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Passenger valuation of interchanges in urban public transport

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ABSTRACT

Understanding how passengers perceive public transport interchanges is important to better explain current public transport mode and route choice behaviour and to better predict future demand levels. In this study we derive how passengers value a public transport interchange in a metropolitan context entirely based on recent, large-scale, Revealed Preference data, explicitly distinguishing between different types and modes of public transport interchanges. For this purpose we estimate three discrete choice models using maximum likelihood estimation, based on over 26,000 passenger route choices observed in June 2023 in the Greater London Area. We find that each public transport interchange is on average valued equivalent to 5 min uncrowded in-vehicle time. Additionally, our model results provide quantitative evidence that cross-platform interchanges between two metro journey legs are valued 20–25 % less negatively than a regular metro interchange where a level change is required. Multimodal bus-metro interchanges and out-of-station interchanges are perceived most negatively by passengers. Passengers value bus-bus interchanges on average about 60 % more negatively than metro-metro interchanges, possibly driven by factors such as comfort, service frequency, reliability and (perceived) safety. Our study results can be used for business case and appraisal purposes, when quantifying the impact of service changes which affect the number or type of interchanges.

1. Introduction

1.1. Relevance

Passengers value different components of the public transport (PT) journey differently. Understanding how passengers perceive these different components – such as in-vehicle time, waiting time or interchanges between PT journey legs – is important to better explain current PT mode and route choice behaviour and to better predict future demand levels. Many studies have shown that passengers associate a substantial disutility with transferring between different PT lines or modes along their PT journey (see for example Van der Waard, 1988, Bovy and Hoogendoorn-Lanser, 2005). Most studies found that each PT transfer adds a fixed disutility to passengers' journey equivalent to 4–20 min in-vehicle time, above and beyond the disutility associated with the required transfer walking time and transfer waiting time (Anker Nielsen et al. 2021). This illustrates the large range of values existing in literature for the valuation of interchanges, stemming from differences in the quality of the interchange location, mode combination and method used, which has ramifications for the accuracy of route choice modelling, flow forecasting and project appraisals. In the remainder of this paper we will refer to this fixed disutility as the PT interchange penalty, sometimes also referred to as transfer penalty.

A detailed understanding of how PT passengers value the interchange penalty is important to quantify the impact of measures which change the number of interchanges or the quality of the interchange of a passenger journey. For example, it enables the quantification of the change in generalised journey time and the subsequent impact on PT ridership and revenue resulting from PT service planning measures, which can feed into appraisal studies. As another illustration, one can use the interchange penalty for different interchange types to quantify the benefits of introducing cross-platform interchanges as opposed to regular interchanges which require level changes. Lastly, an accurate value for the interchange penalty can be used as parameter in strategic transport models and PT assignment models, contributing to a more accurate forecast of PT mode choice and PT passenger flows (e.g. Hamdouch et al. 2011, Nuzzolo et al. 2012).

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1.2. Related work

Over the last decade, numerous studies have been conducted aimed at deriving the passenger valuation of different types of PT interchanges, using different methods. Guo and Wilson (2011) derived interchange penalties for different metro stations in London (UK). In this study survey data from the Rolling Origin Destination Survey (RODS) from the period 1998–2005 was used to obtain chosen paths between stations, combined with modelled journey time data resulting from London's PT assignment model Railplan to derive the attribute values of each path. The study included the contribution of the station layout in terms of number of level changes and escalators to the perceived interchange penalty. Building onto this work, Raveau et al. (2014) estimated route choice models to compare interchange penalties between the metro networks of London and Santiago de Chile. For Santiago a large origin-destination survey conducted in 2008 was used as input, resulting in bespoke interchange penalties for transfers requiring no / ascending / descending level changes (Raveau et al. 2011).

We also identify several studies which estimated interchange valuations relying on user preference studies. Chowdhury and Ceder (2013) and Chowdhury et al. (2014) studied the interchange valuation for PT interchanges, thereby explicitly considering interchange attributes such as real-time information, security and ease of wayfinding. The study results were based on a user preference survey conducted in Auckland, New Zealand. Navarrete and Ortuzar (2013) conducted a Stated Preference (SP) survey among 214 respondents in Santiago de Chile, based on which they derived the interchange penalty for metro-metro, bus-bus and metro-bus interchanges. The survey explicitly considered the qualitative characteristics of the interchange location in terms of availability of escalators and the provision of static and/or dynamic travel information. In Schakenbos et al. (2016) a Stated Preference experiment was executed in the Netherlands to derive interchange penalties when interchanging between two trains, and when interchanging between urban bus / tram / metro and regional / national trains. Based on a Stated Preference study conducted in Madrid, Spain, Garcia-Martinez et al. (2018) derived interchange penalties for PT journeys, distinguishing between the perceived disutility when a PT journey consists of one or two transfers.

Next to studies using survey or Stated Preference data, there are also some studies which relied upon Revealed Preference (RP) data to derive PT interchange penalties. Anderson et al. (2017) collected travel diaries from respondents who travelled in the Greater Copenhagen Area (Denmark) between February 2009 and May 2010. PT journeys were constructed from these diaries, based on which interchange penalties were derived for interchanges between different PT modes during a multimodal PT journey. Using the same dataset, Anker Nielsen et al. (2021) studied the relevance of more detailed interchange attributes such as ease of wayfinding, the presence of shops and escalators in PT route choice. In a study to PT crowding valuation, Yap et al. (2020) additionally derived a generic interchange penalty for urban tram and bus journeys in The Hague, the Netherlands, using large-scale passenger route choice data gathered from Automated Fare Collection (AFC) systems. Yap and Cats (2021) estimated a generic metro-metro interchange penalty as part of their route choice model aimed at deriving the valuation of PT waiting time when being denied boarding due to crowding. Yap and Cats (2021) used observed route choices from the Washington DC metro network derived from the AFC system to construct PT journeys and to derive the respective attribute values of each journey.

