Modelling changes in public transport demand amid disruptive events

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The research conducted in the context of this thesis has led to the production of four articles. Each article is listed below, including the corresponding chapter number in the thesis, the full reference (for the published article) and an author contribution statement.

1. The work in Chapter 2 of this thesis appeared in publication as follows:

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The first author confirms that the main idea of this work was developed by him, as well as the data processing, modelling work, resulting analysis and the writing of the manuscript. The co-authors, Charisma Choudhury and David Watling, provided recommendations and comments throughout the different stages of the manuscript.

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Abstract

Disruptive events, such as natural disasters, social movements or pandemics, can severely impact public transport demand. The relevance of studying the impacts of these events on public transport has been widely recognised in the literature, focusing on the investigation of disruption mitigation, delay management, vulnerability and resilience. Much less attention, however, has been given to understanding passengers' responses amid these events. As a consequence, several gaps in this research area are yet to be addressed. These include a narrow scope in the modelling of passengers' behavioural responses amid disruptive events, the lack of understanding of the role of individual-level factors in those responses (e.g. socio-demographics, attitudes and trip characteristics) and an insufficient examination of passive data sources for aggregate and disaggregate-level analysis (ranging from smart card to more emerging data sources such as aggregate mobility indices). This motivates this research, whose aim is to enhance the understanding of public transport demand during disruptive events. The research conducted here is temporally framed between 2019 and 2022, a period of worldwide high mobility disturbances caused by the COVID-19 pandemic. This period represents a unique opportunity to address existing research gaps in the analysis of disruptive events and public transport demand by leveraging recent literature and data sources.

First, this thesis extends the scope of previous literature on analysing passengers' behavioural responses amid disruptive events by examining passengers' mobility profiles and departure time choices. So far, previous research has adopted a 'trip-reduction' perspective on passengers' responses, limiting the examination to either trip frequency reduction or the shift to another alternative mode. Thus, considering passengers' mobility profiles based on integrating several indicators to describe passengers' behavioural responses, this research enhances the traditional analysis perspective. In addition, this research contributes to the literature by demonstrating how disruptive events of several types affect passengers' trip-scheduling decisions. From a data perspective, this research provides new empirical evidence of the disaggregate-level capabilities of smart card data for analysing passengers' responses amid disruptive events. To achieve this, limitations of smart card data regarding missing attributes for disaggregate-level modelling were addressed. In particular, specific frameworks are proposed to input passengers' preferred arrival times (a key attribute for estimating departure time choice models) and passengers' sociodemographic characteristics based on their home location. Overall, this research adds empirical and methodological contributions supporting the use of smart card data

to better understand passengers' behavioural responses, which, as demonstrated in this research, are more complex than those considered in previous research.

This thesis also addresses the need to elucidate how individual-level factors influence public transport usage amid disruptive events. So far, it has not been possible to generate well-established conclusions about the influence of individual-level factors on passengers' responses amid disruptive events. Previous literature only provides partial comparisons based on effect directions (positive, negative or non-statistically significant), which does not help generate definitive conclusions when the empirical evidence is ambiguous. Difficulties in comparing scattered empirical evidence due to the diversity in the nature, severity, location and temporality of disruptive events have limited such analysis. In this regard, the calamity of the COVID-19 pandemic offers a unique opportunity to address this research gap by leveraging the great amount of empirical findings generated worldwide. Hence, through a comprehensive literature review that revised 36 articles, the statistical consistency in how 15 individual-level factors influence the decrease in public transport usage during the crisis of the COVID-19 pandemic is analysed. Pooled effect sizes are calculated through meta-analyses conducted on each of the 15 individual-level factors using random-effect models (REMs). The results generated here help identify the most influential individual-level factors regarding their effect size. The results also allow to verify the presence of inequality issues related to a more rigid use of public transport by particular passengers' group segments amid the COVID-19 pandemic.

From the aggregate perspective of public transport demand and disruptive events, the potential to use emerging data sources as a proxy for public transport ridership is explored in this work. So far, aggregate-level analyses have been made only possible in those cities where an automatic fare collection system is available, substantially limiting the analysis of public transport ridership levels worldwide. In particular, aggregated mobility indices (AMIs) provided by tech companies and derived from the ordinary use of smartphones have recently emerged as a new data source for transport planners. This data has shown particular value during periods of major disturbances or when other mobility data sources are scarce. Nonetheless, whether AMIs can provide a reliable characterisation of actual ridership change remains largely untested. This study aims to address this research gap by investigating the reliability of using AMIs for inferring ridership changes by offering the first rigorous benchmarking between them and ridership data derived from smart card validations and tickets. For the comparison, monthly and daily ridership data from 12 cities worldwide and two AMIs shared globally by Google and Apple during major changes in 2020-22 are used. The results reveal a high capability of AMIs to align with ridership trends and that AMIs can complement data from smart card records when ticketing is missing or of questionable quality.

Considering the current and future urban challenges, such as climate change, social movements, terrorist attacks and pandemics, the study of public transport demand amid disruptive events is more timely than ever. The outcome of this thesis contributes in this direction, expanding that understanding by addressing key research gaps in previous literature and associated challenges. It is demonstrated in this research that passengers' adaptations are more complex than the current 'trip reduction' approach adopted in the literature. In this regard, this thesis adds to the body of existing knowledge by identifying and modelling passengers' mobility profiles and departure time choices during disruptive events. This research also supports using passive data sources such as smart card data and emerging aggregated mobility indices to analyse public transport demand change amid disruptive events. In particular, by addressing some of the existing challenges of these data sources, their potential to be employed for a broader range of events has been revealed in this research. This research also highlights the role of passengers' associated characteristics on distinctive behavioural responses adopted during disruptive events, recognising a strong presence of inequality. These findings suggest that, regarding disruptive events, public transport agencies and operators should especially focus on the needs of the more vulnerable population segments, who showed fewer opportunities to mitigate the impacts of disruptive events through travel behavioural adaptation. Finally, the findings generated in this thesis can be used to improve the understanding of how passengers adapt their mobility patterns during external disruptions and, therefore, be used by policymakers to act accordingly amid future disruptive events.

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List of Abbreviations

AFC	Automatic fare collection system
AMI	Aggregated mobility index
AMTR	Apple Mobility Trend Reports
CDZ	Census district zones
COS	Cosine distance
DTCM	Departure time choice models
DTW	Dynamic time warping
EP	Episode
GBDT	Gradient boosting decision tree
GCMR	Google COVID-19 Community Mobility Reports
HMI	Human mobility index
LRM	Logistic regression models
LSI	Boarding location similarity index
MED	Mean Euclidean distance
OR	Odds ratio
PAT	Preferred arrival time
PT	Public transport
QMI	Query modified Index
REM	Random effect models
RP	Revealed preference
RRC	Relative ridership change
SD	Schedule delay
SP	Stated preference
STI	Trend similarity index
TSI	Temporal similarity index
TVSD	Travel time valuation of schedule delay

Chapter 1
Introduction

1.1 Background

Public transport[1] keeps cities moving (Ceder, 2020). Public transport accounts for at least 16% of daily trips in cities but up to 45% in European and Asian cities (Aguiléra, 2014; UITP, 2024). Its importance is highlighted by the many benefits public transport has. Public transport is crucial to a city's ability to achieve societal, economic, and environmental prosperity (Fadaei & Cats, 2016; Kwan & Hashim, 2016). Public transport directly addresses social issues, reducing poverty and inequality and improving social cohesion and accessibility in cities (Lucas, 2012). It also connects people and places, boosting employment, increasing productivity and promoting economic growth (Johnson et al., 2017; Bastiaanssen et al., 2020). Moreover, it plays a key role in helping reduce urban traffic congestion, noise and inefficiency in terms of capacity and urban space consumption (Buchanan, 2019). Public transport has also been pointed out as a central element to meet net zero emission targets by reducing street congestion and air pollution generated by private cars (Kwan & Hashim, 2016; Department for Transport, 2021).

Despite its positive contributions and societal benefits, public transport faces increasing challenges (Ceder, 2020; Tirachini & Cats, 2020). The last decades have witnessed significant changes in people's travel behaviour due to evolving lifestyles and the fast advent of new technologies (Lizana et al., 2021). For example, there is evidence that people are making fewer commuting trips but longer ones, spending less total time travelling in a day, and reducing physical shopping trips (Marsden et al., 2018). Travellers are also increasing their expectation of quality of service, pressuring public transport agencies to increase safety, affordability and level of services (dell'Olio et al., 2011; Van Lierop et al., 2017). Fiscal stress as a consequence of the increasing amount of subsidy required to keep public transport systems running has also been mentioned as a major source of concern (Parry & Small, 2009; Serebrisky et al., 2009). In this already complex scenario, the shocks produced by disruptive events such as infrastructure/system failures, natural disasters, terrorist attacks and lately, the COVID-19 pandemic have dynamically contributed to reshaping travellers' consideration of public transport (Currie & Muir, 2017; Nguyen-Phuoc et al., 2018; Ziedan et al., 2023).

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[1] This thesis employs the term public transport to refer indistinctly to other terms used in the literature for the same concept, such as transit, public transportation and mass transit.

The relevance of studying the impacts of disruptive events on public transport has been widely recognised in the literature. Abundant evidence from the transport supply perspective examines disruption mitigation, delay management, vulnerability and resilience (Berche et al., 2009; Mattsson & Jenelius, 2015; Bešinović, 2020; Ge et al., 2022; Yap & Cats, 2022; Bergantino et al., 2024). Significantly less attention has been given to understanding passengers' behavioural responses. Here, the study of passengers' behavioural responses amid disruptive events has been limited to immediate and short-term responses to rail and metro disruptions (Pnevmatikou et al., 2015; Currie & Muir, 2017; Shires et al., 2018; Rahimi et al., 2020). Only lately, due to the COVID-19 pandemic, more evidence has been made available, focussing on middle to long-term behavioural adaptations (He et al., 2022; Ngo & Martin, 2023; Victoriano-Habit & El-Geneidy, 2024).

So far, several challenges have limited the examination of the effect of disruptive events on passengers' travel behaviour. First, travel behavioural adaptations are inherently complex, as there are several possible ways to respond to a disruptive event (Lin et al., 2016). Passengers may decide to cancel the trip, change the departure time, shift to another mode, change the destination or keep the initial itinerary (Parkes et al., 2016; Marsden et al., 2020). Second, observing passengers' responses to disruptions requires data collected over relatively long periods, a task rarely conducted with traditional survey-based data (Victoriano-Habit & El-Geneidy, 2024). In this regard, passive data such as smart cards can capture day-to-day variability in passengers' behaviour very well. However, it frequently lacks the necessary variables for estimating disaggregate models. As a consequence, most applications of smart card data on public transport demand amid disruptive events have been limited to the characterisation of ridership levels (Nazem et al., 2019; Chan et al., 2021; Woo et al., 2021). Third, no definitive conclusions about the effect of individual-level factors (such as socio-demographics, attitudes and trip characteristics) on public transport usage change during disruptions are currently available. Difficulties in comparing existing empirical evidence due to the diversity in the nature, severity, location and temporality of the events examined are only some of the difficulties faced (Zhu et al., 2017; He et al., 2024). Finally, ridership characterisation is still a massive challenge for most cities in developing countries where cash-based systems are the standard. This triggers the need to explore emerging data sources beyond smart card data to look for potential proxies for characterising ridership changes amid disruptive events with broader coverage.

The recent calamity of the COVID-19 pandemic revitalised the interest and importance of addressing most of these challenges. During its different stages, public transport demand was severely impacted, reaching a reduction as high as 90% in many cities during the pandemic outbreak, followed by a slow recovery process. The reductions in travel demand were due to a combination of mobility restriction guidelines imposed by governments and the changes in people's travel behaviour and perceptions towards public transport (Vickerman, 2021). In this context, due to its ubiquitous presence and colossal impact on human mobility, an unprecedented effort to characterise passengers' responses across the different stages of the pandemic was made (Wielechowski et al., 2020; Przybylowski et al., 2021; Vickerman, 2021). This research takes advantage of this unique opportunity to leverage recent literature and data sources provided during the COVID-19 pandemic to address challenges related to the impact of disruptive events on public transport demand.

1.1.1 Disruptive events

A classical definition of 'disruption' in the transport domain is given to the moment when physical infrastructure or the operation of a service or system ceases to work normally, generating significant alterations in transport systems (Ge et al., 2022). This definition frequently considers unplanned infrastructure failures (e.g. bridge collapse), accidents (e.g. human-associated incidents), and planned interventions (e.g. the closure of a rail line for maintenance). Under this perspective, literature examines concepts such as mitigation, delay management, vulnerability and resilience in terms of maximising the availability and the speed to put back infrastructure and for systems to recover when a disruptive event occurs (Berche et al., 2009; Mattsson & Jenelius, 2015; Bešinović, 2020; Ge et al., 2022; Yap & Cats, 2022; Bergantino et al., 2024).

On the other hand, the definition of a disruptive event adopted in this research recognises as such any system-level event that causes people and businesses to see their daily activities significantly modified (Parkes et al., 2016; Kontou et al., 2017; Rahimi et al., 2020). Consequently, it focuses on examining the adaptations in the trip behaviour of travellers as a response to those events. This broader perspective has been used in the literature to highlight that during a disruptive event, what is 'disrupted' is the coordination and realisation of activities and, therefore, the implications for travellers' behavioural responses are the focus of the analysis, going beyond the journey itself (Marsden et al., 2020). In this regard, while the traditional definition emphasises the transport system, the definition used here focuses on the system of activities which the transport system supports (Shires et al., 2018). Mega-events (e.g. Olympic Games), social unrest, natural disasters, public transport strikes, terrorist attacks and the COVID-19 pandemic are considered examples of disruptive events according to this perspective.

The literature in this regard has shown that travel behavioural adaptations as a consequence of disruptive events are inherently complex. In the first place, several ways to respond to an event are possible, which are much more complex than simply trip reduction (Lin et al., 2016). Actually, when the category 'trip reduction' is examined in detail, travel responses such as cancelling, re-timing, changing mode, re-routing, re-scheduling (changing when in the week a trip is made), relocation (change in the destination) and re-allocating (someone else takes over the responsibility to conduct the activity) have been identified (Parkes et al., 2016; Marsden et al., 2020). Underlying the adoption of travellers' specific responses, the literature has recognised several types of constraints, which range broadly from alterations of the system of activity or transport by the events (Nazem et al., 2019; Chan et al., 2021) to individual-level factors (such as gender, age, attitudes or car availability). The integration of these constraints on travel behaviour can be traced as far back as Hagerstrand (1970), whose seminal work proposed the time-geography framework. According to Hagerstrand (1970), at any time, there are three categories of constraints that shape human mobility behaviour: capability constraints (related to the person's capacity to move, such as socio-demographics, physical abilities and budget), coupling (related to the need to be at specific places and at specific times to interact with others, such as work starting times) and authority constraints (related to external regulations that restrict certain activities, places or opening hours). During the COVID-19 pandemic, for example, the adoption of flexible working arrangements (Wöhner, 2022) is an example of changes in the coupling constraints, while lockdowns and curfews imposed by governments (Saha et al., 2020; Gramsch et al., 2022) represent changes in the authority constraints.

1.1.2 Public transport demand change amid disruptive events

Several types of disruptive events have been considered in the analysis of passengers' behavioural responses, which can be categorised depending on their duration in terms of short-term or medium/long-term. Disruptive events that only cause short-term/immediate adaptations have been associated mostly with events or 'incidents' that cause a short-term degradation of normal service levels in trains, metro or buses (Liu et al., 2021; Zhao et al., 2023). Some examples include extreme weather, operation errors, vandalism, human incidents, strikes, etc., for which the range of duration has been reported to be from minutes to some days (Van Exel & Rietveld, 2001; Pnevmatikou et al., 2015; Zhu et al., 2017; Nguyen-Phuoc et al., 2018). Furthermore, whether the disruption is planned or unplanned and, if unplanned, whether it occurs en-route or before a passenger starts the trip, are contexts that have been analysed separately as passenger responses may differ (Lin et al., 2016). On the other hand, studies that examine passengers' medium/long-term behavioural responses amid disruptive events have focussed on investigating their progression before, during and after those events (Woo et al., 2021). In these analyses, there is a need for longitudinal data to observe characteristic stages such as before, during and after the disruption (Nazem et al., 2019). Examples of disruptions in this category are the planned closure of a metro/rail line or station for several months (Nazem et al., 2019; Eltved et al., 2021) and incidents affecting the public transport supply, that by their recurrence, induce medium to long-term changes in passengers' travel behaviour (Bernal et al., 2016). Other examples are 'external' events ('external' with respect to the public transport supply) such as social movements (Chan et al., 2021), natural disasters (Kontou et al., 2017), mega-events (Parkes et al., 2016), terrorist attacks (Prager et al., 2011) and lately the COVID-19 pandemic (Panik et al., 2023).

The characterisation of public transport demand change amid disruptive events has been conducted using both aggregate and disaggregate-level approaches. Aggregate-level studies analyse the impact of disruptive events on ridership levels, focusing on their variation over time. Ridership data contain the aggregated amount of transactions and tickets sold for the entire public transport system or a particular mode (e.g. only the metro ridership in Hong Kong (Chan et al., 2021) or the BRT ridership in Bogota (Arellana et al., 2020)). In these studies, the temporal level of aggregation is usually the day, while temporal frames range from months to years. Aggregate-level studies have focussed on conducting descriptive analysis of ridership variability levels (Eltved et al., 2021) and on understanding its temporal and spatial variability by testing the effect of covariates such as transport infrastructure, sociodemographic characteristics, and the presence of disruptions and authority constraints (e.g. lockdown, curfew) (Bernal et al., 2016; Woo et al., 2021; Borowski et al., 2023). Events examined under this perspective have included the closure of metro stations and rail lines for several months (Nazem et al., 2019; Eltved et al., 2021), recurring train service delays (Bernal et al., 2016), the occurrence of social unrest (Chan et al., 2021), and the COVID-19 pandemic (Zhang et al., 2021). Even though most of these studies employ smart card data, lately, some authors have relied on aggregated mobility indices (AMIs), an emerging data source, to conduct the analysis (Jenelius & Cebecauer, 2020; Fernández Pozo et al., 2022; Padmakumar & Patil, 2022). Finally, the advantage of using an aggregate-level analysis is the explicit observation of ridership changes amid a disruptive event. For instance, Eltved et al. (2021) found a 7% decrease in everyday commuting after the reopening of a 3-month closure of a rail line in the Greater Copenhagen area. During the COVID-19 pandemic, the analysis of ridership showed drops as much as 70%-90% in the major cities of

Sweden (Almlöf et al., 2021), Germany (Kolarova et al., 2021), Greece (Politis et al., 2021), Hungary (Bucsky, 2020) and Chile (Gramsch et al., 2022) (Shixiong Jiang & Canhuang Cai, 2022).

On the other hand, disaggregate-level studies characterise public transport demand by focussing on understanding individual responses amid the occurrence of disruptive events. For instance, short-term behavioural responses have been studied by modelling the shift from public transport to alternative modes using hypothetical disruptive scenarios (Pnevmatikou et al., 2015; Nguyen-Phuoc et al., 2018; Shires et al., 2018; Li & Wang, 2020; Rahimi et al., 2020). This level of analysis is particularly appropriate for investigating the effect of underlying factors on passengers' behavioural responses in terms of their public transport usage change. Factors such as the level of service of mode alternatives (e.g. travel time, crowding level, monetary cost), travellers' associated characteristics, attitudes towards public transport and the situational contexts' characteristics are some of the variables employed. Studies that have analysed medium to long-term responses using a disaggregate-level approach have only been recently available in light of the COVID-19 pandemic. Here, passengers' adaptations have been investigated in terms of reducing public transport trip frequency (Almlof et al., 2021; Das et al., 2021; Downey et al., 2022), choosing public transport among the presence of alternative modes (Bansal et al., 2022; Basnak et al., 2022; Hsieh & Hsia, 2022) and to a lesser extent measuring the intention to use it (Aaditya & Rahul, 2023). The literature, therefore, has narrowed the analysis of passengers' behavioural responses to a public transport 'trip reduction' perspective, paying minimal attention to other possible types of adaptations, such as those related to temporal or spatial trip pattern changes.

1.1.3 The role of individual-level factors

The literature recognises that travellers' resources, abilities, expectations, trip characteristics, as well as their collective and personal set of norms and social constructs, strongly influence passengers' responses amid disruptive events (Kontou et al., 2017). Thus, the literature on short-term events such as service disruptions has found proof that passengers' behavioural responses are influenced by factors such as the information available (e.g. reason for the delay and uncertainty of the duration), availability of alternative modes, levels of service of alternative modes, attitudes, habits, weather, trip purpose and trip frequency (Nguyen-Phuoc et al., 2018; Sarker & Currie, 2023). In particular, sociodemographic characteristics such as car ownership and income level have consistently been associated with avoiding public transport amid service disruptions (Rahimi et al., 2020; Sarker & Currie, 2023). Empirical evidence regarding the influence of gender and age, on the other hand, has been less frequently incorporated. However, there are some findings that suggest that female and elderly passengers are less likely to avoid public transport amid a service disruption (Pnevmatikou et al., 2015; Sarker et al., 2019). Negative attitudes towards public transport have also been correlated positively to the intention to avoid public transport amid a service disruption (Sarker & Currie, 2023), while longer travel times and commuting purposes have been negatively associated with this response (Nguyen-Phuoc et al., 2018; Shires et al., 2018).

Related to passengers' medium to long-term behavioural responses, most evidence has been generated in light of the COVID-19 pandemic. Literature before the pandemic is quite limited, as that evidence comes from employing mostly descriptive analyses using an aggregate-level perspective (Lopez-Rousseau, 2005; Prager et al., 2011; Eltved et al., 2021). Conversely, the influence of individual-level factors on passengers' behavioural adaptations during the COVID-19 pandemic has been broadly studied. Among these factors, the role of the COVID-19 perceived risk (Abdullah et al., 2020; Shelat et al., 2021; Liu et al., 2022; Rankavat et al., 2023) and the possibility of working from home have been considered as being among the most important factors influencing the decision to reduce public transport usage (Schaefer et al., 2021; Soria et al., 2023; Zafri et al., 2023). Related to the influence of passengers' sociodemographic characteristics on the decision to reduce public transport usage during this event, evidence shows a heterogeneous consistency among them regarding their effect direction. For example, car ownership and income levels show consistently positive effects on the decision to reduce public transport usage during the pandemic (Mashrur et al., 2022; Mazanec et al., 2023), similar to the findings for the short-term disruptions. On the other hand, inconsistent effect directions for factors such as gender, age and race are reported. For instance, in the case of gender, some findings indicate that male passengers were more likely to reduce public transport use compared to females (Abdullah et al., 2020; Abdullah et al., 2021; Jiao & Azimian, 2021), whereas other studies found the opposite effect (Beck et al., 2021; Palm et al., 2021), and others found no significant relationship (Aaditya & Rahul, 2023). This uncertainty regarding the direction of the effect can also be observed in other types of factors, such as whether an individual was a regular passenger prior to the COVID-19 pandemic. Here, certain studies indicated a negative impact on reducing public transport trips (Palm et al., 2021) and others a positive one (Aaditya & Rahul, 2023). Overall, despite all the evidence provided in the literature, there is an urgent need to clarify inconclusive effect directions. Moreover, due to several challenges, such as different models, dependent variables, and specifications of explanatory variables, the comparison of effect sizes has eluded the consideration of previous literature. Therefore, a systematic comparison of effect sizes that address these challenges is also yet to be provided.

1.1.4 Data for modelling

1.1.4.1 Disaggregate-level modelling – travel surveys

Based on the literature, the analyses of passengers' behavioural responses amid disruptive events have been conducted primarily using survey-based data. Studies have employed both revealed preferences (RP) and stated preferences (SP) data to collect the targeted dependent variable and high level of detail of passengers' characteristics (Basnak et al., 2022). The use of RP data is frequent in studies where the dependent variable is public transport trip frequency (Abdullah et al., 2020), while SP is more usual in studies where the dependent variable is the shift from public transport to another alternative mode (Shires et al., 2018; Li & Wang, 2020). RP data typically provides actual mobility patterns for the disruption stage corresponding to when the survey was applied, usually during or after the disruption. In comparison, pre-disruption or past travel behaviours are traditionally 'retrieved' in RP data using a retrospective approach, i.e. relying on respondents' memories (Das et al., 2021). Although the norm among these studies is to apply one-wave surveys, a few studies have attempted a multi-episode characterisation, collecting passengers' responses over time. (Beck et al., 2021; Victoriano-Habit & El-Geneidy, 2024). On the other hand, SP data has been mainly used to test passengers' mode choices in hypothetical disruptive scenarios, including different disruption stages and particular situational contexts (Aaditya & Rahul, 2023; Singh et al., 2023). SP data has been particularly useful for researchers because it dramatically reduces the complexity of dealing with RP responses and the heterogeneity in the alternatives' attributes by setting them and their levels beforehand (Arellana et al., 2012; Bansal et al., 2022).

Despite the widespread use of RP and SP data in studying passengers' behavioural responses amid disruptive events, several limitations arise. In particular, as the characterisation of pre-disruption trip patterns in RP data relies on respondents' memories, the responses' quality may suffer greatly depending on the gap between the survey and the time retrospectively inspected. Moreover, RP data make it challenging to collect day-to-day behavioural responses for a long-term period as such implementation involves high costs, extensive time effort, and still the impossibility of retrieving all relevant information (e.g. level of service of unchosen mode/departure time alternatives) (Kusakabe & Asakura, 2014). In the case of SP data, despite their many advantages, it is well known that valuations calculated by SP responses are susceptible to hypothetical bias and behavioural incongruence due to the misperception of respondents of attributes and their levels (Hess et al., 2005). In addition, as both approaches require that the researcher define the target response variables in advance, less room is left to explore adaptations that have not been traditionally reported in the literature. Moreover, the quality of the sample's representativeness and the associated selection process have been substantially reduced in the studies conducted since the pandemic, due to the employment of social media to apply online surveys as a replacement for face-to-face ones (Beck et al., 2021; Das et al., 2021). The risk here is the underrepresentation of population groups with low technology access and the overrepresentation of others, such as those more engaged with social media or with a particular survey topic. Overall, the limitations of RP and SP data give enough reasons to explore other data sources to analyse passengers' behavioural responses amid disruptive events.

