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Transfer penalties in multimodal public transport networks

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ABSTRACT

The disutility of transfers in multimodal public transport goes beyond the additional walking and waiting times. Although the magnitude of this pure transfer penalty has been proven to be an essential element in the structural design of public transport lines, the scarce available research reveals a wide range of values. The aim of this paper is to develop and apply a framework to estimate the value perceived and assigned by commuters to this penalty. This framework includes all the other elements considered by users in the case of a trip involving (potential) transfers, in order to obtain the impact of each one. The framework is based on the discrete choices paradigm and applied to data collected in Madrid, Spain. The results show that the pure transfer penalty is comparable to a 15.2–17.7 equivalent increase in in-vehicle minutes; i.e. longer trips may be preferred to faster alternatives with transfers, even if the additional walking and waiting times are zero. As well as the pure transfer penalty, the model also captures the effects of habit, crowding, walking, waiting and in-vehicle times, information, and the additional effect of intermodality on transfers.

1. Introduction

Continuing a recent upward trend, in 2014, 46% of the population of OECD countries lived in urban areas (OECD, 2016), due to the environmental conditions, economic opportunities and the availability of services. The business, cultural, communication, mobility and everyday requirements of city residents will therefore continue to rise and affect urban travel demand. 64% of total trip-kilometres in 2014 were made in urban environments, and this figure is expected to triple by 2050 (Van Audenhove et al., 2014), resulting in higher emissions, traffic congestion, overloaded infrastructures, scarcity of parking places, higher public transport (PT) demand and urban sprawl, among others.

Transport networks in general and PT networks in particular must be optimised and well-designed to respond to increasingly complex travel patterns in urban areas. The attractiveness of the PT network compared to the car can be increased by reducing barriers to transfers (Nielsen and Lange, 2007). Unimodal and multi-modal PT networks generally involve transfers, points where PT lines intersect within the design of a PT network and where users have to –or choose to– move from one vehicle to another. Hub-and-spoke or feeder-trunk systems impose transfers on a subset of users while direct services do not (Fielbaum et al., 2016). Existing transfer points induce a sub-problem in the design of bus or tram stops and subway or train stations, as many PT users need to transfer

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between different modes to complete their daily trips (Jang, 2003; Hernandez et al., 2016). At a higher level, the design of PT networks requires the study of the spatial arrangement of PT lines to decide *a priori* if transfers are in fact optimal. A current priority in the field of urban mobility is to reduce users' perceived disutility while transferring in order to increase ridership (European Commission, 2013). We believe that the need to transfer itself should also be subjected to scrutiny.

The main aim of this paper is to develop and apply a framework to estimate the penalty perceived by commuters when making transfers in multimodal urban trips. The framework is designed to control for all other elements considered by the users when a trip involves (potential) transfers, to obtain the impact of each one (walking, waiting, in-vehicle time). The relevance of the number of transfers required on a trip is also examined based on the discrete choices paradigm, and applied to data collected in Madrid, Spain. The remainder of this section describes previous efforts to capture the perception of transfers in general.

Several authors have investigated the perception of transfers between different modes of transport and the importance of optimising transfer time for multimodal trips (e.g. Ceder et al., 2013a; or Guo and Wilson, 2011), while other studies have analysed the users' perceptions of transfers from different perspectives (e. g. Cheng and Tseng, 2016; Chowdhury et al., 2014; Guo, 2003; Horowitz and Zlosel, 1981; Navarrete and Ortuzar, 2013). The transfer disutility –known as the transfer penalty– has three different elements: waiting time, walking time from one vehicle to another, and the inconvenience of the transfer itself, which is also known as 'the pure transfer penalty'. Although most studies propose policy measures to reduce the disutility perceived by users when transferring, the third component is impossible to avoid.

Even in an ideal transfer in which walking and waiting times were equal to zero, users would perceive a pure transfer penalty related to factors like the availability of adequate information, safety, security, comfort and convenience, familiarity with the PT system, and frequency of PT use (Currie, 2005; Iseki and Taylor, 2009; Douglas and Jones, 2013). It should be noted that these studies address transfer penalties by focusing on only one transfer; perceptions can be assumed to be different for each transfer depending on its location and number in a complete journey. McCord et al. (2006) and Cheng (2010) stated that reliability issues, lack of information about connections and personal safety while transferring in PT services contributed to anxiety in PT users. The presence of an anxiety factor has recently been reinforced by the results of Cascajo et al. (2016) using focus groups, who found that individuals consider two elements when assessing a transfer within a trip: mental effort and activity disruption.

It is still not clear how far the pure transfer penalty affects the users' choice of different alternatives, some of which involve transfers. Gschwender et al. (2016) and Fielbaum et al. (2016) established that the consideration of a pure transfer penalty is a key element when designing the structure of PT lines in a city: *"Although several parameters play an important role, the value of the transfer penalty is particularly relevant. This makes the empirical study of transfer perception a key element in the immediate agenda of public transport design"* (Fielbaum et al., 2016, page 309). It is evident from such findings that transport planners should consider the value of the pure transfer penalty when designing a PT system, noting that some commuters even choose not to travel by PT if the trip involves a transfer.

The present study aims to achieve its objective by defining the following research questions:

- How does the pure transfer penalty influence users' choice of different alternatives involving transfers?
- How do PT users perceive each component of a transfer when making transfers in a multimodal urban trip?
- Are there significant differences in the perception of transfer penalties when making one and two transfers?

This paper is organised as follows. Section 2 shows the theory applied to model transfers in PT. Section 3 presents the case study, the modelling of utility functions, and the survey design and deployment. Section 4 describes the calibration of the Error Component Logit (ECL) model. Section 5 contains the analysis of the results, and finally Section 6 provides some recommendations for transport managers and the main conclusions of the study.

2. Modelling transfers in public transport

2.1. The analytical framework

The essence of our model lies in the formulation of a generic utility specification capable of representing alternatives that differ in (a) the number of transfers; (b) the modes used in each segment of the trip; (c) the characteristics of the transfer site; and (d) the trip conditions. For our purposes it is particularly relevant to capture what we call the pure transfer penalty, and the variable that does this is precisely the number of transfers. This pure effect is incorporated by defining constants associated to each transfer (if any), so it captures this effect for the first and second transfer, which not only allows us to find the values but to test whether the effect changes with quantity. It should be noted that it includes other factors that can influence choice, some of which are unknown to us; however, if they are present in all the alternatives, they will not affect the difference between constants, which can be interpreted as the relative perception of the pure transfer penalty. This approach assumes that the utility function is well suited to capturing the mental effort associated to an activity disruption (related to the pure transfer penalty) through constants. The generic utility specification is:

$$U(T_j) = \alpha_j + \sum_k \beta_{kj} x_{kj} \tag{1}$$

where $U(T_j)$ represents the utility associated to the number of transfers (j); (β) are the coefficients weighting the attributes (x) of the individual's alternative or choice situation in the (k) spectrum; and (α) is a constant which captures other factors unknown to us: the pure transfer penalty.

In order to estimate the systematic component of utility in Eq. (1) we will use the discrete choices paradigm within the random utility theory. As is well known, this corresponds to a conditional indirect utility function that contains the variables describing the alternatives that are assumed to influence choice (Jara-Diaz, 2007). For synthesis, the random utility theory postulates that individuals (q) choose among different alternatives (A_j) on the basis of their utility (U_{jq}). The modeller assumes that the utility can be measured as a sum of two components: first, a representative utility function (V_{jq}) that can be measured from attributes (x) of the individual's alternative or choice situation, weighted by coefficients (β); the second is a random term (ε) representing the difference between the systematic component and the real utility. This is shown in Eq. (2):

$$U_{jq} = V_{jq} + \varepsilon_{jq} = \sum_k \beta_{jk} X_{jkq} + \varepsilon_{jq} \tag{2}$$

Errors are assumed to have a zero mean. If they are distributed identically and independently (IID) Gumbel, the probability that an individual chooses a particular alternative (A_j) from the available choice sets (A_q) is given by the Multinomial Logit (MNL) model as shown in Eq. (3) (Domencich and McFadden, 1975).

$$P_{iq} = \frac{\exp(\mu V_{iq})}{\sum_{A_j \in A_q} \exp(\mu V_{jq})} \tag{3}$$

where μ is a non-identifiable scale factor that must be normalised. The factor is related to the standard deviation of errors, and is usually set at one, assuming that the explanatory variables are accurate. However, the MNL model has some limitations: (a) it assumes the independence of irrelevant alternatives; (b) it does not consider the order (where relevant); (c) random preferences cannot be represented; (d) it assumes the utility functions of the alternatives are homoscedastic; and finally, (e) it assumes that all observations are independent. As we will now see, some of these assumptions do not hold when dealing with transfers in the way we consider appropriate.

