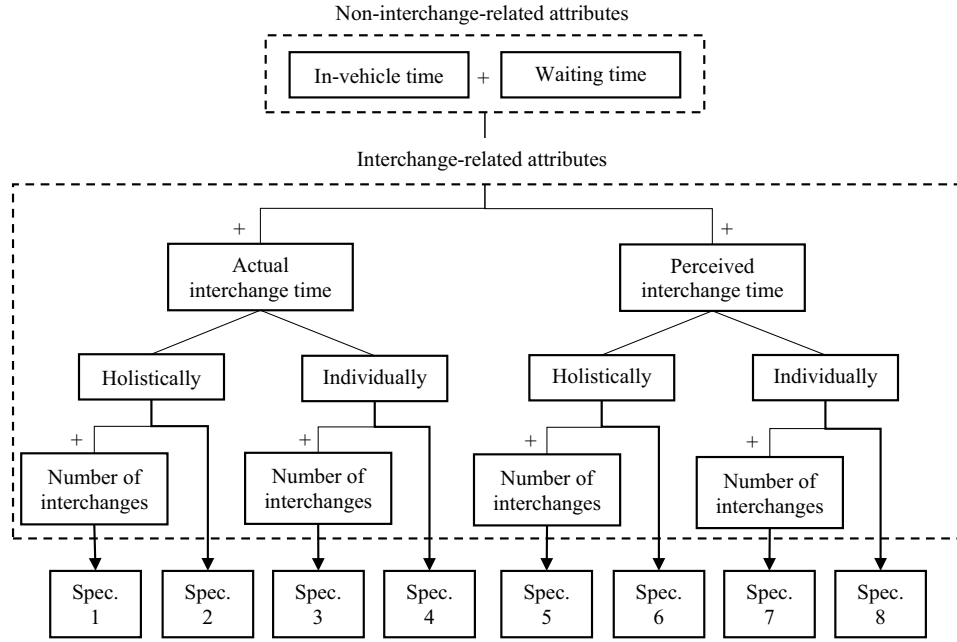
Figure 2. Utility function specifications.

there is no correlation among error terms and no taste variation among individual decision-makers. The first problem becomes severe in the context of route choice modeling in urban rail transit because the limited number of interchanges in urban railways further reduces the diversity of alternative routes for each OD pair and hence causes an extensive existence of overlap among alternative routes. Besides the inevitable and not negligible correlation among error terms, the assumption of no taste variation among passengers may also hurt the MNL model's interpretability and predictability.

To address these issues, Mixed Logit (MXL) models (McFadden and Train 2000) were adopted as they introduce random coefficients and create correlation among the utilities for different alternative routes. In an MXL model, coefficients are divided into two groups, fixed and random, as given by Equation (4). A fixed coefficient means passengers have very similar tastes such that deviations are small enough to be omitted, while a random coefficient means passengers have obvious taste variations among themselves and is composed of the average taste of all passengers and his/her deviation from this mean value, as shown in Equation (5).

$$U_{nj} = \boldsymbol{\theta'}_{\mathbf{n}}\mathbf{x}_{\mathbf{nj}} + \varepsilon_{nj} = (\boldsymbol{\theta'}_{\mathbf{f}}\mathbf{x}_{\mathbf{f}_{\mathbf{nj}}} + \boldsymbol{\theta'}_{\mathbf{r}_{\mathbf{n}}}\mathbf{x}_{\mathbf{v}_{\mathbf{nj}}}) + \varepsilon_{nj} \qquad (4)$$

$$\theta_{r_{nq}} = \overline{\theta}_{r_q} + \mu_{r_{nq}} \sim f\left(\theta_{r_q}|\boldsymbol{\varphi}_{\mathbf{r}_{\mathbf{q}}}\right) \qquad (5)$$