1.3. Study contribution

The key contribution of our study is to derive the valuation of the public transport interchange penalty in a metropolitan context entirely based on recent, large-scale, Revealed Preference data, thereby explicitly distinguishing between different types and modes of PT interchanges. Based on the literature review above, the contributions of our study to the state of the art are as follows:

- *Use of large-scale empirical data.* The majority of studies to the PT interchange penalty so far are based on Stated Preference surveys, or on manually collected or reported survey data. In our study we rely entirely on large-scale, passive route choice data derived from the AFC system in place. As a consequence, model estimates are based on empirical, observed passenger route choice behaviour instead of relying on stated or reported choices. We use empirical data from AFC and Automated Vehicle Location (AVL) systems to populate the attribute levels of the chosen routes, contrary to previous studies using modelled or reported data from surveys or travel diaries. This improves the accuracy of our modelling and contributes to the scalability of our method.
- *Distinguishing different interchange types and modes.* Several studies using stated or reported choice behaviour have included attributes of different interchange locations in the estimated interchange penalty. To the best of our knowledge, our study is the first study using Revealed Preference AFC data to explicitly distinguish between the passenger valuation of different interchange types and modes. We derive interchange penalties for metro-metro, bus-bus and metro-bus interchanges. Furthermore, we estimate bespoke interchange penalties for metro interchanges which require a level change, and for cross-platform metro interchanges without any level changes. For bus interchanges we distinguish between bus interchanges at the same bus stop and between different bus stops. This provides a deeper insight in PT passenger preferences and can further contribute to understanding passenger route choice.
- *Recency.* Our study uses Revealed Preference data from June 2023, thereby providing an update on passengers' interchange valuation using recent, post-pandemic choice behaviour. Our study thus adds to the existing body of evidence, for which data was collected between 5 and 25 years ago.
- *Reproducibility.* Since our work uses passenger data derived from the AFC system, our approach can be repeated for different time periods and for different locations, as long as there is an AFC system in place. This supersedes the need for the (re)collection of – typically expensive – survey data on passenger journeys or preferences.

In this work we estimate three discrete choice models using maximum likelihood estimation (MLE) to derive passengers' valuation of different types of PT interchanges. For this purpose we use passenger route choice data for the Greater London Area from Transport for London, thereby focusing on PT choice behaviour in a metropolitan context. In Section 2 we discuss the structure of the input data, the method for choice set generation and model specification. Section 3 discusses model estimation results and implications. We conclude with conclusions and recommendations for future research in Section 4.

2. Methods and data

In this section, we discuss the data input and data processing steps (Section 2.1), choice set generation (Section 2.2) and the model specification (Section 2.3).

2.1. Data input and processing

We use passenger journey data for all Tuesdays, Wednesdays and Thursdays from the three-week period between 10 and 30 June 2023 as input, totalling nine weekdays. We use mid-week days as post-pandemic demand patterns in London show to be most stable for Tuesdays, Wednesdays and Thursdays. Passenger demand data in this study is derived from the AFC system in place in the Greater London Area under the authority of Transport for London (TfL), which contains all passenger transactions made using an Oyster Card or a Contactless Payment Card (such as a bank card). As a starting point all PT passenger journeys within the Greater London Area entirely made by metro and bus are processed. Passengers are required to touch in with their travel card upon boarding the bus next to the bus driver, whilst 99 % of all metro stations are equipped with closed ticket barriers (Transport for London, 2022). This means that the AFC system provides a reliable and full coverage of PT journeys made by these modes. For metro journeys we include all journeys made using London Underground (LU) or by the Elizabeth Line (EZL) rail line which opened in 2022, which operates as a metro system within central London. PT journeys made on LU or EZL which start or end at one of the 1 % ungated stations are excluded. Passenger journeys made on other rail modes within the Greater London Area – such as the Docklands Light Rail and London Overground – are not included in our study as most of these stations are ungated. For those journeys AFC data does not yield a full coverage, as passengers with certain travel cards (such as monthly or annual passes) may not touch in and out. PT journeys made by bus, London Underground and Elizabeth Line amount to 91 % of all PT journeys made on TfL's network (Transport for London, 2023).

For metro journeys passengers are required to touch in and out at the station gates, which means that the location and timestamp of the first station entry and the last station exit are directly observed and available in the AFC data. For each passenger journey i we can derive the in-vehicle time $t_{ivt,i}$ from the AVL data available. The remainder of the time between the observed station entry and exit time is subsequently allocated as a combination of waiting and walking times $t_{wtt,i}$, which includes access / egress walking times between ticket gate and platform, initial waiting time, interchange walking time and interchange waiting time. Based on the AFC data we cannot further disentangle walking time and waiting time as this would require assumptions on passengers' individual walking speed and information of individual station layouts to derive the most plausible interchange walking times between platforms. Given that the valuation of walking time and waiting time is frequently found to be comparable (e.g. see the meta-analysis by Wardman, 2004), the impact of this on the model estimation results is expected to be small.