Stated Preference experiments are a powerful tool for considering alternatives that do not currently exist. This allows participants to face hypothetical alternatives with a similar attraction and form a set of different choice situations, which is why we chose this method to obtain and create the database. This implies that observations will be dependent, as each participant is given many choice situations, which clearly erodes assumptions (a) and (e) of the MNL model. We therefore decided to move towards the ECL model in the Mixed Logit family to allow correlation between each participant's responses and the dependency between alternatives, correcting for potential heteroscedasticity.

The ECL model is similar to the MNL in Eq. (2) except that it adds an additional error term (η_{jq}) which does not fulfil the properties of ε and can be distributed as the modeller sees fit (Eq. (4)). The ECL is well known for its modelling potential, offering a multinomial logit kernel and inter-alternative and inter-observation correlation of random terms (Ortuzar and Willumsen, 2011). It is estimated using the simulated maximum likelihood method, which finds the coefficients that make the observed data most likely to explain the model accurately.

$$U_{jq} = V_{jq} + \varepsilon_{jq} + \eta_{jq} = \sum_k \beta_{jk} X_{jkq} + \varepsilon_{jq} + \eta_{jq} \tag{4}$$

Errors (η_{jq}) are usually assumed to be normally distributed and allow for a correct treatment of the correlation between the participants' responses.

2.2. Generating data to capture the effects of transfers in public transport

In terms of data, Bradley and Daly (1997) highlight the desirability of combining the strongest features of revealed preferences (RP) and stated preferences (SP) designs. This is why in the general case of transfers, many researchers have assessed the penalties associated with their different components by designing surveys containing both RP and SP (Chowdhury et al., 2014; Douglas and Jones, 2013; Espino et al., 2007; Navarrete and Ortuzar, 2013; Schakenbos, 2014). The use of SP surveys has become common in a wide range of fields such as marketing, transport, health economics, and agricultural and environmental economics (Cherchi and Hensher, 2015), and can elicit responses regarding the behaviour of a single individual or group in order to estimate and identify their preferences.

SP methods have been widely used in the transport field since the 1980 s (Bates, 1988; Bradley and Daly, 1997; Chowdhury et al., 2014; Chowdhury et al., 2015; Douglas and Jones, 2013; Hensher, 1994; Navarrete and Ortuzar, 2013; Schakenbos, 2014), and can be effectively applied to estimate transfer penalties as they measure perceptions and attitudes. As antecedents, Douglas and Jones (2013) describe a SP survey designed to test the difference between 'same platform' and 'up and down' transfers involving escalators or elevators, as well as bus-to-bus and bus/rail transfers, using pair-wise choices presented on electronic tablets. Navarrete and Ortuzar (2013) investigated users' subjective valuations of the transfer experience and the influences of certain variables on transferring between PT modes. Their analysis comprised a qualitative study based on focus groups, a quantitative study consisting of an SP experiment, and the estimation of advanced discrete choice models. Finally, Schakenbos (2014) used an SP design to determine the disutility of a transfer between bus/tram/metro and train to estimate a general mixed logit ECL. The results provide insights into the importance of the different attributes, which are expressed in generalized travel time. Recently, Frei at al. (2017) included the possibility of two transfers in a study of a *"hypothetical flexible transit mode"* competing with the car, using SP but not controlling for other factors such as crowding, real-time information and so on. The research questions posed in the Introduction are therefore still highly relevant.

3. Case study

3.1. City characteristics

The proposed framework was applied to PT users in the inner core of Madrid, the capital of Spain, which has a population of 3.2 million and a density of 5232 inhabitants per km^2. The city of Madrid registers a total of 4 million trips, 69% of which are by bus, metro, light rail and suburban train (CRTM, 2005). The urban bus service is 3562 km in length, has over 200 lines, and around 1900 vehicles (MMO, 2016). The metro network also plays a key role in the city, with 13 lines covering a total length of 287 km. This study focuses on the bus and metro systems, as they are the main urban transport modes in the central core and account for 85% of the total PT trips every working day (CRTM, 2005). Our estimates indicate that approximately 56% of inner circle commuters make a single transfer, while 21% transfer more than once, highlighting the importance of optimising transfers to achieve an efficient and high-quality system.

3.2. Preliminary methodological background

According to Iseki and Taylor (2009), transfer penalties vary between cities, so city-specific studies require a more accurate identification of the variables. Before conducting the RP and SP survey, we identified the most relevant variables potentially affecting the perception of transfers in Madrid by combining a generic literature review with three specific focus groups (see Cascajo et al., 2016). The variables obtained and their corresponding measures are the following:

- Mode: 1 if metro, 0 if bus.
- In-vehicle time: time (min) elapsed while a person is inside a vehicle.
- Walking time: time (min) elapsed from the moment a traveller alights from a vehicle and walks to the next stop or station.
- Waiting time: time (min) elapsed at a stop/station awaiting the arrival of the next vehicle.
- Stairs: takes value 1 if there are stairs (or a difference in level) while transferring and 0 otherwise (it is always 0 in bus-bus transfers).
- Real-time information: takes value 1 if there are panels with dynamic time arrival for the entire intended trip and 0 otherwise.
- Crowding: takes value 1 if the transfer is overcrowded (involving walking and waiting stages) and 0 otherwise.

Cost was not considered a relevant variable for transfers in the focus groups, as 73% of PT users in Madrid have a flat-rate monthly or annual travel card (higher in the commuter group), and the remaining users travel with a 10-journey pass (18%) which offers a discount of up to 40% off each single ticket; only 9% use single tickets. There is no extra cost for metro-metro transfers (only bus-metro or bus-bus). The vast majority of commuters therefore assume the cost as an unchanging variable when travelling on PT, regardless of the number of transfers. Although this prevents the calculation of willingness-to-pay, the key question is the equivalence between the perception of transfers and the minutes spent in-vehicle while travelling. This equivalent in-vehicle minutes (EIVM) is the usual way of reporting and using the disutility of transfers in the literature (e.g. Fielbaum et al., 2016), and can be calculated in our specification.

Based on the discussion above, the generic formulation in Eq. (1) was specified as three equations including the variables. Eqs. (5) (7), shown below, refer to alternatives with zero, one or two transfers respectively. In our particular case (i) varies from zero to two. Our estimates show that only 3% of commuters transfer more than twice in Madrid in their daily trips. (α_i) is equal to zero when there is no transfer. It should be noted that other constant attributes which take the same value in each alternative (i.e. real-time information, stairs, and crowding) cannot be present in all utility functions, as we need a reference case to estimate relative differences.

$$U(T_0) = \beta_{tveh00}\cdot tveh0 + \beta_{mode00}\cdot mode0 + \eta_0 \tag{5}$$

$$\begin{aligned} U(T_1) = {} & \alpha_1 + \beta_{tveh01}\cdot tveh0 + \beta_{mode01}\cdot mode0 + \beta_{twalk11}\cdot twalk1 + \beta_{twait11}\cdot twait1 + \beta_{stair11}\cdot stair1 + \beta_{tveh11}\cdot tveh1 + \beta_{mode11}\cdot mode1 \\ & + \beta_{info1}\cdot info + \beta_{crowd1}\cdot crowd + \eta_1 \end{aligned} \tag{6}$$

$$\begin{aligned} U(T_2) = {} & \alpha_2 + \beta_{tveh02}\cdot tveh0 + \beta_{mode02}\cdot mode0 + \beta_{twalk12}\cdot twalk1 + \beta_{twait12}\cdot twait1 + \beta_{stair12}\cdot stair1 + \beta_{tveh12}\cdot tveh1 + \beta_{mode12}\cdot mode1 \\ & + \beta_{twalk22}\cdot twalk2 + \beta_{twait22}\cdot twait2 + \beta_{stair22}\cdot stair2 + \beta_{tveh22}\cdot tveh2 + \beta_{mode22}\cdot mode2 + \beta_{info2}\cdot info + \beta_{crowd2}\cdot crowd + \eta_2 \end{aligned} \tag{7}$$

A pilot survey with an efficient design was then created using Ngene, a software whose inputs are the variables identified, plus prior parameters and balanced levels drawn from the literature (proposed utility functions for Ngene). Finally, the pilot survey was conducted and an MNL model was calibrated to obtain improved prior parameters using the Limdep NLogit software, before designing the final survey to be given to the participants. Fig. 1 shows the procedure (described in detail in Cascajo et al., 2017) that feeds the model estimation described in the bottom-left corner.