where $\mathbf{x}_{\mathbf{f}_{\mathbf{nj}}}$ is a $1 \times P$ vector of variables with fixed coefficients; $\mathbf{x}_{\mathbf{v}_{\mathbf{nj}}}$ is a $1 \times Q$ vector of variables with random coefficients; $\boldsymbol{\theta}_{\mathbf{f}}$ and $\boldsymbol{\theta}_{\mathbf{rn}}$ are the vectors of fixed coefficients and random coefficients for passenger n, respectively; and ε_{nj} remains the same meaning as the random error with independently, identically distributed extreme value. For random coefficients, $\overline{\theta}_{r_q}$ is the mean value of the q_{th} random coefficient representing the average taste of all passengers and $\mu_{r_{nq}}$ is the deviation of passenger n from the mean value of the q_{th} random coefficient. The random coefficient follows a distribution with density $f\left(\theta_{r_q}|\boldsymbol{\varphi}_{\mathbf{r}_{\mathbf{q}}}\right)$, where $\boldsymbol{\varphi}_{\mathbf{r}_{\mathbf{q}}}$ is a vector of distribution parameters and the number and meanings of parameters depend on

the distribution chosen (such as normal, lognormal, uniform distribution, etc.). It can be inferred that in an MXL model, the unobserved stochastic portion of utility is $\eta_{nj} = \mu_{r_{nq}} x_{r_{njq}} + \varepsilon_{nj}$, instead of random error ε_{nj} alone. Thus, correlations among alternatives are created, the patterns of which depend on the selection of attributes with random coefficients and assumptions of the distributions of taste variation. Once the utility function is specified, a mixed logit model is constructed, the choice probabilities of which are the integrals of standard logit probabilities over possible variables of coefficients. Given the choice and variable data, MXL models could be estimated using the maximum simulated likelihood method. In this paper, all MXL models were estimated by using modified Matlab codes based on the ones developed by Train (2009), with 100 modified Latin hypercube sampling (MLHS) draws (Hess et al. 2006).

Survey design and data

For analyzing passenger perception of single interchanges, detailed infrastructure characteristics and the interchange time of each interchange is indispensable. A field survey was carried out on 30th March and April 13 2017 by four groups of investigators to manually collect and double-check the data for each stage in every interchange. All of the 154 interchange processes of the 51 interchange stations in Shanghai Metro present at that point in time were surveyed, 140 of which were in-station interchanges, 2 cross-platform interchanges and 12 out-of-station interchanges. The survey excluded pseudo-interchanges between two lines or trunk and subsidiary lines at the stations where they share platforms; furthermore, interchanges from a shared platform to/from other lines were not separately considered for the platform-sharing lines.

Passengers' perceived interchange time and their route choices for route-level analysis were investigated using a specifically designed three-part survey shown in Table 2. Each respondent was instructed to answer all the questions. Only questions related to interchanges in the actual route could be skipped if the route chosen was a direct one without interchange. Besides passenger

Table 2. Survey questions for passenger perception of interchanges and route choices.

Part	Questions
I: Socio-economic characteristics and metro usage information	Gender AgeeThe frequency of traveling by metro in one week The days of traveling by metro in one week The purpose of the first metro trip on the latest weekday
II: Actual route choice used in the first metro trip on the latest weekday	The origin and destination stations and metro lines The number of interchange process in the routeeThe interchange station name of each interchange (if applicable) The starting and ending lines of each interchange (if applicable) The perceived interchange time of each interchange (if applicable)
III: Perceived interchange time of familiar interchange process	The interchange station names of the three most familiar interchanges The starting and ending lines of the three most familiar interchanges The perceived interchange time of the three most familiar interchanges

socio-economic characteristics and metro usage information, passengers' actual routes used in the first metro trip on the latest weekday and passengers' perceived interchange time for interchanges were also queried. Note that passengers' perceived interchange time was asked twice. The question in part II was defined as short-term memory-based while the ones in part III was defined as long-term memory-based. Levene's test was used to identify the difference between the two types of perceived interchange time.

