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Modelling trip scheduling decisions of bus commuters amid disruptive events using smart card data

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A R T I C L E I N F O

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A B S T R A C T

Departure time models are key tools for understanding time-varying travel demand. Nonetheless, there is limited research focusing on the analysis of trip scheduling decisions in the context of public transport users. In particular, research on how public transport users adapt departure times when the activity and travel landscape are altered as a consequence of disruptive events (e.g. pandemics, social unrest), is yet to be conducted. Smart card data, which passively records time-stamped departure locations of public transport users, offers the opportunity to investigate such shifts in detail but is yet to be utilised. The paper aims to address these two gaps by using smart card data to investigate the trip scheduling decisions of bus commuters amid disruptive events. This goal is achieved by estimating departure time choice models (DTCMs) for characteristic episodes between 2019 and 2022 for Santiago's bus system, a city affected to different degrees by two types of disruptive events within this timeframe: the COVID-19 pandemic and social unrest. The paper addresses the methodological challenges of calculating schedule delay with smart card data by estimating preferred arrival times as a random variable within a mixed multinomial logit model. The approach is assessed through the valuation of the trade-off between travel time and schedule delay (TVSD), with the results falling within the range of values previously reported in the literature. The model results highlight the existence of multi-temporal differences in the arrival time preferences of bus commuters, as well as in their TVSD amid disruptive events. It was found that bus commuters were less willing to accept an increase in their travel time to reduce their schedule delay during disruptive episodes. The heterogeneity between bus travellers was also explored: recurrent bus commuters exhibited higher TVSDs than occasional commuters. The outcome of this study supports using smart card data as a feasible source to investigate how public transport passengers allocate their trip scheduling both during normal periods and amid external disruptions.

1. Introduction

Departure time choice models (DTCMs) are key tools for analysing the trip scheduling decisions of commuters (Börjesson, 2008; Small, 1982). The modelling of trip scheduling, historically addressed by estimating departure time choice models (DTCMs), has been primarily employed in car commuting with only a few applications that have included public transport (PT) commuting (Peer et al., 2013). The literature has also paid minimal consideration to revealing tangible and measured differences in how travellers trade-off attributes such as schedule delay and travel time on their trip scheduling decisions amid disruptive events (Singh et al., 2023). This is particularly important to study, as temporal travel behaviours can be severely affected by disruptive events, such as pandemics, natural disasters and social unrest (Bergantino et al., 2024; Li et al., 2024; Liu et al., 2023; Lizana et al., 2023). Nonetheless, so far, the literature has almost exclusively focussed on the examination of those events in the context of trip reduction and mode shift, giving less attention to other potential adaptations, such as those related to changes in passengers' departure time preferences (Burris et al., 2023; Ngo and Martin, 2023; Shires et al., 2018; Victoriano-Habit and El-Geneidy, 2024). Therefore, an analysis of the trip scheduling decisions for passengers considering a multi-temporal perspective, which comprises a comprehensive sequence of episodes that cover the time before, during, and after disruptions, is currently missing in the literature. This limitation is largely due to the difficulty in retrieving the necessary attributes for estimating suitable models and in

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harnessing passive data sources (such as smart card data) that allow the analyst to observe departure times over multiple periods. Consequently, the hypotheses proposed for this study are:

H1. Smart card data is a feasible data source for estimating DTCMs for PT users.

H2. Distinctive situational contexts related to disruptive events have associated different valuations of travel time and schedule delay.

H3. Different PT user segments have different trip-timing preferences.

H4. A long-term disruptive event has enduring effects on trip scheduling decisions among PT users.

The examination on the trip scheduling decisions amid disruptive events is conducted in this study using trip records of bus passengers for several episodes collected by smart cards in Santiago's public transport system. This case study is particularly interesting as the city experienced two different types of large-scale disruptive events between 2019 and 2022: massive social protests and the COVID-19 pandemic. The study contributes to the existing literature on the analysis of public transport time-varying demand in two ways: a) providing the first implementation of smart card data for the estimation of DTMCs and b) providing evidence of multi-temporal differences in the trip scheduling decisions among bus commuters depending on situational contexts.

The structure of the paper is as follows: Section 2 offers background information on DTCMs. Section 3 provides details about the data utilized in this study. Next, Section 4 outlines the modelling framework. In Section 5, the methodology employed is discussed, while Section 6 presents the modelling results. Finally, Section 7 summarizes the key contributions of this work and outlines directions for future research.

2. Literature review

The literature review is organised into five subsections addressing the main aspects of this research: (a) fundamentals of departure time choice models (DTCM), (b) challenges in retrieving variables for DTCMs, (c) the role of DTCM in public transport commuting, (d) the impact of disruptive events, and (e) the use of smart card data. The review was based on searches conducted in Scopus, Web of Science, and Google Scholar. For each topic, targeted combinations and variations of keywords, such as "departure time choice," "schedule delay," "public transport," "travel behaviour," "disruptive events," and "smart card data", were used. Inclusion criteria prioritised peer-reviewed articles that offered methodological insights or empirical findings relevant to the hypotheses of this work. The search and selection process was iterative and complemented by backwards and forward snowballing of key articles to ensure coverage of both foundational works and recent developments relevant to this study's context.

2.1. Concepts of departure time choice models

Departure time choice models (DTCMs) are key tools for analysing the trip-scheduling process of commuters (Börjesson, 2008; Small, 1982). These models aim to capture preferences for a specific time of the day for individuals to start their out-of-home activities (Habib, 2021). As each out-of-home activity involves a change of location, the departure time of the out-of-home activity is, by definition, the selected start time of the trip to the destination. In DTCMs, commuters choose their departure time by trying to maximise their satisfaction/utility based on the trade-off of relevant attributes involved in the decision. In this regard, travel time and schedule delay have been the attributes most frequently studied (Arellana et al., 2012; Thorhauge et al., 2016). The concept of schedule delay refers to the disutility caused by being early or late, defined with respect to a preferred arrival time (Tirachini et al., 2014). A traditional definition of schedule delay is, then, the time shift between the actual arrival time and the preferred arrival time (PAT). A commuter's PAT is related to their work start time and may be obtained by explicitly asking the participants about it in specially-designed travel surveys (Börjesson, 2008; Peer et al., 2013). Considering the traditional approach proposed by Small (1982), where only travel time and schedule delay are considered (as monetary cost is considered time-invariant in many cases), the observable utility $V_{s,n}$ to departure in a time-interval alternative s for a traveller n can be expressed as:

$$V_{s,n} = ASC_s + \beta_{TT} TT_{s,n} + E_{s,n}\left(\beta_{SDE} SDE_{s,n}\right) + L_{s,n}\left(\beta_{SDL} SDL_{s,n}\right) \tag{1}$$

where $TT_{s,n}$ is the travel time associated with choosing to depart within interval s for the individual n and ASC_s can be interpreted as the intrinsic attractiveness of each time interval s when the other variables are made equal. $SDE_{s,n}$ and $SDL_{s,n}$ represent the amount of earliness and lateness, respectively, associated with the time period s. They are defined as follows:

$$SDE_{s,n} = PAT_n - AT_{s,n} \tag{2}$$

$$SDL_{s,n} = AT_{s,n} - PAT_n \tag{3}$$

Here, PAT_n is the preferred arrival time at work for commuter n and $AT_{s,n}$ is the arrival time if commuter n chooses to depart in the time-interval s. $AT_{s,n}$ can be obtained by combining the midpoint of the departure time interval s and $TT_{s,n}$. $E_{s,n}$ and $L_{s,n}$ are the earliness and lateness dummy variables, respectively. They play a key role in the specification by ensuring that earliness and lateness are mutually exclusive, i.e. each traveller can be either early or late, but not both at the same time. Thereby, arriving earlier than the PAT ($SDE > 0$ and $SDL = 0$) may be interpreted as generating a dissatisfaction associated with the undesirable use of personal time, while arriving later ($SDL > 0$ and $SDE = 0$) could be understood to account for potential penalties imposed on the commuter due to dissatisfaction of their work-place (e.g. a warning/reduction in the salary) (Watling, 2006). The closer $AT_{s,n}$ is to PAT_n, the lower the amount of schedule delay. However, in day-to-day travel settings, travellers often face a trade-off: travel times are usually highest during the peak period, when schedule delay costs are minimised by arriving close to the preferred time of arrival. This pattern is consistent with the classical scheduling model of departure time choice (Arnott et al., 1990; Small, 1982; Vickrey, 1969), which predicts that travellers accept higher in-vehicle times in order to avoid schedule delay penalties. That trade-off can be calculated by comparing the marginal utilities of the observable utility of the departure time alternatives and has received the name of travel time valuation of schedule delay (TVSD) (Zannat et al., 2021). A typical interpretation of the TVSD is the amount of additional travel time a traveller is willing to accept to reduce one-time unit of schedule delay. The higher the TVSD, the higher the probability a commuter decides to travel when travel time is higher, in order to arrive closer to their preferred arrival time.

2.2. The challenge of retrieving attributes for the estimation of DTCMs

Unfortunately, the specific attributes required to implement DTCMs are seldom available in standard transport data sources. PATs are only available in studies specifically focussed on DTCMs by explicitly asking travellers about it. To deduce PATs when this information is not available, several methodologies have been proposed. Kristoffersson and Engelson (2016), for example, proposed imputing PATs by employing reverse engineering based on previously estimated preferences for departure time. Koppelman et al. (2008) proposed using the observed departure time distribution as an external component during the modelling. On the other hand, Bwambale et al. (2019) argued that such an approach oversimplifies the problem. Thus, they developed a methodology to estimate the trip-timing preferences of commuters as a random variable whose parameters can be obtained within the DTCM. Moreover, even when PATs are available in revealed preference (RP) data, there remains the problem of estimating travel times for the unchosen time-interval alternatives, which are typically not recorded in RP data. In this context, the use of stated preference (SP) data has been seen as a more practical alternative to RP data, being more commonly used for DTCMs (Arellana et al., 2012; Lizana et al., 2021). The SP approach relies on hypothetical scenarios to set the key variables needed for the estimation of DTCMs (Arellana et al., 2012), overcoming the limitations of working with RP data. Nonetheless, despite this advantage, it is well known that valuations calculated by SP experiments are susceptible to hypothetical bias and behavioural incongruence due to the misperception of respondents of attributes and their levels (Fifer et al., 2014; Haghani et al., 2021; Hess et al., 2005). In this regard, joint RP-SP data have been considered a more reliable alternative for DTCMs (Börjesson, 2008).

2.3. DTCMs for PT commuting

So far, little empirical evidence exists for investigating departure time choices for PT commuting (Habib, 2021). In fact, since their early development in the eighties, literature related to DTCMs has focussed primarily on the analysis of trip scheduling of car commuters (Börjesson, 2008; Small, 1982; Thorhauge et al., 2016; Zannat et al., 2021). In the few studies where public transport has not been explicitly excluded from the analysis, either schedule delay has not been considered, and therefore, only generic times of the day (e.g. off-peak/peak) have been specified (Ding et al., 2015; Hossain et al., 2020), or if it has been considered, only a generic TVSD has been estimated regardless of the mode. An exception where a DTCM has been estimated exclusively to study PT commuting, including schedule delay, is the work of Peer et al. (2016). A summary of the studies found where PT trip timing choices have been studied (alone or jointly with other modes) considering the inclusion of schedule delay and travel time in DTCMs is presented in Table 1. It is worth noticing that all these studies relied on survey data to estimate DTCMs (mostly SP surveys).

2.4. Disruptive events and their effect on trip timing decisions

Disruptive events involve a wide range of events that cause complex behavioural responses among PT users (Noureldin and Diab, 2024; Parkes et al., 2016), from incidents related to temporal interruptions in the operation of certain PT modes (e.g. weather conditions, human-associated incidents, strikes, etc.) (Diab and Shalaby, 2019; Van Exel and Rietveld, 2001) to events that, for their significance, cause long-lasting effects on PT users' travel decisions (e.g. natural disasters, pandemics, social movements, terrorist attacks, etc.) (Bernal et al., 2016; Chan et al., 2021; Eltved et al., 2021; He et al., 2024; Nazem et al., 2019; Prager et al., 2011). Despite it has been recognised that the impact of disruptive events on travel behaviour involves a complex set of possible adaptations such as reducing trip number, shifting mode, re-timing, re-routing, and re-scheduling, among others (Marsden et al., 2020), studies have mainly focussed on the first two. In fact, for PT commuting, the examination of passengers' adaptation during a disruption has been exclusively conducted on PT trip reduction (Liu et al., 2023; Victoriano-Habit and El-Geneidy, 2024; Ziedan et al., 2023) and the shift from PT to other modes (Shires et al., 2018; Vallejo-Borda et al., 2022). Only a few pieces of evidence so far provide some insights into the changes in trip-timing decisions for the long term. Singh et al. (2023) found that during the COVID-19 pandemic, the disutility of trip-timing attributes was significantly conditioned by hypothetical vaccination rates presented in their experiment, while Li et al. (2024) illustrated the temporal fluctuation in ridership in Seoul in key periods of the day between 2020 and 2023. Therefore, additional empirical evidence that sheds light on the changes in the sensitivities to schedule delay (primarily related to the establishment of more flexible working arrangements adopted by businesses during a disruptive event (Wöhner, 2022)) and its trade-off with travel time is needed, particularly when the system of activity have been severely impacted. Moreover, the role of distinctive commuter segments on those potential changes is also necessary to investigate as the literature has recognised its relevance in trip-timing decisions (Parkes et al., 2016; Zannat et al., 2021). An analysis like this must rely on revealed disaggregated observations of the departure time choices of PT users during multi-temporal episodes, an approach that remains limited due to data limitations.

2.5. Smart card data for PT demand analysis

Passive data sources have been successfully employed to analyse PT systems, including smart card data (Pelletier et al., 2011), mobility indices (Lizana et al., 2024) and automatic vehicle location of buses (Zannat and Choudhury, 2019). In particular, smart cards used to collect fares in PT systems have become a reliable and well-established data source for analysing PT demand (Cats, 2023; Pelletier et al., 2011). One of the main advantages of smart card data is the possibility of continuously collecting transactions across time and therefore, to gain insight into particular episodes in the past for research purposes. In this context, smart card data has been used to quantify the effect of external disruptions on PT demand patterns (Almlof et al., 2021; Li et al., 2024;

Table 1
Summary of studies and their valuations in the analysis of departure time choices for PT commuting.