3.3. Survey design

This study combines RP and SP designs to measure users' perception of transfers, and to address the pure transfer penalty phenomenon. The survey provides both the RP data on current travel behaviour and the SP data on route choices under scenarios

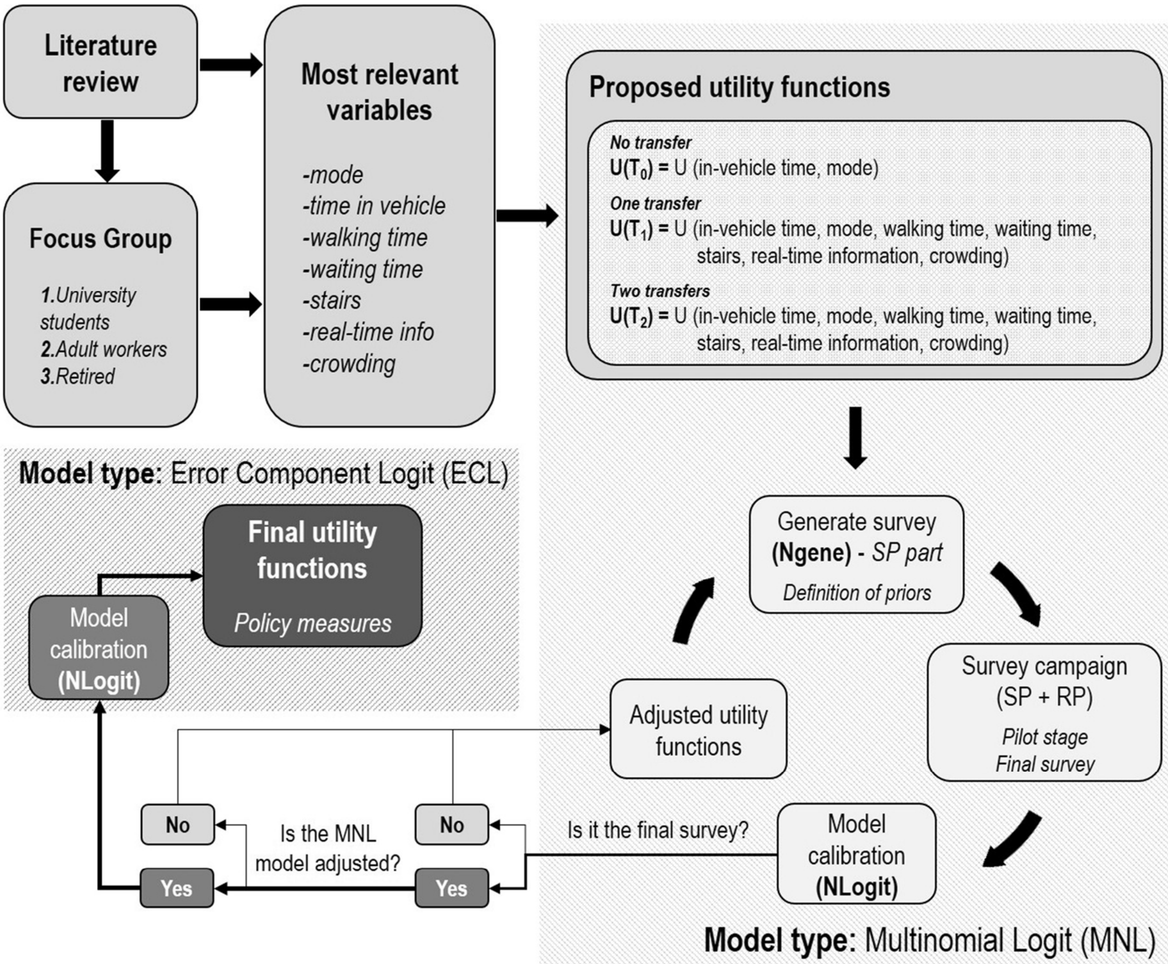

Fig. 1. Methodological chart.

with different types and number of transfers. In line with other researchers (Chowdhury et al., 2015; Navarrete and Ortuzar, 2013), the survey was restricted to commuters due to their higher transfer rates and their ability to imagine hypothetical scenarios (Currie and Loader, 2010). It was divided into three main parts: (A) trip characteristics based on current travel behaviour (RP data); (B) SP choice scenarios; (C) socio-economic/personal information.

Participants were first asked about the characteristics of their daily commute, including all the variables described in Section 3.2 and others (Part A). They were questioned about their occupation, trip purpose, type of ticket purchased, trip origin and destination, trip start time, number of transfers currently made, and other aspects of the trip such as total travel time, waiting and walking time, modes of transport used, in-vehicle time, whether they used mobile apps to see the waiting time for the next vehicle, existence of real time information panels during transfers, and whether they engage in any activity during the trip (listening to music, reading, studying, sleeping and others).

Part C gathered socio-economic and personal information. The questions included gender, age, educational level, household income and household size. There were also some questions about the importance of and satisfaction with certain aspects of transfers (real-time information and mobile network coverage during transfers, or sheltered stops and seating at transfer points). There was an open-ended question for participants to include additional comments.

In Part B, the SP questions must take into consideration the real values of the attributes in the case study in order to present realistic choice situations. Attributes may vary under predefined values at different levels. The questions were designed using Ngene software based on a multi-criteria approach, which compares a number of alternatives in different choice situations on the basis of utility functions.

The final survey was developed based on the pilot survey (see Cascajo et al., 2017) by applying an efficient design, which outperforms orthogonal designs when there is *a priori* information available on the parameters (priors) in cases where this information is correct or similarly stated to be of good quality (ChoiceMetrics, 2014; Rose et al., 2008; Rose and Bliemer, 2009). The pilot survey enabled by applying an efficient design for estimating an ECL. As shown in Fig. 1, this was done by optimising the design for a MNL model and evaluating its behaviour using the; *eval* command in Ngene software to verify its suitability for estimating a

Table 1
Prior parameters and possible levels of attributes considered as input of Ngene software.

Utility function	Coefficients	Prior parameters	Attributes	Levels
U (T_0): no transfer	mode00	0.5000*	Mode	0, 1
	tveh00	−0.3573	In-vehicle time	35, 40, 45
U (T_1): one transfer	constant1	−3.9160	Constant	–
	mode01	0.6236	First mode	0, 1
	mode11	0.6000*	Last mode	0, 1
	tveh01	−0.3705	In-vehicle time in first vehicle	9, 12, 15
	tveh11	−0.3448	In-vehicle time in last vehicle	9, 12, 15
	twalk11	−0.3407	Walking time	2, 4, 6
	twait11	−0.3320	Waiting time	2, 5, 8
	stair11	−0.7000*	Difference in level	0, 1
	info1	0.7000*	Real-time information	0, 1
	crowd1	−1.0272	Crowding	0, 1
U (T_2): two transfers	constant2	−5.7962	Constant	–
	mode02	1.5000*	First mode	0, 1
	mode12	1.5490	Second mode	0, 1
	mode22	1.5000*	Last mode	0, 1
	tveh02	−0.3255	In-vehicle time in first vehicle	4, 7, 10
	tveh12	−0.4372	In-vehicle time in second vehicle	4, 7, 10
	tveh22	−0.2790	In-vehicle time in last vehicle	4, 7, 10
	twalk12	−0.3570	Walking time in first transfer	2, 3, 4
	twalk22	−0.9148	Walking time in second transfer	2, 3, 4
	twait12	−0.4379	Waiting time in first transfer	1, 3, 5
	twait22	−0.3712	Waiting time in second transfer	1, 3, 5
	stair12	−1.1385	Difference in level in first transfer	0, 1
	stair22	−0.7091	Difference in level in second transfer	0, 1
	info2	0.7000*	Real-time information	0, 1
	crowd2	−2.3642	Crowding	0, 1

* Parameters not significantly different from zero at the 95% level from the pilot survey, which were adequately modified to comply with the utility balance criterion.

model of the mixed logit family (ECL in our case). As explained, prior parameters were obtained from a model estimated using the pilot survey. Seven non-significant parameters were adequately modified to comply with the utility balance criterion (Huber and Zwerina, 1996). The resulting priors are shown in Table 1.

After an iterative process Ngene generated 18 choice situations (the number is a multiple of the attribute levels) with three alternatives in each choice (54 alternative options in total). Respondents may take a long time to understand and choose between these choice situations, posing a risk that the survey would be only partially completed. We decided to generate three blocks so that each one could be completed by a different respondent (i.e. the whole SP survey would be completed by three respondents). Each participant answered the block of choices with the fewest number of responses at that particular time, making the answers less correlated between individuals than if only one respondent had completed the survey. However, more respondents are required to comply with the value of the S-estimate. Ngene yielded a value of 25.43 for the S-estimate, which must then be multiplied by the number of blocks to obtain the minimum number of respondents to ensure significance (i.e. 78 respondents are required). It was decided to generate three blocks to exclude the impact of fatigue. Bradley and Daly (1994) recommended not showing more than ten or so choice situations (20 scenarios) per respondent, and in our experiment the respondents who transferred on their daily trips were facing 18 scenarios.