The survey plan and designs were approved by Tongji University (Reference No.: 35,744) and the questionnaire was released from June to August 2017 through an online survey platform. This platform owns a database of registered users who would like to answer questionnaires. A total of 2086 people were randomly sampled from the users whose records showed they live in Shanghai and were emailed the survey link. To ensure respondents were familiar with Shanghai Metro and highly likely to have perceived interchange time based on two types of memories, each individual was filtered by being asked a) whether (s)he lives in Shanghai and b) whether (s)he uses Shanghai Metro every week. Only when both answers were 'yes', was a respondent be allowed to access the questionnaire. All the responses were checked carefully to avoid any missing,

inconsistent or incorrect answers, for example, the name of metro station or the interchange station on the route in Part II or III did not exist in the Shanghai Metro system. After removing all questionable responses, the sample was input for analysis. A total of 748 records of short-term memory-based perceived interchange time covering 144 interchanges were provided by 658 respondents who used routes with at least one interchange on the latest weekday, while 3921 records of long-term memory-based perceived interchange time covering 150 interchanges were contributed by 1461 respondents. Table 3 summarizes the socio-economic and travel characteristics of respondents for the two types of perceived interchange time. Both samples were evenly distributed in gender. Most respondents were adults, with age mainly ranging from 18 to 60 years old. For the trips on the latest weekday, commuting (either going to work or school) was the main travel purpose, accounting for 70%. Shopping and business followed with 9.88% and 8.81%. The distribution of trip purposes matched with the results reported by Shanghai travel survey (Shanghai Municipal Urban and Rural Construction and Transportation Commission et al., 2010) that the main trip purpose of rail users in Shanghai Metro is commuting. As it is also the main trip purpose for people from 18 to 60 as reported, the overall

Table 3. Respondents' socio-economic and metro usage profile.

	Short-term memory-based perceived interchange time		Long-term memory-based perceived interchange time	
Items	N	%	N	%
Gender				
Male	299	45.44	691	47.30
Female	359	54.56	770	52.70
Age				
<18	18	2.74	37	2.53
18–40	543	82.52	1223	83.71
41–60	88	13.37	188	12.87
>60	9	1.37	13	0.89
Frequency of traveling by metro per week				
1–2 times	159	24.16	431	29.50
> 3 times	499	75.84	1030	70.50
Period of traveling the metro during week				
Only weekdays	543	82.52	1145	78.37
Weekdays and weekends	115	17.48	270	18.48
Only weekends	-	-	46	3.15
Purpose of the first metro trip on the latest weekday				
Work: to go to main place of work	459	69.76	-	-
School: to go to school/college etc	12	1.82	-	-
Shopping: to go shopping	65	9.88	-	-
Business: travel in the course of work	58	8.81	-	-
Home: to go home	31	4.71	-	-
Others	22	3.34	-	-
Unknown	11	1.67	-	-
Total	**658**	**100**	**1461**	**100**

ridership and sampled respondent group tend to be young, which indicates the sample representative. More than 70% of the respondents traveled by metro more than 3 times in one week, and most of them used the metro on weekdays. This indicates the respondents surveyed were familiar with Shanghai Metro network, so their answers should be reliable.

For constructing a topological network and modeling route choice, network information, journey time between stations and waiting time of train services in the year of 2017 was either obtained from open data sources or provided by the operator of Shanghai Metro, Shanghai Shentong Metro Co., Ltd., while the surveyed interchange time was used as actual interchange time. Note that the perceived interchange time needed in the route choice models was predicted by the best regression model for the single-interchange–level analysis.

Results and discussions

Single-interchange–level regression analysis

Levene's test shows for 87.27% of interchanges, the distributions of perceived interchange time based on short-term or long-term memories had equal variances and means. For those with unequal means, the averages of long-term memory-based perceived interchange time were a little greater. It indicates passengers basically have consistent perceptions for most of the interchanges that did not change substantially over time, so the two samples of perceived interchange time could be merged for further analysis. All of the 132 interchanges with more than five respondents were chosen for regression analysis.