For each journey made by bus the boarding stop, time and bus route are registered in the AFC data, resulting from the requirement for passengers to touch in when boarding. As passengers are not required to touch out when leaving the bus in London, the alighting stop and time for each passenger journey are inferred using the trip-chaining algorithm for destination inference (Gordon et al. 2013, Sánchez-Martinez, 2017) and otherwise scaled based on the inferred alighting probabilities for each downstream stop (Yap et al. 2023). For bus journeys $t_{ivt,i}$ equals the difference between the inferred alighting time and empirically observed boarding time. The passenger waiting time at the bus stop $t_{wtt,i}$ is calculated as half the observed headway between the bus and its predecessor. We assume that passengers arrive uniformly distributed at the bus stop without explicitly consulting the timetable, which is a common assumption for high frequency bus systems such as in London. By using the actual headways instead of scheduled headways, we capture the impact of service irregularity on extended waiting time in $t_{wtt,i}$.

Individual AFC transactions made by the same card-id are linked together by applying the transfer inference algorithm as described by Gordon et al. (2013). This results in the construction of full, multimodal PT journeys in the London metropolitan area, including the number of interchanges n_{ic} each PT journey is composed of. The actual interchange walking and waiting time of each journey can be derived empirically using the time difference between the boarding time of journey leg $n+1$ and the previous alighting time of journey leg n, which is added to $t_{wtt,i}$. Bus stops and metro stations which are located within the same passenger catchment area are grouped together by applying hierarchical agglomerative clustering as unsupervised learning approach. We use Ward linkage with a distance threshold of 500 Euclidean metres to cluster the first origin stop and ultimate destination stop of each passenger journey into an origin zone $o \in O$ and a destination zone $d \in D$.

We categorise each interchange as identified from the AFC data based on the mode and type of interchange. We indicate whether each journey constitutes a bus-to-bus interchange ic^{bb}, metro-to-metro interchange ic^{mm} or bus-to-metro / metro-to-bus interchange ic^{bm}. When the alighting stop is the same bus stop as the subsequent boarding stop, we classify a bus-to-bus interchange as a same-stop interchange ic^{bb}_{ss}, in contrast to bus interchanges between two different stops ic^{bb}_{ds} where transfer walking time is required. For metro interchanges we distinguish three different types: cross-platform ic^{mm}_{cp} where passengers do not need to change level, a regular interchange ic^{mm}_{rg} where passengers are required to change levels within the station when interchanging, and an out-of-station interchange ic^{mm}_{osi} when passengers need to leave a station through the ticket gates and re-enter another station. For metro interchanges we specify the interchange type for each passenger journey based on the exact line-direction combination of the interchange, as cross-platform interchanges are typically only available for specific interchange directions.

2.2. Choice set generation

To estimate a discrete choice model which includes passengers' interchange valuation, we need to specify several filtering rules to derive an appropriate choice set from all passenger journeys processed from the AFC data.

- *Exclude incomplete and unrealistic journeys*. Journeys with unrealistic journey times (shorter than 2 min or longer than 120 min) and with an unrealistically high number of interchanges (4 or more) are excluded, as this points to either a data error or to a service disruption.
- *Include metro journeys between station pairs with unambiguous routing.* From the AFC data it is not possible to derive the exact route passengers take during the metro leg of their journey between the observed station entry and exit. Especially in a high-density PT network such as London multiple feasible paths may exist between station pairs. In our choice set we only include journeys made between station pairs where there is only one feasible route – that is, an unambiguous route – to make sure that we correctly infer the in-vehicle time and number of interchanges corresponding to the route the passenger took. Therefore, when a PT journey involves a metro leg, we only include journeys between station pairs where there is one acyclic path, or where there is a dominant path in both relative and absolute terms, i.e. the journey time of the 2nd shortest path $\geq$2.0 * 1-shortest path and $\geq$ 1-shortest path + 15 min.
- *Include off-peak journeys.* We only include PT journeys made entirely in the off-peak period 10–16 h or 19–22 h. Journeys made during the peak hours are not included, as passengers' interchange perceptions might differ depending on the crowding levels experienced at various stations during the peak hours. As we do not have sufficient information on station crowding levels, we focus on deriving interchange penalties by mode and type without possible distortion from peak hour crowding levels. Furthermore, only a select number of metro lines in London is equipped with a load weigh system. This implies that for several lines there is no empirical data regarding on-board crowding levels available. We therefore limit our analysis to using off-peak AFC data, as crowding is not expected to be a dominant driver for route choice in the off-peak periods.
- *Only include origin-destination pairs with at least two different observed paths*. In this study we solely include observed paths for each origin-destination pair in our choice set. To estimate a PT route choice model there need to be at least two different, unique, observed paths a_{od} between each clustered origin zone and destination zone (similar to the approach taken in Yap et al. 2023). For each path we require a minimum of 10 observations in total, to prevent the inclusion of paths only chosen during unplanned disruptions.

- *Include interchanges*. For the purpose of this study, at least one of the paths a_{od} included between each OD pair should consist of at least one PT interchange.
- *Include only frequent passengers*. The PT journeys derived from the AFC system have a consistent, pseudonymised card-id which remains consistent during our analysis period when the same card is used. This enables us to derive the frequency with which each unique user travels over a certain OD pair. In our Revealed Preference approach we rely on the observed route attributes as explanatory variables for passenger route choice, which assumes that PT passengers have some degree of *a priori* knowledge on the expected attribute values of chosen and non-chosen paths when making their route choice. Therefore, we only include card users who made at least two journeys between the respective OD pair during the nine weekdays considered in the study.