Authors	Location/ Data	Goal	Mode/ Variables	Day period	Method/ Interval	Valuations
Lizana et al. (2021)	Santiago, Chile/ RP and SP survey	Estimate DTCMs using joint RP/SP data	Public transport & private modes/ Cost, TT, TF, NT, SD	05:00–14:00	MNL, NL/ 15, 30 & 60 min	$TVSD_{RP,ME}$: 1.1–2.4 $TVSD_{RP,ML,}$: 1.9–3.2 $TVSD_{SP}$: 0.7 VOT: 5.9–6.3 USD/h*
Peer et al. (2016)	Netherlands/ RP survey (PDT) & GPS from app	Study the effect of a monetary reward in peak-avoidance	Train/ Reward, TT, SD, NT, CR	05:30–10:30/ 15:00–19:30	MNL, LCCM/ N.A.	$TVSD_{RP,ME}$: 0.43 $TVSD_{RP,ML}$: 0.36 VOT: 15.5 €/h
Aziz and Ukkusuri (2014)	Indianapolis, U.S./ SP survey	Exploring the trade-off between travel time and CO2	Not specified/ TT, SD, greenhouse gas emission	Morning peak period	ML/ N.A.	TVSD: 0.72
Arellana et al. (2012)	Santiago, Chile/ RP and SP survey	Generate a survey design to estimate DTCMs	Public transport & private modes/ Cost, TF, TT, TVV, SD	06:30–10:30	MNL/ 30 min	$TVSD_{ME}$: 1.11 $TVSD_{ML}$: 1.48 VOT: 3.1 USD/ h*

TT: travel time, TF: Transfer time, TTV: travel time variability, SD: schedule delay, NT: number of transfers, CR: crowdedness. MLN: multinomial logit, NL: Nested logit, LCCM: Latent class choice model. TVSD: time valuation schedule delay (minutes of travel time per minute of schedule delay), ME: morning earliness, ML: morning lateness, VOT: Value of travel time savings, N.A.: not applicable. *1 USD = 500CL$.

Lizana et al., 2023). More traditional applications include a wide range of PT demand analysis topics, such as OD matrix estimation (Munizaga and Palma, 2012), route choice modelling (Arriagada et al., 2022), travel pattern identification (Lizana et al., 2023) and data enrichment and integration (Shalit et al., 2023), among others. In particular, passenger segmentation—defined as dividing public transport users into groups with similar observed travel patterns (e.g., trip frequency)—has proven to be a useful approach for identifying specific preferences and behaviours (Cats, 2023; Lizana et al., 2023). In this context, segmentation based on smart card data usually differs from that derived from survey-based data, where socio-demographic characteristics and perceptions of service quality and satisfaction are most often used (Abenoza et al., 2017; Vicente and Reis, 2016). The role of smart card data for analysing the temporal dimension of passengers' travel behaviour has also been demonstrated in previous studies, particularly in modelling active departure delays and heterogeneous arrival patterns. For example, Chen et al. (2023) used Chengdu metro smart card data to investigate passengers' active boarding delays by estimating logit choice models. Similarly, Ingvardson et al. (2018) analysed railway smart card data to develop a two-component mixture distribution of passenger arrivals, distinguishing between random and schedule-driven arrivals. Despite all these applications, to the best of the authors' knowledge, there has not been an attempt to harness smart card data to investigate trip-timing choices using DTCMs for PT commuting.

3. Data

3.1. Case study

Santiago, Chile's capital, was selected as the case study for this research. Santiago has a population of around 7 million inhabitants, and its public transport comprises more than 6.500 buses and seven subway lines. The Santiago's PT system records more than 25 million weekly transactions with a similar share between buses and the metro. Santiago is particularly suitable for the aims of this study as two disruptive events hit the city between 2019 and 2022 that affected the activity system: massive social protests (2019) and the COVID-19 pandemic (2020–2021). Additionally, the selection of this case study offers the unique possibility to benchmark the results of this study against existing SP-RP studies available for this city, a possibility rarely available in other potential case study cities due to the lack of detailed data related to PT commuting. In Santiago's public transport, a smart card called bip! is the primary payment method, allowing the collection of trip data such as the specific time-stamp of the departure time of each trip, the ID of the card and the location where the validation was made. Unfortunately, cards are not personalized, facilitating a quick rotation of the ID cards (Lizana et al., 2023). This means that in an analysis of periods longer than one year, only a reduced number of the original ID cards remained in the system as new ones have replaced them. In addition, like many PT systems worldwide, Santiago's public transport only requires users to tap in when boarding. As such, it is necessary to impute destinations to estimate travel times. This process is conducted by Santiago's transport authority using the methodology developed by Munizaga and Palma (2012). Additionally to the smart card records, millions of actual time stamps generated by on-board GPS devices on buses are available for this study. This information enables a detailed and disaggregated calculation of the actual in-vehicle travel times for each bus service origin-destination stop pair within the network, a crucial aspect for modelling departure time choices.

3.2. Identification of characteristic episodes

Characteristic episodes were selected to investigate the potential existence of different trip-timing preferences and valuations amid disruptive events among Santiago's bus commuters. Events that involved a generalised disruption with lasting effects caused by an alteration in the situational context of the city were targeted. With that aim, ridership levels between 2019 and 2022, a time frame of major disruptions in travel demand for Santiago's public transport (see Fig. 1), were analysed. In this time frame, characteristic episodes that involved considerable changes in bus ridership levels and episodes related to more stable conditions were identified and selected for the estimation of DTCMs for posterior comparison.

Four episodes were selected to investigate potential differences in the trip-scheduling decisions of bus commuters. The first episode, in April 2019 (EP1), characterises a baseline context, i.e., a period without any major disruptive events influencing the departure-time choices of bus commuters (EP1). This week is considered representative of typical temporal patterns of bus users, as it is not affected by disruptions, avoids special events, holidays, school vacations, strikes, and weather anomalies. The second episode, in early March 2020 (EP2), reflects bus commuters' travel behaviour after the social unrest that began on 14 October 2019 in Santiago and lasted until the end of that year. During this period, interruptions to private and public services and to transport supply were frequent. Looting occurred at shops and businesses in the city, and in many places, public infrastructure, including metro stations, buses and stops, was severely damaged. Therefore, early March 2020 represents a moment for the case study when both the activity and transport systems were recovering from that event. Moreover, Episode 2 also directly precedes the point at which the COVID-19 pandemic was considered a global threat to public health. The third episode characterises the post-COVID-19 outbreak. Specifically, a re-opening period in Santiago occurred in November 2020 (EP3) after an extended lockdown imposed by the authorities. In this episode, even though the lockdown was entirely removed, other measures were still in place, such as a curfew, limited opening hours for commercial activities, restrictions on social gatherings and guidelines for social distancing. Public and private companies around this period adopted working from home or flexible in-office working hours. EP3 is, by far, the episode hit by the major contextual disruptions; as such, it is expected that substantial differences may be observed between the trip preferences and valuations among the travellers during this period, in comparison with other episodes. Eventually, restrictive measures started to be lifted in October 2021 as the vaccination programme achieved higher penetration levels. At this time, the curfew was removed, and the operating hours of businesses increased. Therefore, a final episode in April 2022 (EP4), two years after EP2 and EP3, was also chosen to reveal bus commuters' trip-timing preferences in 'after-disruption' settings. The specific periods considered to represent each episode are presented in Table 2. One week of disaggregated smart card data records was available for the episodes. The exception was the re-opening episode (EP3), which was characterised for two weeks to better represent the bus users' travel behaviour amid a much-disrupted context.

It is important to note that the proposed segmentation aims to identify variations in the trip-scheduling choices of bus users in relation to specific events. Therefore, in principle, other weeks might have been chosen to extend the existing series of episodes, and such an approach could reveal additional variability or subtleties in trip-scheduling behaviour. Nevertheless, we believe that the chosen selection is adequate for the aim of this study because: (i) it allows for a manageable number of episodes during the modelling phase, and (ii) it provides sufficient contrast between episodes to capture differences in travel decision-making behaviour effectively.

4. Modelling framework

4.1. Modelling definition

Based on the random utility framework, a departure time choice model (DTCM) considers that a traveller n chooses the time-interval alternative s that maximizes their utility. The utility $U_{s,n}$ is defined as:

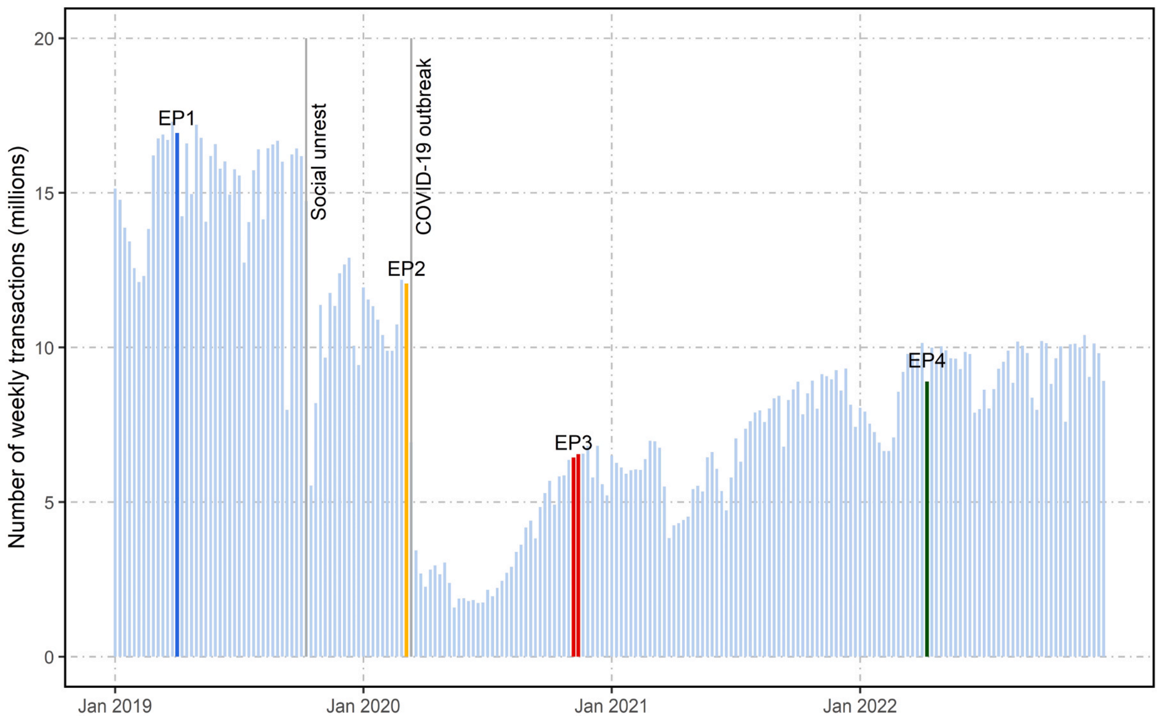

Fig. 1. Weekly bus ridership for Santiago's public transport system between Jan 2019 and Dec 2022. Selected episodes are highlighted in colours. Blue: before-disruptions (EP1), yellow: post-social unrest (EP2), red: post-COVID-19 outbreak (EP3), and green: after-disruptions (EP4). (Further details of each episode are given in Table 2).

Table 2
Study periods considered in this study for the characterisation of each episode.

Episode	Abbreviation	Period
Before-disruptions	EP1	08–12 Apr 2019
Post social unrest	EP2	07–11 Mar 2020
Post-COVID-19 outbreak	EP3	09–13 and 10–13 Nov 2020
After-disruptions	EP4	04–08 Apr 2022

$$U_{s,n} = V\left(X_{s,n}, Z_n, \quad \beta\right) + \varepsilon_{s,n} \tag{4}$$

where $V_{s,n}$ is the observable utility and $\varepsilon_{s,n}$ is a random error component. $V_{s,n}$ depends on $X_{s,n}$ which is the vector of attributes for each time alternative s for the individual n, Z_n is a vector of personal and travel characteristics of a person n, and β is the parameter vector that accounts for the marginal utility of each variable. The observable utility $V_{s,n}$ initially considered for this study was that given by Eq. 1. However, in that specification, the amount of earliness or lateness associated with each departure time alternative requires knowledge of the preferred arrival time (PAT), which is not available in smart card data. To overcome this data limitation the approach proposed by Bwambale et al. (2019) was instead adapted for this work, as it offers a more practical approach compared with other existing methods.

Following that approach, it is reasonable to assume that the PAT varies randomly across travellers following a certain statistical distribution. This is a sound assumption, particularly for the morning period, where most commuters concentrate their arrival preferences around a similar range related to the official work start-times. The distribution parameters of the random variable (i.e. mean and standard deviation) accounts for the heterogeneity of trip timing preferences among commuters and can be obtained during the model estimation using mixed multinomial logit models. Unfortunately, under the proposed approach, the simultaneous estimation of earliness (SDE) and lateness (SDL) presents serious identification and optimisation issues. This occurs because i) the existence of earliness or lateness are treated as mutually exclusive variables (i.e. a person cannot arrive earlier and later at the same time), as described in Eq. (1), and ii) the values of the earliness and lateness dummies depend on the difference between $AT_{s,n}$ and the preferred arrival time (PAT_n), with the latter also being simultaneously estimated. As the optimiser attempts to find the parameters of the PAT distribution, the dummies alternate between 1 and 0, thus resulting in a likelihood function that is not continuously differentiable in the parameters. This led us to deviate from the traditional model formulation in order to find an alternative way to estimate simultaneously the PAT and the schedule delay penalty. Bwambale et al. (2019) propose to use instead a schedule delay function that is behaviourally intuitive and continuously differentiable. The parabolic function fulfils such conditions: it has a minimum where the delay is zero, an indifference range around the PAT, which reflects a small disutility with delays in the vicinity of the PAT and increases when the delay goes further away from the PAT. Nonetheless, it assumes that the marginal utilities of earliness and lateness are symmetric. Imposing a symmetric schedule-delay specification may attenuate the early–late asymmetry frequently observed in commuter behaviour. In conventional scheduling model specifications, lateness is typically associated with a higher marginal penalty than earliness. By constraining both penalties to share a common parameter, the model effectively estimates an average schedule-delay sensitivity. This may imply some degree of overestimation in the preferences of people who arrive later and underestimation in those arriving earlier than their PAT. Thus, the observable utility function that allows the estimation of $\widetilde{PAT}_n$ is given by:

$$V_{s,n} = ASC_s + \beta_{TT} TT_{s,n} + \beta_{SDR}\left(\widetilde{PAT}_n - AT_{s,n}\right)^2 + \ldots + \tag{5}$$

where $\widetilde{PAT}_n$ is a random variable that refers to the preferred arrival time of commuter n, $TT_{s,n}$ are the travel times and $AT_{s,n}$ is the expected arrival time if the commuter decides to depart in the time-interval s, which also depends on the travel time of that time-interval alternative. β_{SDR} and β_{TT} are parameters to be estimated and represent the sensitivity to schedule delay (with "R" indicating the imposed symmetry restriction compared with the traditional formulation) and travel times. The + …+ notation stands for other time-variant attributes that may be relevant in the trip scheduling decisions, such as in-vehicle occupancy, fare, etc.