1.1.4.2 Disaggregate-level modelling – smart card data

Smart card data has become a reliable data source for analysing passengers' travel behaviour (Bagchi & White, 2005; Pelletier et al., 2011; Zannat & Choudhury, 2019). Although smart cards were initially implemented to collect public transport fares, they were promptly used to analyse travel demand (Kusakabe & Asakura, 2014). In fact, smart card data have been used widely in the last ten years to understand the travel behaviour of public transport passengers and provide the necessary inputs to help urban transport planners assess new infrastructure and changes in transit networks (Briand et al., 2017). Automatic fare collection systems (AFC) automatically and continuously store each fare payment of a cardholder and associate it with the ID card. IDs are unique numbers given to smart cards that allow the study of travel habits, trip sequences, and route preferences, among other characteristics (Pelletier et al., 2011). In this way, it is possible to use smart card data to study day-to-day travel demand variability, identifying each cardholder over long-term periods (Kumar et al., 2018). Nonetheless, few studies have employed smart card data to study passengers' behavioural responses amid disruptive events. An exception is Almlöf et al. (2021), who, during the COVID-19 pandemic, used smart card data to study cardholders' number of trips to Stockholm. It is hypothesised that smart card data limitations related to missing attributes have restricted wider applications (such as the need to infer sociodemographic characteristics or passengers' preferences). Overall, there is an evident opportunity to leverage smart cards to examine cardholders' responses amid disruptive events and overcome limitations that have restricted their use.

1.1.4.3 Aggregate-level modelling

The aggregate-level characterisation of public transport demand amid disruptive events has been conducted mainly with ticketing information through digital transactions and smart card validations (Eltved et al., 2021; Woo et al., 2021). As the data is collected at the disaggregate level, the spatial aggregation is flexible, with the most common analyses conducted at the metropolitan area/city and station levels. This passive data collection process allows operators and researchers to observe continuously the variation in ridership levels and relate that variation to the occurrence of disruptive events ranging from short-term events such as transport supply breakdown to global long-term events such as pandemics/epidemics, economic crises and conflicts (Liu et al., 2021; Gramsch et al., 2022). Unfortunately, this kind of approach presents various limitations. First, the previously described analysis is possible only in cities with AFC. As a consequence, the literature on ridership analysis is relatively concentrated on case studies of cities from the U.S. (Teixeira & Lopes, 2020; Xiao et al., 2022; Qi et al., 2023; Ziedan et al., 2023), Eastern Asia (Chan et al., 2021; Woo et al., 2021; S Jiang & C Cai, 2022) and Europe (Vickerman, 2021) and specific cities in countries such as Chile (Gramsch et al., 2022), Colombia (Caicedo et al., 2021) and Canada (Nazem et al., 2019). Another limitation in the use of AFC is their partial coverage regarding all the public transport modes available in a city, such as the case of Bogotá, where smart cards are only available for the bus rapid transit mode (Caicedo et al., 2021). In these cases, there is an inherent difficulty to extrapolate the analysis to the entire public transport demand from the available data. Moreover, there are specific circumstances where ridership data may be partial or of doubtful quality. For instance, during a free bus policy, such as the one adopted in London for several months during the COVID-19 pandemic that aimed to limit the physical contact between drivers and passengers (Vickerman, 2021), the recorded ridership does not represent actual bus demand. Overall, these limitations have generated the need to explore emerging data sources to find proxies for ridership data.

In this regard, emerging data sources generated by the everyday use of smartphones have shown high potential to provide proxies for ridership data. In particular, Wi-Fi signals emitted by smartphones that bus passengers carry (Wang & Zhang, 2020), call detail records (CDRs) of cell phone calls and text exchanges (Sørensen et al., 2018), GPS traces collected by global mobile phone apps and the level of public transport queries in travel planners (Welch & Widita, 2019; Finazzi, 2023) are some of the technologies that have been explored to address this aim. Unfortunately, the effort to leverage Wi-Fi and CDRs has been mainly limited to research purposes and a few case studies, as data availability remains largely restricted (Welch & Widita, 2019). On the other hand, GPS traces collected by phone apps and the apps' number of queries, technologies already part of tech companies' products and services (Strzelecki, 2022), have been used in the last years to generate globally available aggregated mobility indices (AMIs). In the AMIs, the information is aggregated at a city level to describe human mobility over time, offering a near-complete coverage of the urban grid and a large proportion of the population. Big tech companies such as Google and Apple updated daily AMIs for a period of high mobility disturbance between 2020 and 2022 (Apple, 2023; Google, 2023). Other companies, such as Moovit and Citymapper, which run travel planner apps, also offered similar mobility indices (Beck & Hensher, 2020; Fernández Pozo et al., 2022). AMIs, as a proxy for ridership changes, have been widely used in several studies to analyse mobility trends and scenarios (Konečný & Brídziková, 2020; Saha et al., 2020), to assess the effectiveness of mobility restrictions on human mobility (Yilmazkuday, 2021; Hamidi & Zandiatashbar, 2021; Wen et al., 2021; Wu & Shimizu, 2022), in studying COVID-19 transmission (Noland, 2021), pandemic indicators (Kartal et al., 2021; Noland, 2021), air quality (Venter et al., 2020; Rowe et al., 2022) and economic recovery (Zhang et al., 2022), among other topics. Related to the validation of AMIs, so far, preliminary reports based on visual inspection have suggested that AMIs may overestimate the recovery in transport demand after a disruption (Jenelius & Cebecauer, 2020; Fernández Pozo et al., 2022). Nonetheless, a more rigorous assessment to confirm these preliminary findings is yet to be conducted. Moreover, it is worth noticing that no previous study has attempted to examine the potential of AMIs in complementing partial ridership data.

1.2 Research gaps

As the literature review has shown, the investigation of public transport demand change amid disruptive events presents several research gaps, which are summarised next.

RG-1 Narrow scope in the modelling of passengers' behavioural responses to disruptive events.

There is a need to extend the scope of examining passengers' responses amid disruptive events by either integrating several adaptations simultaneously or focusing on adaptations beyond the traditional 'trip-reduction' perspective. Previous research on analysing passengers' responses amid disruptive events has consistently restricted the examination to either trip frequency (Almlof et al., 2021; Das et al., 2021) or the shift from public transport to another alternative mode (Pnevmatikou et al., 2015; Nguyen-Phuoc et al., 2018; Shires et al., 2018; Rahimi et al., 2020). In this way, the complexity of the passengers' adaptations has been significantly overlooked.

Specifically, there is no previous attempt to reveal hidden mobility profiles of passengers based on a multidimensional characterisation of their public transport usage change amid a disruptive event. Such analysis has the potential of considering not only the traditional trip frequency characterisation but also a wider set of indicators (e.g. changes in days travelled, boarding locations, departure time, etc.). Mobility profiles, which represent distinctive groups of passengers in terms of their response profiles (e.g. those that return to the pre-disruptive behaviour vs. those that show lasting changes), can then be related to passengers' associated characteristics (e.g. age, pre-disruption trip characteristics, neighbourhood characteristics, etc.). This analysis would help evaluate whether passengers from more disadvantaged groups have fewer possibilities to adapt their travel behaviour amid disruptive events. Furthermore, the examination of trip-scheduling decisions is also missing in the literature on passengers' behavioural responses amid disruptive events. In this regard, whether the impact of disruptive events on trip-scheduling decisions can be associated with i) adaptations in passengers' arrival time preferences (related to their sensitivity to schedule delay) or ii) changes in passengers' perceptions of public transport attributes have yet to be addressed. Related to i), this can be related to modifications in the capability constraint from the system of activities (e.g. change in working time or more flexibility in starting times), while ii) is related to changes in passengers' attitudes, fear, and expectations toward public transport modes (Wielechowski et al., 2020; Cho & Park, 2021). Examination of potential changes of those sensitivities across several stages of a disruption, including the pre-, during and post-disruption stages, is also yet to be provided. Addressing these gaps will extend the scope of modelling passengers' behavioural responses amid disruptive events.

RG-2 Limited utilization of smart card data for the modelling of passengers' behavioural responses amid disruptive events.

Previous research about examining passengers' responses amid disruptive events has been conducted almost exclusively using survey data. This has constrained the nature of the passengers' behavioural responses studied and, thereby, the scope of the results obtained. Smart card data, on the other hand, have the potential to overcome some of those challenges, achieving extensive coverage of the population to study the changes in public transport usage of those who continued travelling at several stages of a disruptive event. Nonetheless, several challenges have limited smart card data implementation for disaggregate applications, particularly missing attributes (Kusakabe & Asakura, 2014). In fact, depending on the modelling approach pursued, some essential attributes may not be captured by smart card data. Therefore, additional stages need to be developed to provide their imputation. This is the case for sociodemographic characteristics that are rarely available for ID cards. Similarly, in the case of departure time choice models, attributes such as passengers' preferred arrival times and the in-vehicle travel time for the unchosen time interval alternatives are typically unavailable with smart card data. Therefore, there is a research opportunity to overcome those limitations of smart card data for examining passengers' behavioural responses amid disruptive events through disaggregate-level modelling.

RG-3 Absence of a systematic comparison of the influence of individual-level factors on public transport usage amid a disruptive event.

So far, generating well-established conclusions about how individual-level factors influence passengers' behavioural responses amid disruptive events has been exceptionally challenging. Comparisons have been limited by the few studies available and the broad range of events that differ in nature, severity, location and temporality. In addition, diverse contexts, different definitions of the passengers' behavioural responses, dissimilar specifications of the individual-level factors, variable units and modelling frameworks add even more complexity to that task. A comprehensive comparison based on previous literature can help clarify inconsistent findings regarding the relationships between individual-level factors and public transport usage. For example, some studies have reported contradictory associations between gender, age and educational level with public transport usage during the pandemic (Almlöf et al., 2021; Jiao & Azimian, 2021; Palm et al., 2021). Moreover, in addition to the effect directions (positive, negative or non-statistically significant), a quantitative comparison of the magnitude of those effects is also missing in the literature. Therefore, a systematic comparison of the findings scattered across many sources on the effects of individual-level factors on passengers' public transport usage amid disruptive events is yet to be provided when the conditions are met. These conditions were met with the outbreak of the COVID-19 pandemic. In recent years, there has been an incredible amount of evidence that statistically tested the effects of individual-level factors on passengers' decisions to reduce their use of public transport. This situation offered a unique research opportunity to leverage the empirical evidence provided during the COVID-19 pandemic to address the existing gap in the literature. Based on this, it is possible now to synthesise the effect sizes of the relationships between individual-level factors and public transport usage in the context of the COVID-19 pandemic. The results provided here will not only be of empirical value for the COVID-19 pandemic but also for future situations, whether pandemics or other disruptive events.

RG-4 Insufficient evidence of the capabilities of aggregated mobility indices based on data generated from the everyday use of smartphones to be used as a proxy for actual ridership changes.

Among the different emerging data sources employed to provide proxies for public transport ridership, GPS traces collected by phone apps and the apps' number of queries, technologies already part of tech companies' products and services (Strzelecki, 2022), have been used in the last years to generate globally available aggregated mobility indices (AMIs). In this regard, comparing this AMIs and ridership during periods of significant mobility change is especially informative in studying their potential for broader use in these contexts. In this respect, the periods before, during and after a disruptive event and their associated changes in ridership levels provide an unusual 'natural experiment' to test whether AMIs can reasonably replicate ridership changes. So far, comparisons between AMIs that offer proxies for public transport ridership have been provided only tangentially by a few studies that analysed public transport demand during the COVID-19 pandemic. These studies preliminarily reported that AMIs captured the generalised drop in ridership during the pandemic outbreak and that after it, they overestimated ridership recovery (Jenelius & Cebecauer, 2020; Fernández Pozo et al., 2022). However, this evidence is restricted by several limitations that lead to inconclusive findings about the accuracy of AMIs in replicating ridership changes and their potential for widespread future use in public transport planning and operational decisions. They overlooked differences in the methodological approaches used to estimate AMIs, focussed on a few case studies and only analysed short periods. Therefore, the benchmarking required for properly comparing AMIs and ridership data from ticketing is yet to be conducted. Finally, attempts to leverage the complementary role of AMIs on ridership data, such as filling in temporal gaps, have yet to be made. Addressing these gaps is particularly relevant for cities of developing countries, which usually have limited data to analyse their ridership, and AMIs may offer an attractive alternative to measure the impact of disruptive events.

1.3 Objectives

The general research objective of this thesis is to enhance the understanding of public transport demand change amid disruptive events by addressing the four research gaps (RG) identified in the literature review. The general research objective is achieved by considering four research objectives (O), each of which is developed in an individual chapter. Note that a research objective may contribute to addressing more than one research gap.

The four research objectives (O) are defined as follows:

O-1	To compile global evidence of how individual-level factors affect public transport usage of passengers during a disruptive event (addressing RG-3).
O-2	To model profiles of passengers based on the recovery in their public transport usage amid a disruptive event employing smart card data (addressing RG-1 and RG-2).
O-3	To model trip scheduling decisions of bus commuters during several episodes affected by disruptive events employing smart card data (addressing RG-1 and RG-2).
O-4	To assess the potential of aggregated mobility indices based on data generated from the everyday use of smartphones to characterise public transport ridership changes in a context of high mobility disturbances (addressing RG-4).

The research objectives proposed here are addressed in this thesis by focussing on a period of worldwide high mobility disturbances between 2019 and 2022 caused by the COVID-19 pandemic. This period represents a unique opportunity to address existing research gaps in analysing disruptive events and public transport demand by leveraging recent literature and data sources.

1.4 Thesis outline and contributions

This thesis consists of five chapters (Chapters 2-6) that correspond to four articles prepared during this research, with Chapter 6 containing the overall synthesis, discussion, conclusions and future research directions. The association between research gaps, research objectives and chapters is summarised in Table 1-1. A concise summary of the four main chapters is offered next, highlighting the most relevant features addressed in each article as well as their original contributions.

Table 1-1 Association between research gaps, specific objectives and chapters.

Research Gap (RG)	**O-1** **Chapter 2** *Meta-analysis*	**O-2** **Chapter 3** *Mobility profiles*	**O-3** **Chapter 4** *Trip scheduling*	**O-4** **Chapter 5** *AMIs*
RG-1		✓	✓	
RG-2		✓	✓	
RG-3	✓			
RG-4				✓

Chapter 2 presents the paper titled *"Analysing the impacts of individual-level factors on public transport usage during the COVID-19 pandemic: A comprehensive literature review and meta-analysis"*. Despite the notable amount of evidence on the relationships between individual-level factors (such as socio-demographics, attitudes, etc.) and the decrease in public transport usage during the crisis of the COVID-19 pandemic, it has been exceptionally difficult to observe well-established conclusions about those relationships in the literature. Issues associated with the heterogeneity in the definition of travel change outcomes, dissimilar specifications of the individual-level factors, variable units and modelling frameworks and the influence of diverse cultural contexts have interfered so far with the comparability of current evidence. Moreover, there is a necessity for synthesising the effect sizes of those relationships because most of the existing literature only provides analyses based on their effect direction (positive, negative or non-statistically significant), paying less attention to their effect sizes. Hence, this chapter presents a systematic review and meta-analysis of 15 individual-level factors of public transport users that have been reported to have influenced the decision to continue using this mode during the crisis of the COVID-19 pandemic. Empirical evidence from several studies conducted worldwide is merged to synthesise the direction and size effect of those associations. The findings of this chapter offered the first quantitative comparison of the effect of different factors associated with public transport users and their travel behaviour change amid a disruptive event. These findings can help policy-makers understand the impacts of travellers' factors on the decision to reduce public transport usage during future disruptive events and guide public policies accordingly.

Chapter 3 contains the paper *"Using smart card data to model public transport user profiles in light of the COVID-19 pandemic"*. So far, the consequences of disruptive events on passengers' behavioural responses have been mostly analysed in terms of the reduction in their number of trips. This generates a need for the consideration of a broader set of indicators to generate a more comprehensive understanding of passengers' travel patterns. Thus, this chapter aims to identify and model profiles of public transport users who continued travelling after a critical disruption in mobility caused by a long-term lockdown during the COVID-19 pandemic based on a multidimensional consideration of their mobility changes. As a case study, public transport users of Santiago, Chile's capital are analysed, for whom individual-level smart card data records are available. A three-stage framework is developed to integrate i) a data enrichment stage to impute sociodemographic characteristics of travellers, ii) the identification of unseen travel pattern profiles based on mobility changes of public transport users, and iii) the association of the adoption of those profiles by including a set of explanatory variables. Two clusters of public transport users were identified using seven indicators that described the changes in passengers' public transport usage between the pre-pandemic and the reopening. The influence of both pre-pandemic and lockdown travel history, demographic characteristics at the residential level, and card type were considered variables that explain the membership of each cardholder to each mobility profile. The results lead to a better understanding of the strategies that public transport users carried out to satisfy their mobility needs in this context and provide insights as to which policies are most suitable for implementation in public transport systems in a post-pandemic era as well as future events of a similar nature.

Chapter 4 presents the paper *"Modelling trip scheduling decisions of bus commuters amid disruptive events using smart card data"*. This paper aims to add empirical evidence by investigating trip scheduling decisions of bus commuters amid disruptive events using smart card data. 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 disruptive events. 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 validated by obtaining a valuation of the trade-off between travel time and schedule delay (TVSD) in the range of previously reported values. 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. The results also show 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.

Chapter 5 presents the paper *"Investigating the potential of aggregated mobility indices for inferring public transport ridership changes"*. To address the increasing worldwide need to track mobility levels during the outbreak of the COVID-19 pandemic, several data providers made aggregate mobility indices (AMIs) available. Specific indices were provided to characterise the change in public transport demand in urban regions, derived from information and communications technologies, such as GPS of smartphones and trip queries in smartphone applications. Despite the wide popularity of these indices, it still remains largely untested whether AMIs can provide a reasonable characterisation of actual public transport ridership changes and whether they can be used as a reliable source for future crises. The study presented in this Chapter aims to fill that research gap by examining the reliability of using AMIs to infer changes in ridership levels in urban areas. To achieve this, the Chapter offers the first rigorous benchmarking between AMIs and ridership data derived from smart card validations and tickets. Monthly and daily ridership data from 12 cities worldwide and two AMIs shared globally by Google and Apple during 2020-22 are employed for the comparison. Methodological differences in the definition of the indices are addressed before comparisons, and the complementary role of AMIs on traditional ridership data is investigated. The results revealed an unexpected capability of the mobility index based on GPS traces to align with ridership trends, outperforming the index based on public transport direction queries, which performed reasonably only during the first year (2020). The findings also demonstrate that AMIs can complement data from smart card records when ticketing is missing or of doubtful quality. The outcomes of this study provide evidence of the capabilities of AMIs to characterise public transport demand change, which applications may be valuable to face future crises that involve major mobility changes.

Finally, **Chapter 6** contains the discussion and the conclusions. This Chapter summarises the advances made toward achieving the objectives presented in Section 1.3, the original contribution to knowledge, and outlines potential future research avenues.

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Chapter 2

Analysing the impacts of individual-level factors on public transport usage during the COVID-19 pandemic: A comprehensive literature review and meta-analysis

Abstract

Public transport (PT) usage was severely impacted during the COVID-19 pandemic, resulting in up to a 90% reduction in many cities in 2020. Numerous studies have been conducted since then to determine the relationship between individual-level factors (such as gender, attitudes, etc.) and the decrease in PT usage during the pandemic. Despite the evidence provided, findings are dispersed, and for several factors contradictory, making it challenging to reach any generalised conclusion. Furthermore, a comprehensive comparison of the effect sizes among travellers' factors affecting PT use during this period is yet to be compiled. This paper aims to address these gaps by systematically reviewing the existing evidence and synthesising the effect sizes of travellers' factors through a meta-analysis. We first identified 36 studies that statistically assessed the contribution of 15 individual-level factors on PT usage during the COVID-19 pandemic. By merging the empirical evidence of those studies, the direction of the association between those factors and PT usage was analysed. Then, after selecting comparable studies, meta-analyses were conducted for each factor to estimate the corresponding pooled effect sizes. The meta-analysis established that car availability, teleworking opportunities and high educational level contributed the most to reducing PT use during the pandemic. These factors increased the odds of reducing PT usage compared with the pre-pandemic by about three times. Factors such as COVID-19 risk perception, gender, high income and health had a moderate effect on the decision to stop using PT. PT habits, travel distance and physical accessibility also influenced PT use during the pandemic. Geographical location and the pandemic period explained part of the heterogeneity found. The findings provided in this study can help policy-makers understand the impacts of travellers' factors on the decision to reduce PT usage during future pandemics/epidemics and guide public policies accordingly.

Keywords: public transport demand, COVID-19, transit, travel behaviour, meta-analysis, systematic literature review.

2.1 Introduction

Public transport (PT) usage was severely affected during the COVID-19 pandemic. Its lowest levels were reached during the outbreak that occurred in the first half of 2020. In this period, PT demand dropped by up to 80%-90% in cities where stay-at-home orders were implemented (Teixeira & Lopes, 2020; Gramsch et al., 2022). A characterisation of these changes has been provided for cities of different countries, including the US (Liu et al., 2020; Wang & Noland, 2021; Xiao et al., 2022), the UK (Vickerman, 2021), Spain (Fernández Pozo et al., 2022), Germany (Eisenmann et al., 2021), India (Padmakumar & Patil, 2022), Chile (Lizana et al., 2023), and China (Jiang & Cai, 2022), for name some[2]. Even in cities without mandatory restrictions, PT demand experienced drops as high as 60% (Jenelius & Cebecauer, 2020; Mützel & Scheiner, 2022).

Eventually, PT demand started a slow recovery process after governments gradually removed the most restrictive policies from mid-2020. **Figure 2-1** exemplifies this process, presenting a four-year monthly variation (2019 to 2022) of the PT demand in 11 PT systems worldwide. Regarding this recovery process, most evidence indicates that during 2020 and 2021, PT demand remained substantially below pre-pandemic levels. For example, it was reported by Qi et al. (2023) that as late as January 2021, PT demand still exhibited reductions of between 50% and 80% in the 20 cities they analysed in the US. Gramsch et al. (2022) reported a drop as high as 60% at the end of September 2020 in Chile, a similar relative change to the one reported for Madrid (Fernández Pozo et al., 2022). Furthermore, PT demand continued to be lower than pre-pandemic levels even in contexts where successful initial counter-measures against the virus were implemented. Sweden (Jenelius & Cebecauer, 2020), Australia (Beck et al., 2021) and Taiwan (Mützel & Scheiner, 2022) are some of these cases. Given this generalised impact on PT usage and the consequential long-lasting effects, there has been a growing interest in understanding the factors that influenced travellers' decisions to reduce their use of PT.

[2] A summary of studies where the impacts of PT demand on aggregated PT demand was characterised is provided in the supplementary material (see **Table A-1**).

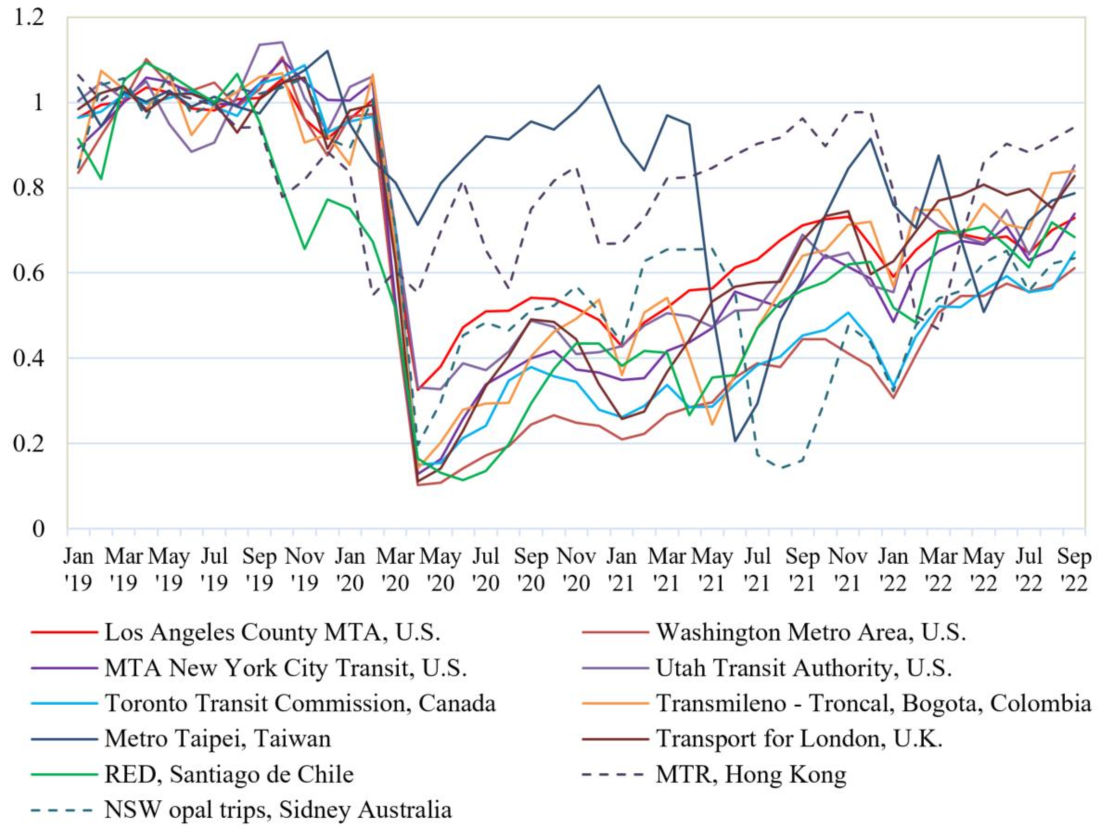

Figure 2-1. Relative change in monthly PT demand for several PT systems. Monthly average PT demand between January and September 2019 was used as a reference (Sources are presented in **Table A-2**).

Individual-level factors, which refer to characteristics or attributes that are specific to each person, have been widely studied to determine their influence on PT usage during the pandemic (Beck et al., 2021; Bansal et al., 2022; He et al., 2022). This literature emerged to characterise these relationships, focusing on describing the effects of individual-level factors such as demographics (El Zein et al., 2022), socioeconomic status (Jiao & Azimian, 2021), and psychological factors (Kim et al., 2021; Downey et al., 2022). Despite the abundant evidence, comparisons of the nature of these relationships have remained limited, and the existing findings are inconclusive and scattered across many sources. Diverse contexts, different definitions of the travel outcomes, dissimilar specifications of the individual-level factors, and variable units and modelling frameworks may be some of the characteristics that have restricted their comparability. Inconsistent findings between the relationships of individual-level factors and PT usage have also been reported, making it even more challenging to establish definitive conclusions. For example, some studies have reported contradictory associations between gender, age and educational level with PT usage during the pandemic (Almlöf et al., 2021; Jiao & Azimian, 2021; Palm et al., 2021). As a result, clear conclusions based on consistent and reliable data analysis are yet to be provided.

Despite the relevance to generating clear conclusions about the effect of individual-level factors on PT usage, most of the existing literature only provides analysis based on their effect direction (positive, negative or non-statistically significant), paying less attention to the comparison of the effect sizes or magnitude of those effects. As recently has been criticised by Parady and Axhausen (2023), literature in transport frequently focuses its analyses and conclusions on whether the effect of a specific factor are statistically significant rather than assessing the effect size of that relationship. Based on this, there is also a necessity for synthesising the effect sizes of the relationships between individual-level factors and PT usage in the context of the COVID-19 pandemic. This paper aims to address these gaps by (i) systematically reviewing studies that quantitatively assessed the influence of individual-level factors on PT usage during the COVID-19 pandemic, (ii) synthesising the effect sizes for each factor through a meta-analysis, (iii) providing a comparison of the pooled effect sizes between factors, and (iv) analysing the role of moderator variables in the pooled effect sizes.