Fig. 2 shows one of the choice sets. It should be noted that the total trip time in the choice with most transfers is always lower than in the alternative option, to comply with the utility balance criterion (Huber and Zwerina, 1996), otherwise almost all the respondents would select the option with the fewest transfers. Total trip time, total walking time and total in-vehicle time are indicated for each choice. The participants were shown a different combination of choices depending on their daily commute, as described in the RP part of the survey. To be more precise:

- if respondents did not usually transfer, they were given 6 simple choice situations and could choose either 0 or 1 transfer.
- if respondents usually transferred once or more, they were given 12 choice situations: 6 choice situations where they could choose either 0 or 1 transfer, and then another 6 to choose either the same alternative with 1 transfer or another with 2 transfers.

The average values and standard deviation of the attributes in the three alternatives of the SP experiment are shown in Appendix A.

3.4. Survey implementation

Once the final survey was designed, it was uploaded to a web page. It was decided to use a web-based format as this has some advantages over paper surveys (Evans and Mathur, 2005). Its potential benefits are: reduced costs of time and money (Cobanoglu

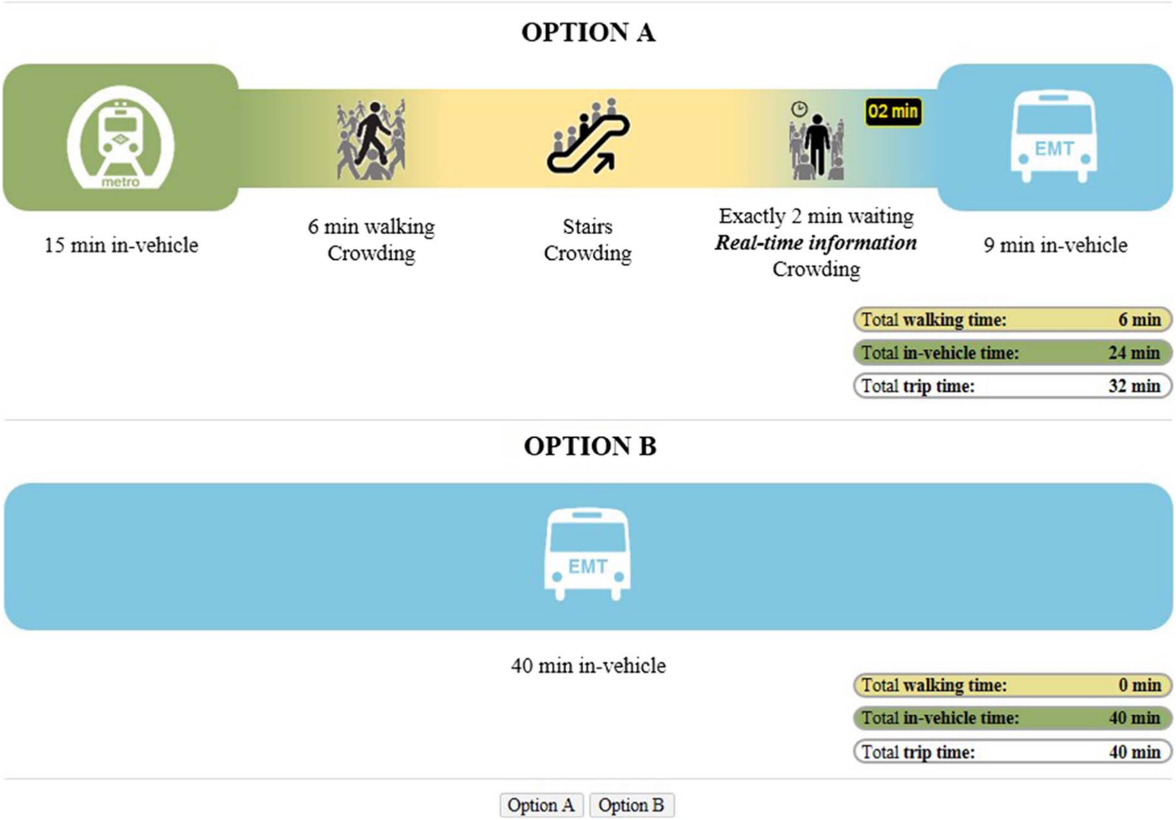

Fig. 2. Survey screenshot: choice situation between no-transfer and one-transfer route.

et al., 2001), speed of delivery and response (Yun and Trumbo 2000), ease of data cleaning and analysis, quick troubleshooting; more complexity can be added (conditional questions can be presented if required, questions can be ordered randomly, etc.); automated data collection; scoring; reporting; access to larger samples (Birnbaum, 2004); less effort by respondents to complete and return than mail surveys (Vicente and Reis, 2010); and absence of interviewer bias (Sills and Song, 2002). However web-based surveys also involve potential bias and limitations due to incomplete or unacceptable responses, lack of online experience/expertise by the respondents, non-response rate, multiple submissions, unclear instructions on how to answer, impersonal, possibility that an unintended person will reply, and data security and integrity (Evans and Mathur, 2005). However web-based surveys have more advantages than disadvantages (Converse et al., 2008; Kaplan et al., 2012; Roztocki and Morgan, 2002; Vingilis et al., 2013).

Respondents were recruited by handing out flyers with a personal access code and all the information required to enter the survey: website address, personal password for completing the survey, information about the project and the option of entering a draw for a gift voucher if the survey was completed. Flyers were distributed (2400 in total) at nine metro stations with two or more lines, and at bus stops in the surrounding area during the morning peak period (7–10 am) for five consecutive weekdays in April 2016 and another five in May 2016. Participation was voluntary. The response rate was around 15%. A €200 gift voucher was offered as an incentive for participation. However, we had problems composing the sample with adult groups. Younger groups had a higher response rate, so we had to conduct two waves in the final survey (the second focused on adult groups) to meet the sample requirements. This survey method resolves some of the disadvantages of web-based survey designs, namely multiple submissions and the non-response rate. Errors and illegible responses could easily be discarded subsequently, and duplicated responses and incomplete surveys could also be monitored. We received 295 valid answers, and we finally selected a random subsample from each location to ensure the representativeness of the target group population (commuters). We avoided the use of sample weights as they can cause problems in the final model when estimating causal effects. Several authors have studied sample weights in models and reported no conclusive results regarding the use of weights or not (Pfefferman, 1993; Schouten et al., 2009; Solon et al., 2013).

The final analysis involved 260 commuters using PT, more than the 78 required as calculated in the previous section: 95% workers and 5% students. The average age was 41 and 60% were women, which reproduces the overall figures for Madrid's commuters according to *Censo 2011* (INE, 2017). All the respondents regularly commuted via PT and their average number of transfers was 1.02 (23% of the respondents did not transfer). The average door-to-door trip time was approximately 39 min, and access and egress times were around 6 and 7 min respectively. Almost 35% of trips had a duration of over 30 min, and only 5% of trips were under 20 min. 10% of respondents said they spent over one hour on their daily trips. 2% of participants habitually commuted with a single ticket, 0.7% travelled with children, while 30% said they used an app to check the time until the next vehicle arrives. 67.6% and 32.4% of participants chose the no-transfer and one-transfer options respectively in the SP choice situations. When asked to choose between making one or two transfers, 68.6% opted for the first option and the remaining 31.4% for the second.

4. Error Component Logit model calibration

The model in this study was developed with two objectives: to be predictive and explanatory. Most models are designed either to achieve (1) the best predictive model, or (2) an explanatory model. For (1) many methods use stepwise variable selection, and (2) requires the consideration of all possible models and variables (Mac Nally, 2000). For this study, the model is calibrated to be predictive, but we also used the outcomes of the process to infer the causal influence of all variables on the intention to transfer. Errors were assumed to be normally distributed. The objective when calibrating the model was to achieve the best value for the log likelihood function and to minimise problems of multicollinearity (i.e. the effect somehow captured by covariances in large parameters).

The ECL model was estimated using Limdep NLogit 4.0, based on the utility functions defined in Eqs. (5)(7). We then included all the other variables from the RP questions to estimate preference variations (i.e. interactions between attributes and socioeconomic variables), and defined new variables from the existing ones. The specification of the variables included in the final model is (see Appendix A for all variables and interactions considered and dismissed as non-significant):

- Intermodality: takes value of 1 if the transfer is metro-bus or bus-metro, and 0 if metro-metro or bus-bus.
- Number of transfers: number of transfers currently made by respondents in their habitual trips.
- Gender: equal to 1 for women and 0 for men.
- Young: takes value of 1 for ages between 15 and 24 and 0 otherwise.
- Reading: is equal to 1 if respondents usually read while travelling and 0 otherwise.