Table 1 shows the number of journeys remaining after applying each abovementioned choice set filtering rule. Resulting from the specific criteria required to estimate a Revealed Preference based choice model which is fit for purpose, only a small proportion of all journeys satisfies all filtering rules. Although AFC data does not provide information on the sociodemographic representativeness of the final dataset, we can check the spatial representativeness of the OD pairs included in the choice set by visualising the origins and destinations using a heatmap (Fig. 1). This shows that both the origins and destinations included provide a good coverage of the Greater London case study area. In line with the PT demand distribution there is a relatively large number of OD pairs to and from central London included in the choice set, but similarly the OD pairs suitably provide coverage of the various parts of outer London.

The resulting choice set characteristics are summarised in Table 2. After applying the abovementioned filtering rules, in total 26,592 empirical route choice observations from 9323 unique PT users are included in the final choice set. 425 unique OD pairs are included with 880 unique paths, resulting in an average of 2.07 observed paths per included OD pair. Specifically for our study there are two or three different observed paths included in the choice set for each of the OD pairs. On average there are 63 observations per OD pair included in the choice set. Fig. 2 shows an illustration of one of the OD pairs included in the choice set from the financial district Canary Wharf in east London to Queens Park in northwest London. It shows two observed routes: one route consists of a first leg using the Elizabeth Line from Canary Wharf (EZL) to Paddington followed by a metro leg on the Bakerloo Line to Queens Park, whilst the second route is formed of two metro journey legs on the Jubilee Line (Canary Wharf (LU) to Baker Street) and Bakerloo Line (Baker Street to Queens Park). The former route – chosen by 46 % of the passengers – has a shorter in-vehicle time but requires a level change interchange at Paddington, whereas the latter route – chosen by 54 % of the passengers – provides a cross-platform interchange opportunity at Baker Street at cost of a longer in-vehicle time.

2.3. Model specification

We estimate a random utility model to derive passenger preferences

Table 1
Choice set filtering steps.

	Number of journeys
Initial metro and bus dataset	76,043,861
No incomplete / unrealistic / non-inferred journeys	61,763,708
Only metro journeys with unambiguous routing	35,883,692
Only off-peak journeys	15,505,595
OD pairs with ≥2 observed paths, with at least one path with ≥1 interchange	129,869
Only frequent PT users	26,592

based on the PT route choice between the observed paths $a_{od} \in A_{od}$ for all origin-destination pairs included in the choice set. The deterministic utility component $V_{a_{od}}$ is a vector of observable attributes with their corresponding weights β and is formulated as linear in parameters. $\varepsilon_{a_{od}}$ reflects the random error term in the utility function. We estimate a path sized logit (PSL) model to alleviate biased model estimates resulting from the possible violation of the assumption that the unobserved utility components of different paths are independent and identically distributed (IID) when estimating a standard multinominal logit (MNL) model. Therefore, we add the path size correction factor $r_{a_{od}}$ as deterministic term to the utility function to correct for potential unobserved correlations between alternative, overlapping paths (Ben-Akiva and Bierlaire, 1999). As shown in Eq.(1) the total disutility of each path $U(V,r,\varepsilon)$is thus composed of the structural, deterministic utility component V, a path size factor r and a random error term ε.

$$U_{a_{od}} = V_{a_{od}} + \beta_{psl} \bullet r_{a_{od}} + \varepsilon_{a_{od}} \tag{1}$$

In this study a node-based formulation of the path size correction factor r is used to reflect overlap between different PT route alternatives based on Dixit et al. (2021), in contrast to link-based overlap frequently used for road networks. This means that overlap is measured in terms of the number of locations where PT passengers make an actual route choice decision – at boarding and transfer stops – instead of across all links of a path. Using the definition of Duncan et al. (2020) the node-based path size term is defined in Eq.(2), where $|s_a^b|$ is the number of decision nodes for path a and $\delta_{s,a}$ is the node-route incidence of decision node s^b belonging to route a. This formulation implies that a more negative value of $r_{a_{od}}$ indicates a higher degree of node overlap between different paths.

$$r_{a_{od}} = \ln\left(\sum_{j\in 1..\left|s_{a_{od}}^b\right|}\left[\left(\frac{1}{\left|s_{a_{od}}^b\right|}\right) * \left(\frac{1}{\sum_{a_{od}\in A_{od}}\delta_{s,a}}\right)\right]\right) \tag{2}$$

A panel effects mixed PSL model is estimated to capture the serial correlations between route choice observations made by the same PT user to prevent an overestimation of the model coefficients. As explained in Section 2.2 we only include PT users who made at least two journeys between a given OD pair in the choice set, thus requiring us to correct for panel effects in our model. We use the unique, pseudonymised card-id to identify multiple PT journeys t made by the same passenger n. The path probability can then be formalised using Eq.(3) where the unconditional probability equals the integral of the product of the repeated choices made by the same PT user (Train, 2002). Due to the integral there is no closed form solution to calculate path probabilities, meaning that maximum simulated likelihood estimation (MSLE) is required to approximate the probabilities by taking draws from a normally distributed density function. To reduce the number of draws required, we use quasi random Halton draws with a deterministic van der Corput sequence (Halton, 1960). To determine the required number of draws, the number of Halton draws is doubled iteratively until there is no statistically significant change in the estimated coefficients.