Note also that Eq. 5 differs from the original specification proposed by Bwambale et al. (2019) in several aspects: a) it explicitly incorporates the influence of travel time in the estimation of schedule delay, and b) it assumes that the arrival preferences (rather than departure time preferences) vary randomly across commuters, which we believe is a more realistic assumption as the departure times are also influenced by the travel times/travelled distances. Moreover, considering the nature of smart card data, in our case it is only possible to utilise in-vehicle travel times (IVT) and the preferred arrival times at the destination stop (PAT-Stop), because travel times are estimated between stop pairs instead of door-to-door as is the case for car commuting. To highlight this, the term $IVT_{s,n}$ and $\widetilde{PATS}_n$ are employed respectively. Finally, it should be noted that a value for $AT_{s,n}$ can be estimated from $IVT_{s,n}$ and the departure time interval s by using the midpoint of the interval, DT_s. Then, the observable utility function employed in this study is:

$$V_{s,n} = ASC_s + \beta_{IVT} IVT_{s,n} + \beta_{SDR}(\widetilde{PATS}_n - (DT_s + IVT_{s,n}))^2 + \ldots + \tag{6}$$

4.2. Model estimation

The logit probability that a commuter n chooses to travel in the departure time interval ($L_{s,n}$), conditional on β and $\widetilde{PATS}_n$, can be expressed as:

$$L_{s,n}\left(\beta, \widetilde{PATS}_n\right) = \frac{e^{ASC_s + \beta_{IVT} IVT_{s,n} + \beta_{SDR}(\tilde{PATS}_n - (DT_s + IVT_{s,n}))^2 + \ldots +}}{\sum_{j \in C} e^{ASC_j + \beta_{IVT} IVT_{j,n} + \beta_{SDR}(\tilde{PATS}_n - (DT_j + IVT_{j,n}))^2 + \ldots +})} \tag{7}$$

where C is the full choice set that consist of M time intervals of I min each. However, as $\widetilde{PATS}_n$ is not observed, the distribution parameters of $\widetilde{PATS}_n$ are unknown. Hence, the conditional probabilities are integrated over $\widetilde{PATS}_n$ according to a mixing distribution defined as $f(\widetilde{PATS}_n|\theta)$, where θ is the vector of parameters of the density distribution (mean and standard deviation). The PAT-Stop distribution parameters are then estimated alongside the rest of the model parameters by specifying a mixed logit probability and then maximising the simulated log-likelihood. Thus, the mixed logit probability $P_{n,s}$ is given by:

$$P_{s,n}(\beta) = \int L_{s,n}\left(\beta, \widetilde{PATS}\right) \cdot f\left(\widetilde{PATS}|\theta\right) d\widetilde{PATS} \tag{8}$$

Eq. 8 is estimated by simulation methods, as it has no closed form. Thus, a simulated log-likelihood is calculated using Halton draws from a certain distribution (e.g. Johnson's distribution, S_B) to estimate the logit probabilities. In this approach, a sample of R values of $\widetilde{PATS}$ are drawn from $f(\widetilde{PATS}|\theta)$, and labelled as $\widetilde{PATS}_r$ ($r = 1, 2, \ldots, R$), where the subscript r refers to the specific draw. Then, the average simulated logit probability can be estimated taking the average over the number of draws as follows:

$$\widehat{P}_{s,n} = \frac{1}{R} \sum_{r=1}^{R} L_{s,n}\left(\beta, \widetilde{PATS}_r\right) \tag{9}$$

where $\widehat{P}_{n,s}$ is an unbiased estimator of $P_{n,s}$ whose variance decreases as R increases. To decide on a suitable number of draws, the number is usually gradually increased until stable modelling results are generated. Thus, the simulated probabilities are inserted in the log-likelihood function for the observed choices, from which we obtain:

$$SLL = \sum_{n=1}^{N} \sum_{j=1}^{J} d_{nj} \ln \widehat{P}_{s,n} \tag{10}$$

where d_{nj} is equal to 1 if the commuter n chooses alternative j. The final simulated likelihood is obtained when the value of θ that maximizes SLL is found.

4.3. Time valuation of schedule delay (TVSD)

Based on the result of the mixed logit models, it is possible to quantify the changes in the trade-off between in-vehicle travel time and schedule delay by comparing the ratio of the partial derivatives of the utility functions with respect to schedule delay and travel time (See Eq. 11). The TVSD measures the additional travel time a commuter would accept to reduce their schedule delay by one unit time. The higher the TVSD, the more importance a commuter gives to schedule delays respecting travel time, and the more willing the commuter is to travel in a departure period with higher travel time in order to arrive closer to their PAT-Stop. In order to estimate TVSD, as the PAT-Stop is a random variable, it is necessary to estimate the average schedule delay for a commuter n, by considering draws from $S_B(\widetilde{PATS}|\theta)$. Considering that the specification employed is indifferent to the difference between earliness and lateness, the schedule delay in draw r is, by definition, the absolute difference between the $\widetilde{PATS}_{n,r}$ and AT_n (See Eqs. 11 and 12). $TVSD_n$ is calculated across individuals using R draws and the TVSD for a specific study period p calculated as the average of the individual $TVSD_n$.

$$TVSD_n = \frac{\partial V / \partial SDR}{\partial V / \partial IVT} = \frac{2\beta_{SD} \widehat{SDR}_n}{\beta_{IVT}} \tag{11}$$

$$TVSD_n = \frac{2\beta_{SDR}}{\beta_{IVT}} \frac{1}{R} \sum_{r=1}^{R} \left| \widetilde{PATS}_{n,r} - AT_n \right| \tag{12}$$

5. Methodology

To test the hypotheses stated in Section 1, the methodology presented in Fig. 2 was followed. It highlights the steps developed to deal with the two main challenges found in using smart card data in DTCMs: estimating the travel times for the unobserved departure time alternatives and obtaining a proxy of arrival time preferences for calculating schedule delay. Moreover, Fig. 2 also emphasizes the iterative process implemented to establish the conditions to successfully estimate a DTCM using smart card data and to allow the intertemporal comparison between the selected episodes.

5.1. DTCM specification

As mentioned earlier, this paper focuses exclusively on bus users. The adoption of this approach, rather than integrating all modes, was guided by two primary considerations: (a) to analyse a mode whose characteristics align well with the scope of this study, specifically, understanding changes in the trade-off between travel time and schedule delay; and (b) to limit the complexity involved in modelling multiple modes and their combinations. Regarding (a), unlike buses, metro travel times are largely time-invariant, which makes it difficult to assess their role in departure time choice models. Regarding (b), including multiple modes would have required considerably more complex model structures, larger samples, and would have risked reducing the stability and comparability of results across episodes. Such an approach would also necessitate accounting for potential mode–route changes and incorporating additional variables such as transfer times, transfer penalties, and fares, which are beyond the scope of this study. Moreover, preliminary analyses with metro users showed that accurately identifying the marginal utility of fare would require more fare variability than is present in the current data. Currently, the metro system has only three fare levels in the morning period, which is insufficient to capture the scheduling behaviour of thousands of choices robustly.

Therefore, after exploring several attributes and specifications, it was resolved to concentrate only on analysing the trade-off between in-

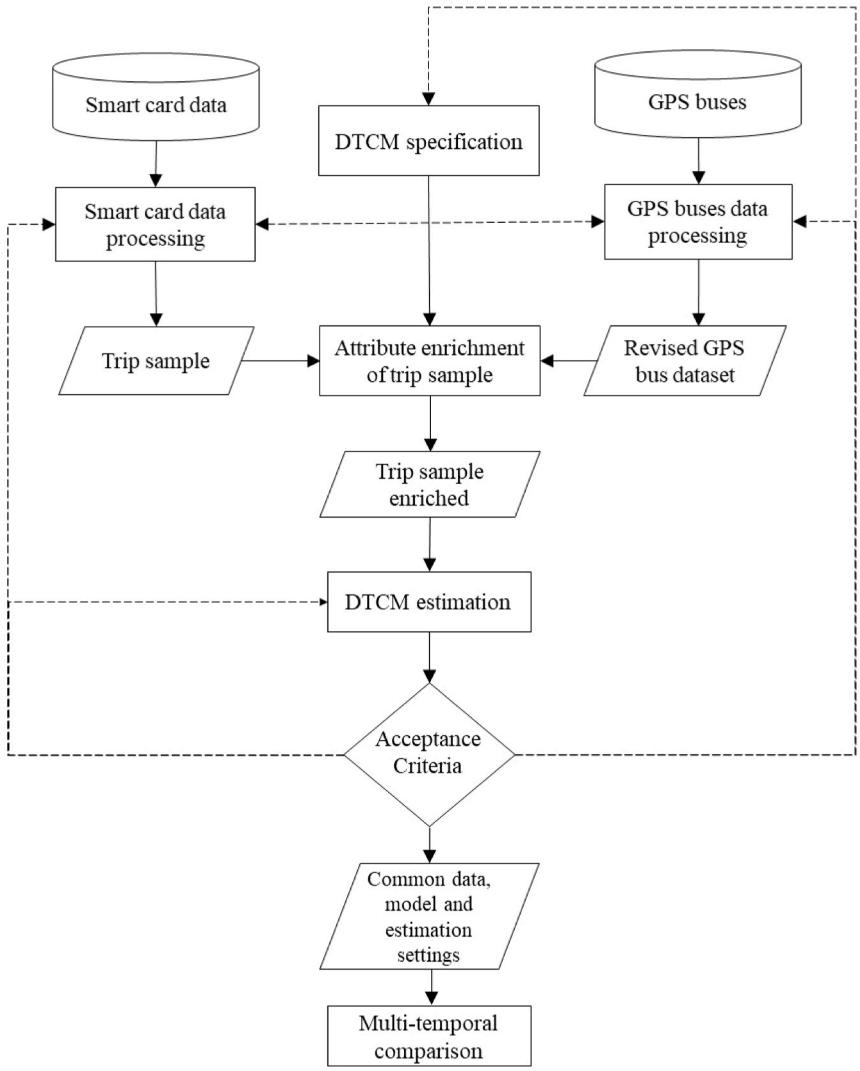

Fig. 2. Methodology implemented in this study.

vehicle travel time and schedule delay. This decision has two aims: a) focussing on the challenge of employing smart card data for the estimation of DTCM (i.e. obtaining travel times for the unchosen time intervals and calculating schedule delay) and the respective assessment of the methodology followed, and b) simplifying the adoption of the same modelling specification to all the episodes analysed. The selected utility function, which considers in-vehicle travel time and schedule delay, offers a specification that, without being sophisticated, is suitable to maintain consistency on the two attributes that this study focuses on across all the investigated episodes, a necessary condition when a comparison of valuations across time is pursued (Börjesson et al., 2022). Bus occupancy, however, was also analysed but not incorporated in the final specification. In particular, bus occupancy, calculated using the approach proposed by Yap et al. (2018) for each time interval and OD stop-pair, was tested in the model using additive and in-vehicle travel time multiplier specifications. Interestingly, early results found that bus occupancy did not have any dissuading effect on travellers' departure time decisions, maybe because bus occupancy was not enough to cause discomfort or because bus users were 'captive' to certain departure times. Nonetheless, the reliability of bus occupancy values and their related results are dubious as the number of passengers on the bus is sub-estimated due to Santiago's bus system's elevated fare evasion (above 30%) (Allen et al., 2019). Hence, although the early results of bus occupancy are enough to prompt interesting further research, they fall outside this study's scope and, therefore, are not addressed here. In this study, we do not explicitly include measures such as average waiting time or its variability. The reason for this decision is that the analysis will finally focus on the 30 highest-demand bus services, which operate with high and stable frequencies during the morning peak period. This consistency minimises variation in waiting times across the choice set, preventing testing its relevance. Moreover, in addition to the selected bus service characteristics, real-time bus arrival information is widely available and utilised in Santiago through public and private mobile applications (Henriquez-Jara et al., 2025). These tools help users reduce perceived uncertainty and better time their arrivals to the bus stops, lessening the impact of irregular service. Given these factors, we consider the direct influence of frequency and reliability on departure time choice to be limited in the context of this study.

The selected time-size interval for the departure time alternatives was established as 15 min, which has been the norm in previous studies (Lizana et al., 2021; Zannat et al., 2021). The morning rush hour was selected as the day period to be modelled, defining a range of departure time alternatives between 06:00 AM and 11:00 AM. This decision was made as in previous studies schedule delays have been found consistently to be statistically significant during the morning peak and seldom in the evening peak (Zannat et al., 2021). The framework adopted in this paper follows the standard in DTCM for public transport, which assumes fixed boarding and alighting stops for the generation of the alternative set (Peer et al., 2016; Arellana et al., 2012). In other words, boarding and alighting locations are not conditioned on the time alternatives, meaning that each user is assumed to use the same stops while facing time-varying in-vehicle travel times and schedule delays. In addition, the potential heterogeneity in trip scheduling decisions among bus commuters was examined using a K-means clustering analysis based on trip frequency for each episode. The optimal number of clusters was determined using the Elbow method, which evaluates the reduction in the total within-cluster sum of squares as the number of clusters increases (see Fig. 3). The results revealed two distinct clusters: cluster 1 comprised individuals with only one trip, while cluster 2 included individuals with two, three, or four trips. Cluster 2 was then defined as more recurrent users, characterised by making at least two trips on different days within the study period for each episode. In contrast, cluster 1 was defined as more occasional users, who were observed only on a single day during the episode. Therefore, two model specifications were computed to compare episodes: a DTCM for the unsegmented bus commuters and a DTCM considering the proposed segmentation. Marginal utilities of schedule delay, travel time and the distribution parameters of PATS were defined as group-specific in the case of the latter specification. It is necessary to clarify that the definition used in this study to segment travellers does not pretend to propose an absolute definition of what is recurrent or occasional but to contrast two groups using a relative differentiation.