Figure 3 shows that perceived interchange time had a strong positive correlation with actual interchange time, while the perception coefficient was negatively correlated with actual interchange time in a non-linear way. With an increase of actual interchange time, perception coefficients gradually decreased but stayed greater than one, indicating psychological amplification played a large role, especially when actual interchange time was shorter than 2 mins. An increasing trend of perceived interchange time existed when interchange form changed from cross-platform to out-of-station as the difficulty of an interchange process increased, while the perception coefficient decreased. Because in-station interchange covered most of the interchange processes in our case, more environment variables were needed to differentiate them. Regarding the
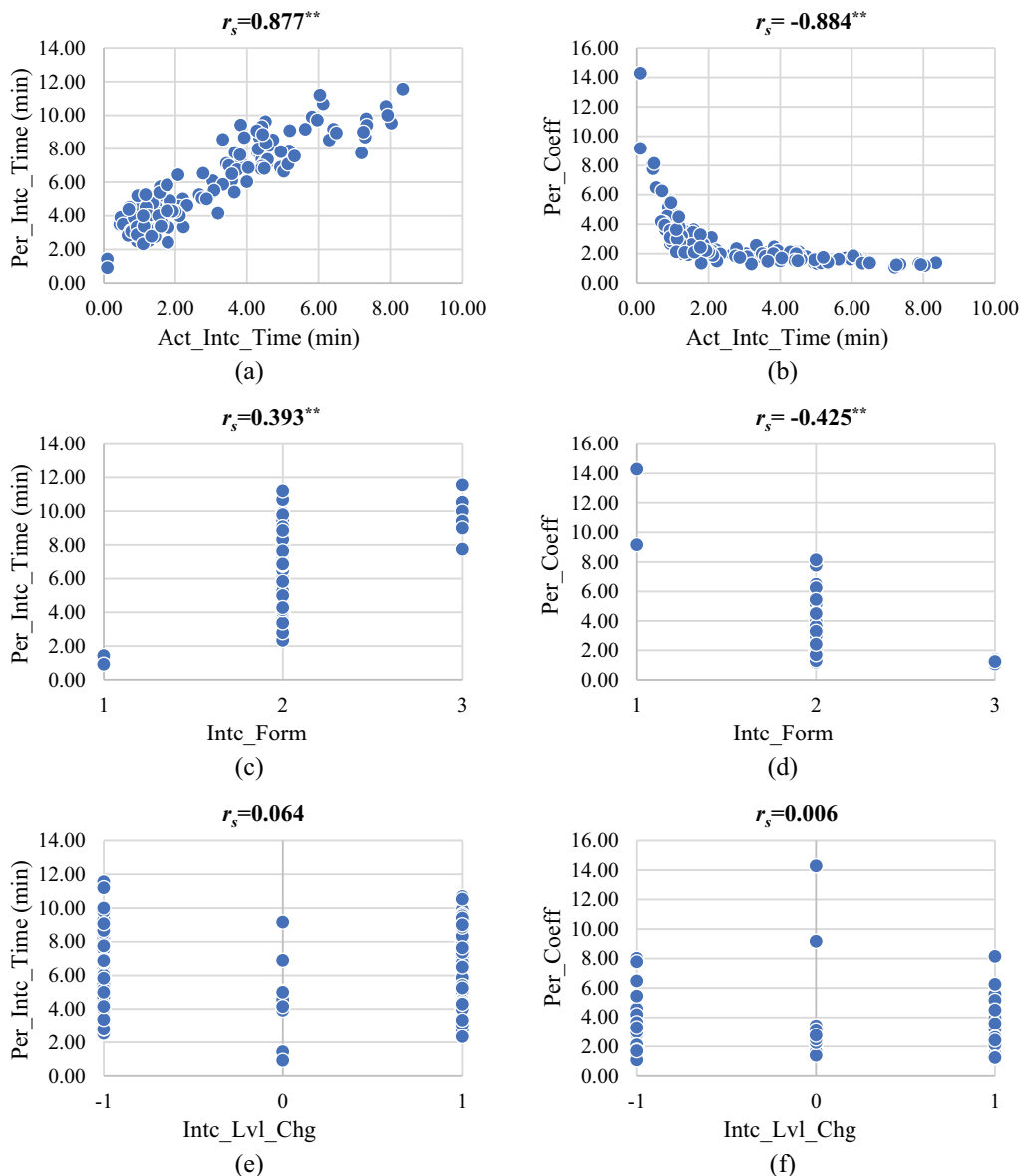