$$P_{n,a_{od}} = \int \prod_{t=1}^{T}\left[\frac{\exp\left(V_{nt,a_{od}} + \beta_{nt,psl} \bullet r_{a_{od}}\right)}{\sum_{a_{od}\in A_{od}}\exp\left(V_{nt,a_{od}} + \beta_{nt,psl} \bullet r_{a_{od}}\right)}\right](\beta)f(\beta)d\beta \tag{3}$$

The structural part of the utility function consists of the in-vehicle time t_{ivt}, the combined walking and waiting time t_{wtt}, the number of interchanges n_{ic} and an alternative specific constant asc for each path $a_{od} \in A_{od}$. The attribute values for t_{ivt} and t_{wtt} are calculated as the median value of the observed journey times from all individual passenger journeys observed for that specific path per 15-minute time window, expressed in minutes. We estimate generic time coefficients β_{ivt} and β_{wtt} in line with London's state of the practice (Transport for London, 2017), which also allows for expressing the interchange penalty equivalent to

Fig. 1. Spatial distribution of origins (left) and destinations (right) included in the choice set.

Table 2
Choice set characteristics.

	Model June 2023
Observations	26,592
Unique users (card holders)	9323
Number of OD pairs	425
Number of paths	880
Average journeys per user per OD pair	2.85
Average number of paths per OD pair	2.07
Average number of observations per OD pair	63

in-vehicle time in minutes independent from the interchange mode. We estimate three different models with an increasing nuance with regards to the type of PT interchange. Model 1 (Eq.(4)) estimates one generic interchange penalty coefficient above and beyond the interchange walking and waiting times. In model 2 (Eq.(5)) this is segmented into mode specific interchange penalty coefficients for bus-bus interchanges β_{ic}^{bb}, metro-metro interchanges β_{ic}^{mm} and multimodal bus-metro / metro-bus interchanges β_{ic}^{bm}. As the number of multimodal interchanges in our final choice set is relatively small, we estimate one generic multimodal coefficient reflecting both bus-to-metro and metro-to-bus interchanges. Model 3, formulated in Eq.(6), estimates interchange penalty coefficients for five different interchange types: for bus-bus interchanges made at the same bus stop (β_{ss}^{bb}), for bus-bus interchanges between two different stops (β_{ds}^{bb}), for cross-platform metro-metro interchanges (β_{cp}^{mm}), for regular metro-metro interchanges requiring a level change within the station environment (β_{rg}^{mm}), and lastly for all out-of-station interchanges (β_{osi}). This last interchange type captures all interchange movements where a passenger is required to move between two different stations through the ticket barriers, either when interchanging between bus and metro or when making an out-of-station interchange between two metro journey legs. The coefficients for waiting / walking time and the interchange penalty are expressed as multiplication factor of the in-vehicle time coefficient, so that these coefficients can be interpreted directly in relation to the in-vehicle time.

$$V = asc + \beta_{ivt} \bullet t_{ivt} + \beta_{ivt} \bullet \beta_{wtt} \bullet t_{wtt} + \beta_{ivt} \bullet \beta_{ic} \bullet n_{ic} \tag{4}$$

$$V = asc + \beta_{ivt} \bullet t_{ivt} + \beta_{ivt} \bullet \beta_{wtt} \bullet t_{wtt} + \beta_{ivt} \bullet \beta_{ic}^{bb} \bullet n_{ic}^{bb} + \beta_{ivt} \bullet \beta_{ic}^{mm} \bullet n_{ic}^{mm} + \beta_{ivt} \bullet \beta_{ic}^{bm} \bullet n_{ic}^{bm} \tag{5}$$

$$V = asc + \beta_{ivt} \bullet t_{ivt} + \beta_{ivt} \bullet \beta_{wtt} \bullet t_{wtt} + \beta_{ivt} \bullet \beta_{ss}^{bb} \bullet n_{ss}^{bb} + \beta_{ivt} \bullet \beta_{ds}^{bb} \bullet n_{ds}^{bb} + \beta_{ivt} \bullet \beta_{cp}^{mm} \bullet n_{cp}^{mm} + \beta_{ivt} \bullet \beta_{rg}^{mm} \bullet n_{rg}^{mm} + \beta_{ivt} \bullet \beta_{osi} \bullet n_{osi} \tag{6}$$

3. Results and discussion

This section presents the results of the model estimation (Section 3.1) followed by a discussion on the implications of the model outputs (Section 3.2).