5.2. Smart card data and bus location processing steps

This step involved processing the smart card data records and bus location datasets to generate suitable inputs for model estimation. Regarding the smart card data, a set of filters was applied with the aim of increasing the quality of the trip samples and focusing on specific data subsets regarding the established goals. The following rules were applied:

- Null entrances were removed. This includes transactions without boarding/imputed alighting stops.
- Only transactions from Monday to Thursday were retained.
- Only bus users with direct trips were considered.
- Transactions with travel time lower than 5 min were removed.
- Only trips in which boarding validation is recorded between 6:00 AM and 11:00 AM are considered.
- Only work-related trips are considered.
- Thirty bus services with the highest usage and common for all episodes were analysed.
- 30.000 unique IDs were sampled for each episode.

This study focused exclusively on users making direct bus trips, as this group allows for a more consistent and straight forward analysis of their trip scheduling decisions. While the proposed methodology does not impose any restriction for including multi-leg trips, doing so would introduce additional complexities, such as transfer coordination and route sequencing, which fall outside the scope of this study. Concerning the work trip purpose rule used in this study, the approach proposed by Devillaine et al. (2012) and applied to the data for Santiago's PT authority is employed. The approach classifies outbound work trips as those whose a) activity duration (defined as the time between the outbound and the return trip) is longer than 2 h, b) it is not the last trip of the day before the activity is performed, and c) the card type used is not student or elderly. The present study adopted this same classification, considering the advantages of the approach and the limitations of the data available to explore more sophisticated techniques (see for example Faroqi et al. (2023)). In particular, the study of Devillaine et al. (2012) was designed and tested for the Santiago's PT system, and secondly and more importantly, it generates a reasonable daily profile of outbound trips. A GPS bus data processing stage was also implemented to ensure that the OD bus stop pairs included in the sample corresponded to services with systematically reliable timestamp records. This filtering

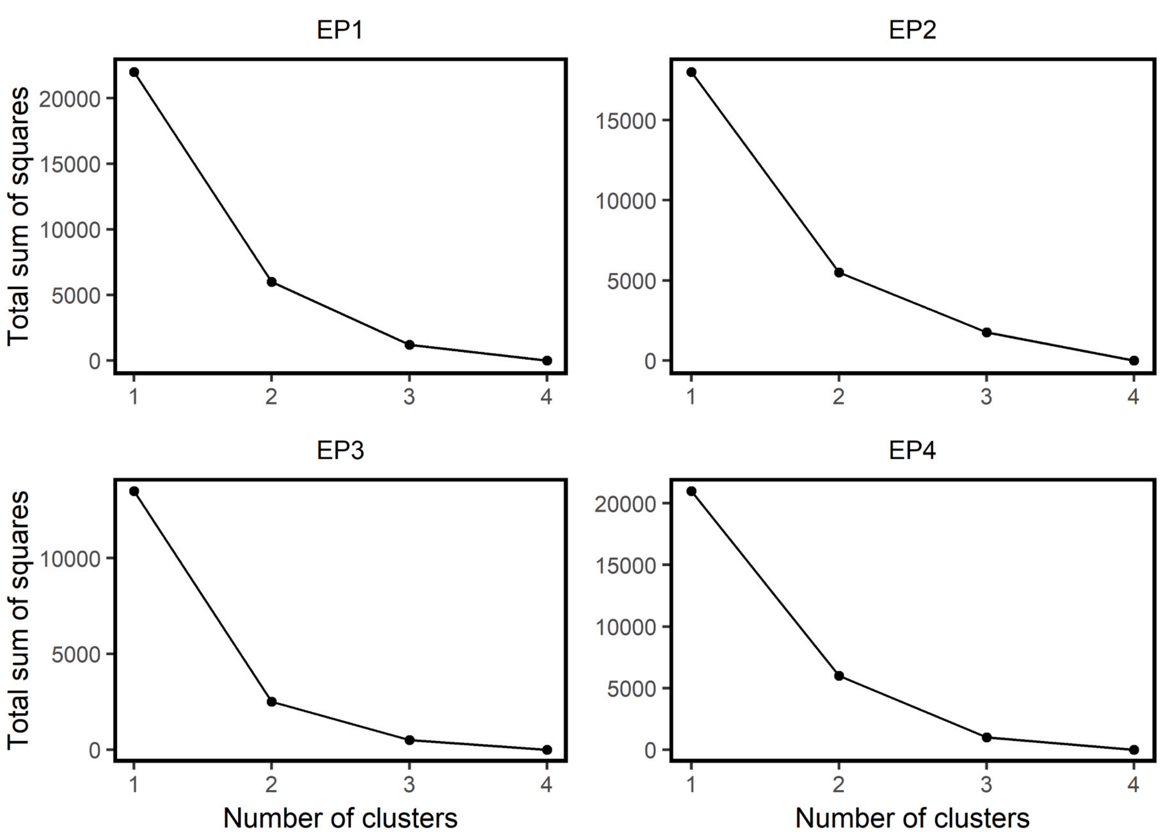

Fig. 3.. Results of the K-means algorithm applied to trip frequency for each episode.

was necessary because inconsistencies were detected in the GPS data for a small number of bus services, such as missing timestamps (likely due to the GPS being turned off) and discrepancies in the recorded sequence of bus stop arrivals compared to the official route (possibly caused by temporary diversions).

In order to develop a sensitivity test of the results to the method for imputing alighting destinations, we returned to the theoretical underpinnings of the Munizaga and Palma (2012) algorithm adopted, particularly with a view to assessing its sensitivity in disrupted scenarios. The basic idea behind the algorithm is to follow the trip chain of a card and identify the alighting position by using the position and time of the next recorded boarding. Specifically, the algorithm achieves this by minimising a measure of generalised time (Tg_i), where i stands for the position of the estimated alighting stop. The variable Tg_i depends on the travel time associated to that position (t_i), the walking time associated to the distance between position i and the position of the next recorded boarding (d_{i-next}), the average walking speed (s_w), a penalisation factor (f_w) obtained from discrete choice models as the disutility of walking-time over in-vehicle-travel-time, and the restriction $d_{i-next} < d$, where d is the maximum distance a person is willing to walk, with a value set at 1000 m. Analysing the algorithm we found that at least two key parameters might potentially be altered as a consequence of disruptive contextual settings: (a) changes in the marginal utility of in-vehicle travel time, which would alter the penalisation factor and reduce the relative weight of walking distance; and (b) a possible increase in users' tolerance for walking distance under disruption. Regarding a), we conducted a brief sensitivity analysis using simulated values, including several travel distances, penalisation factors of 2.5 and 2.0 and their associated reductions of 10%, 20% and 30% (to incorporate the effect of higher in-vehicle travel time marginal disutilities during disruptions). The results showed very little sensitivity of the algorithm in terms of the alighting imputation to the changes in the penalisation factor. This can be explained because Tg_i depends mostly on t_i, which is not affected by the penalisation factor, and the fact that the penalisation factor affects the distance component of all Tg_i (all potential alighting locations). As the algorithm compares Tg_i values and all of them experience some degree of reduction, the solution remains unchanged. For the tested settings, we also found no signs of different solutions when increasing the default distance.

To define the ideal combination of sample size and number of bus services for the analysis, an iterative process was conducted. As Fig. 2 shows, that iterative process involved the interaction between the smart card datasets, bus locations datasets, model estimation and model outputs for each episode. Finding a suitable number of bus services and practical trip sample size was required, as a large number of bus services also involved a large sample size to correctly capture the users' trip scheduling behaviour from thousands of OD bus stop-pairs. However, a sample size that is too large is impractical to employ in the model estimation step due to its computational complexity. To establish these values, bus location datasets were first analysed to find common bus services across all episodes, which also help to ensure the comparability of the model results between episodes. After this process, the identified common bus services were combined with the smart card records. Interestingly enough, it was found that a concentrated proportion of bus services accounted for the majority of the bus usage; less than 30% of the bus services represented more than 70% of the observed transactions. This allowed us to focus on testing a relatively limited number of bus services from 10 to 50 without losing the representativeness of commuters. Multiple iterations demonstrated that using a combination of 30 bus services (that accounted for between 30% and 40% of the observed trips for the studied episodes) and a sample size of 30,000 bus commuters leads to satisfactory results, which is why these values were adopted for the analysis.

5.3. Attribute enrichment process

In order to obtain representative in-vehicle travel times for the complete choice set, a script was developed to calculate the median in-vehicle travel times. This was achieved by establishing travel time profiles for each observed bus origin-destination stop-pair, considering 15-minute intervals. This step combined the output of the three previous tasks: model specification, revised bus location dataset and trip sample. Its output was the generation of trip samples enriched with the in-vehicle travel time for the full choice set of departure time alternatives for the chosen bus service. A moving average smoothing process was then applied to reduce the potential existence of sharp fluctuations. The moving-average median preserves the main directional profile while avoiding noise from atypical spikes, which could bias stated trade-offs. This is particularly relevant considering that there is only a limited number of days of GPS bus data available to conduct this imputation, which could make the data more susceptible to potential noise. Finally, values were assigned to the chosen and unchosen departure time alternatives of each bus commuter observed in the data sample. The estimated in-vehicle travel time represents the time between a specific bus origin-destination stop-pair a user would expect if they decided to depart in a time interval *s*. In this case, in-vehicle travel time includes all en-route delays, such as those coming from dwelling time, strops in traffic lights, traffic congestion, etc., and therefore, represents a reliable characterisation of the level of service experienced by users. Regarding the available time range to travel during the analysed morning period (06:00 AM – 11:00 AM), no restriction was made a priori, assuming that the complete choice set is available for a traveller. This approach has been considered more realistic and safer than assuming that a user's choice set contains only the observed departure time intervals (Sasic and Habib, 2013). The above is particularly true when no additional information is available to account for travellers' schedule flexibility, as in this case. However, it was observed that some bus services were unavailable for some departure time alternatives, particularly for the departure alternatives near 06:00 AM and the time between 10:00–11:00 AM. Therefore, the departure time alternatives for users of those services were adjusted accordingly.

5.4. Estimation of DTCMs and multi-temporal comparison

The model estimation was conducted following the methodology stated in Section 4.2. Several model settings were tested to assess the effect on the results, such as the number of draws and the type of probability distribution to represent the variation in $\widetilde{PATS}_n$. Through an iterative process, the Normal and Johnson S_B distributions were tested, observing that the second demonstrated the highest stability in terms of model convergence. Among the strengths of the Johnson distribution are its great flexibility (no assumption of symmetry is needed) and the feasibility of defining fixed boundaries, which is a relevant property considering the fixed day period analysed in this study (Hess et al., 2005). Therefore, $\widetilde{PATS}_n$ was estimated assuming a Johnson distribution, in which the lower and upper bounds are the extremes of the range of the time-period analysed (6:00 AM and 11:00 AM, respectively). For the simulated likelihood estimation, 500 Halton draws were used, which produced stable parameter estimates across repeated runs with different random seeds. While standard errors and t-statistics are reported, we acknowledge that these reflect only sampling variability and may understate additional uncertainty from simulation noise. Therefore, to assess robustness during the modelling, we tested the model using gradually increased draws in intervals of 100, from 300 to 1000, and the estimates and significance levels remained virtually unchanged. This provides confidence that simulation error is unlikely to have influenced the results of this study. All modelling was conducted using the Apollo package in R (Hess and Palma, 2019). In addition, despite the time alternatives being defined in 15-minute intervals, during model testing, alternative-specific constants (ASCs) were specified under different interval groupings. The results showed that constraining the ASCs of two consecutive 15-minute bins to be equal (effectively creating 30-minute ASC intervals) produced more stable estimates and improved model convergence across different random seeds. This adjustment strikes a balance between maintaining temporal detail and ensuring estimation stability, and was the reason behind its adoption. As acceptance criteria used in the iterative process, issues considered were: a) feasibility of the computation time for estimation, b) appropriateness of the model outputs (marginal utilities and distribution parameters), c) model convergence, d) stability in the model results if different samples were employed. The results of the iterative process generated the adoption of common data, model and estimation settings for all episodes. Finally, a multi-temporal comparison between the model results for each episode was conducted based on TVSDs, marginal utilities and the PAT-Stop density functions.

6. Results

6.1. Model results for the before-disruptions episode

Model results for the before-disruptions episode (EP1) are first analysed. The results of the mixed multinomial logit (Table 3) showed that schedule delay and in-vehicle travel time were relevant attributes to explain the departure scheduling choices of bus commuters, presenting both negative and statistically significant estimates. Related to the overall goodness of fit of the model, the rho-squared is in line with previous works where similar frameworks have been considered (Bwambale et al., 2019; Zannat et al., 2021). An average TVSD of 0.81 was calculated, meaning that bus commuters would accept an increase of 0.81 min in in-vehicle travel time to reduce 1 min of schedule delay. This result is consistent with the range of TVSDs reported in previous studies where departure time choices for PT commuting have been estimated. The valuation is located in the lower range of studies with SP data for the same city (Arellana et al., 2012; Lizana et al., 2021) and moderately higher than the valuations reported using revealed preference data for other cities (Peer et al., 2016). Parameters of the PAT-Stop density function were successfully estimated, and insightful information about the heterogeneity in commuters' arrival time preferences was provided. It was observed that the PAT-Stop density function generated a reasonable proxy of the work starting time range for the Chilean context. This can be observed in Fig. 4**.A**, where the PAT-Stop density function assigns maximum probability to the 08:30–08:45 AM period.

Table 3
Departure time choice model results for the before-disruptions episode (EP1).