Figure 3. Correlation among five variables.

interchange-level change, it was obviously not correlated with either perceived interchange time or perception coefficient, which pointed out it could not represent the influence of environment on interchange processes. Using ascending or descending as an attribute of an interchange process, based on absolute level change, will not reflect reality and may cause distortion.

Three regression models of perceived interchange time under different hypotheses of perception resolution were constructed using the stepwise technique. The descriptive statistics of all independent variables at the process-level, movement-level and stage-level resolution are shown in Table 4. The variances in variables indicated there were wide differences among interchange processes, so that they should not be treated in the same way.

From Table 5, we can see all regression models were significant and showed relatively high predictability. The constant in each model represented the fixed part of the pure penalty, which was not influenced by environment variables. It indicated that each interchange can cause extra psychological time because interchange needs passengers to get off and on trains and may increase uncertainty. It is not surprising that actual interchange time variables in all models were significant and had positive coefficients as they are the essential components of perceived interchange time. On the other hand, interchange environment variables also had significant contributions to the models at different levels. As one of the most important environment variables, the interchange form played a large role at each resolution level. Cross-platform interchange can reduce perceived interchange time more than 1.5 min because of its least difficulty. The out-of-station interchange also had a negative coefficient, which means it can reduce perceived interchange time as well. This may seem counter-intuitive, but because passenger perception coefficients decrease as the actual interchange time rises, it could be explained as counteract the over-estimation caused by long actual interchange time for this type of interchange processes.

The best-performing model was based on process-level resolution, with an adjusted R^2 of 0.845. This suggested that passengers basically perceived interchange as a whole process rather than separate movements or stages, and perceived interchange time was formed based on general feelings. According to this result, every 1 min actual interchange time was enlarged as 1.122 min perceived interchange time, while the percentage of assisted movement distance could help passengers feel like they spent less time in interchange overall. Every 1% increase could reduce 0.034 min perceived interchange time, which implies more assistance infrastructure could be introduced to shorten perceived interchange time.

Table 4. The descriptive statistics of independent variables at different levels.

Hypo-thesis	Independent variables	Mean	Std. Dev	Min	Max	LQ[a]	Median	UQ[a]
All	Cross-platform interchange	0.02	0.12	0.00	1.00	0.00	0.00	0.00
	Out-of-station interchange	0.05	0.22	0.00	1.00	0.00	0.00	0.00
Process-level	Total actual interchange time (min)	3.03	2.06	0.10	8.35	1.32	2.28	4.43
	The grade of total interchange movement distance	2.47	1.15	1.00	4.00	1.00	2.00	4.00
	The percentage of assisted movement distance	0.09	0.07	0.00	0.34	0.05	0.08	0.13
Movement-level	Horizontal movement time (min)	1.88	1.59	0.08	6.38	0.57	1.26	2.81
	Vertical movement time (min)	1.07	0.60	0.00	3.04	0.70	1.00	1.33
	The number of shifts between movements	4.27	3.12	0.00	15.00	3.00	3.00	5.00
	The grade of horizontal movement distance	2.48	1.14	1.00	4.00	1.00	2.00	4.00
	The grade of vertical movement distance	2.44	1.15	1.00	4.00	1.00	3.00	3.00
	The percentage of assisted horizontal movement distance	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	The percentage of assisted vertical movement distance	0.73	0.36	0.00	1.00	0.67	0.91	1.00
Stage-level	Horizontal movement time (min)	1.88	1.59	0.08	6.38	0.57	1.26	2.81
	Ascending vertical movement time (min)	0.52	0.51	0.00	2.59	0.16	0.40	0.71
	Descending vertical movement time (min)	0.55	0.50	0.00	2.59	0.19	0.43	0.72
	The number of shifts between stages	4.40	3.13	0.00	15.00	3.00	3.00	5.00
	The grade of the longest horizontal movement distance	2.46	1.14	1.00	4.00	1.00	3.00	3.00
	The grade of ascending vertical movement distance	2.42	1.12	1.00	4.00	1.00	2.00	3.00
	The grade of descending vertical movement distance	2.49	1.13	1.00	4.00	1.00	2.00	4.00
	The percentage of assisted horizontal movement distance	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	The percentage of assisted ascending vertical movement distance[b]	0.60	0.46	0.00	1.00	0.00	0.91	1.00
	The percentage of assisted descending vertical movement distance[b]	0.60	0.45	0.00	1.00	0.00	0.86	1.00