3.1. Results

For each of the three models the Newton–Raphson method as

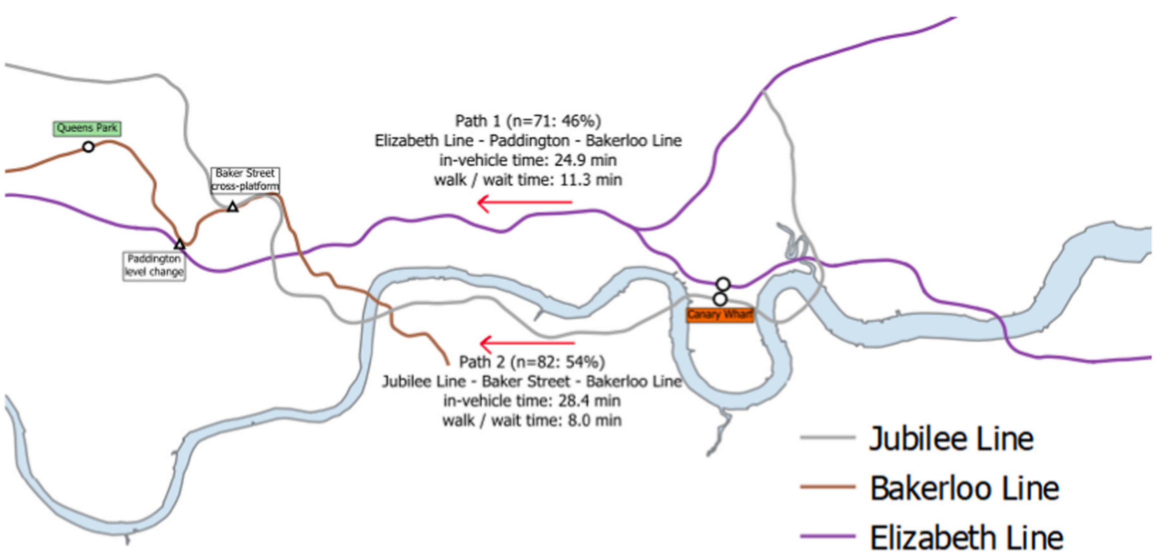

Fig. 2. Observed paths from Canary Wharf to Queens Park included in the choice set.

implemented in PythonBiogeme is used for the maximum simulated likelihood estimation to derive the coefficients which best explain the observed passenger route choices (Bierlaire, 2016). For each of the models 50 Halton draws sufficed to obtain stable estimation results. Models 1, 2 and 3 required 6, 7 and 7 iterations respectively until convergence was reached, with a computation time of 4, 6 and 8 min, respectively using a regular i7 PC. In Table 3 the initial and final log-likelihood, Rho-square and Rho-square-bar, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are reported for the three discrete choice models. We can see that the Rho-square-bar ranges between 0.473 and 0.475 for the estimated models, with generally similar model performance between the three models.

Table 4 presents all estimated coefficients for the three models. For each of the two or three paths between an OD pair there is an alternative specific constant *asc* specified, which was fixed to zero for the first path. In this study we fixed β_{wtt} – which expresses the ratio between the valuation of waiting / walking time and in-vehicle time – to 2.0 for consistency purposes. This ratio is based on the study conducted by Yap et al. (2023) in which a ratio very close to 2.0 was derived from a Revealed Preference study applied to the London PT network using a comparable methodology. Using the results from the model estimated based on off-peak AFC data, Yap et al. (2023) showed that both pre-pandemic (using data from February 2020) and post-pandemic (using data from June 2022) PT passengers value walking / waiting time on average twice as negative as uncrowded in-vehicle time. This is also in line with results found in previous studies (e.g. Wardman, 2004, Bovy & Hoogendoorn-Lanser, 2005) and in line with the state of the practice as implemented in Transport for London's Business Case Development Manual BCDM (Transport for London, 2017). As our three estimated models are using off-peak data, we have consistently used this fixed ratio of 2.0 between walking / waiting time and in-vehicle time. The path size correction factor showed not to be statistically significant for all three models, resulting in the final models to be reduced to panel effects mixed MNL models. From Table 3 we can conclude that all other estimated coefficients are statistically significant, with the absolute value of the robust t-statistic being larger than 1.96. The robust p-value of all estimated coefficients bar β_{ss}^{bb} is smaller than 0.01, indicating highly significant results. The sign of the estimated coefficients is plausible and in line with *a priori* expectations. The in-vehicle time coefficient β_{ivt} is negative whilst the various interchange penalty coefficients – which are expressed as ratio to one minute in-vehicle time – are positive. As we use unlabelled alternatives, the statistically significant *asc* coefficients do not bear any interpretational value but are merely used to reflect preferences not captured by the other attributes in the model.

3.2. Discussion

The estimation results from model 1 show that PT passengers perceive each interchange on average equivalent to 5.03 min uncrowded in-vehicle time. Our study results thus confirm the existence of a fixed time penalty associated with each transfer by PT passengers on top of the required interchange walking and waiting times.

Table 3
Model estimation summary.

	Model 1 Interchange *generic*	**Model 2 Interchange *by mode***	**Model 3 Interchange *by type***
Observations	26,592	26,592	26,592
Sample size	9323	9323	9323
Initial log-likelihood	-19,267	-19,267	-19,267
Final log-likelihood	-10,151	-10,115	-10,124
Rho-square	0.473	0.475	0.475
Rho-square-bar	0.473	0.475	0.474
Akaike Information Criterion (AIC)	20,313	20,224	20,266
Bayesian Information Criterion (BIC)	20,349	20,294	20,330

Table 4
Model estimation results.