	Unsegmented sample		Segmented sample	
Variable	**Estimate**	**Rob t-stat**	**Estimate**	**Rob t-stat**
Marginal utilities				
$\beta_{IVT,all}$	-1.131	(-4.95)		
$\beta_{IVT,oc}$			-1.247	(-6.09)
$\beta_{IVT,re}$			-0.813	(-3.13)
β_{SDR}	-0.439	(-11.87)		
$\beta_{SDR,oc}$			-0.338	(-12.65)
$\beta_{SDR,re}$			-0.591	(-13.48)
$\widetilde{PATS}$ parameters				
μ	0.051 [-0.001; 0.103]	(1.92)		
μ_{oc}			0.196 [0.127; 0.265]	(5.57)
μ_{re}			-0.251 [-0.202; 0.300]	(-10.07)
σ	-0.856 [-0.935; −0.777]	(-21.2)		
σ_{oc}			-0.96 [-1.083; −0.837]	(-15.3)
σ_{re}			-0.822 [-0.911; −0.733]	(-18.02)
Time period specific parameters (ASCs)				
06:00–06:30	0	-	0	-
06:30–07:00	0.324	(11.3)	0.375	(7.32)
07:00–07:30	0.72	(11.81)	0.82	(12.31)
07:30–08:00	0.841	(10.22)	0.981	(13.64)
08:00–08:30	0.762	(8.28)	0.924	(13.3)
08:30–09:00	0.66	(6.53)	0.827	(12.57)
09:00–09:30	0.551	(4.77)	0.702	(10.95)
09:30–10:00	0.826	(5.97)	0.935	(13.13)
10:00–10:30	1.05	(6.41)	1.086	(13.79)
10:30–11:00	1.581	(8.2)	1.51	(15.2)
LL(final)	-85331		-84727	
Adj. Rho-squared	0.029		0.036	
TVSD	0.81			
$TVSD_{oc}$			0.56	
$TVSD_{re}$			1.76	
$\beta_{IVT,re}/\beta_{IVT,oc}$			0.65	
$\beta_{SD,re}/\beta_{SD,oc}$			1.75	

*[] indicates 95% confidence interval (CI).

In terms of the heterogeneity in the trip scheduling decision process among bus commuters, interesting insights were revealed when controlling for the relative recurrence in their bus usage. Model results (presented in Table 3) showed that the marginal utility of schedule delay for recurrent users (defined as those who were observed performing a trip on at least two days) was 1.75 times as high as the one calculated for the occasional group (defined as those observed only during a single day). This dissimilarity in the aversion to arriving at a different time to their PAT-Stop illustrates the expected differences between the two groups; occasional commuters face less negative consequences for the same amount of delay compared with more recurrent commuters. The TVSD found for each category agrees with this finding. A valuation of 1.76 was observed for recurrent commuters and 0.56 for the occasional group. This indicates that regular users are prepared to accept a higher travel time (and therefore to depart at times when the associated travel time was potentially higher) to arrive nearer to their PAT-Stop than occasional commuters are. In addition, according to Fig. 4**.B**, both groups exhibited distinctive PAT-Stop density functions that shed light on the groups' characteristics. For recurrent commuters, it showed its maximum in the neighbourhood of 08:00 AM, while for more occasional bus commuters, the mode is observed to be located almost one hour later around 09:00 AM. These results, in combination with the previous ones, suggest that the recurrent group were likely to be made up of workers with an early and relatively inflexible work start-time. In contrast, occasional workers showed a later and relatively flexible work start-time.

6.2. Multi-temporal comparison - unsegmented bus commuters

Empirical findings for the episodes of post-social unrest (EP2), post-COVID-19 outbreak (EP3) and after-disruptions (EP4), considering the unsegmented bus commuter specification, are presented in Table 4. The coefficients of schedule delay and in-vehicle travel time for EP2 and EP4 showed negative and statistically significant estimates. The exception was the most disruptive episode (EP3), which presented a not statistically significant marginal utility for in-vehicle travel time, likely related to difficulties in linking the levels of this attribute with the observed choices in very disruptive settings. This is in line with the overall poorer goodness of fit of EP3. Based on statistically significant estimates, TVSDs that were respectively 35% and 17% lower than the one calculated for EP1 were calculated for EP2 and EP4. This result indicates a decrease in the willingness to increase travel time to reduce schedule delays during and after the disruptions. Marginal utilities were also compared, with statistically significant differences, in particular for the aversion to schedule delay. These estimates were all lower than the schedule delay estimate observed in EP1 (0.8, 0.5 and 0.9 times for EP2, EP3 and EP4,

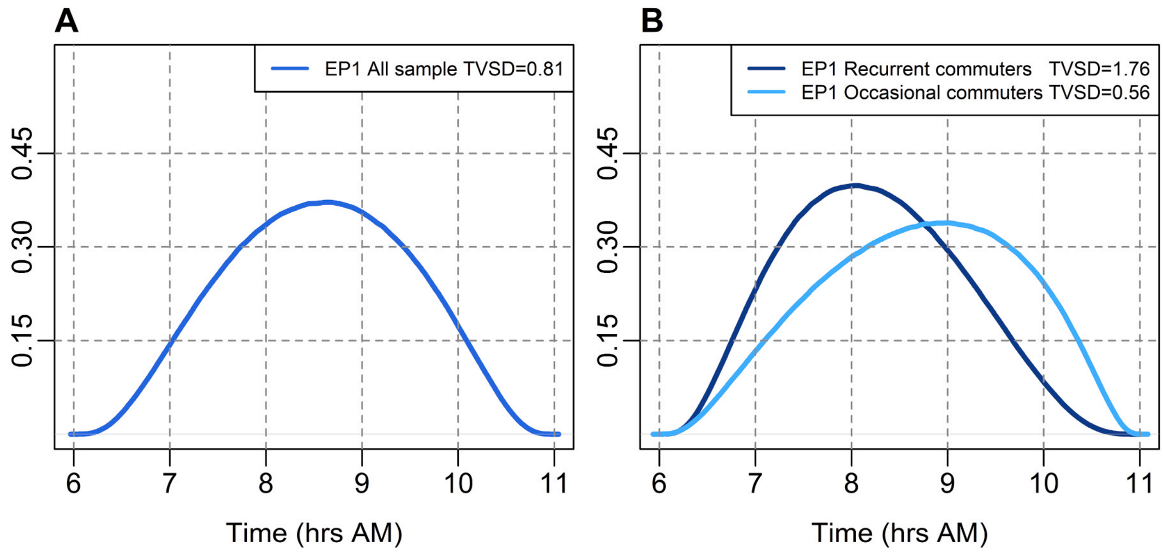

Fig. 4. PAT-Stop density functions for EP1. A) unsegmented sample, and B) segmented sample.

Table 4
DTCMs results considering uncategorised bus commuters. Post-social unrest (EP2), post-COVID-19 outbreak (EP3) and after-disruptions (EP4).

	EP2 2020.03		EP3 2020.11		EP4 2022.04	
Variable	**Estimate**	**Rob t-stat**	**Estimate**	**Rob t-stat**	**Estimate**	**Rob t-stat**
Marginal utilities						
β_{IVT}	-1.262	(-11.73)	0.194	(0.98)	-1.269	(-9.58)
β_{SDR}	-0.336	(-22.43)	-0.218	(-18.73)	-0.405	(-15.00)
$\widetilde{PATS}$ *parameters*						
μ	0.212 [0.184; 0.240]	(14.97)	0.266 [0.224; 0.308]	(12.39)	-0.013 [-0.021; −0.005]	(-3.08)
σ	-0.570 [-0.652; -0.488]	(-13.67)	-0.938 [-1.125; -0.751]	(-9.83)	-0.724 [-0.789; -0.659]	(-21.72)
Time period specific parameters (ASCs)						
06:00–06:30	0	-	0	-	0	-
06:30–07:00	0.125	(3.50)	-0.002	(-0.64)	0.265	(11.79)
07:00–07:30	0.350	(14.21)	0.157	(5.59)	0.567	(19.39)
07:30–08:00	0.317	(12.28)	0.161	(6.08)	0.580	(17.06)
08:00–08:30	0.301	(13.70)	0.166	(5.78)	0.534	(14.92)
08:30–09:00	0.036	(10.28)	0.123	(4.28)	0.323	(9.02)
09:00–09:30	-0.119	(-6.39)	0.163	(6.65)	0.421	(11.05)
09:30–10:00	0.038	(3.38)	0.284	(10.54)	0.610	(12.70)
10:00–10:30	0.209	(7.91)	0.406	(13.10)	0.858	(13.42)
10:30–11:00	0.615	(14.12)	0.675	(16.74)	1.381	(15.53)
LL (final)	-84844		-86407		-85561	
Adj. Rho-squared	0.031		0.010		0.028	
$TVSD_{EPi}$	0.52		NoE		0.67	
$TVSD_{EPi}/TVSD_{EP1}$	0.64		NoE		0.83	
$\beta_{SDR,EPi}/\beta_{SDR,EP1}$	0.77	(6.87)*	0.50	(18.90)*	0.92	(1.26)*
$\beta_{IVT,EPi}/\beta_{IVT,EP1}$	1.12	(1.22) *	NoE	-	1.12	(1.04)*

NoE: Not estimated. *: indicates t-statistics referred to the difference between the estimate of episode *i* and EP1. *[] indicates 95% confidence interval (CI).

respectively). This finding recognises a significant reduction in the aversion to schedule delay in the aftermath of the disruptive episodes, which can be associated with a relaxation in the consequences of arriving at a different time to the PAT-Stop faced by commuters. Nonetheless, a non-significant difference was observed between EP4 and EP1, suggesting a return to pre-disruptive settings.

PAT-Stop density functions were also contrasted, providing evidence of intertemporal changes in the trip-timing preferences for arrival. Fig. 5 provides a glimpse of the progression of the $\widetilde{PATS}$ between episodes, illustrating differences in their deviations and the time of day at which they reached their maximums. Among the differences observed between the PAT-Stop density functions, it is possible to highlight: a) maximum values are shown to occur later in the morning in EP2 and EP3 compared with EP1, b) the density function of EP4 seems to go back to that of the before-disruptions settings, and c) lower standard deviations for the density functions for EP2-EP4 are observed compared with EP1. Regarding a), it may be explained by the adoption of a later work start-time as a benefit to employees during disruptive events, with it being most pronounced, as expected, after the outbreak of the COVID-19 pandemic (EP3). On other hand, the lower heterogeneity in the $\widetilde{PATS}$ observed for later episodes was an unexpected finding, which would denote that in the aftermath of a disruptive event, trip preferences of active users may be more homogenous than in non-disruptive settings.

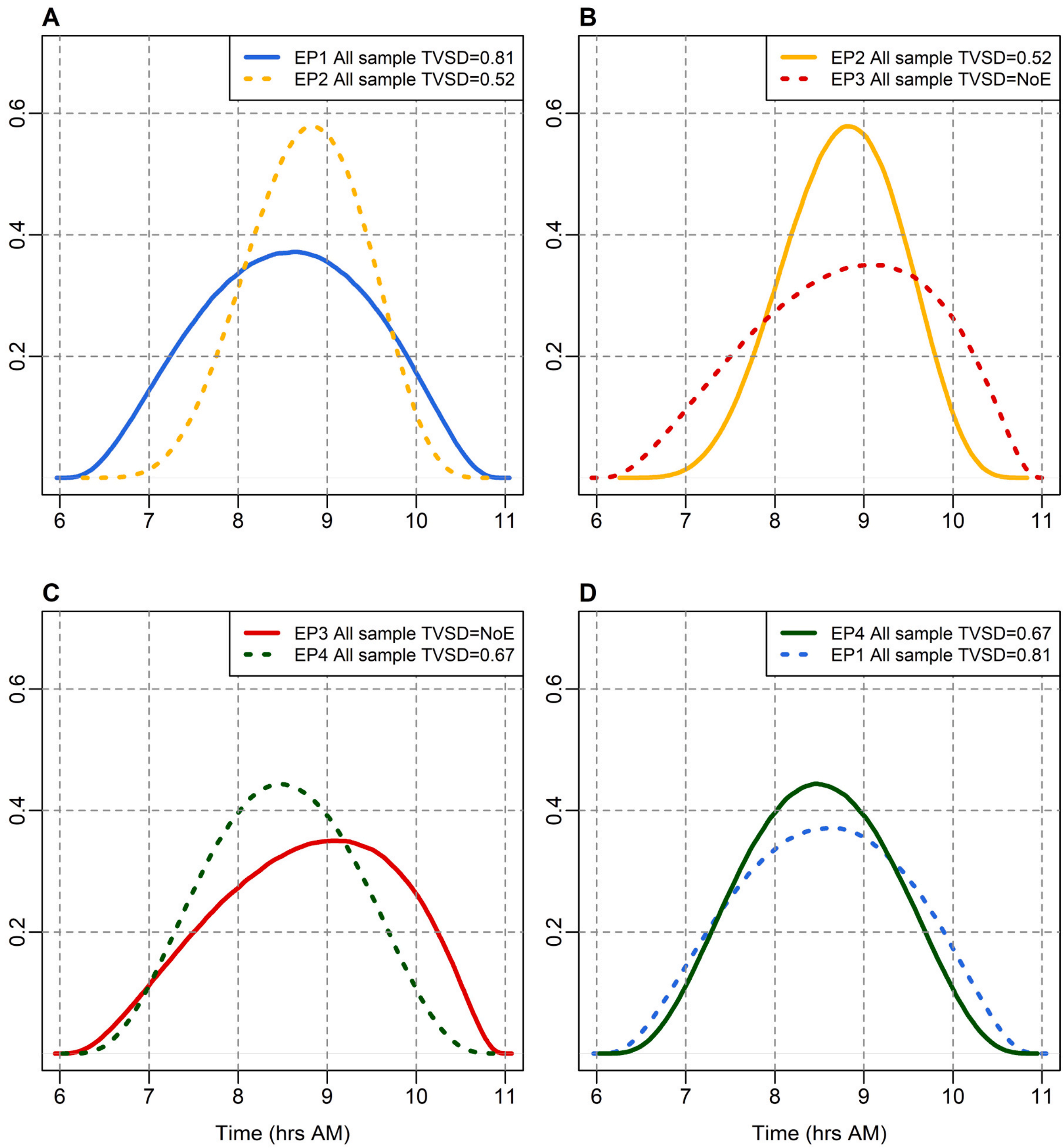

Fig. 5. PAT-Stop density functions for unsegmented sample. A) Comparison EP1-EP2, B) Comparison EP2-EP3, C) Comparison EP3-EP4, and D) Comparison EP4-EP1. NoE: Not estimated valuation.