The rest of this paper is structured as follows. First, the description of the methodology used for the systematic review and meta-analysis is provided in Section 2.2. Section 2.3 discusses the relationship between individual-level factors and the modelling perspectives that characterised individuals' PT usage during the COVID-19 pandemic. Section 2.4 presents the main findings of the estimation and comparison of the pooled effect sizes. Finally, a discussion is given in Section 2.5.

2.2 Methodology

2.2.1 Literature review

The contribution of individual-level factors to using PT during the pandemic was systematically reviewed and summarised, focussing on quantitative evidence. The review was conducted following the methodological procedure described by Wee and Banister (2015). First, search terms that include the following strings ("COVID-19" OR "SARS-CoV-2") AND ("public transport*" OR "public transit") AND ("travel behavio*" OR "mobility pattern*" OR "travel pattern*" OR "demand" OR "usage") were sought in Scopus and WOS. The selection criteria included:

- Research papers published from January 2020 to December 2022, which had been peer-reviewed and written in English.
- Research papers focusing on empirical evidence of the changes in PT demand levels at a disaggregated level during the COVID-19 pandemic.

- Research papers oriented to quantifying statistically the effect of individual-level factors on PT usage during the COVID-19 pandemic.

The search generated a total of 448 studies after the removal of duplicates. Manuscripts were selected in two stages: screening and full reading. In the screening process, titles, abstracts and keywords were analysed, obtaining 197 papers. The excluded studies were found either to be unrelated to travellers' PT usage or COVID-19. In the next stage, we excluded those studies where the application of qualitative methods meant that they did not statistically quantify the effect of any individual-level factor (such as age, gender or attitudes). Forward snowballing was also implemented, incorporating four studies by this means. Therefore, after the full-text assessment based on the inclusion criteria, 36 articles were finally selected for analysis. The literature review results are presented in Section 2.3, which synthesises the different perspectives adopted to study travellers' PT usage during the COVID-19 pandemic (See **Table 2-1**) and the effect direction (positive or negative) of individual-level factors on them (**Table 2-2**).

Table 2-1. Summary of the studies that assessed the impacts of individual-level factors on PT usage during the COVID-19 pandemic.

ID	Authors	Focus	Location/ Date	COVID-19 Context	Data type/ sample size	Dependent variable	Individual-level factor	Model/ model category
				(i) Public transport choice (PTC)				
[1] PTC	Abdullah et al. (2020)	Explore the changes in mode choice in the early stage of the pandemic	Various countries/ May 2020	Depending of the country	Online survey/ 1,203 respondents	Mode choice primary trip purpose	LOS, travellers' characteristics	Multinomial logistic regression/ BIN
[2] PTC	Abdullah et al. (2021)	Explore changes in mode choices	Lahore, Pakistan/ Oct-Nov 2020	Reopening (after the end of full/partial lockdown)	In-person survey/ 1,516 respondents	Choice of use PT vs. solo travel modes	Socio-demographics, trip intensity, safety	Multinomial logistic regression/ BIN
[3] PTC	Bansal et al. (2022)	Investigate the effect of crowding and pharmaceutical and non-pharmaceutical measures on PT choice	London, UK/ Mar-May 2021	During the outbreak	Online SP survey/ 961 respondents	Travel profile scenarios	Preventive measures, LOS, COVID-19 situation, socio-demographics	Multinomial logit, latent class and choice model/ DCM
[4] PTC	Basnak et al. (2022)	Pandemic effects on mode choice considering crowding	Santiago, Chile/ Aug-Oct 2020	Post outbreak	Online and field SP survey/ 455 respondents	Mode choice	LOS, attitudes, preventive measures	Latent class and choice model, Integrated choice model and latent variable/ DCM

ID	Authors	Focus	Location/ Date	COVID-19 Context	Data type/ sample size	Dependent variable	Individual-level factor	Model/ model category
[5] PTC	Chen et al. (2022)	Investigate the role of preventive measures on PT use	Netherlands/ Dec 2020 to Jan 2021	Lockdown	Online SP survey/ 394 respondents	Mode choice by scenario COVID	COVID-19 situation, LOS, preventive measures	Latent class and choice model/ DCM
[6] PTC	Cho and Park (2021)	Compare crowding multipliers before and during the pandemic	Seoul, South Korea/ Oct 2018 & Nov 2020	na	Repeated cross sectional SP, online & in-person survey/ 378 and 623 respondents	Travel profile scenarios	LOS	Mixed logit/ DCM
[7] PTC	Delclos-Alio et al. (2022)	Impact of COVID-19 on tourist PT use	Catalonia, Spain/ Summer of 2019 & 2020	Recovery	In-person survey/ 1,465 respondents	If PT mode is used	COVID-19 situation, socio-demographics	Bivariate Probit Model/ BIN
[8] PTC	Hsieh and Hsia (2022)	Study the factors related to the decision to choose metro	Kaohsiung, Taiwan/ First half of 2020	na	In-person SP survey/ 235 respondents	Metro profile scenarios	LOS, preventive measures, socio-demographics, travel habit	Mixed Logit/ DCM
[9] PTC	Liu et al. (2022)	Understand travel behaviour among adolescent	Guangzhou,, China/ Apr 2020	During and after pandemic peak	In-person survey/ 315 respondents	If an individual travelled by PT	Socio-economics, transport-related attributes, perception	Binomial logistic regression/ BIN
[10] PTC	Marra et al. (2022)	Pandemic effects on PT route choice	Zurich, Switzerland / Spring	Outbreak and post-outbreak	Repeated cross section, travel diary &	PT route choice	LOS	Mixed path size logit model/ DCM

ID	Authors	Focus	Location/ Date	COVID-19 Context	Data type/ sample size	Dependent variable	Individual-level factor	Model/ model category
			2019 & Feb-Jul 2020		GPS data from smartphone app/ 48 ind.			
[11] PTC	Mashrur et al. (2022)	Capture participants' attitudes towards PT	Greater Toronto Area, Canada/ Jul 2020	Partial opening after the first wave	SP & RP, online survey/ 905 respondents	Mode choice by scenario COVID	LOS, preventive measures, COVID-19 situation	Multinomial, nested and mixed logit/ DCM
[12] PTC	Mazanec et al. (2023)	Understand the mode transport choice	Czech republic/ May-Jun 2020	After the end full lockdown	Online survey/ 1,500 respondents	Mode choice	Socio-demographics	Multinomial logistic regression/ BIN
[13] PTC	Rankavat et al. (2023)	Investigate users' perception of mode choice	India/ Oct 2020	After the first pandemic peak	Online and in-person survey/ 411 respondents	Mode choice for work trip purpose	Socio-demographics, transport-related attributes, perception	Multinomial logistic regression/ BIN
[14] PTC	Ross (2021)	Understand the mode transport choice	Tel Aviv, Israel/ Oct-Dic 2020	After the second pandemic peak	Online survey/ 302 respondents	Bus vs. demand-responsive transport	Sociodemographics, risk perception	Binomial logistic regression/ BIN
[15] PTC	Shelat et al. (2022)	Evaluate travellers' behaviour in PT networks	Netherlands/ May 2020	Post outbreak. Many restrictions are still in place	Online SP survey / 513 respondents	Travel profile scenarios	LOS, COVID-19 situation	Latent class and choice model/ DCM

ID	Authors	Focus	Location/ Date	COVID-19 Context	Data type/ sample size	Dependent variable	Individual-level factor	Model/ model category
[16] PTC	Tan and Ma (2021)	Study the choice of rail transit during the pandemic	China/ First months of 2020	Pandemic outbreak	Online survey/ 559 respondents	If an individual chooses rail transit	Sociodemographics, transport-related attributes, safety	Binomial logistic regression/ BIN
(ii) Public transport usage reduction (PTR)								
[17] PTR	Almlöf et al. (2021)	Study of those who continued travelling by PT during COVID-19	Stockholm, Sweden/ Feb, Apr-May & Oct 2020	Recovery	Repeated cross section smart cards & mobile app tickets/ 1.8m	If an individual decreased PT trips by more than 90%	Pre-COVID PT use, @sociodemogra-phics	Binomial logistic regression/ BIN
[18] PTR	Das et al. (2021)	Analyse factors associated with the modal shift from PT to private modes	Several regions of India/ Apr-May 2020	Several phases of nationwide lockdown	Online survey/ 840 respondents	If an individual shifted from PT to private mode	Sociodemographics, transport-related attributes, safety	Binomial logistic regression/ BIN
[19] PTR	Downey et al. (2022)	Study the determinants of changes in PT use	Scotland/ Feb 2021	During the second wave	Online survey/ 994 respondents	If an individual plans to make the same or more PT trips in the future	Attitudes, sociodemographics	Bivariate Probit model/ BIN
[20] PTR	El Zein et al. (2022)	Explore the factors influencing PT use change	Lyon, France/ Feb & Jun 2020	Post 1st wave	Online survey/ 2,298 respondents	If an individual had lower use of PT	Sociodemographics, transport-related attributes, attitudes	Binomial logistic regression/ BIN

ID	Authors	Focus	Location/ Date	COVID-19 Context	Data type/ sample size	Dependent variable	Individual-level factor	Model/ model category
[21] PTR	Elias and Zatmeh-Kanj (2021)	Role of risk perception and hygiene in train use	Israel/ April-May, Dec 2020	During COVID-19 mobility restrictions	Online survey/ 273 respondents	If an individual stopped travelling by PT	Transport-related attributes, attitudes	SEM
[22] PTR	He et al. (2022)	Investigate COVID-19 effect on PT use	US/ Sep-Nov 2020	Recovery	Online survey/ 500 respondents	If an individual stopped or reduced PT use	Sociodemographics, transport-related attributes, health,	Binomial logistic regression/ BIN
[23] PTR	Ito and Kawazoe (2023)	Analyse factors influencing modal shift	Toyama, Japan/ Sep 2020	Recovery	Online survey/ 973 respondents	If an individual changes their transport mode	Sociodemographics attitudes	Multinomial logistic regression/ BIN
[24] PTR	Jiao and Azimian (2021)	Analyse factors associated with mode choice during the second phase	US/ Oct 2020	Second pandemic phase	Online survey/ >10,000 respondents	If an individual made fewer PT trips	Sociodemographics, health status, anxiety	Binomial logistic regression/ BIN
[25] PTR	Khadem Sameni et al. (2021)	Understand the factors associated with the shift from subway to other modes	Teheran, Iran/ Apr 2021	Second wave peak and recovery	Online survey/ 411 respondents	If an individual shifted from the subway to other modes	Sociodemographics transport-related attributes	Binomial logistic regression/ BIN
[26] PTR	Palm et al. (2021)	Investigate the factors associated with	Toronto & Vancouver, Canada/	Recovering from the first wave	Online survey/ 4,710 respondents	If an individual stopped travelling by PT	Sociodemographics, disability, built-environment	Binomial logistic regression/ BIN

ID	Authors	Focus	Location/ Date	COVID-19 Context	Data type/ sample size	Dependent variable	Individual-level factor	Model/ model category
		avoid travelling by PT	May 2020					
[27] PTR	Soria et al. (2023)	Study the factors associated with abandoning PT use	Chicago, US/ Jan-Feb 2021	Third wave and recovery	Online survey/ 5,648 respondents	If an individual abandon the use of PT	Socioeconomics, transport-related attributes	Binomial logistic regression/ BIN
[28] PTR	Zafri et al. (2023)	Study the change in the frequency of travel by PT	Bangladesh / Jul-Aug 2020	First wave	Online survey/ 804 respondents	If an individual recovered pre-COVID PT usage	Socioeconomics, transport-related attributes, perceptions	Binomial logistic regression/ BIN
[29] PTR	Vallejo-Borda et al. (2022)	Investigate the decision to shift from PT to other modes	Several Latin American capitals/ Sep 2020	Vary depending on the country	Online survey/ 3,803 respondents	If an individual shifted from PT to another mode	Attitudes and risk perception, sociodemographics	SEM-MIMIC/ SEM
				(iii) Public transport trips (PTT)				
[30] PTT	Beck et al. (2021)	Effect of preventive measures and crowding on PT use	Australia/ Three different waves in 2020	Depending of the wave	Online survey/ 1,074, 1,457 & 956 respondents	Number of PT trips	Travellers' characteristics, attitudes and perceived risk	Zero-inflated poisson regression/ CNT
[31] PTT	Kim et al. (2021)	Effect of perceptions on PT use	Seoul, South Korea/	na	Online survey/ 537 respondents	Frequency of PT use	Attitudes, perceived risk, sociodemographics	SEM/ CNT

ID	Authors	Focus	Location/ Date	COVID-19 Context	Data type/ sample size	Dependent variable	Individual-level factor	Model/ model category
			Sep-Oct 2020					
[32] PTT	Parker et al. (2021)	Factors that affect PT usage intensity	US/ Jan-Dec 2020	Outbreak and recovery	Panel data, GPS & survey/ 1,267 respondents	Total number of trips	Sociodemographics, land-use, COVID-19 situation	Binomial regression/ CNT
[33] PTT	Schaefer et al. (2021)	Estimate of the reduction in the use of three PT modes	Hannover, Germany/ Jun 2020	Post 1st wave, main restrictions lifted	Online survey/ ~3,000 respondents	Reduction in PT trips, number of days per month	Sociodemographics, perceived risk	OLS/ CNT
(iv) Public transport - Intention outcomes (PTI)								
[34] PTI	Aaditya and Rahul (2023)	Understanding the willingness to use personal modes vs shared modes	Odisha, India/ Sep-Oct 2021	Main restrictions relaxed	SP & RP, online & in-person survey/ 467 respondents	Willingness to choose non-shared modes and PT	COVID history, attitudes and risk perception, preventive measures	Ordered logit/ DCM
[35] PTI	Zhang et al. (2021)	Understand the behavioural intentions of PT passengers	Tianjin, China/ Feb-Apr 2020	Period under first-level response	Online survey/ 983 respondents	Intention to use the subway during COVID-19	Attitudes, customer satisfaction.	SEM/ SEM
[36] PTI	Zhao and Gao (2022)	Study latent constructs on PT travel decision	Beijing, China/ Nov 2020	Four-month low-infection period. Preventive	Online survey/ 761 respondents	Intention to use PT	Attitudes and risk perception, sociodemographics	SEM-MIMIC/ SEM

ID	Authors	Focus	Location/ Date	COVID-19 Context	Data type/ sample size	Dependent variable	Individual-level factor	Model/ model category
				measures still in place				

BIN: model with binary outcome (logistic regression and bivariate Probit); DCM: discrete choice model (multinomial, mixed, latent class or latent variable logit models); CNT: count outcome models (OLS, negative binomial and Poisson regression) SEM; Structural equations modelling; @: aggregated factor, usually at neighbourhood or city-area levels; LOS: modes' level of service; SP: Stated preferences: RP: revealed preferences, na: information not available.

2.2.2 Meta-analysis

A meta-analysis is a statistical procedure that combines and summarises the results of multiple studies (Borenstein, 2009). In the transport domain, this technique has been applied mainly in transport economics (Button, 2019). However, examples can also be found in works that studied the relationships between transport and employment (Bastiaanssen et al., 2020), the built environment (Laura et al., 2021) and cognitive mechanisms (Hoffmann et al., 2017). The typical output of a meta-analysis includes a single pooled effect size and a confidence interval. As homogeneity in terms of the nature of the effect sizes is a pre-requisite for conducting any meta-analysis (Hoffmann et al., 2017), choosing studies based on the same modelling approach has been shown as a feasible way to deal with this issue (Bastiaanssen et al., 2020). As a result, this consideration led to the selection in our study of the effect sizes reported for studies using logistic regression models (LRMs), which included a total of 16 studies. The two main advantages of this model approach were the comparable specification of the individual-level factors across studies, which increased the number of comparable effect sizes available, and its straightforward interpretation of its effect sizes (in terms of odds ratios).

After identifying the studies that had used LRMs, effect sizes (coefficients) of the individual-level factors and a measure of their statistical significance (standard errors, *p*-values or *t*-statistics) were compiled. Random-effect models (REMs) were then fit to estimate the pooled effect size for each individual-level factor. For this, we followed the "gold standard" in meta-analysis, calculating the weights for each effect size as the inverse of its squared standard error, assigning the greatest importance to the most precise associations (Littell et al., 2008). It may be noted that REMs are employed in meta-analysis when there is both within-study and between-study heterogeneity in the effect sizes (Bastiaanssen et al., 2020). REMs produce a lower statistical significance and a wider confidence interval (CI) than a fixed-effect model. Consequently, they are widely accepted in meta-analysis studies as a more conservative modelling approach that leads to more robust pooled/combined effect sizes (Borenstein, 2009). We also took into account the clustered structure of some associations to avoid bias in the weight of each effect size, as more than one association/effect size (k) can be provided per study (N) for the same factor. Additionally, we included both significant and non-significant effects in the meta-analysis, as it is known that dropping the latter may increase the risk of bias in the pooled effect size (Button, 2019). We also tested the influence of the geographical region and the pandemic period in the pooled effect sizes between studies.

2.3 Systematic literature review results

2.3.1 Overview

The systematic review identified 36 studies where the impacts of individual-level factors on travellers' PT usage during the COVID-19 pandemic were statistically tested (see **Table 2-1** for a comprehensive summary). Most existing evidence came from data collected during different periods in 2020 and only a few from later periods (with only six in the first half of 2021). The studies were mainly conducted in Asia (16), Europe (10) and North America (6), with a large number concentrated in the US, China, India and the Netherlands. With a few exceptions (Almlöf et al., 2021; Marra et al., 2022), almost all selected papers relied on online surveys distributed digitally, such as social platforms like Facebook and Instagram, emails to PT-oriented groups, and links shared by respondents. The obvious limitations of this approach, as recognised by these studies, concern the overrepresentation of respondents with internet access and the underrepresentation of PT passengers without internet. Traditional questionnaires included sections asking for demographic and socioeconomic characteristics, travel behaviour at the time of the survey and during the pre-pandemic, and respondents' perceptions of COVID-19 risk and associated mitigation strategies. Studies based on both revealed and stated preferences (SP) may be found among the selected literature. The studies that employed revealed preferences aimed to quantify the intensity of travellers' PT usage. When pre-pandemic PT usage was needed, retrospective information was asked of participants, which clearly relied on the accuracy of participants' memories. As many as nine studies adopted an SP approach. This approach allowed them to generate a dataset of choices based on different levels of the attributes of the considered modes and to explore travellers' mode choice decisions in hypothetical scenarios. The hypothetical scenarios included different COVID-19 emergency contexts (in terms of number of new cases, death toll and vaccination scenarios) (Bansal et al., 2022) and the different virus mitigation measures (e.g. disinfection in PT buses, social distancing) (Bansal et al., 2022).

2.3.2 PT usage characterisation in individual-level studies

The selected studies characterised the PT usage of travellers during the COVID-19 pandemic using different definitions of the dependent variable. Based on the nature of the dependent variable, four main categories of studies were identified: (i) studies that analysed the decision to choose PT among the presence of alternative modes (16 studies), (ii) studies that focused on measuring if travellers reduced the number of PT trips compared with the pre-pandemic (13 studies), (iii) studies that measured the intensity of PT use by considering the number of trips made by travellers (4 studies), and (iv) studies that investigated the intention/willingness to use PT (3 studies).

In category (i), mode choice was the main outcome observed (Das et al., 2021; Chen et al., 2022). In this category, discrete choice models (DCMs) and logistic regressions (LRMs) were commonly employed. Category (ii) includes outcomes such as whether individuals reduced their trips made by PT during the pandemic (4 studies), whether they stopped at all (4 studies) or whether they shifted from PT to an alternative mode (5 studies). The modelling approach widely adopted in this category was logistic regression. In category (iii), studies employed modelling approaches for continuous outcomes such as OLS, binomial and zero-inflated Poisson. Category (iv) shows studies where ordered outcomes were considered in structural equations modelling under different behavioural theories (Zhang et al., 2021). Specific details of the specification of the PT outcome variable and modelling approach are provided in **Table 2-1**. As the selected studies considered different directions to define the PT outcome variables (e.g. to choose PT vs not choose PT), it was necessary to adopt one direction and transform ('flip') the effects found for the definition that employed the opposite one. Therefore, the adopted consensus was to reflect the effects of individual-level factors on a pro-reduction view of PT usage during the pandemic. Consequently, the PT usage outcomes for categories (i) and (ii), for instance, characterise the decision of not choosing PT and reducing PT trips/shifting from PT to an alternative mode. The same consensus is kept for the rest of this work to obtain a more straightforward interpretation of the effect of individual-level factors.

2.3.3 Effect direction of individual-level factors on PT usage

This section summarises the relationships reported in the selected 36 studies between individual-level factors and the reduction of PT usage in the context of the COVID-19 pandemic. A total of 15 different individual-level factors were identified: demographics (gender, age, race and ethnicity, education, children and household size), socioeconomic status (income, car availability, teleworking possibilities, and full-time employment), perceived importance to the COVID-19 risk and mitigation strategies, healthcare needs (disability and poor health) and transport-oriented attributes (pre-COVID frequent PT user, travel distance, and PT physical accessibility). The analysis of the selected papers also identified different approaches used to consider the effect of individual-level factors on PT usage: (a) direct effects, (b) interaction effects, and (c) explaining class membership, being the first one (a) the most frequent. A list of these factors and their associated relationships with PT usage reduction may be found in **Table 2-2**.

Table 2-2. Summary of the effect directions of individual-level factors on the reduction of PT usage during the COVID-19 pandemic.

ID	Gender (Male)	Age (Older adults)	Race & ethnicity	Educa-tion	Children	House-hold size	Income	Car availa-bility	Tele-working	Full-time employ-ment	COVID-19 risk perception	Healthcare needs	Frequent PT user	Travel distance	PT access time
[1] PTCm	+							+		ns	+			-	
[2] PTCm	+			+			ns	+							
[3] PTC	+MSK	+CRO, -MSK	-MVC	+CRO			+C19, +MSK								
[4] PTC	-CRO	C					C								
[5] PTC	C	C		C	C					C					
[6] PTC															
[7] PTC															
[8] PTC	ns	+			+		ns	ns		ns			-,+[PM], +[NM]		
[9] PTCm	+						+, ns	+, ns			+			-	
[10] PTC															
[11] PTC	ns	+					+	+	+, ns						
[12] PTCm								+		-					
[13] PTCm	+	+					+				+			-	
[14] PTCm	ns	ns													
[15] PTC	C	C											C		

ID	Gender (Male)	Age (Older adults)	Race & ethnicity	Educa-tion	Children	House-hold size	Income	Car availa-bility	Tele-working	Full-time employ-ment	COVID-19 risk perception	Healthcare needs	Frequent PT user	Travel distance	PT access time
[16] PTCm										-	+				+
[17] PTR	+@	+@	+@	-@			+@			-@			-		
[18] PTRm	+	+					+			+	+			+	+, ns
[19] PTR		ns				-					+		ns, +[PM]		
[20] PTRm	ns	ns		+, ns	ns			+, ns	+, ns		+, ns		-, ns		
[21] PTR											-				
[22] PTRm	ns	ns	-, ns		ns	ns	+	+				-	ns		
[23] PTRm	ns	ns													
[24] PTRm	+	-	+	+		-	+				+	-			
[25] PTRm							+								
[26] PTRm	-	-	-, ns			ns	+	+		-	+	ns	-		
[27] PTRm	-	+	-				+	+	+	-	+		-		
[28] PTRm							+		+		+				
[29] PTR		-			-	+	-				+				
[30] PTT	-	+, -					+, -		+, -		ns, -		-, ns		
[31] PTT											+				
[32] PTT															

ID	Gender (Male)	Age (Older adults)	Race & ethnicity	Educa-tion	Children	House-hold size	Income	Car availa-bility	Tele-working	Full-time employ-ment	COVID-19 risk perception	Healthcare needs	Frequent PT user	Travel distance	PT access time
[33] PTT	ns, -RISK	-, +RISK		ns, +RISK			+		+, +RISK		+		+		
[34] PTI	ns							+		-	+		+[>PM]		
[35] PTI															
[36] PTI	ns	ns		ns			+	ns		-			-		

Footnotes of **Table 2-2**. '+': positive statistically significant association; '-': negative statistically significant association; 'ns': no statistically significant; significance considered at 0.1; '@': aggregated specification; 'm': Study included in the meta-analysis; 'C': explaining class-membership; empty space: association not reported/not studied; '[]': Indicate effect of being a frequent user of private modes [PM] and [NM] non-motorized modes; the inclusion of the next abbreviations indicates that the association reported is towards that variable; 'MSK': mandatory use of face mask, 'CRO': crowding on PT modes, 'MVC': massive vaccination; 'C19': COVID-19 new cases, 'RISK': COVID-19 risk perception.

For the direct effects approach (a), **Table 2-2** highlights the fact that demographic factors presented heterogeneous effect directions across studies, with a mix of positive, negative and non-significant effects for the same factor. For instance, in the case of gender, 37% of the associations indicated that male travellers were more likely to reduce PT use compared to females (Abdullah et al., 2020; Abdullah et al., 2021; Jiao & Azimian, 2021), whereas 16% found the opposite effect (Beck et al., 2021; Palm et al., 2021), and 47% found no significant relationship (Aaditya & Rahul, 2023). Similarly, only 39% of the studies that reported results for age showed that older adults were more likely to reduce PT usage (Mashrur et al., 2022). In the case of race and ethnicity, evidence is also contradictory, with some associations reporting a positive association (Jiao & Azimian, 2021) and others a negative one (Soria et al., 2023). **Table 2-2** shows that educational level was positively related to reducing PT use (El Zein et al., 2022), and that household size presents negative effects (the higher the household size, the lower the reduction in PT use) (Jiao & Azimian, 2021). The evidence presented for the presence of children at home agrees that this factor did not cause any significant effect on travellers' PT use.

Regarding socioeconomic status, the influence of income level, car availability, teleworking, and full-time employment show more agreement across studies. For income level, 14 studies (78%) found a positive association between this factor and the reduction in PT usage (Parker et al., 2021; Schaefer et al., 2021). This result suggests that individuals of higher income levels were more likely to reduce PT use during the pandemic than travellers of lower levels. For car availability, ten associations (71% of the reported effects) presented statistically significant positive relationships (Palm et al., 2021; Mazanec et al., 2023), while for teleworking, 76% of the associations also found significant positive effects on the reduction of PT use (Schaefer et al., 2021; Mashrur et al., 2022). Regarding full-time employment, some studies reported that such travellers tended to use more PT more often (negative effect) than students, freelancers or the unemployed (Zhao & Gao, 2022; Aaditya & Rahul, 2023). However, other works found the opposite relationship (Das et al., 2021).