To verify the potential influence of the attributes of each participant's daily commute on their answers to the SP questionnaire, we penalised any alternatives with longer than observed travel time components. Eight variables were defined to represent these differences in time, of which only two were significant (see Table 2). They were calculated as follows (where (*i*) could be total trip, walking, waiting and in-vehicle times, (*p*) if the difference between the time shown in the SP question and their current daily commute time is positive and (*n*) if negative):

$$habit_{ip} = (time\ SP_i - time\ RP_i); if\ time\ SP_i > time\ RP_i \tag{8}$$

$$habit_{in} = |(time\ SP_i - time\ RP_i)|; if\ time\ SP_i < time\ RP_i \tag{9}$$

Finally, all significant variables and interactions were included in the final ECL model (Table 2). We also considered non-significant variables for a better understanding of the transfer perception (for example, variables that are non-significant in $U(T_1)$ but significant in $U(T_2)$), in the case they do not cause multicollinearity problems. All significant variables have the expected signs and values. The ECL model (with a log likelihood value of −1474.041) is an improvement on the MNL model with the same variables (with a log likelihood value of −1631.936). Table 2 also shows transfer penalties expressed in EIVM.

McFadden pseudo R-squared represents an excellent fit. McFadden (1979) stated "while the R^2 index is a more familiar concept to planners […], it is not as well behaved as the rho-squared measure for ML estimation". The relationship between both indices establishes that a value of rho-squared equal to 0.51 is equivalent to a value of R^2 greater than 0.8 (Domencich and McFadden, 1975). Hence the model is robust and reliable and can be used to recommend policy actions and to understand users' perception of transfers.

5. Discussion of results

The following analysis focuses on both the coefficients of Table 2 (predictive approach), and on the non-significant variables reported in Appendix A (explanatory approach).

5.1. Walking, waiting and in-vehicle times

As expected, all time-related variables (walking, waiting and in-vehicle times) are negative, and all are statistically significant (p-value < 0.05). Walking time for the first transfer is perceived slightly worse in $U(T_2)$ than in $U(T_1)$, but better if compared to the second transfer in $U(T_2)$. When making two transfers, the effect of walking time in the second transfer is almost double that of the first transfer. This illustrates the need to minimise the walking times in transfers at the end of a trip. Walking time also depends on gender (significantly different from zero at the 90% level) in $U(T_1)$, with women penalising this factor 1.27 more than men. This finding is in line with Wardman et al. (2001), who found that walking time is valued 23% higher in women, and Navarrete and Ortuzar (2013) who reported a penalty of 4.05.

Waiting time is also more poorly perceived in $U(T_2)$ than in $U(T_1)$. More specifically, waiting time in the second transfer is perceived to be 20% worse than in the first transfer when making two transfers. In-vehicle times follow the same trend. However, the time spent in the last vehicle in $U(T_2)$ is better perceived than other trip times. It is natural for users to be less concerned about transfer penalties when they are closer to their destination. To estimate comparisons in EIVM, we set an average value of 0.3571 and 0.3772 when making one and two transfers respectively. These figures are used to calculate the EIVM columns in Table 2.

Apart from the statistically significant relationship between walking time and gender in $U(T_1)$, we found no other dependency

Table 2
Results of the ECL model.

Attributes	$U(T_0)$: no transfer (*1557 observations*)			$U(T_1)$: one transfer (*2754 observations*)			$U(T_2)$: two transfers (*1197 observations*)		
	Coef.	EIVM	Sig.	Coef.	EIVM	Sig.	Coef.	EIVM	Sig.
Constant (capturing the pure transfer penalty)	–	–	–	−5.4441	−15.245	0.0012	−6.6619	−17.661	0.0011
Mode	0.2722	2.965	0.0001	–	–	–	–	–	–
Intermodality in first transfer	–	–	–	−0.7804	−2.185	0.0082	−0.8712	−2.310	0.0147
Intermodality in second transfer	–	–	–	–	–	–	−1.2413	−3.291	0.0016
In-vehicle time in first vehicle	−0.0918	−1.000	0.0000	−0.2866	−0.803	0.0001	−0.3818	−1.012	0.0002
In-vehicle time in second vehicle	–	–	–	−0.4275	−1.197	0.0000	−0.4329	−1.148	0.0001
In-vehicle time in third vehicle	–	–	–	–	–	–	−0.3169	−0.840	0.0005
Walking time in first transfer	–	–	–	−0.2802	−0.785	0.0011	−0.3384	−0.897	0.0360
Interaction between walking time and gender in first transfer	–	–	–	−0.0748	−0.209	0.0503*	–	–	–
Walking time in second transfer	–	–	–	–	–	–	−0.6013	−1.594	0.0204
Waiting time in first transfer	–	–	–	−0.4076	−1.141	0.0000	−0.4660	−1.235	0.0000
Waiting time in second transfer	–	–	–	–	–	–	−0.5521	−1.464	0.0000
Difference in level in first transfer	–	–	–	0.2553	0.715	0.2235*	−0.5490	−1.455	0.1742*
Difference in level in second transfer	–	–	–	–	–	–	−0.5027	−1.333	0.1248*
Real-time information	–	–	–	0.1474	0.413	0.4309*	0.6577	1.744	0.0428
Crowding	–	–	–	−1.2993	−3.638	0.0000	−1.3209	−3.502	0.0034
Interaction between crowding and young	–	–	–	−0.8625	−2.415	0.0423	–	–	–
Number of transfers currently made	–	–	–	0.1154	0.323	0.5923*	0.7959	2.110	0.0102
Reading while travelling	–	–	–	−0.0014	−0.004	0.9965*	−0.5602	−1.485	0.0485
Difference between total trip time shown in SP choice situations and total trip time revealed (when positive)	–	–	–	−0.000,040	−0.00,001	0.0479	−0.000,102	−0.00,027	0.0012
Difference between total waiting time shown in SP choice situations and total waiting time revealed (when negative)	–	–	–	0.000,018	0.00,005	0.3996*	0.000,068	0.00,018	0.0164
η_q	1.8000	–	0.0000	0.0206	–	0.8972*	1.3650	–	0.0000

Log likelihood function = −1474.041.
Log likelihood constants only = −1723.027.
McFadden Pseudo R-squared = 0.5128.
Chi squared = 3103.075 (37 degrees of freedom) (Sig. = 0.0000).
* Not significantly different from zero at the 95% level.

between walking and in-vehicle times and other variables (such as age, number of transfers and whether travelling with children).

Utility functions indicated that the most severely penalised time varied between alternatives. If only one transfer was made, the waiting time produced the maximum disutility (followed by in-vehicle time and walking time). However, when transferring twice, walking time was poorly perceived in the second transfer, followed by in-vehicle time in the second vehicle, then waiting time. These results are comparable to those of other studies (which involved only one transfer). Navarrete and Ortuzar (2013) reported that waiting time was the most severely penalised, followed by initial and final walking times. Iseki and Taylor (2009) and Walle and Steenberghen (2006) stated that waiting times are more valued than walking times. Iseki and Taylor (2009) concluded that out-of-vehicle times were perceived by PT users as being more onerous than in-vehicle times. Ceder et al. (2013b) studied this statement in depth and concluded that users showed a greater preference for the scenario that was perceived as most conservative (less difference in range of out-of-vehicle times). These results are similar to those found in the literature for one transfer, although transferring twice induces a change. For example, it is significant that walking times are critical when making two transfers.

5.2. Modes, intermodality and stairs

Although the proposed utility functions (Eqs. (5)(7)) included the mode (which was not statistically significant), we decided to replace it with intermodality in the final model. Users negatively perceive a transfer which involves changing the mode of transport. While this could be assumed to be due to the existence of stairs, they are not significant in the model, suggesting that the impact may derive from the fact that users do not perceive the PT system as an integrated network. The impact of intermodality in the second transfer of $U(T_2)$ is comparable to a 3.3 increase in EIVM, giving an idea of the magnitude of the problem. We found no interaction between intermodality and gender, age, ticket type or travelling with children. It is also noteworthy that if no transfers are made, travelling by metro provides higher utility than travelling by bus, which is in line with a study by Currie (2005).

5.3. Habits

The results reveal that commuters in Madrid tend to make one transfer. The coefficient of the number of transfers currently made by participants in $U(T_1)$ is not significant, showing there is no relationship between transferring once and transferring habits. However, this variable has a positive effect in trips involving two transfers. Users with transfer experience perceive a utility of almost 0.80 per transfer currently made. This habit may offset the impacts of intermodality or crowding.