6.3. *Multi-temporal comparison - segmented bus commuters*

Modell outputs for the specification that considers the segmentation of bus commuters by their relative bus usage are presented in Table 5. This specification of the utility function led to a significant improvement in the fit of the DTMCs estimated, a result supported by obtaining LR Statistics above the critical value for all episodes and by observing an increased adjusted rho-squared compared with the base specification. Moreover, the user segmentation allows meaningful differences between the bus commuters to be identified, as is described next.

The progression of the TVSD for the recurrent commuter group presented ratios relative to EP1 of 0.5 (EP2) and 0.3 (EP3), revealing a drastic reduction in the willingness to increase travel time to reduce schedule delay during the aftermath of disruptive episodes. These results are explained by higher marginal utilities of in-vehicle travel time and a reduction in the disutility of schedule delay observed in EP2 and EP3. In particular, it was found that marginal utilities for in-vehicle travel time for EP2 and EP3 were 1.6 and 2.1 times that observed in EP1. By contrast, the marginal utilities for schedule delay were calculated to be 0.9 and 0.6 times the one estimated for EP1. Conversely, the findings for occasional commuters were more diverse, likely related to their associated characteristics. The group displayed a reduction in the disutility of schedule delay, similar in magnitude to the one experienced for the recurrent group, but a non-significant variation in the disutility of in-vehicle travel time. In terms of changes in the TVSD for this user segment, it was found that the reduction observed in EP2 was only 16% of the TVSD observed in EP1. More insightful differences between the two groups were revealed when analysing the PAT-Stop density functions presented in Fig. 6. Fig. 6.**B**, in particular, illustrates the finding that $\widetilde{PATS}$ for occasional commuters shifted notably to later arrival time preferences in EP3. In contrast, the arrival preferences for recurrent commuters exhibited less flexibility to change across episodes.

A comparison between EP1 and EP4 gives valuable insight into the existence of lasting changes in the trip scheduling preferences of bus

Table 5
DTCMs results for the segmented bus commuter specification. Post-social unrest (EP2), post-COVID-19 outbreak (EP3) and after-disruptions (EP4).

	EP2 2020.03		EP3 2020.11		EP4 2022.04	
Variable	**Estimate**	**Rob t-stat**	**Estimate**	**Rob t-stat**	**Estimate**	**Rob t-stat**
Marginal utilities						
$\beta_{IVT,oc}$	-1.202	(-7.79)	0.609	(0.74)	-1.123	(-7.01)
$\beta_{IVT,re}$	-1.302	(-4.07)	-1.667	(-2.00)	-1.422	(-7.79)
$\beta_{SDR,oc}$	-0.267	(-11.14)	-0.178	(-13.69)	-0.317	(-13.46)
$\beta_{SDR,re}$	-0.507	(-12.27)	-0.329	(-6.24)	-0.545	(-14.2)
$\widetilde{PATS}$ parameters						
μ_{oc}	0.378 [0.336; 0.420]	(17.7)	0.493 [0.110; 0.876]	(2.52)	0.099 [0.051; 0.147]	(4.05)
μ_{re}	-0.133 [-0.177; -0.089]	(-5.91)	-0.196 [-0.278; -0.114]	(-4.66)	-0.273 [-0.312; -0.234]	(-13.63)
σ_{oc}	-0.568 [-0.785; -0.351]	(-5.14)	-0.994 [-1.786; -0.202]	(-2.46)	-0.747 [-0.833; -0.661]	(-16.98)
σ_{re}	-0.591 [-0.681; -0.501]	(-12.85)	-0.676 [-0.912; -0.440]	(-5.62)	-0.732 [-0.808; -0.656]	(-18.79)
Time period specific parameters (ASCs)						
06:00–06:30	0	-	0	-	0	-
06:30–07:00	0.153	(6.05)	0.003	(1.49)	0.307	(9.46)
07:00–07:30	0.407	(12.31)	0.172	(1.67)	0.645	(17.98)
07:30–08:00	0.399	(12.21)	0.183	(1.73)	0.682	(16.99)
08:00–08:30	0.397	(13.00)	0.191	(1.61)	0.649	(18.06)
08:30–09:00	0.136	(3.79)	0.150	(1.50)	0.439	(11.29)
09:00–09:30	-0.030	(-2.03)	0.186	(4.63)	0.523	(11.99)
09:30–10:00	0.095	(3.31)	0.293	(8.77)	0.676	(12.66)
10:00–10:30	0.207	(6.46)	0.384	(6.38)	0.862	(13.67)
10:30–11:00	0.522	(9.55)	0.607	(4.88)	1.296	(15.22)
LL (final)	-84233		-85804		-85061	
Adj. Rho-squared	0.038		0.017		0.033	
$TVSD_{oc}$	0.47		NoE		0.58	
$TVSD_{re}$	0.81		0.49		0.93	
$TVSD_{oc,EPi}/TVSD_{oc,EP1}$	0.84		NoE		1.04	
$TVSD_{re,EPi}/TVSD_{re,EP1}$	0.46		0.28		0.53	
$\beta_{SDR,re}/\beta_{SDR,oc}$	1.90	(5.81)*	1.80	(2.86)*	1.72	(5.94)*
$\beta_{SDR,oc,EPi}/\beta_{SDR,oc,EP1}$	0.79	(2.03)*	0.53	(4.97)*	0.94	(1.20)*
$\beta_{SDR,re,EPi}/\beta_{SDR,re,EP1}$	0.86	(2.96)*	0.56	(12.3)*	0.92	(0.89)*
$\beta_{IVT,re}/\beta_{IVT,oc}$	1.18	(0.31)*	NoE	-	1.27	(1.64)*
$\beta_{IVT,oc,EPi}/\beta_{IVT,oc,EP1}$	0.96	(0.29)*	NoE	-	0.90	(0.77)*
$\beta_{IVT,re,EPi}/\beta_{IVT,re,EP1}$	1.60	(1.53)*	2.05	(1.03)*	1.75	(3.33)*

NoE: Not estimated. *: indicates t-statistics referred to the difference between the estimate of episode *i* and EP1. *[] indicates 95% confidence interval (CI).

commuters. It was found that as late as April 2022 (EP4), recurrent commuters still displayed a TVSD 0.5 times the valuations observed for EP1 (0.93 vs 1.76), while occasional commuters have recovered their pre-disruption valuation (0.58 vs 0.56). Marginal utilities of schedule delay have returned to the values of EP1 for both groups, presenting no significant difference. In the case of the disutility of travel time, a significant change was only observed for recurrent commuters, presenting an estimate equal to 1.75 times that observed in EP1, which is essentially the reason for the low TVSD still observed in EP4. Related to lasting changes in the PAT-Stop density functions, Fig. 6.**D** depicts the finding that regular commuters have almost returned to their pre-disruptions arrival time preferences. In contrast, some more noticeable changes can be observed for occasional commuter preferences.

7. Discussion of results

This study investigates trip scheduling decisions of bus commuters amid disruptive events by estimating departure time choice models (DTCMs) for characteristic episodes affected to different degrees by two types of disruptive events within this timeframe: the COVID-19 pandemic and social unrest. The study examined the shift in the trade-off between travel time and schedule delay (TVSD) across the selected episodes while addressing the methodological challenges of calculating schedule delay with smart card data by estimating preferred arrival times as a random variable within a mixed multinomial logit model. Next, we discuss each of the hypotheses proposed in the Introduction Section and then review the methodological limitations of this study and future research directions.

7.1. Interpretation of findings

H1. Smart card data is a feasible data source for estimating DTCMs for PT users:

The modelling results of the mixed logit models demonstrated that smart card data is a feasible data source for estimating DTCMs even when preferred arrival times (PAT) are unknown. In particular, for the pre-disruptive episode, satisfactory marginal utilities for travel time (TT) and schedule delay (SDR) were observed, as well as a valuation of the trade-off between travel time and schedule delay (TVSD) in line with the findings reported in previous studies (Lizana et al., 2021; Peer et al., 2016; Arellana et al., 2012). In particular, a TVSD of 0.81 was estimated for the before-disruptions episode, a value located at the lower end of the values reported previously based on stated preferences experiments (Arellana et al., 2012; Lizana et al., 2021) and in the upper end of studies where revealed data was implemented (Peer et al., 2016). Moreover, a

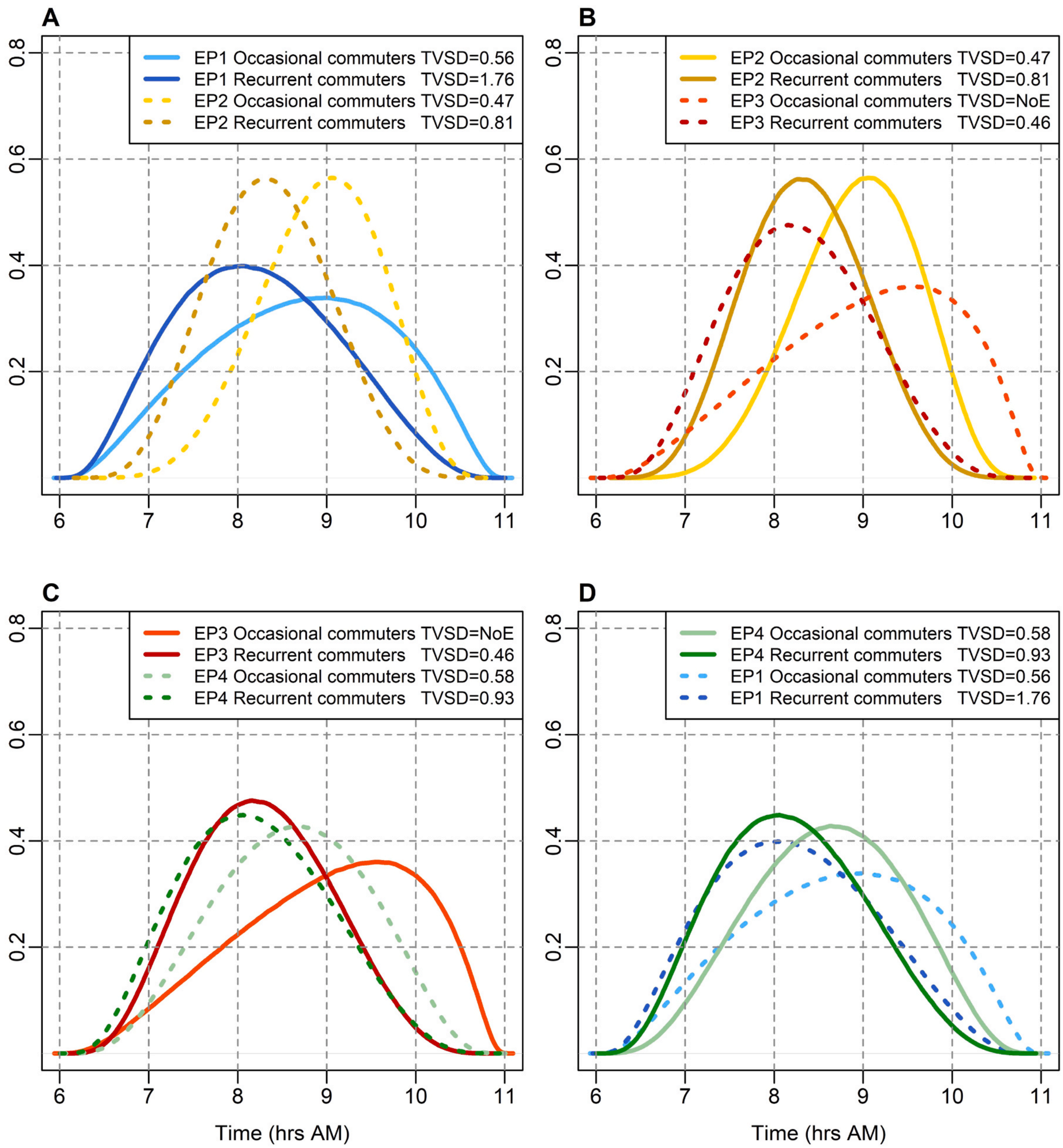

Fig. 6. PAT-Stop density functions for segmented bus commuters. A) Comparison EP1-EP2, B) Comparison EP2-EP3, C) Comparison EP3-EP4, and D) Comparison EP4-EP1. NoE: Not estimated valuation.

reasonable proxy of the preferred arrival times at the bus destination stop (PAT-Stop) for the case study considered was achieved. In particular, the implementation of a mixed logit approach enabled the accounting for heterogeneity in trip-timing preferences among bus commuters by explicitly calculating a density function of their preferred arrival times at the bus destination stop (PAT-Stop). Such a function depicts a maximum probability for the 08:30–08:45 AM period, which aligns with the expected start working times. Regarding the goodness of fit of the results, the proposed approach achieved an explanatory power in line with the results reported in previous studies where smart card data is the main source of data (Arriagada et al., 2022; Lizana et al., 2023) and in studies where a similar approach has been implemented (Zannat et al., 2021; Bwambale et al., 2019). Nonetheless, despite this finding and the fact that key coefficients (e.g. travel time and schedule delay) remained stable in sign and order of magnitude across episodes, we recognise the need to enhance the explanatory power of the proposed model. This was particularly relevant on EP3, the episode that characterised the most disruptive scenario, which yielded the lowest explanatory power. This may reflect misspecification or the need for contextual covariates (e.g. variable curfews, service cuts). Therefore, ways to impute richer data on personal attributes, such as sociodemographic characteristics, personal preferences, revealed preferred arrival times, and details of work arrangements, for public transport users could eventually help to overcome this issue (Kusakabe and Asakura, 2014). These attributes, together with a more comprehensive consideration of level-of-service attributes, contextual factors such as service availability, curfew restrictions, and temporary policy changes during disruption periods, could help in this direction.