In order to analyse the influence of COVID-19 risk perception, studies included travellers' perception of the severity of the virus and the importance they gave to the implementation of mitigation strategies, such as hygiene/cleanliness, social distancing and mandatory use-of-face masks (Abdullah et al., 2020; Zhao & Gao, 2022; Aaditya & Rahul, 2023). The studies tested these variables directly on the PT outcome (specifying dummies) (Palm et al., 2021; El Zein et al., 2022; Soria et al., 2023) or indirectly following a latent variable approach based on five-point Likert scales indicators (Abdullah et al., 2020; Rankavat et al., 2023). As expected, the perception of the severity of the virus and the importance given to mitigation strategies showed positive correlation when they were used together to construct a latent variable and showed a positive effect on the reduction of PT use when specified separately (Abdullah et al., 2020). A total of 17 positive associations (77%) showed that the higher the importance given to the COVID-19 risk and mitigation strategies among travellers, the higher the reduction in travellers' PT use (Basnak et al., 2022; Vallejo-Borda et al., 2022). However, more complex psychological mechanisms through which travellers adjusted their behaviour by the changes in their attitudes and perceptions to use PT were also recognised by Kim et al. (2021), Zhang et al. (2021) and Vallejo-Borda et al. (2022).

Unexpected effect directions were found for the factors that account for individuals' healthcare needs. Travellers with a disability and those with poor health showed a positive association with the use of PT during the pandemic, compared to individuals without these conditions (Jiao & Azimian, 2021; Palm et al., 2021; He et al., 2022). Potential explanations may be found in this group's low availability of alternative modes. Significant effects were also found for transport-related factors such as travel distance (for commuting trips), PT physical accessibility and whether a traveller was a pre-COVID frequent PT user. The evidence showed that travelling frequently by PT during the pre-pandemic negatively impacted people's decision to reduce PT (Palm et al., 2021; Soria et al., 2023), providing evidence that pre-pandemic mobility habits also played a key role in the decision of whether to use PT during the pandemic. Regarding travel distance, two studies reported negative effects (Abdullah et al., 2020; Liu et al., 2022), meaning that longer travel distances showed a negative association with the reduction in PT use. In the case of PT physical accessibility, its effect showed that during the pandemic, the longer the access time to get a PT service, the higher the reduction in PT use (Das et al., 2021; Tan & Ma, 2021).

More complex influences of individual-level factors were also studied by considering their role modifying the effects of other variables (category (b), 3 studies) or to account for taste variation among travellers using a latent class approach (category (c), 3 studies). In the former, travellers' characteristics such as gender, age, income, educational level and ethnicity were found to modify the effects of PT crowding (CRO), the number of COVID-19 cases (C19), the implementation of mandatory face masks (MSK) and the share of the population vaccinated (MSV) on the choice of PT mode (Bansal et al., 2022; Basnak et al., 2022). For instance, it was found that female and elderly travellers showed a higher sensitivity to crowding in PT modes. The mandatory use of face masks in PT modes had a smaller influence on male travellers than on females and a relatively greater positive effect on elderly passengers. Schaefer et al. (2021) also stated that people who worked from home feared catching the virus more when using PT, highlighting the complex relationship between attitudes and travel behaviour. In the latter category, the role of individual-level factors was to help define groups of travellers that share a more homogenous perception of disutility in terms of level of service attributes (e.g. travel time, travel cost, crowding) (Chen et al., 2022; Shelat et al., 2022). In this case, the relationship observed was the association of an individual to a cluster rather than a direct or interaction effect. For instance, it was identified in these works that the cluster associated with female travellers, the elderly and high-income perceived a higher adverse impact of the time travelled in PT and a higher positive effect of preventive measures such as social distancing in PT modes.

In conclusion, individual-level factors played various roles regarding how they were included in a given study. The most frequent approach among them was their specification as direct explanatory variables of the changes in travellers' PT use during the pandemic. It was found from the evidence gathered in this approach that for many factors (e.g. gender, age), the findings revealed contradictory results, making it difficult to establish clear conclusions. Moreover, as the analysis in this section relied only on the effect direction of each association, the relevance in term of the effect size of those effects still need to be provided.

2.4 Meta-analysis results

2.4.1 Preparation

To ensure the comparability of the effect sizes of individual-level factors on PT usage, studies that employed logistic regression models (LRMs) were specifically chosen. This choice was made based on the analysis of the 36 selected studies, which showed that the selection of LRM-based studies provided the potential for the most robust synthesis by offering the highest number of comparable individual studies compared with other modelling approaches. LRMs were used as a modelling approach in both of the two main categories of PT usage studies, namely those to (i) choose/not choose PT and (ii) reduce PT usage. LRMs have the advantage of involving the specification of individual-level factors as direct explanatory variables of PT usage (rather than as interaction effects). Another characteristic of LRMs that facilitated the cross-study comparison is the fact that most of their factors were specified as dummies, which removes potential difficulties associated with the measurement units. For instance, income was usually specified as a discrete number of categories with similar qualitative thresholds across studies (low/mid/high-income).

An additional advantage of LRMs is that there is a straightforward interpretation of their coefficients. The exponential value of a coefficient indicates the corresponding variables’ contribution in terms of its odds ratio. In general, an odds ratio is defined as the ratio of the probability of the occurrence of an event relative to the probability of the event not occurring. As LRMs were applied in category outcomes (i) and (ii), the interpretation based on the odds ratios is defined as the probability of reducing PT trips/choosing an alternative mode (not PT) relative to the event this not occurring. In the case of category (i) studies, the alternative modes were car or ride-hailing. An odds ratio higher than one indicates that the factor analysed increases the probability of the event (reducing PT usage/not choosing PT in our case), while a value lower than one indicates the opposite. If, for example, the odds ratio associated with a certain dummy variable were 2.0, that would mean that an individual with that characteristic has odds of ‘reducing PT usage’ two times higher than someone without that characteristic. Similarly, if an odds ratio is lower than one, let us say 0.5, an individual with that attribute has odds of ‘reducing PT usage’ 50% lower than individuals without that characteristic. In cases where the PT usage outcome needed to be transformed to fit the adopted consensus, the respective odds ratios were re-estimated by taking their inverse.

2.4.2 Pooled effect sizes

A total of 16 comparable studies that examine the effect of individual-level factors using LRMs were finally included in the meta-analysis. We performed meta-analyses separately for the 15 factors shown in **Table 2-2**. A standardisation was required to ensure that all the factors specified as dummy variables shared the same reference category. The category references adopted for the demographic factors in the meta-analysis were: gender (1:male; 0:female), age (1:>65 years old; 0:first age category level, which frequently ranged from 18 to 35 years old depending on the study), race and ethnicity (1:Black/Hispanic/Indigenous; 0:White), high-educational level (1:University/college degree, 0:no degree), children (1:presence of children at home; 0:otherwise) and household size (1:two or more; 0:otherwise). Similarly, for socioeconomic factors, we defined references for income (1:high-income level; 0:low-income level), car availability (1:at least one car owned or available; 0:no car available/owned) and employment (1:full-time employment: 0:student/not employed). Additionally, healthcare needs (1: condition of disability or poor health; 0: otherwise), travel frequent PT user (1:pre-COVID frequent PT user; 0:otherwise) and travel distance (1:travel distance longer than 5km, 0:travel distance shorter than 5 km). In the case of teleworking, several frequency categories were included (1: 1-2 days per week, 3-4 days per week, etc.), considering as a reference category the possibility of no teleworking. Similarly, the studies specified physical accessibility to PT using several dummy categories (10-20 min, >20 min, etc.), adopting as reference category walking times lower than 6.5 min. Finally, the COVID-19 risk perception factor was measured by specifying dummies and five-point Likert scale variables. In this case, the interpretation of the odds ratio is then associated with the increase in the odds of reducing PT use during the pandemic by increasing one unit of COVID-19 risk perception. **Table A-3** in the Appendix offers a detailed description of the associations employed for this factor.

For some dummy associations, the reference category was transformed ('flipped') to agree with the criteria mentioned previously, i.e. to relate to reductions in PT use. In the case of two-category dummy variables, the procedure to obtain the transformed odds ratio is straightforward in LRMs and only involves taking the inverse of the exponential LRM coefficients, as the magnitude of the standard errors is the same. In the case of multiple categories, the procedure to estimate the transformed effect size is similar, but the standard errors need to be re-estimated using, for example, Fieller's method. Applying the previously mentioned criteria allowed the generation of comparable effect sizes. Finally, three important statistical level thresholds observed from the literature were considered for comparison: 10%, 5%, and 1%. The 10% level, despite being more relaxed than the conventional 5%, is recommended to be included when sample sizes are small, which is the case for many of the factors included in this study. Nonetheless, pooled effect sizes which are significant at this level should be treated cautiously, due to the higher chances of rejecting a true null hypothesis (i.e. detecting an effect that isn't there) compared with the stricter levels.

Figure 2-2 illustrates the synthesised effect sizes and confidence intervals (CIs) for the associations of individual-level factors with the reduction of PT usage across comparable studies based on the previously mentioned random effect models. Nine pooled effect sizes were found to be statistically significant (six at a significant level of 1%, one at 5%, and two at 10%) and six not significant. Among the non-significant, it can be found older adults, race and ethnicity, children, household size, full-time employment, and PT physical accessibility, whose p-values were higher than the more relaxed threshold adopted (10% significant level). **Figure 2-2** also shows that repeatedly, the CIs are comparable among the associations within each individual-level factor (i.e., within-study variability is reasonably constant across studies). However, as the mean of the pooled effect sizes, represented by the blue diamond, is not contained in all CIs for a specific factor, a substantial heterogeneity between studies can be seen. In fact, we found that the statistic I2 indicated the presence of a relevant heterogeneity among the effect sizes of the studies analysed. As most of the I2 values of the factors meta-analysed ranged from 60% to 90%, it was possible to infer that the observed differences in effect sizes in each individual-level factor were due to real differences in the underlying effect rather than just random variation. This outcome ratified the choice of random effect models to estimate the pooled effect sizes to handle both within- and between-study heterogeneity.

Among the factors meta-analysed, car availability, teleworking and high educational level were the factors with the largest pooled effect sizes. In the case of car availability, all the studies consistently reported odds ratios higher than 1, indicating a positive association (+) between car availability and the reduction of PT usage during the pandemic. The overall random effect for this factor was equal to an OR^+ of 4.17 (CI: 1.84; 9.44, *p*=<0.001***). This result suggests that individuals who owned or had at least one car available during the pandemic have odds of reducing their PT usage compared with the pre-pandemic almost four times higher than those without this possibility. Similarly, the odds of reducing PT usage were shown being three times higher for individuals with the possibility of teleworking compared to those who did not (OR^+=3.08, CI:1.46; 6.50, *p*=0.003***). The next individual-level factor in terms of magnitude was high educational level. Based on the pooled effect of this factor (OR^+=2.11, CI:1.11; 4.01, *p*=0.023**), we found that travellers with a university or college degree had odds of reducing PT usage that were about two times the one of those individuals without one.

A second group of individual-level factors, including gender (male), income, COVID-19 risk perception and healthcare needs, showed a more modest pooled effect size. Those who identified themselves as male showed odds 20% higher to reduce PT usage than those who identified themselves as female (OR+=1.20, CI:0.99; 1.45, *p*=0.058*). Many authors explain this by the fact that females had fewer transport mode options than males, alluding to social and cultural aspects (Das et al., 2021). For instance, women typically earn lower wages compared to men, which impacts their capacity to afford private transportation. Additionally, from a cultural standpoint, a lack of financial independence in certain cultures leads women to depend more on shared or public transport, resulting in fewer opportunities to discontinue its use, even during severe events. High income presented similar strength (OR^+=1.33, CI:1.10; 1.61, *p*=0.003***); individuals with high-income levels showed odds of decreasing PT usage 33% higher than those from the lowest income level. The combined effect for the risk perception of COVID-19 showed an OR^+=1.32 (CI:1.18; 1.49, *p*=<0.001***). This implies that the odds of reducing PT usage for those who experienced higher degree of concern associated with the severity of the virus were 1.3 times higher than those who stated a lower concern. Regarding the healthcare needs factor associated with disability conditions and poor health, the meta-analysis estimated a pooled OR^-=0.88 (CI: 0.81; 0.96, *p*=0.034**). This indicates a negative association between this factor and the reduction of PT use. In particular, the odds of a person with this condition travelling less by PT were 12% lower than individuals without it (i.e. suggesting a positive effect with using PT).

For the transport-related factors only the pooled effect of travel distance and non-frequent PT users were found statistically significant (at 1% and 10% significant levels, respectively), while the pooled effect of PT physical accessibility was found not statistically significant at 10% level (p-value greater than 0.10). The factor travel distance showed that the odds of reducing PT usage for travellers with longer travel distances than 5 km were 14% lower than someone with shorter distances (OR^{-} = 0.86, CI: 0.80; 0.92, *p*=<0.001***). A negative pooled effect size was found for the factor pre-COVID frequent PT user (OR^{-}= 0.84, CI: 0.70; 1.01, *p*=0.068*). This means frequent pre-pandemic PT users had odds of reducing PT use 16% lower than non-frequent PT users. In case of PT physical accessibility, its pooled effect indicated an additive relationship with PT usage reduction (OR^{+ns} = 2.16, CI: 0.82; 5.75, *p*=0.121).

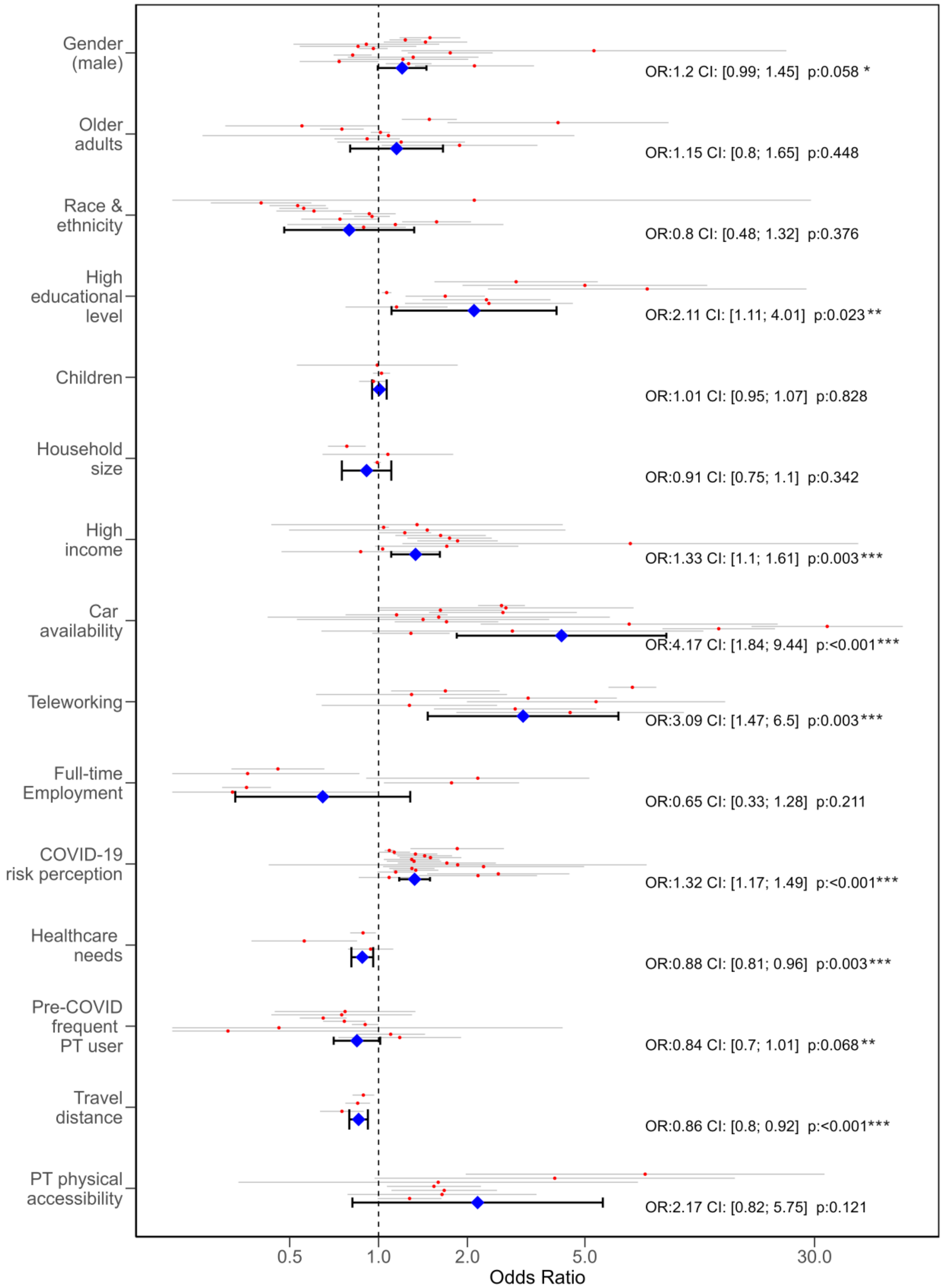

Figure 2-2. Effect sizes of individual-level factors on PT usage reduction during the COVID-19 pandemic. Blue diamonds represent pooled effects. Confidence intervals at 95%. Significant at: * 10% level; ** 5% level; *** 1% level. The vertical line (Odds Ratio equal 1) indicates no effect.

The remaining individual-level factors were not statistically significant at a 10% level (*p*-values greater than 0.10). This occurred because their CIs crossed the threshold of 1, which is the boundary between an odds ratio defining a positive or negative association between an explanatory variable and the dependent variable. This means that for those factors, the heterogeneity among the associations reported in terms of direction and size did not allow us to establish with statistical certainty whether they were associated positively or negatively with a reduction in PT usage. This situation was observed for employment, whose OR^{-ns} = 0.65 (CI: 0.35; 1.19, *p*=0.211) indicated that the odds of reducing PT usage of travellers with full-time jobs were 35% lower than other groups. Another factor with a similar outcome was older adults (OR^{+ns}= 1.15, CI: 0.80; 1.65, *p*=0.447). For this factor, even though the pooled effect estimated a positive effect on the reduction of PT usage, this was not statistically significant. For race and ethnicity, the combined effect showed an OR^{-ns} of 0.80 (CI: 0.48; 1.32, *p*=0.376), meaning that someone who belongs to one of these categories had odds 20% lower than white individuals. The pooled effect size of the presence of children at home (OR^{+ns}=1.01, CI: 0.95; 1.06, *p*=0.828), and household size (OR^{+ns}= 0.91, CI: 0.75, *p*=0.342) were also not significant, as their pooled effects were located very close to 1, indicating no effect on PT usage reduction.

2.4.3 Subgroup and influence analyses

To account for different research contexts and the category of the dependent variable specification, we applied a subgroup analysis, which allows us to determine whether the inclusion of moderator variables can explain that some associations produce lower or higher odds ratios than others (Laura et al., 2021). Two hypotheses that were defined a priori were tested: there are statistically significant differences in the pooled effect sizes depending on (H1) the geographical region of the study and (H2) the period of the pandemic when the surveys were delivered. In order to investigate H1 and H2, two dummy moderators were statistically tested. For the definition of the region, effect sizes were grouped into geographical areas, namely the Asia region and the North America/Europe (NA/EUR) region. For the pandemic period, two groups were defined, considering that most of the studies were conducted between March 2020 and April 2021. We decided to define one group as those studies conducted by surveys delivered between March and August 2020 (representing the outbreak and the first recovery process) and the second group with data from Sept 2020 to April 2021 (associated with later waves and lower mobility restrictions). The geographical split of North America and Europe (NA/Eur) versus Asia was chosen to indirectly explore differences in several domains, including public transport dependence, variations in COVID-19 policies and restrictions, behavioural differences in risk perceptions and constraints for particular sociodemographic groups. In particular, in Asia, many cities have higher public transport dependency than European and North American cities (Aguiléra, 2014; UITP, 2024). Moreover, Asia (particularly East Asia) implemented tougher measures (e.g. early lockdowns, contact tracing) than the NA/Eur regions, where more variation in the level of restrictions was observed. Regarding behavioural differences, Asia has been recognised for greater compliance with public health recommendations. Finally, the existence of differences in the constraints that affect mobility strategies for certain sociodemographic groups between the regions analysed is hypothesised. For example, in the Asia region, from a cultural standpoint, a more generalised lack of financial independence can lead women to depend more on shared or public transport, resulting in fewer opportunities to discontinue its use, even during severe events. Despite the reasonable differences explained above that support the choice of geographical split considered for the subgroup analysis, several caveats should be acknowledged. Firstly, this approach oversimplifies sub-regional differences (e.g. Canada may have shown significant differences with the U.S.). Also, the approach does not consider city-level characteristics that can differ substantially from a national context. Considering these limitations, the geographical split chosen here should be considered an exploratory exercise and their results interpreted cautiously.

Additionally to the two hypotheses presented, we also analysed differences among the pooled effect sizes depending on the category of the PT outcome employed in the studies (PTC vs PTR) and the metric types used in specific factors. Related to the latter, we tested for the factor COVID-19 risk perception, whether its different specifications (dummy vs Likert) generated dissimilar pooled effect sizes. In addition, an influence analysis was performed to assess the effect of excluding associations whose values differed substantially from the overall effect. This analysis allows us to observe the sensitivity in the pooled effect sizes to certain studies, enabling further analysis of the robustness of the results. The identification of outliers was conducted iteratively for each factor until all CIs of each association overlapped with the confidence interval of the pooled effect. Nonetheless, as excluding outliers may lead to biased results in meta-analyses, it is recommended to use its outcomes cautiously (Borenstein, 2009). **Table 2-3** presents the results for the subgroup and influence analyses. **Table 2-3** presents for each moderator the p-value that tests whether the effect sizes differ significantly between subgroups. Moreover, a column named "Δ Odds-Ratio" indicates whether the Odds-Ratio for a subgroup is higher or lower than the Odds-Ratio of the unsegmented sample. Thus, '+' is used to represent a higher OR for a subgroup compared with the OR of the unsegmented sample when the effect sizes statistically differ between subgroups, '-' is used to represent a lower OR for a subgroup compared with the OR of the unsegmented sample when the effect sizes statistically differ between subgroups and, 'ns' to highlight a non-significant difference in the effect sizes between subgroups. It is important to note that **Table 2-3** also displays the p-value for the specific OR of each subgroup. That means there is a possibility of observing statistically significant differences in the OR between subgroups but individual odds ratios for some of the subgroups that are not statistically significant.

The results shown in **Table 2-3** indicate that (H1) the geographical region successfully accounted for variation in the observed effect sizes, while (H2) the pandemic period was found to be significant only for one factor. Statistically significant differences were found between the pooled effect sizes of gender (*p*=<0.001***), older adults (*p*=0.102*), educational level (*p*=0.004***) and full-time employment (*p*=0.033**) of the Asian and NA/EUR regions. In particular, it was found that factors such as gender and age have almost no impact in explaining the reduction in PT use in studies conducted in the NA/EUR region (OR^{-ns}=0.94, *p*=0.473 and OR^{-ns}=0.91, *p*=0.708). In contrast, for the Asia region, the same factors increased the odds of reducing PT use by almost 50% (OR^{+}=1.51, *p*=<0.001*** and OR^{+}=1.68, *p*=0.077*). The difference observed was even higher when the educational level was analysed (OR^{+}=4.22, *p*=<0.001*** for the Asian region and OR^{+}=1.51, *p*=0.014** for the NA/EUR region). Cultural and social differences between the regions analysed may explain these dissimilarities. Regarding the pandemic periods, we found differences statistically significant only for the effect sizes of the factor pre-COVID frequent PT user. In particular, the result showed that during the first period of the pandemic being a pre-COVID frequent PT user was irrelevant to explain the decision of travelling by PT (OR^{-ns}=0.94, *p*=0.373). However, this changed during the second period, where those who were regular users of PT presented odds of reducing PT 41% lower than those who were not (OR^{-}=0.71, *p*=<0.001***).

Regarding the role of the type of the modelling PT outcome in the effect sizes, the results showed significant differences only for gender and car availability. It was observed for gender that this factor was only relevant among PTC studies (OR^{+}:1.50 vs. OR^{+ns}:1.01). In the case of car availability, despite its effect was significant for both approaches (PTC and PTR studies), it was significantly higher for the former (OR^{+}:8.32 vs. OR^{+}:2.05). These results suggest that gender and car availability had more relevance in models where the dependent variable was specified as the decision of choosing/not choosing PT during the COVID-19 pandemic. We also tested for potential differences in the effect sizes of the factor COVID-19 risk perception, as for this factor the effect sizes of dummy and ordinal variables were retrieved. However, the subgroup analysis showed no relevant dissimilarity (*p*=0.704).

In the influence analysis, the exclusion of outliers generated three main outcomes: some factors increased their consistency becoming statistically significant, some reduced substantially their effect size, and others did not show a relevant difference. Among the factors that became significant were race and ethnicity, and PT physical accessibility. The analysis showed that for PT physical accessibility (which original OR and *p*-value were 2.16 and 0.121, respectively), the exclusion of its most extreme effect size (OR=8.0) caused a more consistent pooled effect (OR^{+}=1.55, CI: 1.03; 2.33, *p*=0.038**). Similarly, for race and ethnicity, the exclusion of the effect size provided by Jiao et al (2021) (OR=1.2) resulted in this factor becoming statistically significant (OR^{-}=0.65, CI: 0.44; 0.94, *p*=0.021**). The most substantial change in terms of effect size was observed for car availability and teleworking, which decreased the magnitude of their effect from 4.2 to 1.8, and 3.1 to 2.3, respectively.

Table 2-3. Subgroup and influence analyses for the effect sizes of individual-level factors on PT reduction during the COVID-19 pandemic.