[a]LQ – the lower quartile; UQ – the upper quartile.
[b]The undetermined values caused by dividing by zero are substituted by zero.

Table 5. Estimation results of regression models based on different perception resolutions.

	Process-level		Movement-level		Stage-level	
Variables	θ	t-value	θ	t-value	θ	t-value
Constant	2.848***	13.932	2.391***	8.325	3.007***	17.428
Cross-platform interchange	−1.785**	−2.547	−1.769**	−2.351	−2.003**	−2.611
Out-of-station interchange	−1.624***	−3.691	−1.160*	−1.916	−1.975***	−3.900
Total actual interchange time (min)	1.122***	23.049	-	-	-	-
The percentage of assisted movement distance	−3.440***	−2.899	-	-	-	-
Horizontal movement time (min)	-	-	0.967***	5.326	1.316***	14.339
Vertical movement time (min)	-	-	0.592**	2.576	-	-
The grade of horizontal movement distance	-	-	0.428*	1.847	-	-
The number of shifts between stages	-	-	-	-	0.106**	2.548
F-value	179.845***		144.935***		138.753***	
Adjusted R^2	0.845		0.818		0.808	

***p ≤ 0.01.
**p ≤ 0.05.
*p ≤ 0.1.

This finding clearly pointed out that the pure penalty should be determined based on environment variables of each interchange process, especially its interchange form and level of assistance, instead of an identical value for all interchange processes in most applications. Higher expediency would greatly change passengers' impression and reduce their perceived interchange time of one interchange process. This gave some implications for both transport designers and operators. When an interchange process is being designed, the cross-platform form is worth more priorities than in-station and out-of-station forms if available. For existing interchanges, more effort could be put in upgrading their ease of use by installing more infrastructure to assist passengers' movements, both horizontally and vertically.

Route-level discrete choice model considering the influence of interchange

All route choice models were estimated with the actual route choices of respondents in Shanghai Metro network. The records of eight passengers who took unnecessarily tortuous routes were screened out to avoid generating superfluous alternative routes and estimation bias, hence, 650 passengers' route choices were used for estimating route choice models. A total of 520 passengers' route choices (80%) were used for estimation, while the remaining 130 passengers' route choices (20%) for validation in MNL models. Stratified sampling according to each OD pair's shortest travel time was adopted to avoid bias. Alternative route sets were generated with quantitative constraints being 25 min for absolute difference, 100% for relative difference and 3 for the maximal number of interchanges in the first step and the predetermined rank threshold

being 5 in the second step. A total of 3906 alternative routes were generated, on average six routes for each OD pair.

Table 6 presents the estimation results of multinomial logit models with different utility function specifications. Most variables passed significance tests except the actual interchange time of the third interchange in Model 3 and the number of interchanges in Model 7. Log-likelihood is an indicator of the relative explanatory power of a model. Less negative values in the log-likelihood are associated with a greater ability of a model to explain the pattern of choices in the data, while adjusted Rho-squared is used to measure the goodness-of-fit describing how well a model fits a set of observations. For models with similarly structured specifications shown in Figure 2, the results indicated that the model using perceived interchange time always outperformed the model using actual interchange time, no matter whether interchange processes were considered individually or holistically or the number of interchanges was added. The higher predictive ability provided strong evidence that perceived interchange time better quantified the influence of interchanging, not only because it included the perception influence but also because it integrated environment variables.