H2. Distinctive situational contexts related to disruptive events have associated different valuations of travel time and schedule delay:

The results indicate that distinctive situational contexts, particularly those associated with disruptive events, are linked to significant variations in the valuation of travel time and schedule delay. This finding suggests that individuals' timing preferences are not indifferent to the situational contexts, but instead adapt to the specific constraints and uncertainties imposed by each context (in the case of this paper, pre-disruptions (EP1), after social unrest (EP2), after the COVID-19 outbreak (EP3), and post-disruptions (EP4)). In particular, we observed that bus commuters were less willing to accept additional travel time to reduce their schedule delay during EP2 and EP3, primarily related to a reduction in the disutility of schedule delay (i.e. reflecting a lower sensitivity to on-time arrival). The observed reduction in schedule delay aversion after the disrupted periods is plausibly linked to changes in work arrangements, such as those observed in the post-COVID period that saw an increase in workplace flexibility and the adoption of hybrid/remote work models (Wöhner, 2022). Nonetheless, we acknowledge that the dataset used in this study does not contain disaggregate information on individual workplace policies or remote-work uptake, which limits our ability to attribute the behavioural shifts to these specific mechanisms. In particular, it remains a promising direction for future research integrating attitudinal or employer-level data on work flexibility with travel behaviour data, which would allow a more precise examination of how disruptions reshape departure time choices. From a policy perspective, the corroborated hypothesis highlights the potential need for adjustments in transport supply during disruptive events, such as by examining the provision of additional services in the vicinity of traditional, more heavily demanded periods to account for the identified valuation shifts. It is also necessary to highlight that although the estimated PAT-density parameters were statistically significant and stable across specifications, their associated confidence intervals were wider during the disruptive episodes. This greater uncertainty implies that the magnitude of the resulting TVSD estimates and therefore the inferred behavioural differences across episodes should be interpreted with appropriate caution.

H3. Different PT user segments have different trip-timing preferences:

The findings of this study confirmed differences in how distinct traveller groups assess time-varying trip attributes, which aligns with the existing literature (Singh et al., 2023; Peer et al., 2016). In particular, it was found that more frequent commuters consistently showed higher TVSD than the group described as more occasional commuters. This result suggests that recurrent bus users are more willing to travel at times when travel time is higher to arrive near their PAT-Stop. Conversely, more occasional bus users are more likely to travel at times when travel time is relatively lower, despite increasing their schedule delay (earliness or lateness); in other words, they are less sensitive to schedule delay. The PAT-Stop density functions also revealed insightful differences between the two groups. Occasional commuters showed a later arrival preference than more frequent ones and were more flexible in adjusting their schedules depending on the situational context. In contrast, the PAT-Stop density function of more frequent bus commuters showed evidence of being more rigid in response to contextual changes. As an implication of these findings, it is possible to consider that the flexibility of occasional users may contribute positively to system resilience under disruptions, while the rigidity of more frequent users could create concentrated pressure on peak services, especially in crises (e.g., strikes, pandemics). Moreover, the rigidity of more frequent commuters suggests that they are less responsive to demand-management policies, meaning that service reliability and schedule adherence may be more critical for this group.

H4. A long-term disruptive event has enduring effects on trip scheduling decisions among PT users:

Mixed results were observed concerning the presence of long-term changes in the trip-scheduling process of bus commuters (H4). In particular, it was found that the TVSD in the latest episode (EP4) was lower (0.83 times) than in the before-disruptions episode (EP1). However, no significant differences were found between the marginal utilities of schedule delay and in-vehicle travel time for EP4 and EP1. Moreover, the results also showed that the PAT-Stops density functions of these two episodes appear to converge, despite still exhibiting minor differences. In addition, when making the same comparison but controlling for commuter groups, the TVSD of occasional commuters returned fully to their before-disruptions levels. In the case of more frequent bus users, despite the schedule delay penalty being still 8% lower, such a difference was not statistically significant. These results are in agreement with more recent literature that has shown a consistent loss of the work flexibility gained during the COVID-19 pandemic (Adrjan et al., 2025). Nonetheless, we also found evidence that shows more frequent bus commuters still have their TVSD in EP4 shifted compared to EP1. In particular, this group showed a significant difference in the disutility of travel time, which was found to be 1.75 times higher. This generates a TVSD 0.5 times lower than the one obtained for the same group in EP1, indicating a persistent higher aversion to travel during periods of the day associated with higher travel times to arrive on time. Regarding this finding, it supports the hypothesis that distinct user groups not only make different assessments of the trip-timing attributes but also experience dissimilar changes as a consequence of disruptive events (Singh et al., 2023). It is likely that the recovery process is still ongoing, and eventually, further periods should be analysed to complete the picture and reach a definitive conclusion.

7.2. Limitations and future works

Several methodological choices and limitations influenced our study. Below, we outline these aspects and highlight directions for future research.

a) Earliness and lateness penalties: One important limitation of this study lies in the assumption that earliness and lateness have symmetric penalties. While this restriction is necessary in the modelling framework to conduct simultaneous estimation of schedule delay and the preferred arrival time, it does not necessarily reflect real-world preferences (Peer et al., 2016; Arellana et al., 2012). Unfortunately, in this study, it is not possible to assess the extent of any potential bias that this assumption may induce, given the limitations of the available data. Intuitively, it is plausible to consider that the imposed symmetry restriction could lead to an overestimation in the preferences of people who arrive later and to an underestimation of those arriving earlier than their PAT. The logic of this potential implication relies on the fact that the model estimates an averaged schedule delay penalty that weights both earliness and lateness, where in traditional models the latter is usually higher than the former. Nonetheless, this hypothesis remains a speculation that future research could assess if empirical data with known PAT were available. Potential ways to overcome the symmetry issue include considering estimating PATs in a stage prior to model estimation, i.e., adopting a sequential approach instead of simultaneously estimating the PAT and the dummies. Nonetheless, that approach has shown its own limitations and particular data requirements (Koppelman et al., 2008).

b) Focus on bus users: This study focused exclusively on bus users, which, despite allowing a controlled analysis of departure time choice, does not capture the broader behavioural dynamics of a fully integrated multimodal public transport system. By excluding the metro, the analysis overlooks potential interactions between departure time decisions and mode or route choices. Future research should extend the proposed framework to incorporate multiple modes within an integrated setting. This would require addressing additional complexities such as transfer times, transfer penalties, fare structures, and mode-route switching behaviour, while also managing the associated computational processing time. Including multimodal users would enable a more comprehensive understanding of travel scheduling decisions and their interdependencies across the public transport network. As this study focused exclusively on users making direct bus trips, changes in the TVSDs across episodes for multi-leg trip users were not explored. Future work could extend the analysis to include multi-leg trips, providing a more comprehensive view of departure time decisions across the entire public transportation system.

c) Attributes: While the exclusion of waiting time and reliability measures is justified by the high frequency of the selected bus routes and the availability of real-time information, these conditions may be considered particular to this study's setting. First, the assumption of time-invariant waiting times may not hold on bus services with less stable frequencies or over longer modelled periods of time. Second, the analysis focuses on a bus system where access to real-time information is available to users, which may not reflect the behaviour of users without access to such information. Therefore, to generalise the proposed methodology to a whole public transport network or to users facing greater uncertainty in travel conditions, waiting time and reliability measures should be incorporated. Future research should explore these aspects by incorporating more diverse services and a wider range of attributes. In this study, in-vehicle travel times for each time interval were estimated using a moving-average median approach. This method preserved the main directional profile while reducing noise from atypical spikes that could bias the estimated travel time trade-offs. However, we acknowledge that, while pragmatic, it smooths over some within-interval variability and may limit the precision of trade-off estimates, particularly under conditions of fluctuating congestion and unreliable travel times.

d) Bus services considered: Our analysis favours high frequency services over less intensive ones. By considering a subsample of bus services in which a major proportion of trips are concentrated, an inherent bias toward higher-frequency services is introduced, reducing the representation of lower-frequency services in the analysis. Therefore, the results of this work are representative of the behaviour of passengers who primarily use higher-frequency bus services, while leaving for future research the question of testing the broader representativeness of the results.

e) Single-dimension departure time choice decision: the proposed modelling framework focuses exclusively on departure time choice and does not account for potential mode or route changes. While this is a practical assumption given the scope and data constraints of this study, we acknowledge that complex interactions between departure time and route choice may exist. Therefore, future work should further examine the interplay between departure time and mode-route choices. Such an effort would enable the formulation of a joint modelling approach and offer more robust insights into user behaviour regarding simultaneous decisions in public transport systems. The main challenges in incorporating route-choice changes into the study of trip scheduling through DTCM with passive data are: dealing with model estimation time and identification due to the need to simultaneously simulate preferred arrival times; analytical and computational constraints when considering multiple temporal episodes, as in this study; and, not least, establishing route choices for a large and complex network like Santiago's. The latter would require, among other things, datasets covering a longer observation period than those used in this study (e.g., at least one month of transactions) (Arriagada et al., 2022). Future work could also extend the framework adopted in this paper by relaxing the assumption of fixed boarding and alighting stops. This would require a longer observation period to capture enough variability in users' stop choices, as well as a modelling structure capable of jointly representing departure time, route, and mode choices. Incorporating this broader choice set would allow exploring how spatial flexibility in stop selection interacts with temporal flexibility in departure time decisions.

f) Multi-episode data: a limitation of this study arises from the fact that Santiago's smart card system is non-personalised, which restricts the ability to keep a panel structure across episodes. In addition, our estimation focuses on cards that are active for only 1–2 days in the most disruptive episodes, which may overrepresent the occasional user segment and limit our capacity to analyse stable, long-term behavioural changes. Future research should explore enhanced card-linkage techniques, such as probabilistic matching or integration with personalised user data, to improve panel retention and better capture the diversity of user behaviours over extended periods. Addressing these issues would enable more robust longitudinal analyses and provide deeper insights into the temporal dynamics of travel behaviour. Moreover, while the episodes analysed in this study were selected to avoid the overlap with bus operational disruptions, future research would focus on incorporating validation exercises or sensitivity testing in alighting estimation under altered network conditions to quantify potential biases. This would ensure greater confidence in inferred destination data, particularly when analysing the behavioural impacts of atypical events that affect bus services.

g) Size of the sample: the study of each of the episodes considered in this study is restricted to analysing only one week per episode. While this approach enabled the integration of multiple datasets and the management of the substantial computational burden associated with modelling four distinct episodes, it inevitably limits the ability to capture potential week-to-week dynamics in users' trip-scheduling behaviour. This design choice may overlook short-term behavioural adjustments that could emerge during transitional periods following disruptive events. Future research could address this limitation by incorporating multi-week or continuous panel data to examine the temporal evolution of departure time preferences. Such an approach would provide a richer understanding of how behaviour stabilises or adapts over time. Moreover, from a validation perspective, an important next step would be to select a single situational context with data available over a more extended period (e.g. one month) and repeat the analysis for the additional weeks. Such an exercise would allow robustness to be tested and provide evidence on whether parameter estimates and PAT distributions remain consistent.

8. Conclusions

Departure time choice models (DTCMs) are key tools in understanding time-varying travel demand. To the authors' knowledge, the study reported here is the first to employ smart card data to estimate such models, thereby understanding public transport user travel behaviour. This study makes a key contribution in this area by integrating several techniques within a single framework to overcome the intrinsic challenges of smart card data, such as estimating schedule delay, an unobserved attribute in passive data sources. By establishing a comprehensive methodology that permitted a multi-temporal comparison between characteristic episodes of Santiago's PT case study, the study is the first to provide evidence of the differences in the trip scheduling process among bus commuters considering characteristic contextual situations. The model results highlight the existence of multi-temporal differences in the arrival time preferences of bus commuters, as well as in their TVSD amid disruptive events. It was found that bus commuters were less willing to accept an increase in their travel time to reduce their schedule delay during disruptive episodes. The heterogeneity between bus travellers was also explored: more frequent bus commuters exhibited higher TVSDs than occasional commuters.

While our findings are preliminary and require further investigation, they demonstrate the feasibility of using smart card data to investigate how public transport passengers allocate their trip scheduling both during normal periods and amid external disruptions. This work also offers the potential to open up a research line for more applications of smart card data in PT time-varying demand analysis, for which a point-by-point limitation and future research discussion are provided. Ultimately, the proposed methodology can be utilised to comprehend how commuters allocate their activities during external disruptions in various scenarios. Peak spreading, congestion pricing and the analysis of time-varying transport demand flow patterns are other applications of this approach.

CRediT authorship contribution statement

Maximiliano Lizana: Writing – review & editing, Writing – original

draft, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **David Watling:** Writing – review & editing, Supervision. **Charisma Choudhury:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they do not have any known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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References

Abenoza, R., Cats, O., Susilo, Y., 2017. Travel satisfaction with public transport: Determinants, user classes, regional disparities and their evolution. Transp. Res. Part A Policy Pract. 95, 64–84. https://doi.org/10.1016/j.tra.2016.11.011.

Adrjan, P., Ciminelli, G., Judes, A., Koelle, M., Schwellnus, C., Sinclair, T., 2025. Working from home after COVID-19: evidence from job postings in 20 countries. Labour Econ. 96, 102751. https://doi.org/10.1016/j.labeco.2025.102751.

Allen, J., Muñoz, J.C., Ortúzar, J. d D., 2019. On evasion behaviour in public transport: Dissatisfaction or contagion? Transp. Res. Part A Policy Pract. 130, 626–651. https://doi.org/10.1016/j.tra.2019.10.005.

Almlof, E., Rubensson, I., Cebecauer, M., Jenelius, E., 2021. Who continued travelling by public transport during COVID-19? Socioeconomic factors explaining travel behaviour in Stockholm 2020 based on smart card data. Eur. Transp. Res Rev. 13 (1), 31. https://doi.org/10.1186/s12544-021-00488-0.

Arellana, J., Daly, A., Hess, S., de Dios Ortúzar, J., Rizzi, L.I., 2012. Development of surveys for study of departure time choice: two-stage approach to efficient design. Transp. Res. Rec. J. Transp. Res. Board 2303 (1), 9–18. https://doi.org/10.3141/2303-02.

Arnott, R., De Palma, A., Lindsey, R., 1990. Economics of a Bottleneck. J. Urban Econ. 27, 111–130.

Arriagada, J., Munizaga, M., Guevara, A., Prato, C., 2022. Unveiling route choice strategy heterogeneity from smart card data in a large-scale public transport network. Transp. Res. Part C Emerg. Technol. 134, 103467. https://doi.org/10.1016/j.trc.2021.103467.

Aziz, H.M.A., Ukkusuri, S.V., 2014. Exploring the trade-off between greenhouse gas emissions and travel time in daily travel decisions: Route and departure time choices. Transp. Res. Part D Transp. Environ. 32, 334–353. https://doi.org/10.1016/j.trd.2014.07.016.