Moderator	Subgroup	N	k	Odds -ratio	95% CI	*p*-value	I2(%)	*p*-value sub group	Δ Odds-Ratio
Gender (male)		12	14	1.20	0.99; 1.45	0.058	80		
Location	Asia		6	1.51	1.25; 1.83	<.001	27	<.001***	+
	NA/EUR		8	0.94	0.79; 1.11	.473	78		-
Period	>Sep 2020		7	1.29	0.92; 1.56	.172	80	.945	ns
	Feb-Aug 2020		7	1.22	0.88; 1.67	.226	82		ns
PT outcome	PTC		6	1.50	1.18; 1.92	<.001	24	.011**	+
	PTR		8	1.01	0.84; 1.22	.869	79		ns
Outliers exc.		10	12	1.32	1.11; 1.55	.011	71		
Older adults		8	9	1.15	0.80; 1.65	.448	83		
Location	Asia		3	1.68	0.94; 3.02	.077	85	.102*	+
	NA/EUR		6	0.91	0.59; 1.42	.708	82		-
Period	>Sep 2020		4	0.99	0.52; 1.89	.980	66	.549	ns
	Feb-Aug 2020		5	1.28	0.76; 2.14	.340	88		ns
Outliers exc.		7	8	1.02	0.77; 1.34	.886	79		
Race and ethnicity		4	11	0.80	0.48; 1.32	.376	87		
Outliers exc.		3	10	0.64	0.44; 0.94	.021	81		
Educational level		3	8	2.11	1.11; 4.01	.023	87		
Location	Asia		3	4.22	2.27; 7.84	<.001	16	.004***	+
	NA/EUR		5	1.51	1.09; 2.08	.014	82		-
Period	>Sep 2020		6	2.48	0.91; 6.81	.077	89	0.60	ns

Moderator	Subgroup	N	k	Odds -ratio	95% CI	*p*-value	I2(%)	*p*-value sub group	Δ Odds-Ratio
	Feb-Aug 2020		2	1.55	0.36; 6.29	.554	70		ns
Outliers exc.		2	5	2.55	0.94; 6.92	.064	77		
Children at home		2	3	1.01	0.95; 1.07	.828	54		
Household size		3	3	0.91	0.75; 1.11	.342	80		
High Income		10	11	1.33	1.10; 1.61	.003	75		
Location	Asia		7	1.40	1.03; 1.90	.031	23	.721	ns
	NA/EUR		4	1.30	0.99; 1.69	.053	87		ns
Period	>Sep 2020		6	1.38	1.07; 1.78	.013	83	.720	ns
	Feb-Aug 2020		5	1.28	0.93; 1.75	.123	60		ns
PT outcome	PTC		4	1.13	0.74; 1.72	.550	11	.357	ns
	PTR		7	1.41	1.12; 1.79	.003	83		ns
Outliers exc.		9	10	1.26	1.05; 1.51	.012	67		
Car availability		8	13	4.17	1.84; 9.44	<.001	93		
Location	Asia		4	5.30	1.28; 10.90	.022	95	.681	ns
	NA/EUR		9	3.63	1.21; 10.90	.021	92		ns
Period	>Sep 2020		3	3.68	0.82; 16.53	.089	28	.928	ns
	Feb-Aug 2020		10	4.46	1.52; 13.11	.006	94		ns
PT outcome	PTC		5	8.32	3.13; 22.15	<.001	97	.047**	+
	PTR		8	2.05	0.77; 5.44	.119	63		-
Outliers exc.		5	10	1.78	1.39; 2.28	<.001	66		
Teleworking		3	8	3.09	1.47; 6.50	.003	90		
Outliers exc.		2	7	2.33	1.57; 3.46	<.001	55		
Full-time employment		6	6	0.65	0.33; 1.28	.211	89		
Location	Asia		3	1.14	0.41; 3.14	.797	82	.033**	+
	NA/EUR		3	0.37	0.32; 0.44	<.001	4		-
COVID-19 risk perception		10	17	1.32	1.17; 1.49	<.001	72		
Location	Asia		10	1.37	1.18; 1.58	<.001	4	.586	ns
	NA/EUR		7	1.28	1.07; 1.48	.011	78		ns
Period	>Sep 2020		6	1.38	1.11; 1.72	<.001	84	.723	ns
	Feb-Aug 2020		11	1.31	1.11; 1.54	<.001	33		ns
Specification	Dummy		9	1.32	1.10; 1.51	.004	75	.904	ns
	LV-Likert		8	1.34	1.15; 1.56	<.001	4		ns
PT outcome	PTC		6	1.33	1.09; 1.63	<.001	17	.994	ns
	PTR		11	1.33	1.12; 1.58	<.001	75		ns

Moderator	Subgroup	N	k	Odds -ratio	95% CI	*p*-value	I2(%)	*p*-value sub group	Δ Odds-Ratio
Outliers exc.		9	16	1.26	1.20; 1.54	<.001	51		
Healthcare needs		3	3	0.88	0.81; 0.96	.003	61		
Pre-COVID frequent PT user		4	9	0.84	0.70; 1.01	.068	59		
Period	>Sep 2020		4	0.94	0.82; 1.07	.373	38	.005***	+
	Feb-Aug 2020		5	0.71	0.62; 0.82	<.001	11		-
Travel distance		2	3	0.86	0.80; 0.92	<.001	33		
PT physical accessibility		2	7	2.17	0.82; 5.75	.121	35		
Outliers exc.		2	6	1.54	1.02; 2.33	.038	30		

Significant at: * 10% level; ** 5% level; *** 1% level. The column “Δ Odds- Ratio” indicates with ‘+’ a higher OR for a subgroup compared with the OR of the unsegmented sample when the effect sizes statistically differ between subgroups, with ‘-’ a lower OR for a subgroup compared with the OR of the unsegmented sample when the effect sizes statistically differ between subgroups and, with ‘ns’ a non-significant difference in the effect sizes between subgroups. Only factors with a minimum of N=2 and k=3 per subgroup were included in the analysis. ‘exc,’: excluded.

2.5 Discussion

To our knowledge, the review reported here is the first study to provide a comprehensive review of the effects of individual-level factors on public transport (PT) usage during the COVID-19 pandemic. We conducted such a comparison by systematically reviewing the existing evidence and performing a meta-analysis of the effect sizes of the individual-level factors across comparable studies. The systematic review identified 36 relevant studies executed between 2020 and 2021, of which 16 generated data that could be analysed through a meta-analysis. By choosing comparable studies and factor specifications for the meta-analysis, we were able to compare the factors’ pooled effect sizes. Our study complements early works presented in the light of the pandemic (De Vos, 2020; Gkiotsalitis & Cats, 2020; Tirachini & Cats, 2020), by being the first to quantitatively summarise the impacts of individual-level factors on people’s PT usage and to offer a comprehensive comparison between them.

The systematic review found that individual-level factors exhibited heterogeneous levels of consistency in terms of the effect direction reported across studies. Regarding this, two main groups of individual-level factors were observed. Factors such as car availability, teleworking, high-level income, high educational level and COVID-19 risk perception showed consistent positive associations with the reduction of PT use compared with the pre-pandemic across studies. On the other hand, ambiguous effect directions were found for factors such as gender (male), age (older adults), race and ethnicity, and employment. For these inconclusive effects, the mean of the pooled effect size and their confidence interval helped to determine their effect directions statistically. We obtained, then, that males and older adults were factors positively related to the reduction of PT usage, while employment (full-time) showed a negative association. However, of them, only the pooled effect of gender was statistically significant. We also found that contextual factors such as the region where studies were conducted and the pandemic period helped to understand factors' effect differences. In particular, when controlling for region (North America/Europe vs. the Asia region), we found that the effects of gender and age were only statistically significant for studies conducted in the latter group. Cultural and social differences may explain these differences. The findings of this study can help us understand specific population groups' restrictions and needs during pandemics/epidemics. The results highlight the relevance of inequality associated with the use of PT during the COVID-19 pandemic by some of the more vulnerable population segments: women, older adults, people with healthcare needs, those without the possibility of teleworking and those who travel longer distances. From a social point of view, public transport authorities should consider the needs of these population segments when deciding to adjusting service levels in the event of a pandemic (DeWeese et al., 2020).

Notable differences in the effect size of each factor in reducing travellers' probability of using PT during the pandemic were also found. Unexpectedly, the meta-analysis revealed that people's car availability was the factor with the highest negative effect on the use of PT during the pandemic. Its pooled effect revealed that individuals with at least one car available had odds to reduce their PT use during the pandemic four times the odds of those individuals without that possibility. Similarly, the possibility given to some individuals to work from home increased their odds of reducing PT trips by about three times compared to those without teleworking availability. A more modest effect on PT usage was observed for the other individual-level factors. Factors such as gender, high income level, and COVID-19 risk perception only increased the odds of travelling less by PT by no more than 30%. The meta-analysis also revealed that with the available evidence, it was not possible to generate reliable pooled effects for factors such as age and employment because of the high inconsistency of their effects. The substantial difference observed in this study among the impact of travellers' associated factors on PT usage highlights the need in the transport domain for not only discussing effect directions, but also comparing effect sizes (Parady & Axhausen, 2023). While the results of this study reflect the contribution of individual-level factors on the decision of public transport usage during a great-scale disruption as it was the COVID-19 pandemic, a caveat to research is that the study was conducted without incorporating explicitly public transport supply differences, which may not fully reflect real-world conditions. In fact, it is reasonable to have expected differences in the public transport supply constraints for the case studies due to distinctive COVID-19 guidelines and pandemic stages. Therefore, it remains untested in this study how these differences may have influenced the effect of the individual-level factors analysed. Nonetheless, the role of public transport supply differences may have been moderated as many case studies adopted policies to maintain public transport frequencies and services during the COVID-19 pandemic. These policies were implemented mainly to support essential workers, follow social distance guidelines and reduce crowding. However, it is also reported that despite maintaining frequencies in peak hours, many PT systems reduced the number of services in less crowded periods, including overnight. Tokyo, Taipei, Santiago de Chile, Stockholm, and New York City are only some examples (Jenelius & Cabecauer, 2020; Gkiotsalitis & Cats, 2021; Gramsh et al., 2022; Jian & Cai, 2022).

How much of the effects observed in this review associated with the reduction in PT usage are still present today seems a relevant interrogation to addressing policies to encourage PT use. How many of those who shifted from PT to private modes have returned and how these processes can be supported remains to be seen. Habits and attitudes developed by travellers during the pandemic on alternative modes to PT may also play a key role next (Hoffmann et al., 2017). Additionally, the impact of new trends and technologies related to electro-mobility, such as EVs, e-bikes and e-scooters (Reck et al., 2022), and autonomous vehicles on travellers' mode choice decisions has only started to be assessed (Yuen et al., 2022). In this scenario, where the possibility of teleworking and online shopping have also been established, it is unlikely to expect a complete recovery of individual PT usage for everyone. Therefore, growing subsidies to PT systems may be required to keep fare prizes at bay, avoiding increasing existing inequalities on already vulnerable population segments, which PT usage has demonstrated to be less adaptable, even in the most severe circumstances like the COVID-19 pandemic.

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Chapter 3

Using smart card data to model public transport user profiles in light of the COVID-19 pandemic

Abstract

The COVID-19 pandemic caused an unprecedented impact on public transport demand. Even though several studies have investigated the change in the use of public transport during the pandemic, most existing studies where large passive datasets have been considered focus on the drop in ridership at the aggregate level. To address this gap, this research aims to identify and model profiles of passengers considering their public transport recovery after the long-term lockdown in Santiago, Chile, during the early stage of the pandemic. The methodology proposed a three-stage approach associated with the analysis of smart card records. First, cardholder residential areas were identified to enrich the available data by integrating demographic information from the census. Then, a clustering analysis was applied to recognise distinctive classes of users based on their public transport usage change between the pre-pandemic and the post-lockdown phase. Finally, two different models were implemented to uncover the relationships between class membership and travellers' characteristics (i.e. travel history and demographic characteristics of their residential area). Results revealed a heterogeneous recovery of public transport usage among passengers, summarising them into two recognisable classes: those who mainly returned to their pre-pandemic patterns and those who adapted their mobility profiles. A statistically significant association of travel history with the mobility adaptation profile was found, as well as with aggregate socio-demographic attributes. These insights about the extent of heterogeneity and its drivers can help in the formulation of specific policies associated with public transport supply in the post-pandemic era.

Keywords: public transport, COVID-19, smart card data, travel behaviour, disruption, machine learning.

3.1 Introduction

The outbreak of COVID-19 in the world caused a significant change in people's mobility patterns as a result of people's fear of the virus's consequences, government measures, changes in transport provision and the emergence of new trends, such as teleworking and online shopping (Abdullah et al., 2020; Bin et al., 2021; Zannat et al., 2021). Although the existing literature suggests that the demand for all modes was affected by the pandemic, the evidence shows that public transport usage was the most negatively impacted (Wielechowski et al., 2020; Przybylowski et al., 2021; Vickerman, 2021).

Many studies to date have investigated the impact of COVID-19 on travel behaviour, focusing on the consequences on mode choices and risk perception (Abduljabbar et al., 2022). The evidence suggests that public transport has lost attractiveness while people prefer individual modes such as private car and non-motorized modes (Eisenmann et al., 2021). The negative perception toward public transport has also been associated with high contagion risk and an increase in crowding aversion (Kolarova et al., 2021). Most of the current analyses have, however, been conducted using online surveys, either cross-sectional (Bucsky, 2020) or considering a limited number of waves (Beck & Hensher, 2021; Molloy et al., 2021). Additionally, studies where passive data have been used have focused mainly on drops in ridership (mostly in aggregate levels) without exploring the linkage with the characteristics of the individual, their travel history and/or spatial attributes (Abduljabbar et al., 2022). Due to this limitation, the characterisation of the recovery in mobility patterns of public transport users that continued travelling after lockdowns remains limited.

This prompts this research, where we aim to identify and characterise profiles of public transport passengers who continued travelling after a critical disruption in mobility caused by a long-term lockdown, considering the recovery in their public transport usage. Therefore, we hypothesise that in response to the COVID-19 pandemic and associated restrictions, groups of passengers have experienced heterogeneous changes in their travel behaviour. Moreover, we postulate that adopting a particular mobility profile in the post-lockdown period can be explained by the characteristics of the travellers – their pre-pandemic and lockdown travel history and attributes of the home location. A three-stage approach was proposed to describe and model public transport users' profiles based on an analysis of smart card data for Santiago de Chile.

The research thus aimed to expand the findings of previous works related to the impact of COVID-19 on individual public transport use by:

- Using individual-level smart card data records with extensive coverage over the population to study the changes in public transport usage of those who continued travelling in a post-lockdown phase.
- Proposing a comprehensive set of indicators to describe passengers' public transport usage change between the pre-pandemic and the post-lockdown.
- Revealing hidden mobility adaptation profiles of frequent pre-pandemic passengers that illustrate the variability in the public transport usage recovery.
- Associating explanatory factors to each profile to obtain insights as to which policies are most suitable for implementation in public transport systems in a post-pandemic era.

The remainder of this paper is structured as follows. First, in Section 3.2, an overview is given of the impact of COVID-19 on public transport and the role of smart card data in travel behaviour analysis. Then, Section 3.3 describes the data used, including a description of the context of the pandemic in the period analysed associated with the study case. The methodology followed in this study is described in Section 3.4, divided into three subsections: residence estimation, clustering analysis and modelling. Section 3.5 presents the main results, followed by the conclusions in Section 3.6.

3.2 Literature review

3.2.1 Impact of COVID-19 on public transport usage

The COVID-19 pandemic has had substantial impacts on human mobility. The effect of COVID-19 on public transport ridership, in particular, was dramatic, with the greatest reduction during the lockdown periods. In fact, during the most challenging periods of the pandemic, the drop in ridership was as much as 70%-90% in the major cities of Sweden (Almlöf et al., 2021), Germany (Kolarova et al., 2021), Belgium (Tori et al., 2023), Greece (Politis et al., 2021), Chile (Gramsch et al., 2022), US (Wang & Noland, 2021) and Hungary (Bucsky, 2020). However, although the COVID-19 pandemic has disrupted all forms of travel (Eisenmann et al., 2021), trip reductions have not been the same for all transport modes. The existing evidence indicates a significant shift of commuters from public transport to individual modes such as private car and non-motorised modes (Abdullah et al., 2020). For example, Bucsky (2020) reported that the modal split of public transport decreased from 42% to 18% in Budapest, while private car usage increased from 43% to 65%. Kolarova et al. (2021), using an online survey applied in Germany in April 2020, also reported a significant shift from public transport to private modes. The evidence shows that despite the lifting of mobility restrictions and the success of several vaccination campaigns worldwide, passengers have remained reluctant to use public transport services again (Almlöf et al., 2021). Some of the causes which have been associated with this behaviour have been the perceived contagion risk (Przybylowski et al., 2021), the fear of the virus's consequences (Abdullah et al., 2020), and the changes in people's time use due to the pandemic adaptations related for example to teleworking and online shopping (Bin et al., 2021; Zannat et al., 2021).

Although many studies to date have investigated the impact of COVID-19 on travel behaviour, most of them have been conducted using online surveys, either cross-sectional (Bucsky, 2020; Kolarova et al., 2021) or considering a limited number of waves (Beck & Hensher, 2021; Molloy et al., 2021). Such online surveys typically have small sample sizes, have a limited capability to capture the day-to-day variability in people's mobility, have not been particularly focused on public transport and rely on respondents' memories to reconstruct pre-pandemic travel patterns. On the other hand, passive data sources such as smart cards, GPS traces and mobile phone records, which have digital mobility footprints of many people over time, can help overcome those limitations (Zannat & Choudhury, 2019), complementing the analyses of people's mobility adaptation through the COVID-19 outbreak. In particular, several studies have implemented smart card data to analyse at an aggregate level (system level, by area or station) the change in the public transport demand caused by the pandemic (Jenelius & Cebecauer, 2020; Rodriguez Gonzalez et al., 2021; Zhang et al., 2021; Fernández Pozo et al., 2022). In comparison, only a few attempts to study the impact of COVID-19 at an individual level considering smart cards have been carried out. Two exceptions are Almlöf et al. (2021), who studied the propensity to stop travelling during the pandemic in Stockholm, and Carney et al. (2022), who focused on accessibility issues on senior cardholders of the West Midlands, England, between 2019 and 2020. Then, the characterisation of the recovery in mobility patterns of public transport users that continued travelling after lockdowns remains limited.

3.2.2 Passenger profiling using smart card data

Smart card data has become a reliable and extensive data source to analyse travellers' travel behaviour and improve public transport planning (Pelletier et al., 2011). Many large-medium cities in the world have implemented Automatic Fare Collection systems (AFC) to collect public transport payments, but also to analyse the public transport travel demand (Kusakabe & Asakura, 2014). Smart cards automatically and continuously store each fare payment of transit users and associate it with an ID card. IDs are unique numbers given to smart cards that allow the study of travel habits, trip sequencing and route preferences, among other characteristics

(Pelletier et al., 2011). Each fare payment usually saves information about the card ID, timestamp, service number, card type and fare. In this way, it is possible to use smart card data to study travel demand changes, and to identify anonymously public transport users in different periods, which is a significant advantage compared with traditional data sources (Zannat & Choudhury, 2019).

In previous studies, user profiling has been carried out with smart card data considering passengers' interpersonal and intrapersonal travel behaviour to reveal unseen patterns (He et al., 2018). That exploration has usually been implemented with non-traditional transport models, such as machine learning techniques to classify users depending on their public transport frequency use (Briand et al., 2017). The literature shows that methods such as hierarchical clustering analysis and K-means have been widely implemented on smart card data to group cardholders based on their trip regularity. For instance, He et al. (2018) and El Mahrsi et al. (2017) used smart card data to classify public transport users depending on their trip frequency. Clustering techniques can also be implemented to group cardholders regarding their spatial-temporal trip patterns Egu and Bonnel (2020).

3.3 Data

3.3.1 Case study

Smart card data from Santiago de Chile at the individual level were available for this study. Santiago's public transport involves a complex system that integrates urban buses, the underground (that is called Metro) and an inter-urban rail. The system serves a population of around seven million inhabitants, with 4.5 million transactions daily before the outbreak of COVID-19. The system consists of around 7.000 buses, more than 10,000 bus stations, 379 bus routes and seven metro lines with 136 stations and a length of 140 km. **Figure 3-1** shows the spatial distribution of bus stops and metro/rail stations and three sociodemographic characteristics of the population in the metropolitan area of Santiago across 352 census district areas considering 34 municipalities. A smart card (called bip!) is the only payment method accepted in Santiago's public transport system. Transaction information is recorded and associated with a unique anonymous ID card. Tapping in the card is requested only to board public transport modes, at which time passive data are recorded, such as the card ID, timestamp, and bus service/metro station. The smart card system of Santiago does not gather information about the alighting stops. Instead, the methodology developed by Munizaga and Palma (2012) is applied to infer alighting information. That method identifies alighting locations following the trip chain of an ID card during the day and examining the position and time of the boarding. Then the alighting stop of a trip is estimated considering the boarding position of the next transaction through the minimization of a generalized travel time function. Adult cards are not customized. Hence, they may eventually be shared among multiple users. It may be noted that bus fare evasion has been recognized as an issue for Santiago's authorities. Therefore, the smart card data may provide a conservative estimate of the ridership in the Santiago public transport system.

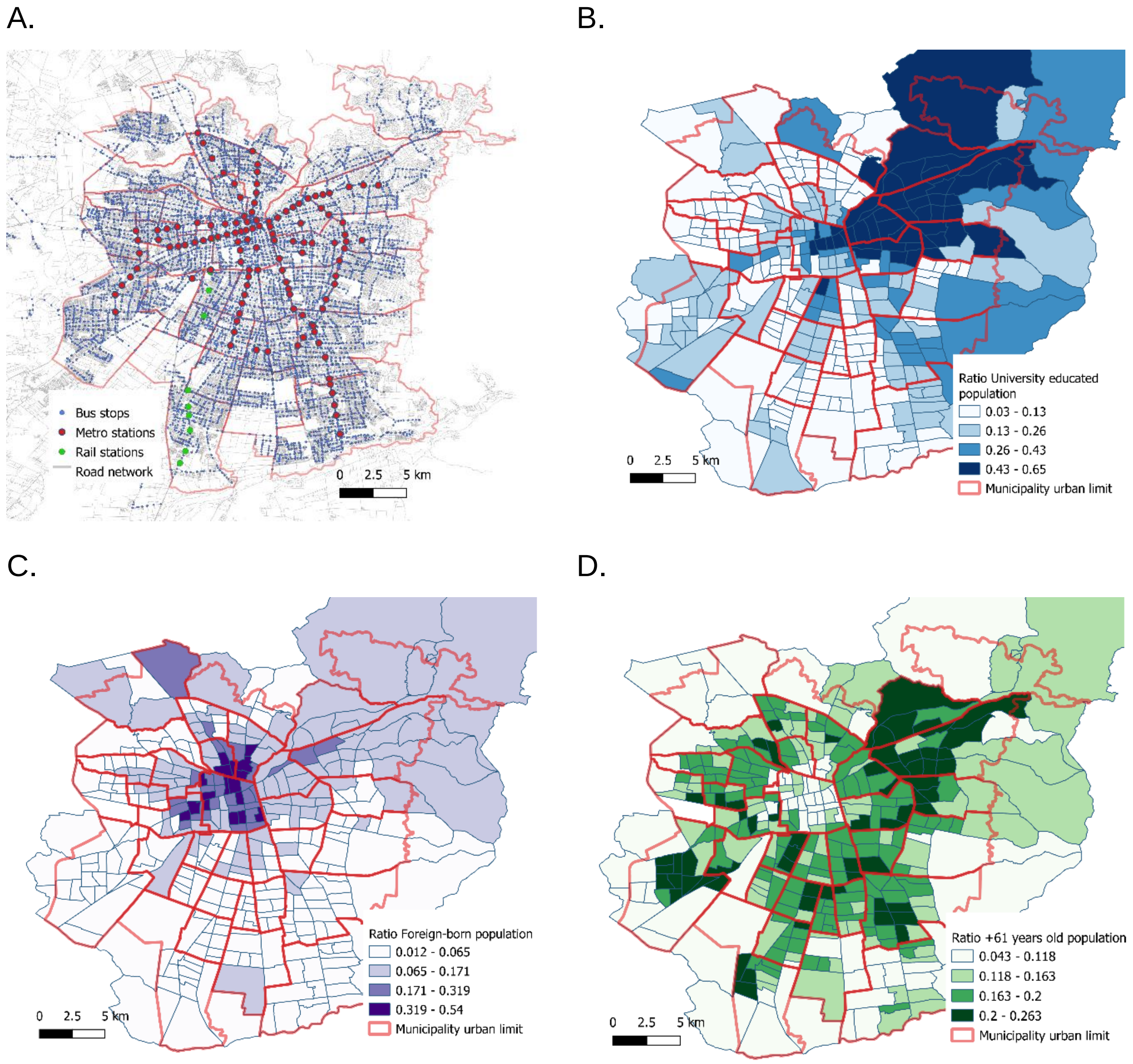

Figure 3-1. Spatial distribution in Santiago's Metropolitan area by census district zone of (A) Public transport stops/stations, (B) Ratio of university-educated population, (C) Ratio of foreign-born population, and (D) Ratio of the elderly population.

3.3.2 The COVID-19 Pandemic in Chile

The first case of COVID-19 in Chile was confirmed on 3 March 2020, and the Chilean government applied the first measures to face the spread of the virus on 16 March 2020. The first lockdown was implemented in Chile on 26 March in seven municipalities of Santiago, and during the entire pandemic, this measure was applied at a municipality level, avoiding implementing a national lockdown. Under this strategy, each municipality could enter or exit a lockdown depending on the number of new cases confirmed and the availability of critical care beds (Bennett, 2021). Even with the implementation of this tactical strategy to tackle the spread of the virus, the number of new cases and deaths increased sharply. Then, the authorities decreed a total lockdown for Santiago on 15 May 2020; this unified lockdown lasted until 27 July, when the first municipalities were released (see **Figure 3-2**, red line, for lockdown progression in Santiago's municipalities). The same month the government announced the "step-by-step" strategy, establishing five possible phases for municipalities depending on the outbreak's severity. Phase 1 meant total lockdown, Phase 2 lockdown only on weekends, while Phase 3 to Phase 5 meant the end of lockdowns but continuing with restrictions at different levels (Villalobos Dintrans et al., 2021). Thereby, on the last days of July, the first municipalities in the Metropolitan area of Santiago started to transition from Phase 1 to Phase 2. Gradually other municipalities followed the same trend. Therefore, many of Santiago's municipalities were still under lockdown on weekends between August and September. This situation is depicted in **Figure 3-2**, where the share of municipalities under lockdown spiked every weekend during the second half of 2020. Eventually, by 5 October, all of Santiago's metropolitan area had been lifted from Phase 1, being municipalities in Phases 2 and 3. From 16 November to 27 of the same month, no lockdowns were in place; however, substantial restrictions were still present (a curfew, face-to-face classes were still not allowed, gyms and events were not permitted to open yet, mandatory use of face-mask and social distancing protocols were active, among others). Chile's mass COVID-19 vaccination campaign would start only in February 2021, and Santiago's Metropolitan area would enter new full lockdowns during 2021.

3.3.3 Study period

Following the aim of this study, homogeneous periods were identified during 2020 to characterise passengers' PT usage recovery, in particular of those travellers that were active during the pre-pandemic and after the lockdown. **Figure 3-2** illustrates the variation of the two factors used to identify the appropriate study period: the share of the municipalities of Santiago’s metropolitan area under lockdown and the daily variation of public transport demand. Thus, three key periods of 2020 were chosen: pre-pandemic (PP), lockdown (L) and reopening (O). Regarding the extension of each period, although the literature has considered one week, such as a minimum unit to observe a cycle related to travel behaviour, we decided to use two weeks. Thus, smart card data records of Santiago de Chile’s public transport system between March 2-15 were used to illustrate pre-pandemic public transport use, data from June 15-21 and July 6-12 for the lockdown period, and transactions between November 9-20 for the reopening period. For the lockdown, two non-consecutive weeks were chosen to capture any natural between-month variability in this period. The reopening period chosen is still a settling-in time for urban mobility. Mobility and, in particular, public transport ridership continued changing highly during 2021 as a consequence of new waves of the virus that were tackled with new full lockdowns enacted in the metropolitan area. During the reopening, many offices continued teleworking, some called their employees back to face-to-face work, and others adopted a hybrid scheme. This means mobility was significantly lower during this period than in the pre-pandemic. In fact, movement trends provided by Google indicated 41.5% lower activity in workplace locations during the reopening compared with the pre-pandemic weeks.