After knocking out models with insignificant variables, the models with Specifications 1 and 8 were the best models for those using actual interchange time and perceived interchange time, respectively. For the model applying actual interchange time, it was better to represent the influence of interchange by total actual interchange time and separately considering the number of interchanges. However, the same was not true for the models using perceived interchange time. In that case, passengers consider interchange processes individually without the influence of the number of interchanges. This difference could be understood as the

Table 6. Estimation results of multinomial logit models with different specifications.

	Actual interchange time applied				Perceived interchange time applied			
Specification	1	2	3	4	5	6	7	8
In-vehicle time	−0.325***	−0.310***	−0.330***	−0.322***	−0.331***	−0.329***	−0.337***	−0.338***
	(−12.354)	(−12.737)	(−12.306)	(−12.574)	(−12.351)	(−12.598)	(−12.296)	(−12.347)
Waiting time	−0.573***	−1.360***	−0.548***	−1.004***	−0.608***	−1.045***	−0.576***	−0.656***
	(−3.811)	(−13.563)	(−3.621)	(−8.327)	(−3.999)	(−9.998)	(−3.743)	(−4.830)
Interchange time								
Total	−0.324***	−0.429***	-	-	−0.307***	−0.395***		
	(−6.526)	(−9.389)			(−6.767)	(−10.013)		
1st interchange	-	-	−0.287***	−0.295***	-	-	−0.260***	−0.263***
			(−5.264)	(−5.492)			(−5.242)	(−5.331)
2nd interchange	-	-	−0.472***	−0.760***	-	-	−0.501***	−0.584***
			(−4.341)	(−7.515)			(−5.045)	(−8.729)
3rd interchange	-	-	−0.958	−1.747***	-	-	−0.570**	−0.701***
			(−1.813)	(−2.993)			(−2.485)	(−3.560)
The number of interchanges	−2.444***	-	−2.060***	-	−1.600***	-	−0.653	-
	(−6.172)		(−4.589)		(−3.683)		(−1.097)	
Log-likelihood	−218.59	−240.26	−216.89	−228.08	−216.86	−224.07	−214.29	−214.90
Adjusted ρ^2	0.757	0.732	0.762	0.748	0.759	0.750	0.765	0.763

***$p \leq 0.01$.
**$p \leq 0.05$.
*$p \leq 0.1$.

Table 7. Estimation result of mixed logit route choice model.

		μ		σ		Relative weights
Variables		Value	t-value	Value	t-value	
In-vehicle time	Random	−0.424***	−8.070	0.139***	3.227	1.000
Waiting time	Fixed	−0.770***	−4.489	-	-	1.816
Interchange time						
1st interchange	Random	−0.335***	−4.711	0.320***	2.766	0.790
2nd interchange	Fixed	−0.686***	−7.286	-	-	1.618
3rd interchange	Fixed	−0.823***	−3.316	-	-	1.941
Log-likelihood	210.825					
Adjusted ρ^2	0.770					

***$p \leq 0.01$.

perceived interchange time has already considered the fixed part of the pure penalty, so there was no need to count it twice, and individual perceived interchange time can represent diverse interchange processes more properly. The model with Specification 8 had the best performance, with an adjusted Rho-squared of 0.763. For the training set with 520 passengers' records, the model's hit rate of alternatives was 94.7%, while the one for the choice condition was 84.2%. For a test set with 130 passenger records, the hit rate of alternatives was 94.1% while the one with the choice condition was 81.5%.

Based on this specification, the MXL models were developed with all coefficients initially assumed to be random with normal distributions. According to the estimation results, coefficients with insignificant standard deviations were removed from random coefficients. The final estimation result in Table 7 shows all coefficients were significant and the adjusted Rho-squared increased to 0.770, indicating the MXL model's predictive value exceeded all MNL models. It demonstrated that passengers only had taste variations in terms of in-vehicle time and the perceived interchange time for the first interchange on a route, with a 0.139 and 0.320 as standard deviation, respectively. The coefficients of the other three attributes had very little deviation, so they were regarded as fixed. In other words, passengers perceived the unit disutility of the first interchange differently but agreed on the ones of the other two interchanges.