We also verified the hypothesis that individuals are influenced by their trip habits. When participants were presented with a choice situation with a longer total trip time than their usual daily trips, they perceived a disutility. The same applies if the total waiting time in the choices was higher than their usual total waiting time. Coefficients are low but significant, implying that habit related to times is not a crucial variable, but one that users will always unconsciously consider when facing a route choice decision. On the other hand, habits related to walking and in-vehicle times were not found to be significant.

5.4. Crowding and information

The disutility produced by crowded scenarios is slightly higher when making two transfers than only one. Crowding implies that a large number of people gathered together in a limited space can influence transfer perceptions, and is one of the most significant variables in the utility functions after the constants. Its impact is comparable to a 3.6 increase in EIVM, highlighting its importance. Crowding is more penalised by young users in $U(T_1)$ with a total coefficient of -2.16 (1.66 times higher than the rest), while this variable is not significant in $U(T_2)$. Crowding is not dependent on gender, age or number of transfers.

Real-time information at stops and stations, along with the number of transfers currently made by the participants, reinforces the idea that commuters in Madrid tend to make one transfer. This variable is not significant in $U(T_1)$ but it is in $U(T_2)$, with an impact of 1.7 EIVM, implying that real-time information gains in importance when the number of transfers increases.

We measured preference variations between real-time information and gender, age, use of transport apps and education level, and none were statistically significant.

5.5. Activities while travelling

Activities undertaken while travelling may influence the utility derived from travel episodes (Rasouli and Timmermans, 2014). For instance, reading and listening to music both lead to a more positive evaluation of the PT commute (Varotto et al., 2017). However, we do not know the differences between the utility of these activities in the various stages of a trip: travel, waiting and transfer time. The qualitative study conducted in Madrid revealed that activity disruption was a key variable when transferring (Cascajo et al., 2017). The analysis of the RP data also confirmed that 70% of respondents read during their trip, while 53% used their smartphones and 20% listened to music. However, the model found only reading to be significant in $U(T_2)$ (as opposed to listening to music, studying, sleeping or using the mobile phone). The analysis of the RP data showed that the percentage of commuters reading while using PT increased with the number of transfers. Specifically, 75% of users who usually transferred twice or more read in the vehicle, while this figure decreased to 70.6% if they transferred once and 67.2% if not at all. It could be assumed that users who read are more affected in the case of two transfers, thus increasing the perceived disutility. Further research is required into the influence of activities when transferring to accurately quantify their effects.

5.6. Pure transfer penalty

Finally, once we controlled for all the other elements in a transfer, constants in $U(T_1)$ and $U(T_2)$ were defined to capture what we call the pure transfer penalty, without any other inconvenience caused by other activities in a transfer (walking, additional waiting, information, etc.); i.e. the disutility generated merely by the interruption of the trip. Although other types of characteristics unknown to us may also be present, this would not influence the difference between constants, so it can be interpreted as the relative perception of the pure transfer penalty. The impact of the pure transfer penalty is perceived as 15.2 and 17.7 EIVM when making one and two transfers respectively. The difference in the pure transfer penalty between the no-transfer and one-transfer option is much greater than the difference between transferring once and twice, suggesting that it decreases progressively as the number of transfers increases. According to Cheng (2010), crowding is included in the concept of the pure transfer penalty, so its impact would be even higher.

It should be noted that socioeconomic variables such as income, gender, age and education were included in the model as dummy variables and found to be non-significant. This meant that *a priori* the perception of the pure transfer penalty is not distributed across the population. However, more specific research is required.

Frei et al. (2017) assessed the demand for a flexible PT service by conducting an SP survey in which, among other variables, the number of transfers varied across the choice scenarios. The results show that the cost associated to making transfers is equivalent to 4.9 min and 10.9 min of car in-vehicle travel time for one and two transfers respectively. These results cannot be compared to ours, however, for two reasons: unlike ours, their model does not include variables such as crowding, real-time information or activities while travelling; and transfers are described only by number, without any time-consuming activities such as walking and waiting while transferring. This is probably the reason why their results show the disutility of the second transfer to be more than double the first, while we obtained a modest 22% increase but a relevant increase in the perception of walking while making the second transfer.

It is therefore crucial to identify and measure clearly the factors affecting the pure transfer penalty to influence and minimise its effect. More research is therefore required along these lines.

6. Conclusions

This paper describes the methodology used to establish and apply a framework to estimate the penalty perceived by commuters when making transfers in multimodal urban trips. It includes the design of an experimental survey with revealed and stated preference questions to model transfer penalties and determine the elements of the pure transfer penalty in a public transport network, controlling for all other elements. A case study was carried out in Madrid, Spain, and the survey was given to commuters. An Error Component Logit model was calibrated. The findings are potentially very useful for analysing trends and providing policy recommendations, and contribute to an understanding of users' perception of transfers in multimodal urban networks.

The results for the traditional variables show that when only one transfer is made, waiting times are perceived by commuters as causing more disutility than in-vehicle and walking times, similar to the findings of other studies. However, these relative values change when commuters make two transfers, as walking times are perceived as more onerous. Crowding, intermodality and habits were also found to be significant in the transfer process.

By controlling for the variables explained above we were able to isolate the effect of a transfer as a pure interruption of the trip: a pure transfer penalty, which influences users' decisions. This phenomenon was mainly captured by appropriate constants in the utility functions. We found that the magnitude of the pure transfer penalty impact is similar to a 15.2–17.7 increase in EIVM, and is 22% higher in the case of two transfers. This suggests that a traveller would prefer a somewhat longer non-transfer alternative to a single transfer, even in an ideal transfer in which walking and waiting times are equal to zero. As stated in the preliminary steps (focus groups) of this study, variables such as mental effort and activity disruption are components of the pure transfer penalty. Other variables that may explain this perception include anxiety, crowding (one of the variables in the model), fear of unexpected delays, accessibility to stops or stations, incomplete information, uncertainty, safety and security (Cheng, 2010). In addition, controlling for walking, waiting and other variables proved to be important, as walking perception in the second transfer increases notably.

These findings suggest certain policy measures that would be worth studying and evaluating. If traditional variables –walking, waiting and in-vehicle times– are difficult to vary, acting on the quality of the transfer points could reduce the associated disutility. For instance, a pleasant environment (roof, seating, plants), good information such as signs, panels and audio messages (particularly when the transfer involves intermodality) and communication facilities (i.e. Wi-Fi, good mobile coverage) would be a step in this direction. Acting on the design of the system by increasing the frequency and/or capacity of vehicles would reduce both crowding and waiting times. Again, a trade-off emerges between users' and operators' costs. Our results for the pure transfer penalty underline the paramount importance of properly valuing transfers when designing public transport line structures, as shown by Fielbaum et al. (2016).

The study is limited to urban PT commuters, so it would be interesting to replicate this research with long-distance commuters, tourists or senior citizen groups, who would perceive transfers differently. Future research efforts should focus on determining the contribution of each of the variables explaining the pure transfer penalty. It would also be interesting to rank their importance in users' perceptions and study how far they are affected by the application of information measures or planning decisions. Another line of research would be to replicate the SP experiment using a Bayesian D-efficient design, and compare differences in results between both methods. Further research is also required to gain a better understanding of the relationship between transferring and activities pursued while travelling. This study is the first step in the quantification of the pure transfer penalty, as its results have shown this to be a crucial component in users' route choice decisions involving transfers.

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Appendix A

See Tables A.1–A.3

Table A.1
Descriptive analysis of the variables considered in the design of the SP experiment.

Attributes	$U(T_0)$: no transfer		$U(T_1)$: one transfer		$U(T_2)$: two transfers	
	Average	Std. deviation	Average	Std. deviation	Average	Std. deviation
First mode	0.443	0.497	0.611	0.502	0.667	0.485
Second mode	–	–	0.667	0.485	0.611	0.502
Third mode	–	–	–	–	0.667	0.485
In-vehicle time in first vehicle	41.663	3.338	12.477	2.699	5.697	2.312
In-vehicle time in second vehicle	–	–	12.010	2.644	5.133	2.022
In-vehicle time in third vehicle	–	–	–	–	6.323	2.753
Walking time in first transfer	–	–	3.895	1.822	2.901	0.811
Walking time in second transfer	–	–	–	–	2.657	0.880
Waiting time in first transfer	–	–	5.660	2.570	2.544	1.833
Waiting time in second transfer	–	–	–	–	2.667	1.662
Difference in level in first transfer	–	–	0.497	0.500	0.376	0.485
Difference in level in second transfer	–	–	–	–	0.334	0.472
Real-time information	–	–	0.557	0.497	0.491	0.500
Crowding	–	–	0.336	0.471	0.233	0.423

Table A.2
List of variables not included in the final model –dismissed as non-significant.