The progression of the overall public transport demand in Santiago during 2020 is shown in **Figure 3-2**, displaying a massive reduction in the use of the system after the start of the outbreak. In fact, the demand reached an average of 4.3m transactions on weekdays during the pre-pandemic, but in the total lockdown, a barely daily average of 0.6m transactions was recorded. As the lockdowns were eased, the public transport demand started to recover, reaching a plateau around the reopening period, with an average of 2.3m transactions registered on weekdays. On the other hand, most of the services of Santiago’s PT system operated in the reopening almost at the same frequencies compared with the pre-pandemic weeks. Minor adjustments were implemented in specific services to strengthen frequencies during peak hours and reduce them in periods of low demand, particularly associated with the metro operation. The recovery of the frequency of services after the reduction implemented during the lockdown was supported by authorities even though the high drop in ridership to ensure social distance protocols and give reliability to users in terms of the level of service of public transport.

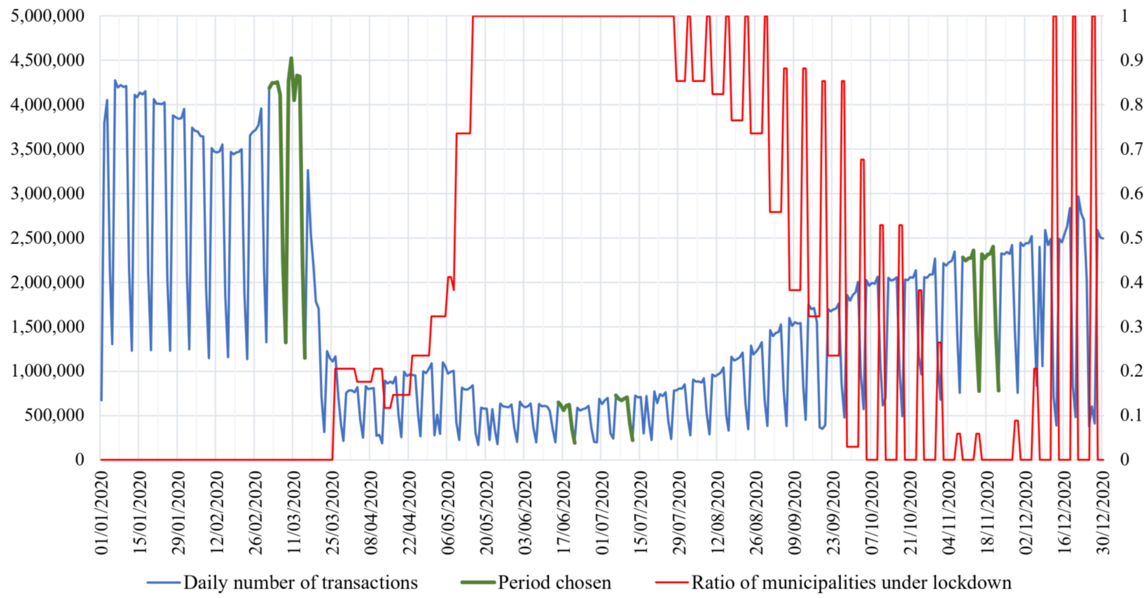

Figure 3-2. Daily variability of public transport demand and lockdowns in the metropolitan area of Santiago during 2020.

Figure 3-3A illustrates the differences between the trip distribution during business days (Monday to Friday) for the pre-pandemic and reopening periods for the overall demand. Differences are evident not only in terms of the number of trips but also in terms of their distribution. Morning and evening peaks were displaced (passengers carried out their morning trips later and the return ones earlier), and the difference in the demand between peak and out-of-peak hours were reduced. Also, the noon peak, a typical characteristic of Chilean cities, almost disappeared. In addition, **Figure 3-3B** shows the proportion of cardholders regarding the number of weekdays travelled by period. The graph displays that during the reopening period, the proportion of passengers that travelled only one or two days in the two-week window increased compared with the pre-pandemic period, while the proportion of cardholders that travelled more than two days declined.

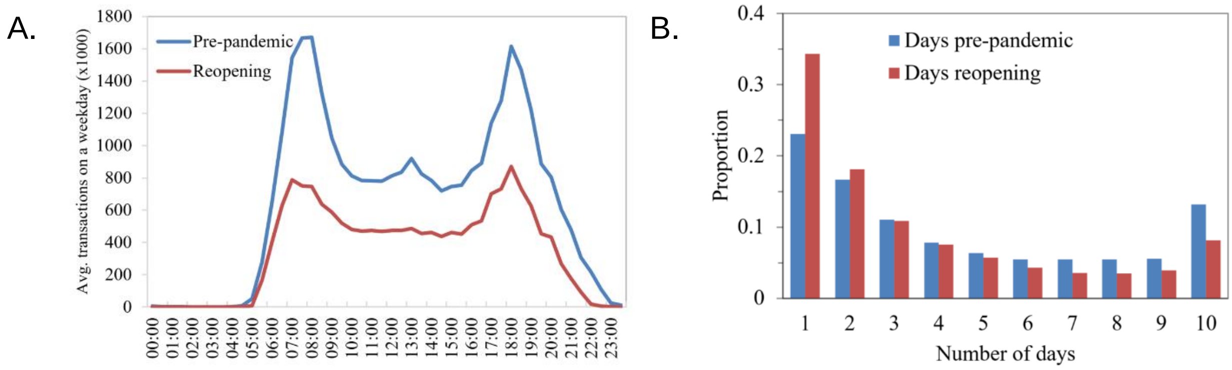

Figure 3-3. (A) Ridership distribution on weekdays, per period analysed (average values every 30 minutes). (B) Proportion of cardholders regarding the number of weekdays travelled.

3.4 Method

3.4.1 General framework

A three-stage approach was proposed to identify and model profiles of public transport users who continued travelling after the lockdown based on their travel behaviour recovery (**Figure 3-4**). The first stage considered the enrichment of smart card data through the estimation of the residential area of cardholders and the imputation of aggregate demographic characteristics from the Chilean Census, using the pre-pandemic period records. Secondly, seven indicators were proposed to measure the intrapersonal variability of public transport usage between the reopening phase and the pre-pandemic period. Then, the K-means algorithm was applied to identify discrete recovery profiles by splitting cardholders into classes with more homogenous public transport recovery. Finally, Gradient Boosting Decision Tree (GBDT) and logistic regression model (LRM) were applied to relate explanatory variables to the previously-identified clusters. Variables such as individuals' travel history during pre-pandemic and lockdown, card type and aggregate demographic characteristics were used to explain class membership.

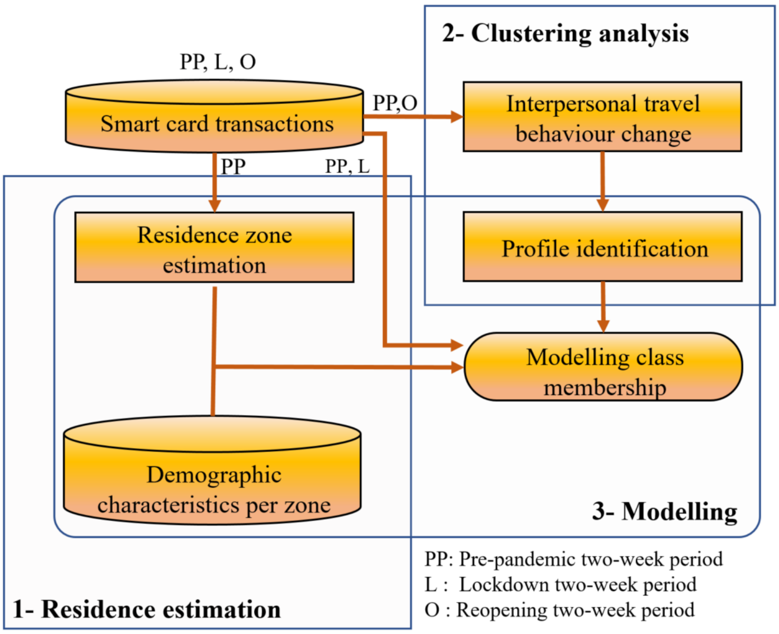

Figure 3-4. Flow chart with the three-stage approach implemented in this study.

3.4.2 Residential zone estimation and demographic characteristics per zone

As Santiago's public transport system does not collect users' socioeconomic information, we used the socioeconomic characteristics of the predicted home location of the cardholders as a proxy of user characteristics. This information was retrieved from the Chilean Census, that in 2017 gathered sociodemographic data across the country through household surveys. Information such as gender, age, educational level, employment and migrants can be spatially analysed at three levels of aggregation: blocks, census district zones (CDZ) and municipalities. After analysing the three levels, we chose CDZ, as it offers an intermediate spatial resolution of the population characteristics of the metropolitan area and matches better with the criteria used in the residential location procedure. A total of 352 CDZ for the metropolitan area of Santiago were considered. **Table 3-1** describes the aggregate sociodemographic variables, estimated as the ratio between a target population and the total population for a particular CDZ. These shares should be interpreted as a characterisation of the area where a cardholder lives instead of individual demographic conditions. This approach is particularly appropriate for Santiago's context due to its elevated level of urban and social segregation that causes a high homogeneity in demographic characteristics within neighbourhoods (Gainza & Livert, 2013).

To associate sociodemographic information of the CDZ, the potential residential location of cardholders must be found. We adapted the methodology implemented by Amaya et al. (2018), who proposed to estimate the residential location of a cardholder as the centre of gravity of the coordinates associated with the first transaction of each day, by implementing the DBSCAN algorithm (Ester et al., 1996). DBSCAN is a clustering technique whose advantage on residential estimation is the recognition of outliers. The algorithm was applied over the spatial coordinates of the first trip's boarding coordinate of each day throughout the two pre-pandemic weeks only to those cardholders that carried out trips for at least three days in that period. As parameters, we used 1 km as the maximum distance between two coordinates to be considered part of the same spatial cluster. This value reflects a walkable distance between cardholders' real residence and their reachable bus stops. At least 40% of the total first boarding coordinates were required to make up a residential cluster. **Figure 3-5** summarises the steps followed to estimate the residential location of cardholders in this work using smart card transactions. As a final step, the gravity centre of the boarding coordinates of a certain cardholder that only present one residential cluster is assigned to a unique CDZ.

3.4.3 Clustering analysis

The second stage involved the clustering of cardholders based on the change in their public transport usage between the pre-pandemic and the reopening period. Here, three steps were followed: data processing, estimating intrapersonal travel variability and clustering considering interpersonal differences.

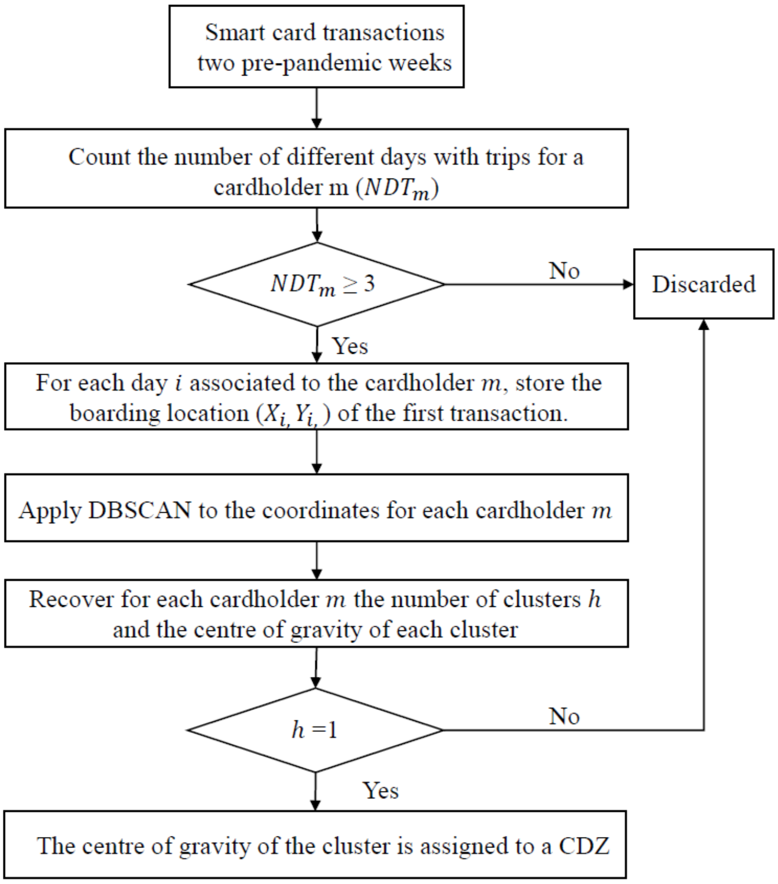

Figure 3-5. Framework implemented to identify residential location.

3.4.3.1 Data processing

Even though disaggregate smart card data is a rich data source to study public transport demand patterns, the literature also recognises the need to include a data processing step to analyse and clean such data (Ordóñez Medina, 2018). In the present study, to obtain suitably cleaned data, a sequence of criteria were considered as determined by the study's goals, the data quality and the pandemic context. The cleaning criteria are listed below; we have also included the number of remaining ID cards after successively applying each criterion.

- Keeping cards that only were active on both pre-pandemic and reopening weekdays (1,385,711 cards).
- Only adults and elderly cards were analysed (1,028,460 cards).
- Removing card IDs with multiple tap-ins (947,800 cards).
- Cardholders at least carried out trips on three different days during the 14-day period in the pre-pandemic weeks (415,762 cards).
- Only cards with an estimated residential location remained (379,115 cards).
- ID cards with no imputed information at all about the alighting stops were removed (360,190 cards).

First, validation records were analysed to identify active cards during the pre-pandemic and the reopening weeks. 3.9 million different cards were active during the pre-pandemic and 2.7 million during the reopening period. However, the analysis found that from the total cards active during the reopening, only 1.38 million cards could be traced to the pre-pandemic period. We hypothesise that the remaining corresponded to travellers that renewed their cards between both periods (possible causes could be the loss or damage of the card) and to the arrival of new travellers. Therefore, for non-traced cards, there was no way to infer whether a user had lost/ changed cards or discontinued using PT. To overcome this data limitation, we focus on those cardholders that are traceable between the pre-pandemic and the reopening period. An example where a comparable approach is considered is Egu and Bonnel (2020), who applied a similarity analysis strictly on traceable public transport users.

Invalid records are recommended to be filtered (Gong et al., 2017). Consequently, cards that were validated more than once in a very short time were removed. The tap-in-only format and the lack of personalisation of the smart cards may induce using one card for multiple validations in a row (usually associated with trips with relatives). An examination showed that a 60-second lapse was an appropriate cut-off point to detect multi-transactions. Then, cards with multi-transactions were not considered to avoid including this noise that may affect the analysis. On the other hand, the analysis of specific public transport users can help to reveal more meaningful findings (Gutiérrez et al., 2020). In particular, student cards were not included because most classes remained online during November 2020. Therefore, more meaningful conclusions for a post-pandemic era may be obtained by observing non-student users.

The last criteria were implemented to identify cardholders' residential locations and, in this way, add additional features to the data. Residential location identification allowed the retrieval of aggregate socioeconomic characteristics from census areas and their association with where cardholders lived. It is important to notice that implementing these criteria may lead to the analysis of more habitual travellers. This limitation was not unique to our work, and previous works where smart card data have been used considered criteria that lead to focus the analysis on regular travellers (Espinoza et al., 2018; Caicedo et al., 2021). Considering all these criteria assures the replicability of the analysis carried out in this work in different contexts, facilitating their comparison.

3.4.3.2 Intrapersonal variability indicators

The second step in the clustering analysis stage, according to **Figure 3-4**, was the estimation of the indicators that describe the change in individuals' public transport use, considering a multidimensional characterisation. Then, the intrapersonal pattern comparison was based on seven mobility indicators that describe the change in the public transport use of frequent passengers of the pre-pandemic period (PP) that continued travelling after the lockdown (O). In particular, three similarity indices were adapted from Egu and Bonnel (2020) to measure these changes.

Firstly, a day-sequence similarity index (DSI) was estimated. For each period p (PP and O) and cardholder m, a boolean vector $D_m^p = \left(d_{m,1}^p, d_{m,2}^p, \dots, d_{m,N}^p\right)$ of length N equal to 10 was defined (representing the 10 business days of the two consecutive weeks considered per period), where d_n takes value one if there was at least one trip during that day, otherwise, the value is 0. Then the similarity measure between D^{PP} and D^O for each cardholder m was calculated considering the simple matching distance, as follows:

$$DSI_m(D_m^{PP}, D_m^O) = \frac{\sum_{n=1}^{N}\left(1 - d_{m,n}^{PP}\right)\left(1 - d_{m,n}^{O}\right) + \sum_{n=1}^{N} d_{m,n}^{PP} d_{m,n}^{O}}{N} \tag{3-1}$$

Where $\sum_{n=1}^{N}\left(1 - d_{m,n}^{PP}\right)\left(1 - d_{m,n}^{O}\right)$ represents the number of days where D_m^{PP} and D_m^O are zero and $\sum_{n=1}^{N} d_{m,n}^{PP} d_{m,n}^{O}$ is the number of days where D_m^{PP} and D_m^O are one. The two vectors are considered similar when there is a mutual absence or presence of trips on the same days between both periods. The DSI also gives values between 0 (a completely different day sequence pattern) and 1 (the same), facilitating its interpretation.

Additionally, two indices were used to measure the similarity of public transport usage at individual level in terms of the temporal and spatial patterns of active passengers between the pre-pandemic and reopening weeks. In terms of similarity, public transport usage between two periods may be considered similar for a particular cardholder if the same proportion of trips is distributed similarly during the day or if they are distributed similarly in terms of the boarding locations. Thus, for the temporal and spatial intrapersonal variability, a temporal (TSI) and boarding location (LSI) similarity indices are proposed. Let us define T_m^{PP} and T_m^O as the total number of trip registered in the system for a cardholder m during the ten-weekday period during the pre-pandemic (PP) and the reopening (O). Then, for the TSI, h_r^{PP} and h_r^O indicate the number of transactions h registered during the period of the day r, for the PP and the O. While for the LSI, l_z^{PP} and l_z^O are the number of transactions l registered in the location z, also, for both pandemic periods. Then TSI and LSI were estimated as follows:

$$TSI_m = 1 - \frac{1}{2}\sum_{r=1}^{R}\left|\frac{h_{r,m}^{PP}}{T_m^{PP}} - \frac{h_{r,m}^{O}}{T_m^{O}}\right| \tag{3-2}$$

$$LSI_m = 1 - \frac{1}{2}\sum_{z=1}^{Z}\left|\frac{l_{z,m}^{PP}}{T_m^{PP}} - \frac{l_{z,m}^{O}}{T_m^{O}}\right| \tag{3-3}$$

where R refers to the total number of periods within a weekday that make up the temporal grid for public transport demand and Z represents the total number of CDZ from where boarding was carried out. Note that by definition $\sum_r h_r/T$ and $\sum_z l_z/T$ for any cardholder and pandemic period are equal to one. In this way, the TSI and LSI measure how different was the distribution of public transport trips in terms of the temporal and spatial variation between the pre-pandemic and reopening period. We decided to use the TSI above other methods, such as Dynamic Time Warping (DTW) or the distance between two empirical Cumulative Distribution Functions (eCDFs), due to the TSI's interpretability advantage over the distance value calculated using these methods. TSI and LSI do not depend on the variation in the number of trips between both periods. If the relative temporal or spatial distribution of the trips is the same between both pandemic periods, the difference estimated is zero, and TSI/LSI are equal to 1. By way of contrast, if the temporal or spatial travel pattern for a specific cardholder has changed completely and there is no match between the two periods, the second term is 1, and the similarity indices take the value of 0. Therefore, independently of whether a cardholder reduced their trip intensity in terms of the number of trips or the days travelled, TSI and LSI analyse only the differences in terms of how the trip distribution has changed temporally (across the day) and spatially (in terms of the areas where a cardholder boards public transport modes). To identify the proper total number of periods of the day R, the criterion of homogenous periods associated with the overall demand in the system and the fare scheme in Santiago's public transport was applied. Then an R equal to eight was used, considering the next time intervals: before 7:00 am, 7 to 9 am, 9 to 12 pm, 12 to 2 pm, 2 to 4 pm, 4 to 6 pm, 6 to 8 pm and after 8 pm. For the LSI estimation, the spatial grid was defined using the 352 Census zones defined in Section 4.2, and required matching them with the location of the boarding of each trip. Therefore, for the TSI, the comparison between trip distributions was made among the eight-time intervals, each of which represents a particular time period during the day, and for the LSI, the analysis was made on the variation in boarding trips among 352 zones distributed across the city.

The remaining five indicators describe the variation between the reopening and pre-pandemic period of variables usually used to characterise public transport usage when smart card data is available. Those variables are the total number of trips, the number of segments per trip, bus usage and the time of the first transaction of the day. All of these were calculated on the ten weekdays of the two periods. Bus usage is estimated as the ratio between the number of validations made on the bus mode and those made in all public transport modes during the ten workdays in each pandemic period. We incorporate this variable to identify whether passengers have systematically reduced or increased the use of the bus mode compared with the metro/rail, as some evidence suggests that metro/rail is more positively rated than buses during the pandemic. The variable time of the first transaction of the day is estimated by averaging the time of all workday's first transactions, using as a reference midnight (00:00). The definition of trips and trip segments associated with smart card transactions was adopted from Munizaga & Palma (2012). **Table 3-2** presents the seven indicators with their characteristic values per period calculated on the final dataset.

3.4.3.3 Clustering

Once the indicators that describe intrapersonal public transport usage variability had been estimated, the next step was to use them to identify classes of passengers with similar mobility profiles. K-means, a well-known hard clustering algorithm, was then implemented, aiming to partition the data set into a predefined number of clusters. This technique is considered one of the easiest and fastest clustering algorithms (Viallard et al., 2019) and has demonstrated a high performance due to its capacity to handle big data samples (Ma et al., 2013). As a result of the clustering stage, the optimum number of clusters K was found, and a class membership was assigned to each cardholder depending on the impact of the COVID-19 pandemic on their public transport usage. Note that K-means is sensitive to the scale of the variables used because it relies on the Euclidian distance to measure the similarity between data points. Therefore, it is necessary to standardise the variables used to avoid those with larger magnitudes dominating the distance calculation and biasing the clustering assignment. Hence, the Z-score normalisation is implemented, a technique that allows obtaining a mean equal to 0 and a standard deviation equal to 1 for each of the features considered.

3.4.4 Modelling

Although revealing unseen mobility profiles based on grouping public transport passengers can give a valuable comprehension of the impact of the pandemic on a post-COVID-19 era, understanding the variables that underlie the adoption of a particular profile may drive meaningful insights. Thus, the class membership of each cardholder was studied using the categorical label assigned to each cardholder as a dependent variable and travel history, card type and aggregate demographic characteristics as a set of explanatory variables. Two models were used to complement each other, a Gradient Boosting Decision Tree (GBDT) and a Logistic Regression Model (LRM). On the one hand, GBDT provides the relative importance of each explanatory variable used in the classification, capturing complex, non-linear relationships with no distributional assumptions. Here, higher values mean that the feature contributes more to reducing error in the classification. The relative importance score is a helpful tool for identifying the most influential features. It is frequently used to simplify the model, particularly by guiding the removal of low-importance features when the dimensionality of the datasets is high. Unfortunately, GBDT does not show how the variables affect the outcome. Therefore, an LRM is also estimated to overcome this limitation in the GBDT capabilities. LRMs provide an easy interpretation of the variables' effects through their coefficient estimates, explicitly informing of the direction and magnitude of the variables' effects. Nonetheless, LRMs can only measure direct, linear relationships between the explanatory variables and the outcome variable. Then, considering both models is considered the best option to provide a more comprehensive perspective into the relationship between features and outcome for this study. For the LRM, following equation (3-4), P_k is the probability that a cardholder m belongs to the cluster k, which depends on a linear function V_k (Equation (3-5)), where α, β, μ and γ are the regression coefficients and x are a set of explanatory variables associated with each observation. If K+1 clusters are considered, only K linear functions are estimated, indexed by k. Therefore, each probability associated to the cluster k will have its own set of regression coefficients except from the base cluster, which probability is estimated as $1-\sum_{k=1}^{K} P_k$.

$$P_{k,m} = \frac{e^{V_{k,m}}}{1+\sum_{l=1}^{K} e^{V_{l,m}}} \; for\; l = 1, \ldots, K \tag{3-4}$$

$$V_{k,m} = \sum_{r} \alpha_{k,r} x_{m,r}^{THPP} + \sum_{s} \beta_{k,s} x_{m,s}^{THL} + \mu_k x_m^{CT} + \sum_{t} \gamma_{k,t} x_{m,t}^{CRL} \tag{3-5}$$

For both models, GBDT and LRM, the set of explanatory variables included travel history during pre-pandemic (THPP), travel history during the lockdown (THL), card type (CT) and aggregate demographic factors associated with the census area where each cardholder resides (CRL). A detailed description of each indicator is given in **Table 3-1**.

Table 3-1. Explanatory variables used to model cardholders' class membership.

Dimension	Variable	Description
Travel history lockdown (THL)	Lockdown trips	Total number of weekday trips associated to each card during the lockdown period.
Travel history pre-pandemic (THPP)	PP trips - weekdays	Total number of weekday trips associated to each individual card during the pre-pandemic period.

Dimension	Variable	Description
	PP trips - weekend	Total number of weekend trips associated to each individual card during the pre-pandemic period.
	PP days travelled weekdays	Number of different weekdays with trips associated to each card during the pre-pandemic period.
	PP avg. travel time per trip	Average travel time per trip associated to each individual card during the pre-pandemic period.
Demographic characteristics of the traveller (CT)	Senior card	Dummy. 1 if the card is a senior card, 0 if it is an adult card.
Characteristics of the travellers' residential location (CRL)	Share - Women	The ratio between the women population and the total population, per CDZ.
	Share - Age <13	The ratio between the <13 years old population and the total population, per CDZ.
	Share - Age +60	The ratio between the +60 years old population and the total population, per CDZ.
	Share - Foreign born	The ratio between the foreign-born population and the total population, per CDZ.
	Share - Students	The ratio between the population that declared to be students and the total population, per CDZ.
	Share - University educated	The ratio between the population that have a university degree and the total population, per CDZ.
	Share - Workers	The ratio between the population that declared do paid work and the total population, per CDZ.

3.5 Results

3.5.1 Public transport user profiles

A summary of the characteristic values of the seven mobility indicators used to capture individuals' public transport usage variability between the pre-pandemic and the reopening period is presented in **Table 3-2**. As was expected, an overall comparison between periods indicated a reduction in trip intensity (46% in the number of trips) and a significant adaptation in the temporal and spatial patterns (on average, only 40% of the cardholders' spatial-temporal travel patterns of the pre-pandemic were observed in the reopening).

Table 3-2. Mobility indicators considered to measure interpersonal variability of public transport (PT) usage change between the pre-pandemic and reopening period.