	Model 1 Interchange *generic*	**Model 2 Interchange *by mode***	**Model 3 Interchange *by type***
Coefficients	**Value (robust t-value)**	**Value (robust t-value)**	**Value (robust t-value)**
asc_1 – alternative specific constant 1	0 (fixed)	0 (fixed)	0 (fixed)
asc_2 – alternative specific constant 2	+0.535** (+14.6)	+0.505** (+13.7)	+0.511** (+14.2)
asc_3 – alternative specific constant 3	+1.01** (+10.5)	+0.954** (+9.89)	+0.964** (+9.79)
β_{ivt} – in-vehicle time	-0.116** (-39.6)	-0.117** (-38.8)	-0.115** (-35.9)
β_{wtt} – walking / waiting time	+2.00 (fixed)[1]	+2.00 (fixed)[1]	+2.00 (fixed)[1]
β_{ic} – interchange (generic)	+5.03** (+12.9)		
β_{ic}^{bb} – interchange (bus-bus)		+7.10** (+3.19)	
β_{ic}^{mm} – interchange (metro-metro)		+4.41** (+11.3)	
β_{ic}^{bm} – interchange (bus-metro, metro-bus)		+10.3** (+7.11)	
β_{ss}^{bb} – interchange (bus-bus, same stop)			+6.62* (+2.33)
β_{ds}^{bb} – interchange (bus-bus, different stop)			+7.25** (+2.81)
β_{cp}^{mm} – interchange (metro, cross-platform)			+3.59** (+4.31)
β_{rg}^{mm} – interchange (metro, level change)			+4.66** (+11.1)
β_{osi} – interchange (out-of-station)			+9.50** (+6.33)

robust t-values in parentheses. * robust $p < 0.05$; ** robust $p < 0.01$
[1] *Fixed for the ratio wait/walk time: in-vehicle time as found in Yap et al. (2023) based on uncrowded post-pandemic data for London*

When we analyse the breakdown of the perceived interchange penalty for interchanges between different modes (model 2), our results show that the average metro-metro interchange is valued equivalent to 4.4 min in-vehicle time. In contrast, PT passengers value the average bus-bus interchange – equivalent to 7.1 min in-vehicle time – more negatively compared to metro-metro interchanges. A possible explanation is that most metro-metro interchanges between LU and/or EZL occur within an enclosed station environment with typically good facilities such as seating, lighting and the provision of real-time arrival information, which does not apply to all bus stops. Furthermore, due to the high-frequent and generally reliable metro services in London (frequencies typically range between 15 and 36 trains per hour) passengers may perceive these interchanges less negatively due to the limited implications of missed connections, as waiting times are expected to be small. Interchanges between buses in an unprotected outside environment may be perceived as less comfortable – and at some times and locations potentially less safe. Passengers might associate a larger degree of uncertainty to the expected waiting times for bus-bus interchanges due to lower service frequencies, a larger service variability resulting from interactions with road traffic, and the absence of real-time bus arrival information for some bus stops. Model 2 shows that a multimodal PT interchange between bus and metro (in either direction) is valued at 10.3 min in-vehicle time on average, therefore being perceived more negatively than both bus-bus and metro-metro interchanges. We can expect that passengers associate the largest disutility with multimodal bus-metro interchanges, as passengers are required to enter (leave) the physical metro station from (to) the bus stop by touching in (out) again at the ticket barriers. Additionally, naturally this type of interchange is associated with a larger degree of uncertainty in terms of finding the correct stop (wayfinding) and regarding the expected arrival time of the next PT mode.

When analysing the valuation of different types of interchanges in model 3, our study results show that the disutility for bus-bus interchanges at the same stop (6.6 min) is lower than for bus-bus interchanges between different bus stops (7.3 min), even after accounting for the longer interchange walking time. This is a plausible result which might be explained by the larger degree of uncertainty PT passengers perceive in finding the location of the next boarding stop. We also find that an average cross-platform interchange between two metros without any level changes is perceived less negatively (3.6 min) compared to a regular metro-metro interchange requiring at least one level change (4.7 min). This confirms the value of realising cross-platform interchanges in reducing the total generalised journey time for a PT journey. Compared to a regular metro-metro interchange the convenience of a cross-platform interchange can be thus translated into a 20–25 % reduction in the average interchange penalty perceived by passengers. Lastly, one can conclude that interchanges which require passengers to move between two different stops / stations – be it between a metro station and bus stop for bus-metro interchanges or between two different metro stations – are valued most negatively, equivalent to 9.5 min in-vehicle time.

The results from our study are compared to results found in previous studies in Table 5. Overall, we can conclude that the estimated coefficients are well within the range found in previous studies conducted for the London PT network and worldwide. Interestingly, the average metro-metro interchange penalty of 4.41 min found in our study is comparable to the metro-metro interchange penalty of 4.9 min found by Guo and Wilson (2011) based on OD survey data derived between 1998 and 2005 in London. In addition, our results are within the same range as the interchange valuation currently adopted by Transport for London for appraisal studies. Furthermore, the overall interchange penalty of 5.03 min is very similar to the tram/bus interchange penalty of 4.8 min derived from AFC data in the Netherlands by Yap et al. (2020). In the latter study, this interchange penalty resulted from the most generic model which was estimated based on demand data during the peak hours correcting for in-vehicle time, waiting / walking time and crowding. When comparing the metro interchange valuation from our study to older studies conducted between 1998 and 2008 in London and Santiago, we observe that our results suggest a slightly less negative interchange valuation. This might be explained by passengers having more access to real-time arrival information on the platform or via their mobile phones nowadays, potentially reducing the uncertainty associated with interchanges. Another possible explanation is the improvement of the interchange facilities over time in terms of attractiveness, safety and accessibility.