Bergantino, A.S., Gardelli, A., Rotaris, L., 2024. Assessing transport network resilience: empirical insights from real-world data studies. Transp. Rev. 1–24. https://doi.org/10.1080/01441647.2024.2322434.

Bernal, M., Welch, E.W., Sriraj, P.S., 2016. The effect of slow zones on ridership: an analysis of the Chicago Transit Authority "El" Blue Line. Transp. Res. Part A Policy Pract. 87, 11–21. https://doi.org/10.1016/j.tra.2016.02.007.

Börjesson, M., 2008. Joint RP–SP data in a mixed logit analysis of trip timing decisions. Transp. Res. Part E Logist. Transp. Rev. 44 (6), 1025–1038. https://doi.org/10.1016/j.tre.2007.11.001.

Börjesson, M., Kouwenhoven, M., de Jong, G., Daly, A., 2022. Can repeated surveys reveal the variation of the value of travel time over time? Transportation 50 (1), 245–284. https://doi.org/10.1007/s11116-021-10243-y.

Burris, M., Brown, A., Gupta, H., Wang, J., Figueroa-Medina, A.M., del Valle-González, C. A., del Valle-Pérez, A.F., 2023. Factors influencing traveler use of transit before, during, and after the COVID-19 pandemic. J. Public Transp. 25. https://doi.org/10.1016/j.jpubtr.2023.100058.

Bwambale, A., Choudhury, C.F., Hess, S., 2019. Modelling departure time choice using mobile phone data. Transp. Res. Part A Policy Pract. 130, 424–439. https://doi.org/10.1016/j.tra.2019.09.054.

Cats, O., 2023. Identifying human mobility patterns using smart card data. Transp. Rev. 44 (1), 213–243. https://doi.org/10.1080/01441647.2023.2251688.

Chan, H.-Y., Ma, H., Zhou, J., 2021. Public transportation and social movements: learning from the Hong Kong anti-extradition bill protests. Transp. Res. Rec. J. Transp. Res. Board 2676 (2), 553–566. https://doi.org/10.1177/03611981211044466.

Chen, X., Jiang, Y., Ingvardson, J., Luo, X., Nielsen, O.A., 2023. I can board, but I'd rather wait: active boarding delay choice behaviour analysis using smart card data in metro systems. Transp. Res. Part C Emerg. Technol. 174, 103747. https://doi.org/10.1016/j.tra.2023.103747.

Devillaine, F., Munizaga, M., Trépanier, M., 2012. Detection of activities of public transport users by analyzing smart card data. Transp. Res. Rec. J. Transp. Res. Board 2276 (1), 48–55. https://doi.org/10.3141/2276-06.

Diab, E., Shalaby, A., 2019. Metro transit system resilience: understanding the impacts of outdoor tracks and weather conditions on metro system interruptions. Int. J. Sustain. Transp. 14 (9), 657–670. https://doi.org/10.1080/15568318.2019.1600174.

Ding, C., Mishra, S., Lin, Y., Xie, B., 2015. Cross-nested joint model of travel mode and departure time choice for urban commuting trips: case study in Maryland–Washington, DC region. J. Urban Plan. Dev. 141 (4). https://doi.org/10.1061/(asce)up.1943-5444.0000238.

Eltved, M., Breyer, N., Ingvardson, J.B., Nielsen, O.A., 2021. Impacts of long-term service disruptions on passenger travel behaviour: a smart card analysis from the Greater Copenhagen area. Transp. Res. Part C Emerg. Technol. 131. https://doi.org/10.1016/j.trc.2021.103198.

Faroqi, H., Saadatmand, A., Mesbah, M., Khodaii, A., 2023. Enriching smart card data with the trip purpose attribute. J. Public Transp. 25. https://doi.org/10.1016/j.jpubtr.2023.100072.

Fifer, S., Rose, J., Greaves, S., 2014. Hypothetical bias in stated choice experiments: is it a problem? And if so, how do we deal with it? Transp. Res. Part A Policy Pract. 61, 164–177. https://doi.org/10.1016/j.tra.2013.12.010.

Habib, K.N., 2021. Departure time choice modeling. Int. Encycl. Transp. 504–508. https://doi.org/10.1016/b978-0-08-102671-7.10374-4.

Haghani, M., Michiel, C.J., Bliemer, M., Rose, J., Oppewal, H., Lancsar, E., 2021. Hypothetical bias in stated choice experiments: Part II. Conceptualisation of external validity, sources and explanations of bias and effectiveness of mitigation methods. J. Choice Model. 41, 100322. https://doi.org/10.1016/j.jocm.2021.100322.

He, S.Y., Tao, S., Sun, K.K., 2024. Attitudes towards public transport under extended disruptions and massive-scale transit dysfunction: a Hong Kong case study. Transp. Policy 149, 247–258. https://doi.org/10.1016/j.tranpol.2024.02.008.

Henriquez-Jara, B., Arriagada, J., Tirachini, A., 2025. Impact of real-time information on passenger satisfaction across varying public transport quality levels in 13 Chilean cities. Transp. Res. Part A Policy Pract. 200, 104622. https://doi.org/10.1016/j.tra.2025.104622.

Hess, S., Bierlaire, M., Polak, J.W., 2005. Estimation of value of travel-time savings using mixed logit models. Transp. Res. Part A Policy Pract. 39 (2-3), 221–236. https://doi.org/10.1016/j.tra.2004.09.007.

Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. J. Choice Model. 32. https://doi.org/10.1016/j.jocm.2019.100170.

Hossain, S., Hasnine, M.S., Habib, K.N., 2020. A latent class joint mode and departure time choice model for the Greater Toronto and Hamilton Area. Transportation 48 (3), 1217–1239. https://doi.org/10.1007/s11116-020-10092-1.

Ingvardson, J.B., Nielsen, O.A., Raveau, S., Nielsen, B.F., 2018. Passenger arrival and waiting time distributions dependent on train service frequency and station characteristics: a smart card data analysis. Transp. Res. Part C Emerg. Technol. 90, 292–306. https://doi.org/10.1016/j.trc.2018.03.006.

Koppelman, F.S., Coldren, G.M., Parker, R.A., 2008. Schedule delay impacts on air-travel itinerary demand. Transp. Res. Part B Methodol. 42 (3), 263–273. https://doi.org/10.1016/j.trb.2007.10.006.

Kusakabe, T., Asakura, Y., 2014. Behavioural data mining of transit smart card data: a data fusion approach. Transp. Res. Part C Emerg. Technol. 46, 179–191. https://doi.org/10.1016/j.trc.2014.05.012.

Kristoffersson, I., Engelson, L., 2016. Estimating preferred departure times of road users in a large urban network. Transportation 45 (3), 767–787. https://doi.org/10.1007/s11116-016-9750-2.

Li, X., Lee, S., Yoo, C., 2024. Unveiling the spatial heterogeneity of public transit resilience during and after the COVID-19 Pandemic. J. Public Transp. 26. https://doi.org/10.1016/j.jpubtr.2024.100091.

Liu, Y., Osorio, J., Ouyang, Y., 2023. How long it took transit ridership to recover from disruptive events: a review into the recent history. J. Public Transp. 25. https://doi.org/10.1016/j.jpubtr.2023.100051.

Lizana, M., Choudhury, C., Watling, D., 2023. Using smart card data to model public transport user profiles in light of the COVID-19 pandemic. Travel Behav. Soc. 33. https://doi.org/10.1016/j.tbs.2023.100620.

Lizana, M., Choudhury, C., Watling, D., 2024. Investigating the potential of aggregated mobility indices for inferring public transport ridership changes. PLoS One 19 (1), e0296686. https://doi.org/10.1371/journal.pone.0296686.

Lizana, P., Ortúzar, J. d D., Arellana, J., Rizzi, L.I., 2021. Forecasting with a joint mode/time-of-day choice model based on combined RP and SC data. Transp. Res. Part A Policy Pract. 150, 302–316. https://doi.org/10.1016/j.tra.2021.06.006.

Marsden, G., Anable, J., Tim, C., Iain, D., James, F., Lesley, M., Helen, R., Jeremy, S., 2020. Studying disruptive events: Innovations in behaviour, opportunities for lower carbon transport policy? Transp. Policy 94, 89–101. https://doi.org/10.1016/j.tranpol.2020.04.008.

Munizaga, M.A., Palma, C., 2012. Estimation of a disaggregate multimodal public transport Origin–Destination matrix from passive smartcard data from Santiago, Chile. Transp. Res. Part C Emerg. Technol. 24, 9–18. https://doi.org/10.1016/j.trc.2012.01.007.

Nazem, M., Lomone, A., Chu, A., Spurr, T., 2019. Analysis of travel pattern changes due to a medium-term disruption on public transit networks using smart card data. Transp. Res. Procedia 32.

Ngo, N.S., Martin, A., 2023. A case study on the impacts of COVID-19 on bus ridership, bikesharing, and equity in a small U.S. county. J. Public Transp. 25. https://doi.org/10.1016/j.jpubtr.2023.100065.

Noureldin, M.G., Diab, E., 2024. Impacts of long-term transit system disruptions and transitional periods on travelers: a systematic review. Discov. Cities 1 (1). https://doi.org/10.1007/s44327-024-00015-5.

Parkes, S.D., Jopson, A., Marsden, G., 2016. Understanding travel behaviour change during mega-events: lessons from the London 2012 Games. Transp. Res. Part A Policy Pract. 92, 104–119. https://doi.org/10.1016/j.tra.2016.07.006.

Peer, S., Knockaert, J., Koster, P., Tseng, Y.-Y., Verhoef, E.T., 2013. Door-to-door travel times in RP departure time choice models: An approximation method using GPS data. Transp. Res. Part B Methodol. 58, 134–150. https://doi.org/10.1016/j.trb.2013.10.006.

Peer, S., Knockaert, J., Verhoef, E.T., 2016. Train commuters' scheduling preferences: Evidence from a large-scale peak avoidance experiment. Transp. Res. Part B Methodol. 83, 314–333. https://doi.org/10.1016/j.trb.2015.11.017.

Pelletier, M.-P., Trépanier, M., Morency, C., 2011. Smart card data use in public transit: a literature review. Transp. Res. Part C Emerg. Technol. 19 (4), 557–568. https://doi.org/10.1016/j.trc.2010.12.003.

Prager, F., Beeler Asay, G.R., Lee, B., von Winterfeldt, D., 2011. Exploring reductions in London Underground passenger journeys following the July 2005 bombings. Risk Anal. 31 (5), 773–786. https://doi.org/10.1111/j.1539-6924.2010.01555.x.

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

Shalit, N., Fire, M., Ben-Elia, E., 2023. A supervised machine learning model for imputing missing boarding stops in smart card data. Public Transp. 15 (2), 287–319. https://doi.org/10.1007/s12469-022-00309-0.

Shires, J.D., Ojeda-Cabral, M., Wardman, M., 2018. The impact of planned disruptions on rail passenger demand. Transportation 46 (5), 1807–1837. https://doi.org/10.1007/s11116-018-9889-0.

Singh, J., Homem de Almeida Correia, G., van Wee, B., Barbour, N., 2023. Change in departure time for a train trip to avoid crowding during the COVID-19 pandemic: a latent class study in the Netherlands. Transp. Res. Part A Policy Pr. 170, 103628. https://doi.org/10.1016/j.tra.2023.103628.

Small, K., 1982. The scheduling of consumer activities: work trips. Am. Econ. Rev.

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

Tirachini, A., Hensher, D.A., Bliemer, M.C.J., 2014. Accounting for travel time variability in the optimal pricing of cars and buses. Transportation 41 (5), 947–971. https://doi.org/10.1007/s11116-014-9515-8.

Vallejo-Borda, J.A., Giesen, R., Basnak, P., Reyes, J.P., Mella Lira, B., Beck, M.J., Hensher, D.A., Ortuzar, J.D., 2022. Characterising public transport shifting to active and private modes in South American capitals during the COVID-19 pandemic. Transp. Res. Part A Policy Pr. 164, 186–205. https://doi.org/10.1016/j.tra.2022.08.010.

Van Exel, N., Rietveld, P., 2001. Public transport srikes and traveller behaviour. Transp. Policy 8.

Vicente, P., Reis, E., 2016. Profiling public transport users through perceptions about public transport providers and satisfaction with the public transport service. Public Transp. 8, 387–403. https://doi.org/10.1007/s12469-016-0141-z.

Vickrey, W., 1969. Congestion theory and transport investment. Am. Econ. Rev. 59 (2), 251–260.

Victoriano-Habit, R., El-Geneidy, A., 2024. Why are people leaving public transport? A panel study of changes in transit-use patterns between 2019, 2021, and 2022 in Montréal, Canada. J. Public Transp. 26. https://doi.org/10.1016/j.jpubtr.2024.100087.

Watling, D., 2006. User equilibrium traffic network assignment with stochastic travel times and late arrival penalty. Eur. J. Oper. Res. 175 (3), 1539–1556. https://doi.org/10.1016/j.ejor.2005.02.039.

Wöhner, F., 2022. Work flexibly, travel less? The impact of telework and flextime on mobility behavior in Switzerland. J. Transp. Geogr. 102. https://doi.org/10.1016/j.jtrangeo.2022.103390.

Yap, M., Cats, O., van Arem, B., 2018. Crowding valuation in urban tram and bus transportation based on smart card data. Transportmetr. A Trans. Sci. 16 (1), 23–42. https://doi.org/10.1080/23249935.2018.1537319.

Zannat, K., Choudhury, C.F., Hess, S., 2021. Modeling departure time choice of car commuters in Dhaka, Bangladesh. Transp. Res. Rec. J. Transp. Res. Board 2676 (2), 247–262. https://doi.org/10.1177/03611981211039840.

Zannat, K.E., Choudhury, C.F., 2019. Emerging big data sources for public transport planning: a systematic review on current state of art and future research directions. J. Indian Inst. Sci. 99 (4), 601–619. https://doi.org/10.1007/s41745-019-00125-9.

Ziedan, A., Brakewood, C., Watkins, K., 2023. Will transit recover? A retrospective study of nationwide ridership in the United States during the COVID-19 pandemic. J. Public Trans. 25, 100046. https://doi.org/10.1016/j.jpubtr.2023.100046.