Indicator	Description	Pre-pandemic		Reopening		Variation		
		Mean	Median	Mean	Median	Mean	Median	SD
PT trip intensity								
PT total weekday trips	Total PT trips in the ten weekday	17.69	18.00	9.60	8.00	-8.09	-8.00	8.55
Trip segments per trip	Average PT trip segments per trip	1.4	1.33	1.33	1.16	-0.07	0.00	0.4
Day SI (DSI)	Day-sequence similarity index	-	-	-	-	0.52	0.50	0.29
PT mode use								
Bus usage	Ratio between bus transactions and total PT transactions (%)	50.77	51.28	48.24	50.00	-2.52	0.00	0.29
PT temporal variability								
Time first transaction	Average hour when the first transaction of the day is made	9.73	9.09	11.11	10.53	1.38	0.75	3.64
Temporal SI (TSI)	Temporal similarity index	-	-	-	-	0.43	0.44	0.27
PT spatial variability								
Location SI (LSI)	Boarding location similarity index	-	-	-	-	0.40	0.40	0.28

For clustering cardholders, the K-means algorithm was applied using as observations each of the cardholders of the final dataset and as features the seven indicators that describe the change of cardholders' public transport usage. Therefore, under the K-means approach, cardholders that have similar variations in their public transport usage during PP and reopening were grouped in the same class. The number of clusters was obtained using the silhouette score, which maximized its value when the number of clusters was equal to two (see **Figure B-1**). This criterion was also confirmed, considering the interpretability of the clustering results and the outcomes obtained in the membership modelling related to other numbers of clusters. Thereby, two well-defined classes of users were detected regarding their public transport usage recovery after the lockdown period. The algorithm classified 47% of the users as members of cluster 1 and 53% as members of cluster 2. The cluster profiling regarding the value distribution of the indicators used for each cardholder class is shown in **Figure 3-6**. Looking at these results, two apparent labels emerge to describe the clusters. Members of cluster 1 were those close to recovering (total or partially) their pre-pandemic mobility patterns in the post-lockdown period; therefore, the name "returner" was given to them. By contrast, cluster 2 was made up of those users whose public transport usage was more highly impacted; thus, they received the label "adapters. The label 'returner' is justified by the substantial impact of the full lockdown located between the two periods used. This period in Santiago saw a 90% reduction in ridership, extensively affecting PT users' mobility patterns. Therefore, most PT users were allowed to return to their 'normal' mobility patterns only after the lockdown was eased, a context where the label 'returner' comes from. Nonetheless, it is acknowledged that the referred cluster may incorporate specific groups of travellers that may not have changed their mobility patterns during the lockdown (e.g. some essential workers). For them, it is agreed that a label like 'keepers' could have been a more appropriate option. Nonetheless, due to the group size with this characteristic being substantially smaller than the 'returners', it is reasonable to select the last to better represent the behaviour of travellers in the cluster.

The differences between the two classes were evident. The returners' cluster showed a median for the variation of total trips of -2.4, which means that 50% of this group almost recovered their trip intensity. By contrast, the same measure was -14.5 trips for the adapters, exhibiting that 75% of their members had a reduction equal to or higher than 10 trips from the pre-pandemic period to the reopening. The distribution of DSI values showed that 75% of the members of returners recovered at least 50% of their trip sequence during the reopening, whilst 75% of the cardholders that belong to the adapters' class showed a much greater change and reproduced less than 40% of their pre-pandemic trip sequence. The average time when the first transaction of a day is made also showed a remarkable difference between the two classes. Returners seem to have maintained the time of their first transaction, showing a median very close to zero variation. In the adapters' cluster, on the other hand, 75% of their members exhibit a delay in their first trips carried out during the reopening compared with the pre-pandemic of at least 0.5 hours, with a median value of around three hours for the class. Regarding TSI and LSI, in the returners' cluster, at least 50% of the cardholders had the temporal and location indices above 0.5, which means that during the reopening period, they carried out a minimum of 50% of their trips in the same time periods and locations that they did during the pre-pandemic. In comparison, 50% of the adapters reached only around 0.25 (25%) similarity with their pre-pandemic behaviour in terms of the period of the day when trips are made and boarding locations in the reopening period.

It is important to note that returners, although belonging to the cluster that recovered most of their pre-pandemic public transport use during the reopening, still exhibited a non-negligible variation in their temporal and spatial trip distributions. We interpret this result as an inherent impact of COVID-19 on people’s activities and time use that were still highly present during the post-lockdown period (Molloy et al., 2021). Bus usage did not display an evident dissimilarity between the two user segments if their medians were analysed.

Furthermore, because the literature has exclusively reported the reduction in public transport demand during the pandemic, the expected findings were that all the clusters would show values for trip intensity below the pre-pandemic levels. However, returners illustrated a different situation. The results indicated that around 25% of their members carried out more trips during the reopening than the pre-pandemic. Also, around 50% of their members had an increase in the average number of trips per day and the number of trip segments per trip. Finally, although the clustering analysis indicated that the optimal number of clusters was two, it was evident that the actual number of different strategies that describe all passengers may be as many as the sample size. Therefore, the clusters found were the best aggregation of those adaptations, which inherently limit the visualization of all the strategies related to the changes in public transport usage but help with the interpretation of the main ones.

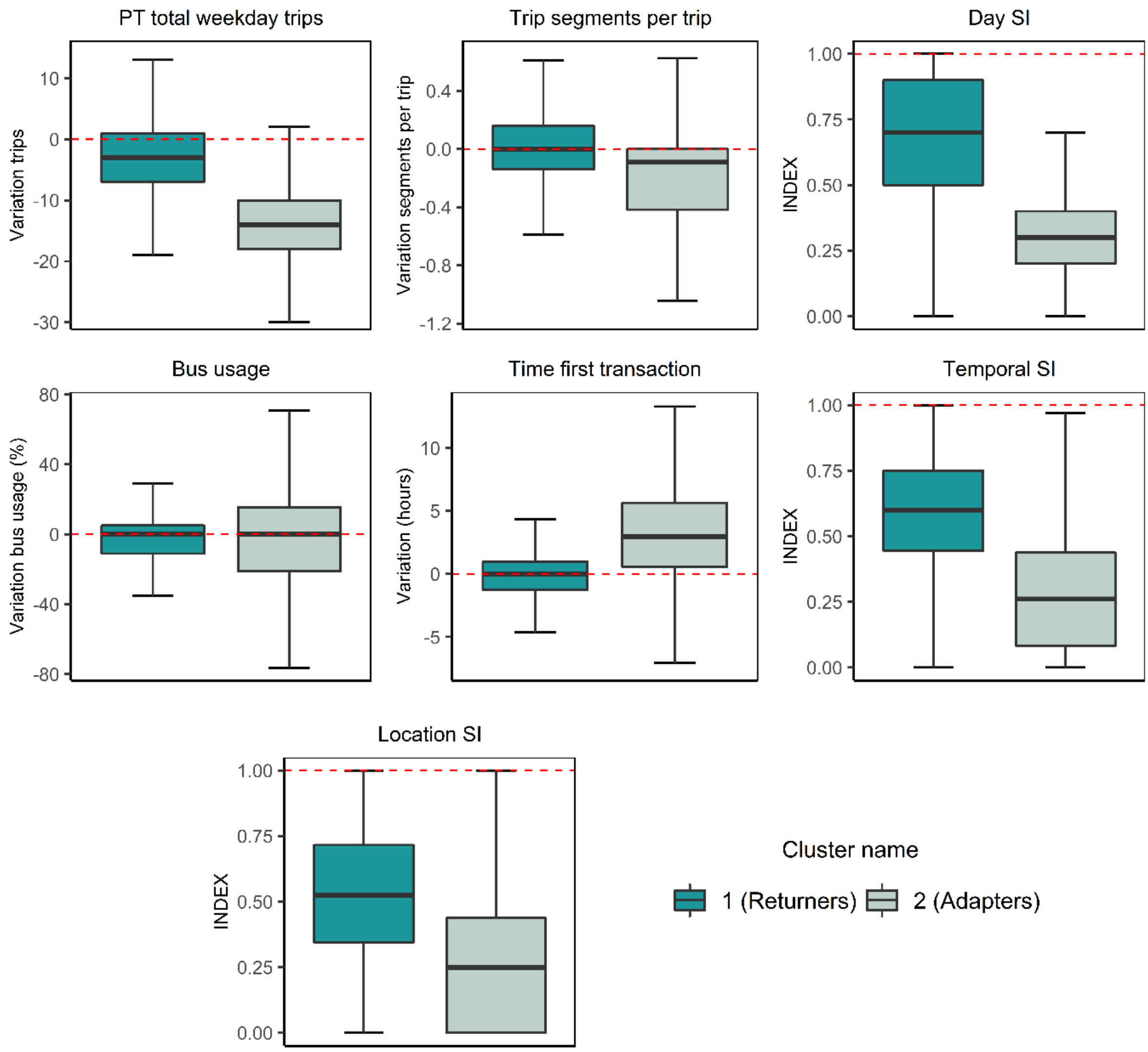

Figure 3-6. Cluster profiling by variation in mobility indicators. Red dashed lines indicate the condition of no change between the reopening and the pre-COVID-19 period.

3.5.2 Modelling user profiles

This research adopted GBDT and LRM, intending to explore the link between explanatory variables such as travel history, card type and aggregate demographic characteristics with each cluster profile found in the previous section (returners and adapters). GBDT was implemented to provide information about the most important explanatory features associated with class membership. Each indicator mentioned in **Table 3-1** was ranked depending on its relative importance. The relative importance is associated with the number of times a variable is chosen for splitting the sample over all trees. The GBDT model was fitted using a set of parameters, including the number of trees, the learning rate and the maximum tree depth. As the literature suggests, a five-fold cross-validation method was implemented to find the final setting and to control overfitting. The final set of parameters included a shrinkage value of 0.1, 100 trees and a depth equal to 5. On the other hand, the LRM was estimated using Equations (3-4) and (3-5), considering the binary nature of the labels found. A Nagelkerke R-value of 0.11 and an acceptable accuracy of 62.1% and 62.5% were obtained for the LRM and GBDT respectively, results in line with those achieved in previous works where comparable data and methods have been implemented (Almlöf et al., 2021). Specific outcomes of GBDT and LRM are presented in **Table 3-3**.

Table 3-3. Modelling results, GBDT and binomial logistic regression.

	GBDT		Binomial logistic regression			
Variable	Ranking	Relative importance	Odds value	Coefficient	Standard error	Significance
Intercept			2.233	0.803	0.193	<0.001
Travel history lockdown (THL)						
Lockdown trips	1	49.4%	1.097	0.093	0.001	<0.001
Travel history pre-pandemic (THPP)						
PP trips - weekdays	2	28.5%	0.956	-0.045	0.001	<0.001
PP trips - weekend	5	4.0%	1.054	0.053	0.002	<0.001
PP days travelled weekdays	3	6.7%	0.937	-0.065	0.003	<0.001
PP avg. travel time per trip	4	4.8%	1.003	0.003	0.003	<0.001
Demographic characteristics of the traveller (CT)						
Senior card (Adult ref.)	6	1.4%	1.474	0.388	0.021	<0.001
Demographic characteristics of the travellers' residential location (CRL)						
Share - Women	8	1.1%	0.164	-1.804	0.338	<0.001
Share - Age 00-13	13	0.4%	-	-	-	-
Share - Age +61	11	0.5%	3.794	0.134	0.266	0.003
Share - Foreign-born	9	0.8%	1.414	0.347	0.079	<0.001
Share - Students	12	0.5%	5.488	1.703	0.297	0.003
Share - University educated	7	1.3%	0.697	-0.361	0.050	<0.001
Share - Workers	10	0.6%	2.497	0.915	0.236	0.002

*The reference class (0) is the adapters' cluster. "-" indicates a non-significant variable.

First, GBDT identified three types of variables depending on their relative importance (RI). The first category, comprising around 80% of the total RI, includes the variables number of trips during lockdown (49.4%) and the number of trips on weekdays during the pre-pandemic (28.5%). A second group are those characteristics that describe travel history during the pre-pandemic period, such as average travel time per trip (4.8%), weekdays travelled (6.7%), weekend trips (4.0%) and if the card was a senior one (1.4%). Finally, aggregate demographic factors were the attributes with the lowest RI scores. It is important to note that this does not imply that residential attributes are not relevant, but rather, as is usual in supervised machine learning, variables that result in the most significant set of partitions during the learning process end up showing more relevance (Victoriano et al., 2020). Thus, variables with low importance should be tested using complementary methods such as logistic regression for an appropriate interpretation. Moreover, we hypothesise that the low importance that GBDT assigned to the residential location characteristics is due to the aggregate nature of those variables, gaining more explanation from the variables with a cardholder-level variability. The findings regarding the focus of relative importance in two variables is in line with other studies where GBDT have been implemented with smart card data. In those studies, travel history variables frequently rank first, presenting one or two variables with the greatest relative importance (Tang et al., 2020).

In the LRM, the odds values are estimated as the exponential of the coefficients (see **Table 3-3**). A value of 1 indicates that a variable has no influence on the class membership, a value greater than one indicates an increase in the likelihood that an individual is in the returners' cluster, and if the value is smaller than one means a negative effect. Thus, variables of travel history that increase the probability of being part of the returners' class are the number of trips during the lockdown, weekend trips in the pre-pandemic and the average travel time per trip in the pre-pandemic. In particular, the odds value of trips during lockdown was 1.097, which indicates that as trips carried out in this period increase by one, the odds of a cardholder being in the returners' cluster will increase by 9.7%. Namely, those who travelled in the most challenging period of the pandemic showed a higher probability of recovering their pre-COVID travel patterns during the post-lockdown stage. The odds that a cardholder belongs to the returners' cluster increases by 5.4% with each trip made on weekends during the pre-COVID period. It may imply that those who carried out more weekend trips (usually associated with non-mandatory activities) probably were more engaged with public transport or had fewer options to choose alternative modes. Moreover, the higher the number of observed pre-pandemic weekday trips, the easier it was for the users to reduce their public transport demand and, consequently, to belong to the adapter cluster. We believe that having a higher pre-pandemic trip intensity can be associated with more flexibility in terms of trip purpose, period of time and mode available, allowing passengers to develop a higher adaptation during the reopening.

Additionally, this result suggests that those with more “compact” mobility during weekdays in the pre-pandemic could recover more of their previous mobility patterns than those with higher trip intensity on weekdays. The last travel history indicator, average travel time per trip during the pre-pandemic, showed that the greater its magnitude, the more likely it is that a cardholder belongs to the returners’ cluster. The result helps to understand the characteristics of each user segment: higher travel times in Santiago are associated with the municipalities with the lowest income (Gschwender et al., 2016).

Equity aspects were also present in our results. Related to the card type involved, the results indicated that if a senior cardholder was active during the reopening, there was more chance that the person belonged to the returners’ cluster than users with adult cards. This result may initially seem counterintuitive when compared with the existing literature that has found that seniors avoided public transport during the pandemic (Schaefer et al., 2021; Zhao & Gao, 2022). However, given that this study only considered cards that were active in both periods, we hypothesize that most of the senior cardholders that could have had the chance to stop using public transport made that decision at the early start of the pandemic and were already out of the PT system during the reopening. Therefore, we are observing the behaviour of those seniors who likely had no choice rather than to continue using the system during the reopening period, and in that context, the result reveals that if a senior cardholder was active during the reopening, they had more chance to have recovered their pre-pandemic public transport use. This finding is significant because it provides evidence of heterogeneous responses among the members of the same vulnerable group.

Finally, the effect of the residential area characteristics assigned to cardholders was consistent with the presence of inequality in Santiago’s metropolitan area and similar to the one reported in other contexts of the Global South (Caicedo et al., 2021; Vallejo-Borda et al., 2022). In terms of the effect of the home-area demographic factors, results indicated that the higher the share of worker and immigrant population in the areas where cardholders were assigned, the higher the probability they had returned to their pre-COVID public transport use patterns. In fact, as is mentioned by Abduljabbar et al. (2022), public transport is a key mode, especially for specific groups of the population, such as workers and non-nationals, who could face more constraints in deciding freely whether to travel or not. In contrast, cardholders whose residences were located in areas with a higher share of women and university-educated individuals were less likely to be in the returners’ cluster. Indeed, gender (female) and higher educational level/income have been associated widely with a higher reduction in public transport use (Abdullah et al., 2020).

3.6 Conclusion

To our knowledge, the study reported here is the first study where a large passive data source collected during the pandemic of COVID-19 is used to analyse the recovery in public transport (PT) demand at a disaggregate level based on a multidimensional approach. This work complements existing literature by analysing the changes in the public transport usage of pre-pandemic users that continued travelling after a long-term lockdown, using smart card data records from the public transport system of Santiago de Chile. The observed results are in reasonable agreement with previous work carried out in the Global South, where sociodemographic disparities have been linked with the change in public transport usage caused by the COVID-19 disease (Caicedo et al., 2021; Vallejo-Borda et al., 2022). However, this study extends existing empirical evidence, demonstrating that the public transport usage recovery among passengers that continued travelling after the lockdown was dissimilar.

Two clusters of public transport users were identified using seven indicators that described the changes in passengers' public transport usage between the pre-pandemic and the reopening. One class of cardholders was named as returners as they showed a pronounced return to their pre-pandemic public transport use during the reopening, whilst the second class was labelled as adapters as they exhibited the greatest changes. Although the class labelled as returners showed a slight change in travel intensity and bus usage between the pre-pandemic and reopening periods, temporal and spatial public transport use patterns showed more strongly evident adaptations, which is in line with previous findings based on ridership analysis during the pandemic (Mützel & Scheiner, 2021). Finally, using disaggregate smart card data it was possible to detect that not all passengers reduced their public transport trip intensity during the reopening. In fact, as many as 25% of the members of the returners' cluster showed an increase in the number of trips during weekdays. This finding is unexpected, and challenges existing literature as, to the best of our knowledge, no evidence of trip intensity increase during the reopening stage that followed the first lockdowns in 2020 has been reported. We speculate that those cardholders could be users that shifted to a type of employment demanding higher mobility due to the pandemic restrictions, likely related to providing services at customers' locations.

The influence of both pre-pandemic and lockdown travel history, demographic characteristics at the residential level and card type were considered as potential variables to explain the membership of each cardholder to each mobility profile using GBDT and logistic regression. The pre-pandemic trip intensity showed a heterogeneous impact on the change in public transport usage between the reopening and pre-pandemic periods. Cardholders that carried out more trips on weekdays during the pre-pandemic showed a greater likelihood of belonging to the adapters' class. In contrast, those who made more pre-pandemic weekend trips were most likely to have a returner profile. Public transport usage during lockdown was also considered, showing that those who continued travelling during the lockdown exhibited a higher probability of belonging to the returners' cluster.

The modelling results for the area-level socio-demographic can be interpreted from two different perspectives. Regarding prediction performance, the GBDT results that report low relative importance scores for these variables indicate that area-level socio-demographic data have substantially lower prediction capabilities than the rest of the features tested. This result suggests that from a perspective that only focuses on prediction, it would be possible to reduce the dimensionality of the dataset by removing area-level socio-demographic data (among other variables) from the model without significantly affecting its prediction capabilities. From an inference and empirical point of view, however, the results of the LRM clarify that area-level socio-demographics play a key role in people's mobility patterns. In fact, LRM's modelling results found statistically significant effects for these variables, suggesting that their consideration is relevant to better understand PT users' mobility adaptations.

Using that evidence, our findings confirmed the relationship between the spatial distribution of sociodemographic characteristics across the city and the changes in PT use during the first stage of the pandemic. As **Figure 3-1** depicted, the highly-educated population, the presence of immigrants and the population's age were characteristics greatly concentrated in specific areas of the city. This inequality issue was also observed on the PT level of service. Indeed, longer PT travel times were related to a lower PT use adaptation. Longer PT travel times in Santiago have been historically associated with commuting trips from the city periphery to its centre-northeast area, where the number of services is higher and the users are more affluent. In this regard, the lowest capacity of these users to adapt their PT use could be related to the mandatory need for in-person work as soon as the lockdown finished and, secondly, by their strong dependency on specific PT services. This last element would have made them extremely vulnerable to service changes during the opening, which certainly was mitigated by PT authorities' decision to keep PT services and frequencies as close as possible to the pre-pandemic. Therefore, to reduce urban inequalities when future disruptions such as a new pandemic happens, particular emphasis in policy development should be placed on the specific needs of vulnerable and PT-dependent sectors of the population.

Although smart card data is a rich source to explore travel behaviour, individual demographic information of each passenger is typically missing. In fact, individual demographic characteristics, the possibility of teleworking, and an assessment of travellers' risk perception toward public transport could have helped to give a deeper understanding of the profiles found. In our results, the hidden effect of those variables may be represented indirectly by the travel history variables. Therefore, although this work demonstrates the advantages of exploring individual travel behaviour of public transport users, it does not replace the richness provided by traditional surveys in terms of individual explanatory variables. If suitable data is available in future, combining such a survey with passive data will be an interesting direction for future research.

Our finding allows us to conceive three main implications, which expand the current understanding of the changes of COVID-19 on public transport demand and give insights into the post-pandemic scenario but also to eventual new pandemics. Firstly, given that temporal and spatial patterns of public transport passengers have changed considerably, efforts to characterise these adaptations should be made continuously during the pandemic and even in the post-pandemic to propose and adjust services where required. Secondly, as equity disparities are related to a higher recovery of the pre-pandemic public transport use during the reopening, measures that provide benefits to captive cardholders should be considered to support that recovery but also, to mitigate the greater post-lockdown need for mobility found for a considerable proportion of cardholders. For example, as a complement to the pay-as-you-go scheme in Santiago's public transport, travel passes could be a policy in that direction. Finally, our results imply that as an aftermath of the pandemic, public transport systems may experience severe difficulties in recovering their pre-pandemic ridership during the post-COVID-19 period. In fact, even though the return of pre-pandemic users to public transport modes in the reopening, a substantial proportion of them carried out fewer trips than the pre-COVID-19. This suggests that government policies to ensure the sustainability of public transport will be needed for a long-term period. This support will ease the pressure on PT operators to reduce PT supply or increase fares, which may only worsen given the public transport situation. Although this recommendation is theoretically possible in many government-supported public transport systems worldwide, it is a huge challenge for the Global South, where public transport is less regulated, and often there is no direct subsidy.

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Chapter 4

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

Abstract

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 validated by obtaining a valuation of the trade-off between travel time and schedule delay (TVSD) in the range of previously reported values. 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.

Keywords: departure time choice, schedule delay, public transport, disruption, resilience, transit, travel behaviour.

4.1 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 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 4.2 offers background information on DTCMs. Section 4.3 provides details about the data utilized in this study. Next, Section 4.4 outlines the modelling framework. In Section 4.5, the methodology employed is discussed, while Section 4.6 presents the modelling results. Finally, Section 4.7 summarizes the key contributions of this work and outlines directions for future research.

4.2 Literature review

4.2.1 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:

$$V_{s,n} = ASC_s + \beta_{TT}TT_{s,n} + \beta_{SDE}SDE_{s,n} + \beta_{SDL}SDL_{s,n} \tag{4-1}$$

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. Thus, the early and late schedule delays (SDE and SDL, respectively) are defined as:

$$SDE_{s,n} = max(0, PAT_n - AT_{s,n}) \quad (4\text{-}2)$$

$$SDL_{s,n} = max(AT_{s,n} - PAT_n, 0) \quad (4\text{-}3)$$

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 $TT_{s,n}$. 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, travel times are usually higher when schedule delay is lower, creating the trade-off that this paper studies. 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.

4.3 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 (Hess et al., 2005). In this regard, joint RP-SP data have been considered a more reliable alternative for DTCMs (Börjesson, 2008).

4.3.1 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 4-1**. It is worth noticing that all these studies relied on survey data to estimate DTCMs (mostly SP surveys).

Table 4-1. 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, ME: morning earliness, ML: morning lateness, VOT: Value of travel time savings, N.A.: not applicable. *1 USD = 500CL$.

4.3.2 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.

4.3.3 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. Smart card data has been employed in a wide range of PT demand analysis topics, including OD matrix estimation, route choice modelling, travel pattern identification, and clustering analysis of passengers, among others (Cats, 2023). Such data has also been used to quantify the effect of external disruptions on PT demand patterns (Almlof et al., 2021; Li et al., 2024; Lizana et al., 2023). 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.

4.4 Data

4.4.1 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.

4.4.2 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 **Figure 4-1**), 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.

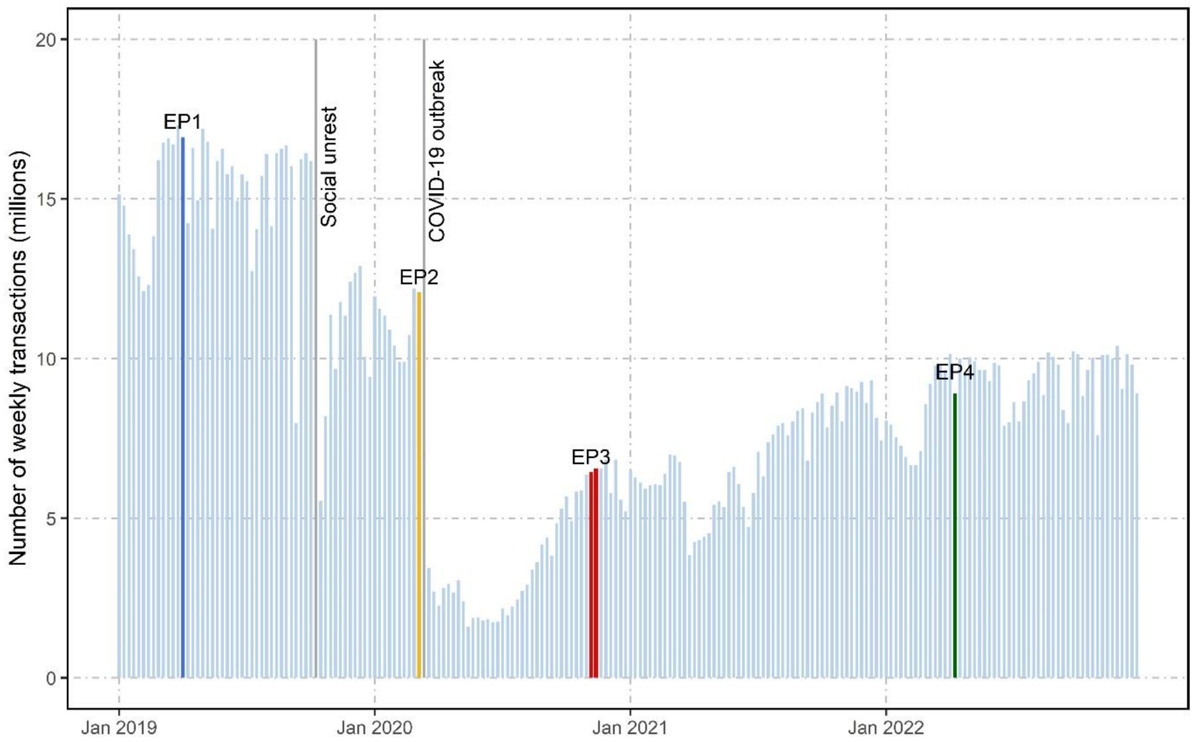

Figure 4-1 Weekly ridership for Santiago's bus system between Jan 2019 and Dec 2022. Selected episodes are highlighted in colours. Blue: before-disruptions (EP1), yellow: post-social unrest (EP2), red: post-COVID-19 outbreak (EP3), and green: after-disruptions (EP4). (Further details of each episode are given in **Table 4-2**).