The relative weights, calculated by dividing the mean values of coefficients by the one of in-vehicle time showed that 1 min waiting time equaled 1.816 min in-vehicle time, which is close to 2.0 times applied by many transport authorities. The weights of perceived interchange time increased sequentially. The weight of the first interchange time was the smallest, equivalent to 0.790 min in-vehicle time; meanwhile, the weights of the second and third interchanges were much higher, 1.618 and 1.941 min in-vehicle time, respectively. The interchange time of the first interchange may have been weighted less than in-vehicle time because perceived interchange time had already magnified actual interchange time by adding a fixed value (2.848 min).

The relationship among the weights for different interchanges interestingly shows that the influence of interchange did not linearly increase. The ratio of coefficients between the first and second interchange was 2.048, while the ratio between the second and third interchange was only 1.200, so the rate of increase declined as the number of interchanges went up. This also implies that for the same interchange process, if its order on a route is different, passengers may give it different weights. If one route includes more than one interchange, then the later an interchange happens, the bigger negative impact each unit of perceived interchange time will have. This finding was different from Wardman and Hine (2000), who found that the second interchange had a smaller effect than the first.

The models suggested that in future information provision systems information about interchange processes should be provided and route recommendations for passengers should not only focus on in-vehicle time, total journey time, and the number of interchanges, but also pay attention to the perceived interchange time and the order of each interchange. Every single interchange on a route has a different influence on passengers' route choices and the influence of passenger perception should not be ignored. Information about interchanges could help passengers to pick their most preferred routes. When passengers are facing different alternative routes with the same in-vehicle and waiting time but different interchanges, they do not always choose routes with fewer interchanges, because more interchanges does not definitively mean more

inconvenience and disutility. For example, two cross-platform interchanges might outperform an out-of-station interchange in some circumstances. For one interchange, when it occurs in a particular route will also affect how much influence it will have. The diverse combinations of interchanges in alternative routes play a large part in passengers' final route choice decisions.

Conclusions

Interchange is an important part of an urban railway network that helps passengers travel more efficiently but may cause some inconvenience. This paper investigates how interchange affects passengers' route choices in urban rail transit, at both single-interchange and route levels. The main findings of this study are summarized as follows:

- Passenger perception did magnify the interchange time and should be considered. Perceived interchange time was a good representative of the influence of interchange at the single-interchange level. It is larger than actual interchange time due to the influence of passenger perception at interchange process-level, with the ratio between them decreasing with the increase of actual interchange time, but always greater than one.
- Interchange environment variables did have an impact on passenger perception, so it could be inferred that pure penalty in traditional applications should not be an identical value but vary accordingly. Cross-platform and out-of-station interchange may have a lower pure penalty while a higher level of assistance could help reduce perceived interchange time.
- The best way to quantify the influence of interchange on route choice was by using perceived interchange time on one route individually, without the number of interchanges. Perceived interchange not only took different interchange processes into account but also captured the impact of the number of interchanges and their orders.
- The weights varied among interchanges with different orders on one route. The later an interchange happened on a route, the bigger negative impact each unit of perceived interchange time had. Regarding variance, passengers only showed taste variations in terms of the perceived interchange time of the first interchange on a route.

These findings will help better predict the route choices of passengers in demand modeling and provide more helpful information to passengers for route choice in ATIS. By further introducing crowding impacts in the future, the route choice model can be developed as a part of dynamic transit assignment models to predict passenger patterns when a brand-new or modified urban rail network is proposed.

ORCID

Yan Cheng http://orcid.org/0000-0003-2946-5322

Data availability statement

The data that support the findings of this study are available from the corresponding author, Y. Cheng, upon reasonable request.

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