4. Conclusions and recommendations

In this study we derive the valuation of the public transport interchange penalty in a metropolitan context entirely based on recent, large-scale, Revealed Preference data, explicitly distinguishing between different types and modes of PT interchanges. Applied to the metropolitan PT network of London using more than 26,000 route choices observed in June 2023, we find that each PT interchange is on average valued as equivalent to 5 min uncrowded in-vehicle time. Our study provides quantitative evidence that cross-platform interchanges between two metro journey legs (equivalent to 3.59 min) are valued 20–25 % less negatively than a regular metro interchange where a level change is required (equivalent to 4.66 min). This illustrates how the realisation of cross-platform interchanges can reduce the total generalised journey time experienced by passengers, and as such can contribute to increasing PT demand levels. The explicit distinction between valuing cross-platform and regular interchanges in our work allows for capturing the benefits of scheduling cross-platform interchanges, which otherwise would have been overlooked or only been assessed qualitatively. Our study results can also be used for business case and appraisal purposes, when quantifying the impact of PT service changes which affect the number or type of interchanges. The less negative interchange valuation for bus-bus interchanges at the same stop compared to interchanging between two different bus stops highlights the benefit of same

Table 5
Results comparison.

Study	Year of data collection	Method	Location	Interchange type	Interchange penalty (minute)
Guo and Wilson (2011)	1998–2005	OD survey	London (UK)	metro-metro	4.9
Raveau et al. (2014)	1998–2005	OD survey	London (UK)	metro-metro (level change ascending)	6.18
				metro-metro (level change descending)	5.35
Raveau et al. (2014)	2008	OD survey	Santiago (Chile)	metro-metro (level change ascending)	8.59
				metro-metro (level change descending)	5.86
Raveau et al. (2011)	2008	OD survey	Santiago (Chile)	metro-metro (generic)	8.5
Anker Nielsen et al. (2021)	2009–2011	Travel diaries	Copenhagen (Denmark)	urban PT (generic)	5.4–12.1
Yap et al. (2020)	2015	AFC data	The Hague (Netherlands)	tram-tram, tram-bus	4.8
Garcia-Martinez et al. (2018)	2016	SP survey	Madrid (Spain)	urban PT (1 interchange)	15.2
				urban PT (2 interchanges)	17.7
Yap and Cats (2021)	2017	AFC data	Washington DC (USA)	metro-metro	8.48
Transport for London (2017)	2017	BCDM	London (UK)	rail-rail, rail-metro	5.0
				metro-metro	3.5
This study	2023	AFC data	London (UK)	urban PT (generic)	5.03
				metro-metro (generic)	4.41
				metro-metro (cross-platform)	3.59
				metro-metro (level change)	4.66
				bus-bus (generic)	7.10
				bus-bus (same stop)	6.62
				bus-bus (different stop)	7.25
				bus-metro, metro-bus	10.3
				out-of-station	9.50

stop interchanges. This insight can be used to schedule bus routes with the largest interchange volumes at the same stop when possible. Overall, we can conclude that multimodal bus-metro interchanges and out-of-station interchanges in general are perceived most negatively by passengers. It highlights the potential of designing convenient and well signposted interchanges to reduce the disutility associated with this type of interchange. Passengers value bus-bus interchanges on average about 60 % more negatively than metro-metro interchanges, possibly driven by factors such as comfort, service frequency, reliability and (perceived) safety. This insight can form a starting point for exploring how to reduce the inconvenience experienced whilst interchanging at bus stops, for example by providing real-time arrival information, appropriate seating and lighting.

We formulate several recommendations for future research. First, it is recommended to include station specific interchange attributes – such as wayfinding, the availability of shops, escalators and lifts – to obtain a deeper understanding of factors contributing to passengers' interchange perception. In our study we have focused on generic interchange mode and type characteristics which can be obtained from AFC data and network topology data, so that these parameters can be used directly in PT assignment and simulation models. This could however be extended by including station specific information to derive more disaggregate or station specific interchange penalties using a Revealed Preference, AFC based approach. Second, it is recommended to further explore the relation between the service frequency and the perceived interchange penalty. Using the scheduled service frequency, PT lines can be classified as either high frequency or low frequency service. This can shine light on whether there are different interchange penalties for transfers from high-frequent to low-frequent PT services, compared to low-frequent to high-frequent PT transfers. Similarly, this could be extended by explicitly distinguishing between the valuation of bus-to-metro interchanges and metro-to-bus interchanges. Third, we recommend exploring how interchanges are valued during peak hours, thereby explicitly taking into account on-board and station crowding levels. This is of particular relevance for metropolitan PT networks where high on-board and station crowding levels can be observed, which can influence the valuation of interchanges in route choice behaviour. For this purpose, the utility functions could be expanded by specifying the in-vehicle time valuation as function of the on-board crowding level (e.g. as done in Yap et al. 2023). Crowding levels on-board trains and buses can be derived from data from Automated Passenger Count (APC) systems if available, or estimated from AFC boarding and alighting transactions. We also recommend exploring how the interchange valuation changes as a function of station crowding. Station crowding levels for each station and time of day can be expressed by a level of service (LOS), based on which LOS specific interchange penalties could be derived. LOS specific interchange penalties would enable to quantify how the interchange valuation changes when appraising the benefits of station crowding relief schemes. Fourth, we recommend obtaining a deeper understanding of the heterogeneity of passengers' interchange perceptions. This could be achieved by extending our modelling framework by estimating mixed logit or latent class models, or via the estimation of choice models segmented by journey purpose or time of day.

CRediT authorship contribution statement

Oded Cats: Writing – review & editing, Writing – original draft, Methodology. **Howard Wong:** Writing – review & editing, Writing – original draft, Data curation. **Menno Yap:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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