Category	Attributes	Specification
Socioeconomic variables	income	Net household monthly income (euro). Divided into five segments: < 1000; 1000–2000; 2000–3000; 3000–5000; > 5000
	gender	Is equal to 1 for women and 0 for men
	age	Computed and divided into four segments: 15–24; 25–39; 40–54; 55–69. We also sought to divide into other different segments
	young	Takes a value of 1 for ages between 15 and 24 and 0 otherwise
	old	Takes a value of 1 for ages between 55 and 69 and 0 otherwise
	education	Level of education (no schooling completed; secondary school certificate; vocational training qualification; bachelor's degree)
Common trip	ttimerp	Total trip time (min) revealed
	walktimerp	Walking time (min) in each transfer. The number of variables is equal to the number of transfers currently made
	waittimerp	Waiting time (min) in each transfer. The number of variables is equal to the number of transfers currently made
	vehtimerp	In-vehicle time (min) in each transfer. The number of variables is equal to the number of transfers currently made plus one
	stairsrp	Number of stairs revealed in each transfer. The number of variables is equal to the number of transfers currently made
	children	Takes a value of 1 if travelling with children's pushchairs and 0 otherwise
	ticket	Type of ticket commonly used (single ticket, multiple tickets or travel card)

(*continued on next page*)

Table A.2 (*continued*)

Category	Attributes	Specification
Habits	habitimn	Difference (min) between total trip time shown in SP choice situations and total trip time revealed (when negative)
	habitwaip	Difference (min) between total waiting time shown in SP choice situations and total waiting time revealed (when positive)
	habitwalkp	Difference (min) between total walking time shown in SP choice situations and total walking time revealed (when positive)
	habitwalkn	Difference (min) between total walking time shown in SP choice situations and total walking time revealed (when negative)
	habitvehp	Difference (min) between total in-vehicle time shown in SP choice situations and total in-vehicle time revealed (when positive)
	habitvehn	Difference (min) between total in-vehicle time shown in SP choice situations and total in-vehicle time revealed (when negative)
	app	Takes a value of 1 if respondents use apps to see the time before the next vehicle and 0 otherwise
Activities[1]	study	Takes a value of 1 if studying while travelling and 0 otherwise
	music	Takes a value of 1 if listening to music while travelling and 0 otherwise
	phone	Takes a value of 1 if using the mobile phone while travelling and 0 otherwise
	sleep	Takes a value of 1 if sleeping while travelling and 0 otherwise
	nothing	Takes a value of 1 if doing nothing while travelling and 0 otherwise
Importance and satisfaction[2]	infoI	Importance of real-time information. Takes a value from 0 to 100
	infoS	Satisfaction with real-time information. Takes a value from 0 to 100
	cellcoverageI	Importance of mobile phone coverage. Takes a value from 0 to 100
	cellcoverageS	Satisfaction with mobile phone coverage. Takes a value from 0 to 100
	shelterI	Importance of sheltered stops. Takes a value from 0 to 100
	shelterS	Satisfaction with sheltered stops. Takes a value from 0 to 100
	seatsI	Importance of available seating. Takes a value from 0 to 100
	seatsS	Satisfaction with available seating. Takes a value from 0 to 100
	transferI	Importance of transfers. Takes a value from 0 to 100
	transferS	Satisfaction with transfers. Takes a value from 0 to 100

1: Activities were also grouped into study-read, and music-phone.

2: Segments of all attributes were defined by 20 and 25, and the importance was multiplied by satisfaction, dividing the result into 4 and 5 segments.

Table A.3
List of interactions not included in the final model–dismissed as non-significant.

Main attribute	In interaction with
Walking time	Age, young, old, children, number of transfers
In-vehicle time	Age, young, old, children, number of transfers
Intermodality	Gender, age, young, old, children, number of transfers, ticket
Real-time information	Gender, age, young, old, app, education
Crowding	Gender, age, old, number of transfers

References

Bates, J., 1988. Econometric issues in stated preference analysis. J. Transport Econ. Policy 22 (1), 59–69.

Birnbaum, M.H., 2004. Human research and data collection via the internet. Annu. Rev. Psychol. 55, 803–832. http://dx.doi.org/10.1146/annurev.psych.55.090902.141601.

Bradley, M.A., Daly, A.J., 1994. Use of the logit scaling approach to test for rank-order and fatigue effects in stated preference data. Transportation 21 (2), 167–184. http://dx.doi.org/10.1007/BF01098791.

Bradley, M.A., Daly, A.J., 1997. Estimation of logit choice models using mixed stated preference and revealed preference information. Proceedings of the Sixth International Conference on Travel Behaviour, Quebec 1, 117–133.

Cascajo, R., Garcia-Martinez, A., Monzon, A., 2017. Stated preference survey for estimating passenger transfer penalties: design and application to madrid. Eur. Transport Res. Rev. 9 (42), 1–11. http://dx.doi.org/10.1007/s12544-017-0260-x.

Cascajo, R., Herrero, F., Monzon, A., 2016. Identifying the Variables Affecting Users' Perception of Transfers in Multimodal Urban Trips through Focus Groups in Two Spanish Cities: Vitoria and Madrid. TRANSyT Working Paper 2016-01-EN, Universidad Politécnica de Madrid, 2016. https://goo.gl/q3v6q3. (accessed 10 October 2017).

Ceder, A., Chowdhury, S., Taghipouran, N., Olsen, J., 2013a. Modelling public-transport users' behaviour at connection point. Transp. Policy 27, 112–122. http://dx.doi.org/10.1016/j.tranpol.2013.01.002.

Ceder, A., Hadas, Y., McIvor, M., Ang, A., 2013b. Transfer synchronization of public transport networks. Transp. Res. Rec. 2350, 9–16. http://dx.doi.org/10.3141/2350-02.

Cheng, Y.H., 2010. Exploring passenger anxiety associated with train travel. Transportation 37 (6), 875–896. http://dx.doi.org/10.1007/s11116-010-9267-z.

Cheng, Y.H., Tseng, W.C., 2016. Exploring the effects of perceived values, free bus transfer, and penalties on intermodal metro-bus transfer users' intention. Transp. Policy 47, 127–138. http://dx.doi.org/10.1016/j.tranpol.2016.01.001.

Cherchi, E., Hensher, D.A., 2015. Workshop synthesis: stated preference surveys and experimental design, an audit of the journey so far and future research

perspectives. Transport Survey Methods: Embrac. Behaviou. Technol. Changes 11, 154–164. http://dx.doi.org/10.1016/j.trpro.2015.12.013.
ChoiceMetrics, 2014. Ngene 1.1.2 User Manual & Reference Guide.
Chowdhury, S., Ceder, A., Sachdeva, R., 2014. The effects of planned and unplanned transfers on public transport users' perception of transfer routes. Transport. Plan. Technol. 37 (2), 154–168. http://dx.doi.org/10.1080/03081060.2013.851511.
Chowdhury, S., Ceder, A., Schwalger, B., 2015. The effects of travel time and cost savings on commuters' decision to travel on public transport routes involving transfers. J. Transp. Geogr. 43, 151–159. http://dx.doi.org/10.1016/j.jtrangeo.2015.01.009.
Cobanoglu, C., Warde, B., Moreo, P.J., 2001. A comparison of mail, fax and web-based survey methods. Int. J. Market Res. 43 (4), 441–452.
Consorcio Regional de Transportes de Madrid (CRTM), 2005. Encuesta domiciliaria de movilidad de 2004 en la Comunidad de Madrid. https://goo.gl/8nsq6r (accessed 10 October 2017).
Converse, P., Wolfe, E.W., Huang, X., Oswald, F.L., 2008. Response rates for mixed-mode surveys using mail and E-mail/Web. Am. J. Eval. 29 (1), 99–107. http://dx.doi.org/10.1177/1098214007313228.
Currie, G., 2005. The demand performance of bus rapid transit. J. Public Transport. 8, 41–55.
Currie, G., Loader, C., 2010. Bus network planning for transfers and the network effect in Melbourne, Australia. Transp. Res. Rec. 2145, 8–17. http://dx.doi.org/10.3141/2145-02.
Domencich, T., McFadden, D., 1975. Urban Travel Demand: A Behavioural Analysis. North-Holland, Amsterdam.
Douglas, N.J., Jones, M., 2013. Estimating transfer penalties and standardised income values of time by stated preference survey. Aust. Transport Res. Forum 1–21.
Espino, R., Martín, J.C., Román, C., 2007. Análisis de la calidad del transporte de pasajeros. Un estudio de la disposición a pagar por no trasbordar. X Encuentro de Economía Aplicada, Logroño, Spain.
European Commission, 2013. Thematic Research Summary: Passenger Transport. https://goo.gl/rDGorQ (accessed 10 October 2017).
Evans, J.R., Mathur, A., 2005. The value of online surveys. Internet Res. 15 (2), 195–219. http://dx.doi.org/10.1108/10662204510590360.
Fielbaum, A., Jara-Diaz, S.R., Gschwender, A., 2016. Optimal public transport networks for a general urban structure. Transport. Res. Part B: Methodol. 94, 298–313. http://dx.doi.org/10.1016/j.trb.2016.10.003.
Frei, C., Hyland, M., Mahmassani, H.S., 2017. Flexing service schedules: Assessing the potential for demand-adaptive hybrid transit via a stated preference approach. Transport. Res. Part C: Emerg. Technol. 76, 71–89. http://dx.doi.org/10.1016/j.trc.2016.12.017.
Gschwender, A., Jara-Diaz, S.R., Bravo, C., 2016. Feeder-trunk or direct lines? Economies of density, transfer costs and transit structure in an urban context. Transport. Res. Part A: Policy Practice 88, 209–222. http://dx.doi.org/10.1016/j.tra.2016.03.001.
Guo, Z., 2003. Assessment of the Transfer Penalty for Transit Trips in Downtown Boston. A GIS-based Disaggregate Modeling Approach. Master Thesis, Massachusetts Institute of Technology, United States.
Guo, Z., Wilson, N., 2011. Assessing the cost of transfer inconvenience in public transport systems: a case study of the London Underground. Transport. Res. Part A: Policy Practice 45 (2), 91–104. http://dx.doi.org/10.1016/j.tra.2010.11.002.
Hensher, D.A., 1994. Stated preference analysis of travel choices: the state of practice. Transportation 21 (2), 107–133. http://dx.doi.org/10.1007/BF01098788.
Hernandez, S., de Monzon, A., Ona, R., 2016. Urban transport interchanges: A methodology for evaluating perceived quality. Transport. Res. Part A: Policy Practice 84, 31–43. http://dx.doi.org/10.1016/j.tra.2015.08.008.
Horowitz, A.J., Zlosel, D.J., 1981. Transfer penalties: Another look at transit riders' reluctance to transfer. Transportation 10 (3), 279–282. http://dx.doi.org/10.1007/BF00148463.
Huber, J., Zwerina, K., 1996. The importance of utility balance in efficient choice designs. J. Mark. Res. 33, 307–317. http://dx.doi.org/10.2307/3152127.
Instituto Nacional de Estadística (INE), 2017. Censo 2011. Spanish Statistical Office. http://www.ine.es/ (accessed 10 October 2017).
Iseki, H., Taylor, B.D., 2009. Not all transfers are created equal: towards a framework relating transfer connectivity to travel behaviour. Transport Rev. 29, 777–800.
Jang, T.Y., 2003. Causal relationship among travel mode, activity, and travel patterns. J. Transp. Eng. 129 (1), 16–22. http://dx.doi.org/10.1061/(ASCE)0733-947X(2003) 129:1(16).
Jara-Diaz, S.R., 2007. Transport Economic Theory. Elsevier, Oxford.
Kaplan, S., Bekhor, S., Shiftan, Y., 2012. Web-based survey design for unravelling semi-compensatory choice in transport and urban planning. Transport. Plan. Technol. 35 (2), 121–143. http://dx.doi.org/10.1080/03081060.2012.651874.
Mac Nally, R., 2000. Regression and model-building in conservation biology, biogeography and ecology: the distinction between –and reconciliation of– 'predictive' and 'explanatory' models. Biodivers. Conserv. 9, 655–671. http://dx.doi.org/10.1023/A:1008985925162.
Metropolitan Mobility Observatory (MMO), 2016. MMO Report 2014. Transport Research Centre, Universidad Politécnica de Madrid. https://goo.gl/LgBsJc (accessed 10 October 2017).
McCord, M.M., Wirtz, J., Mishalani, R.G., 2006. Passenger waiting time perceptions at bus stops. J. Public Transport. 9 (2), 89–106.
McFadden, D., 1979. Chapter 15: quantitative methods for analyzing travel behaviour on individuals: some recent developments. Behavioural travel modelling. David Hensher, Peter Stopher, Croom Helm (Eds.).
Navarrete, F.J., Ortuzar, J.D., 2013. Subjective valuation of the transit transfer experience: the case of Santiago de Chile. Transp. Policy 44 (6), 138–147. http://dx.doi.org/10.1016/j.tranpol.2012.10.006.
Nielsen, G., Lange, T., 2007. Network Design for Public Transport Success – Theory and Examples. 10th International Conference on Competition and Ownership of Land Passenger, Hamilton Island, Queensland, Australia.
Organisation for Economic Co-operation and Development (OECD), 2016. OECD Regions at a Glance 2016. OECD Publishing, Paris. https://goo.gl/7nFf3n (accessed 10 October 2017).
Ortuzar, J.D., Willumsen, L.G., 2011. Modelling Transport, 4th ed. John Wiley & Sons, Chichester (United Kingdom).
Pfefferman, D., 1993. The role of sampling weights when modeling survey data. Int. Stat. Rev. 61 (2), 317–337. http://dx.doi.org/10.2307/1403631.
Rasouli, S., Timmermans, H., 2014. Judgments of travel experiences, activity envelopes, trip features and multi-tasking: a panel effects regression model specification. Transport. Res. Part A: Policy Practice 63, 67–75. http://dx.doi.org/10.1016/j.tra.2014.02.012.
Rose, J.M., Bliemer, M.C., Hensher, D.A., Collins, A.T., 2008. Designing efficient stated choice experiments in the presence of reference alternatives. Transport. Res. Part B: Methodol. 42 (4), 395–406. http://dx.doi.org/10.1016/j.trb.2007.09.002.
Rose, J.M., Bliemer, M.C., 2009. Constructing efficient stated choice experimental designs. Transport Rev. 29 (5), 587–617. http://dx.doi.org/10.1080/01441640902827623.
Roztocki, N., Morgan, S.D., 2002. The use of web-based surveys for academic research in the field of engineering. Proc. Eng. Manage. Global Environ. 33–38.
Schakenbos, R., 2014. Valuation of a transfer in a multimodal public transport trip. A stated preference research into the experienced disutility of a transfer between bus/tram/metro and train within the Netherlands. Master Thesis, University of Twente, Netherlands.
Schouten, B., Cobben, F., Bethlehem, J., 2009. Indicators for the representativeness of survey response. Survey Methodol. 35 (1), 101–113.
Sills, S.J., Song, C., 2002. Innovations in survey research: an application of web-based surveys. Social Sci. Computer Rev. 20 (1), 22–30.
Solon, G., Haider, S.J., Wooldridge, J.M., 2013. What are we weighting for? J. Human Resources 50 (2), 301–316.
Van Audenhove, F.J., Korniichuk, O., Dauby, L., Pourbaix, J., 2014. The Future of Urban Mobility 2.0 - Imperatives to shape extended mobility ecosystems of tomorrow. Arthur D. Little. https://goo.gl/4Vn2n7 (accessed 10 October 2017).
Varotto, S.F., Glerum, A., Stathopoulos, A., Bierlaire, M., Longo, G., 2017. Mitigating the impact of errors in travel time reporting on mode choice modelling. J. Transp. Geogr. 62, 236–246.

Vicente, P., Reis, E., 2010. Using questionnaire design to fight nonresponse bias in web surveys. Social Sci. Computer Rev. 28 (2), 251–267. http://dx.doi.org/10.1177/0894439309340751.

Vingilis, E., Seeley, J., Wiesenthal, D., 2013. Street racing and stunt driving in Ontario, Canada: Results of a web-based survey of car and racing enthusiasts. Transport. Res. Part F: Traffic Psychol. Behaviour 21, 30–42. http://dx.doi.org/10.1016/j.trf.2013.08.003.

Walle, S.V., Steenberghen, T., 2006. Space and time related determinants of public transport use in trip chains. Transport. Res. Part A: Policy Practice 40, 151–162. http://dx.doi.org/10.1016/j.tra.2005.05.001.

Wardman, M., Hine, J., Stradling, S., 2001. Interchange and travel choice, volume 1 Institute for Transport Studies, Leeds.

Yun, G.W., Trumbo, C.W., 2000. Comparative response to a survey executed by post, e-mail, & Web form. J. Computer-Mediated Commun. 6 (1).