Four episodes were selected to investigate the trip-scheduling processes of active bus commuters in the distinctive episodes. The first episode in April 2019 characterises a baseline context, i.e., a moment without any disruptive event influencing the decision to choose departure time of bus commuters (EP1). The second episode in early March 2020 (EP2) depicts bus commuters' travel behaviour after a social unrest. Massive social protests started on 14 October 2019 in Santiago and lasted until the end of the year. During this period, interruptions to private and public services and the 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. Early March was selected to represent this period because this was the nearest date that was not affected by the summer season (which runs traditionally between late December and February in the south hemisphere) at the time that offers more stable conditions in terms of the situational context in the city (that include the re-establishment of PT services and the absence of new demonstrations).

The third episode characterised 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 business 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 4-2**. 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.

Table 4-2. 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

4.5 Modelling framework

4.5.1 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:

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

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 Equation (4-1). 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, in this approach, the simultaneous estimation of earliness (SDE) and lateness (SDL) presents serious estimation identification issues. This is because the existence of earliness or lateness (mutually exclusive) requires the PAT, which is also being calculated simultaneously. 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. Then the observable utility function that allows the estimation of $\widetilde{PAT}_n$ is given by:

$$V_{s,n} = ASC_s + \beta_{TT} TT_{s,n} + \beta_{SD} (\widetilde{PAT}_n - AT_{s,n})^2 + \cdots + \qquad (4\text{-}5)$$

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_{SD} and β_{TT} are parameters to be estimated and represent the sensitivity to schedule delay 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 Equation (4-5) 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:

$$V_{s,n} = ASC_s + \beta_{IVT}IVT_{s,n} + \beta_{SD}(\widetilde{PATS}_n - (DT_s + IVT_{s,n}))^2 + \cdots + \qquad (4\text{-}6)$$

4.5.2 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:

$$L_{s,n}\left(\beta, \widetilde{PATS}_n\right) = \frac{e^{ASC_s + \beta_{IVT}IVT_{s,n} + \beta_{SD}(\widetilde{PATS}_n - (DT_s + IVT_{s,n}))^2 + \cdots +}}{\sum_{j \in C} e^{ASC_j + \beta_{IVT}IVT_{j,n} + \beta_{SD}(\widetilde{PATS}_n - (DT_j + IVT_{j,n}))^2 + \cdots +})} \qquad (4\text{-}7)$$

where C is the full choice set that consist of M time intervals of I minutes 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 (that includes the mean μ and standard deviation σ). 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:

$$P_{s,n}(\beta) = \int L_{s,n}\left(\beta, \widetilde{PATS}\right) \cdot f\left(\widetilde{PATS}|\theta\right) d\widetilde{PATS} \qquad (4\text{-}8)$$

Equation (4-8) 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 $\widetilde{PATS}_r$ $(r = 1,2, \dots, R)$, 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:

$$\hat{P}_{s,n} = \frac{1}{R}\sum_{r=1}^{R} L_{s,n}\left(\beta, \widetilde{PATS}_r\right) \quad (4\text{-}9)$$

where $\hat{P}_{n,s}$ 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:

$$SLL = \sum_{n=1}^{N}\sum_{j=1}^{J} d_{nj} ln\hat{P}_{s,n} \quad (4\text{-}10)$$

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.

4.5.3 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 Equation (4-11)). 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 Equation (4-11) and (4-12)). $TVSD_n$ is calculated across individuals using *R* draws and the TVSD for a specific study period *p* calculated as the average of the individual $TVSD_n$.

$$TVSD_n = \frac{\partial \mathrm{V}/\partial \mathrm{SD}}{\partial \mathrm{V}/\partial \mathrm{IVT}} = \frac{2\beta_{SD}\widehat{SD}_n}{\beta_{IVT}} \quad (4\text{-}11)$$

$$TVSD_n = \frac{2\beta_{SD}}{\beta_{IVT}}\frac{1}{R}\sum_{r=1}^{R}\left|\widetilde{PATS}_{n,r} - AT_n\right| \quad (4\text{-}12)$$

4.6 Methodology

To test the hypotheses stated in Section 4.1, the methodology presented in **Figure 4-2** is 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, **Figure 4-2** 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.

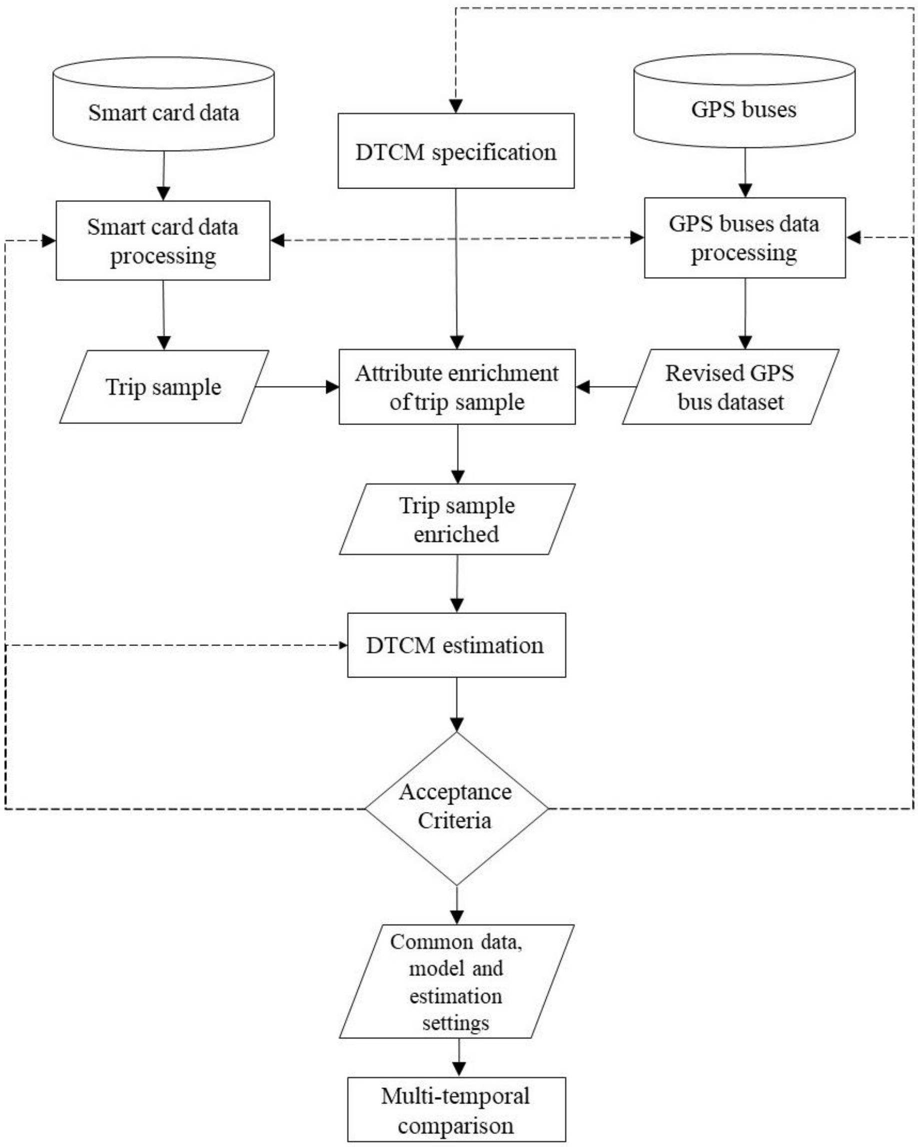

Figure 4-2. Methodology implemented in this study.

4.6.1 DTCM specification

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

The selected time-size interval for the departure time alternatives was established as 15 minutes, 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). In addition, the potential existence of differences in the trip schedule decisions among bus commuters was also tested. This was done by segmenting users into two groups depending on their relative bus usage. Recurrent users were then defined as those who conducted at least two trips on different days within the study period for each episode, while occasional users were characterised as those who were only observed 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.

4.6.2 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 (trips with interchanges are not included).
- Transactions with travel time lower than 5 minutes 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.

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 hours, 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 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)). Nonetheless, some limitations need to be acknowledged. Firstly, the rules considered for the assignment of the work trip purpose are not strict enough to avoid including a broader set of trip purposes in that category, such as running errands or shopping. A potential consequence of this limitation would be the estimation of distorted valuations by adding more flexible activity purposes in the analysis. Secondly, the methodology applied for Santiago does not include the leverage of any land-use information, which may have helped improve the trip purpose estimation. Finally, the study does not provide a validation of their result by cross-referring them with data from travel surveys. Despite these caveats, the methodology of Devillaine et al. (2012) generated a reasonable daily profile of outbound trips, which makes it suitable for this study.

To define the ideal combination of sample size and number of bus services for the analysis, an iterative process was conducted. As **Figure 4-2** 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% to 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.

4.6.3 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. 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.

4.6.4 Estimation of DTCMs and multi-temporal comparison

The model estimation was conducted following the methodology stated in Section 4.4.2. 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 $[c, d]$ are the extremes of the range of the time-period analysed (6:00 AM and 11:00 AM, respectively). The mean μ of the Johnson distribution represents the central tendency of the distribution. As μ depends on a specific transformation of the variable, three different outcomes are possible: $\mu = 0$; the distribution is symmetric and the mean is close to the midpoint $(c + d)/2$, $\mu < 1$; the distribution is left-skewed and the mean is closer to c (the lower bound) or $\mu > 1$; the distribution is right-skewed, and the mean is closer to d (the upper bound). The standard deviation σ measures how dispersed the data distribution is (a higher σ means the distribution is more spread out in the range $[c, d]$. To find the proper number of draws, they were gradually increased in intervals of 100, from 300 to 1000, finding that 500 draws produced stable modelling results. All modelling was conducted using the Apollo package in R (Hess and Palma, 2019). 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.

4.7 Results

4.7.1 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 4-3**) 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 minutes in in-vehicle travel time to reduce 1 minute 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 **Figure 4-3A**, where the PAT-Stop density function assigns maximum probability to the 08:30-08:45 AM period.

Table 4-3. 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_{SD}	-0.439	(-11.87)		
$\beta_{SD,oc}$			-0.338	(-12.65)
$\beta_{SD,re}$			-0.591	(-13.48)
$\widetilde{PATS}$ *parameters*				
μ	0.051	(1.92)		
μ_{oc}			0.196	(5.57)
μ_{re}			-0.251	(-10.07)
σ	-0.856	(-21.2)		
σ_{oc}			-0.96	(-15.3)
σ_{re}			-0.822	(-18.02)
ASC				
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	

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 4-3**) 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 **Figure 4-3B**, 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.

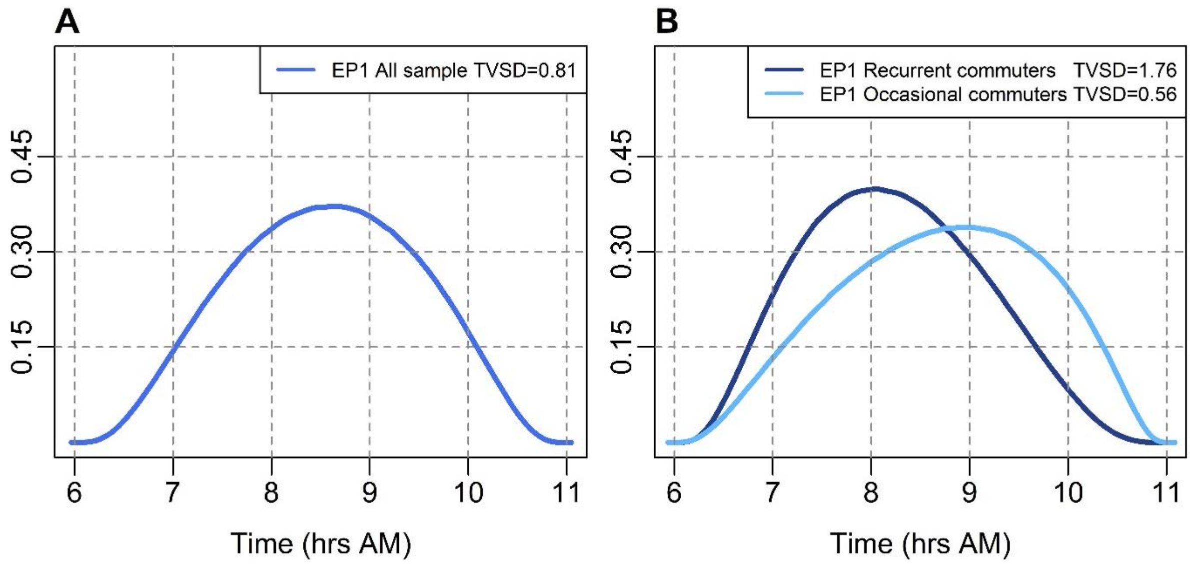

Figure 4-3. PAT-Stop density functions for EP1. (A) Unsegmented sample. (B) Segmented sample.

4.7.2 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 4-4**. 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, 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. **Figure 4-4** 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.

Table 4-4. 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_{SD}	-0.336	(-22.43)	-0.218	(-18.73)	-0.405	(-15.00)
$\widetilde{PATS}$ *parameters*						
μ	0.212	(14.97)	0.266	(12.39)	-0.013	(-3.08)
σ	-0.570	(-13.67)	-0.938	(-9.83)	-0.724	(-21.72)
Time period specific parameters (ASC)						
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)

	EP2 2020.03		EP3 2020.11		EP4 2022.04	
Variable	**Estimate**	**Rob t-stat**	**Estimate**	**Rob t-stat**	**Estimate**	**Rob t-stat**
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	
$\beta_{SD,EPi}/\beta_{SD,EP1}$	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.

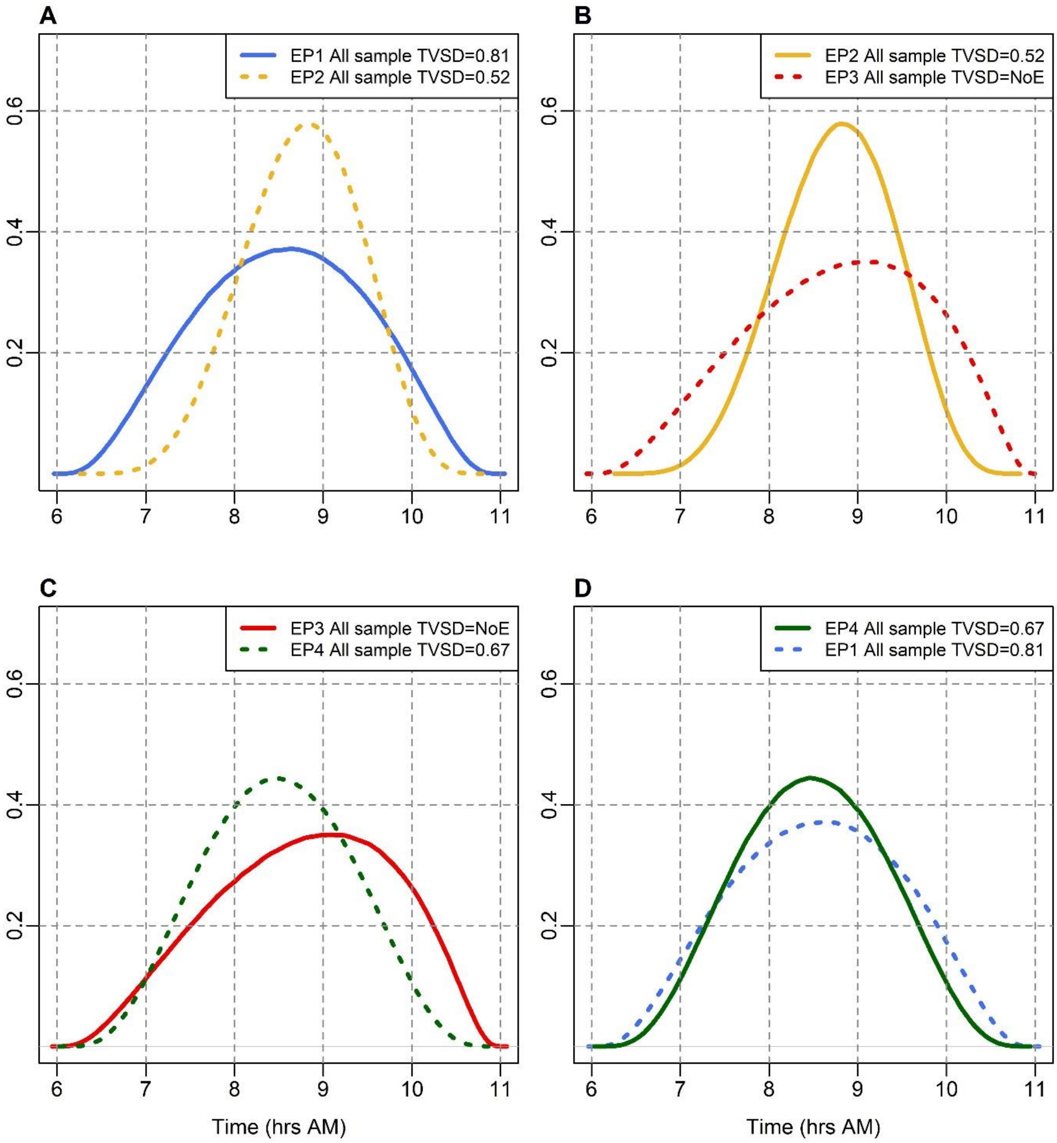

Figure 4-4. PAT-Stop density functions for unsegmented sample. (A) Comparison EP1-EP2. (B) Comparison EP2-EP3. (C) Comparison EP3-EP4. (D) Comparison EP4-EP1. NoE: Not estimated valuation.

4.7.3 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 4-5**. 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.

Table 4-5. 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)
$\beta_{SD,oc}$	-0.267	(-11.14)	-0.178	(-13.69)	-0.317	(-13.46)
$\beta_{SD.re}$	-0.507	(-12.27)	-0.329	(-6.24)	-0.545	(-14.2)
$\widetilde{PATS}$ *parameters*						
μ_{oc}	0.378	(17.7)	0.493	(2.52)	0.099	(4.05)
μ_{re}	-0.133	(-5.91)	-0.196	(-4.66)	-0.273	(-13.63)
σ_{oc}	-0.568	(-5.14)	-0.994	(-2.46)	-0.747	(-16.98)
σ_{re}	-0.591	(-12.85)	-0.676	(-5.62)	-0.732	(-18.79)
Time period specific parameters (ASC)						
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	
$\text{TVSD}_{oc,EPi}/\text{TVSD}_{oc,EP1}$	0.84		NoE		1.04	
$\text{TVSD}_{re,EPi}/\text{TVSD}_{re,EP1}$	0.46		0.28		0.53	
$\beta_{SD,re}/\beta_{SD,oc}$	1.90	(5.81)*	1.80	(2.86)*	1.72	(5.94)*
$\beta_{SD,oc,EPi}/\beta_{SD,oc,EP1}$	0.79	(2.03)*	0.53	(4.97)*	0.94	(1.20)*
$\beta_{SD,re,EPi}/\beta_{SD,re,EP1}$	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.

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 **Figure 4-5**. **Figure 4-5B**, in particular, illustrates the finding that $\widehat{PATS}$ 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 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, **Figure 4-5D** 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.

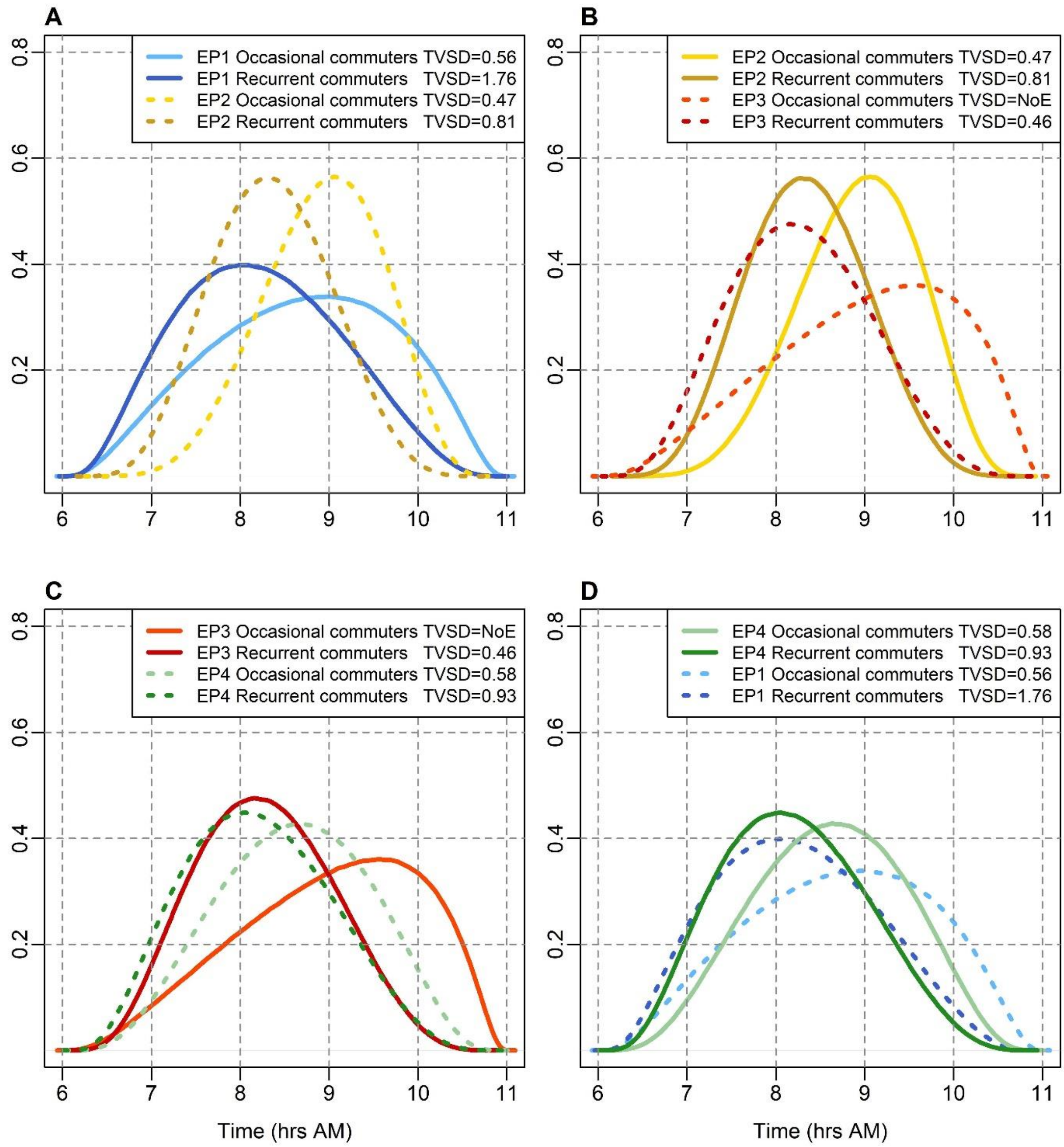

Figure 4-5. PAT-Stop density functions for segmented bus commuters. (A) Comparison EP1-EP2. (B) Comparison EP2-EP3. (C) Comparison EP3-EP4. (D) Comparison EP4-EP1. NoE: Not estimated valuation.

4.8 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. This study provides a key contribution in this area, integrating several techniques in one framework to overcome intrinsic challenges of smart card data, such as the estimation of schedule delay, an unobserved attribute in passive data sources. Our model results demonstrate that smart card data is a feasible data source for estimating DTCMs (H1). In particular, satisfactory marginal utilities for travel time and schedule delay were observed, as well as a valuation of the trade-off between travel time and schedule delay (TVSD) for the pre-disruptive episode in line with the findings reported in previous studies conducted in the same city. 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). The framework also allows for the explicit visualisation of the density function of the preferred arrival times at the bus destination stop (PAT-Stop), accounting for the heterogeneity of trip-timing preferences among bus commuters.

By establishing a comprehensive methodology that permitted a multi-temporal comparison between characteristic episodes of Santiago's PT case study, this study is the first to provide evidence of the differences in the trip scheduling process among bus commuters during particular episodes (H2). In our case these being pre-disruptions (EP1), after social unrest (EP2), after the COVID-19 outbreak (EP3), and post-disruptions (EP4). In particular, it was 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. These results align with previous findings conducted during the pandemic, which demonstrated more flexible working arrangements (Wöhner, 2022).

Consistently with previous literature, the findings of this study confirmed the differences in how distinct traveller groups assess time-varying trip attributes (H3). It was found that the group defined as recurrent commuters showed consistently higher TVSD than the group described as occasional commuters. This result suggests that recurrent bus users are more prepared to travel at times when travel time is higher to arrive near their PAT-Stop. Conversely, occasional bus users are more likely to travel at times when travel time is relatively lower, despite increasing their schedule delay (earliness or lateness). The PAT-Stop density functions also revealed insightful differences between the two groups.

First, occasional commuters showed later arrival preferences than regular commuters. These results agree with previous works where differences in the trip scheduling decisions between office employees and self-employees have been analysed (Shin, 2019; Zannat et al., 2022). For example, Zannat et al. (2022) also reported a preference for later arrival for self-employees and a lower willingness of this group to depart when travel times are higher. In this regard, office employees with more regular commuting trips may face more fixed schedules that encourage them to depart despite the high travel time experienced around rush hours. Moreover, occasional commuters were more flexible in changing depending on the situational context. In contrast, the PAT-Stop density function of recurrent bus commuters presented evidence of being more rigid when faced with contextual changes. Unfortunately, it was not possible to find previous studies discussing this subject. Nonetheless, this outcome seems in line with the previously described differences regarding the day-to-day trip scheduling decision flexibility between the two groups.

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 between the marginal utilities of schedule delay and in-vehicle travel time of EP4 and EP1 were found. The results also showed that the PAT-Stops density functions of these two episodes seem to converge despite still showing minor differences. Nonetheless, when making the same comparison but controlling for commuter groups, it was revealed that the TVSD of occasional commuters returned fully to their before-disruptions levels. Conversely, the recurrent group showed a TVSD of 0.93, a value 0.5 times lower than the one obtained for the same group in EP1, and a significant difference in the disutility of travel time (which was found to be 1.75 times higher). In this regard, the evidence seems to support 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. It is highly likely, in any case, that the recovery process is still ongoing in Santiago, and eventually, further periods should be analysed to complete the picture and reach a definitive conclusion.

Finally, identifying shifts in how PT commuters value time and schedule delay is crucial when external disruptions affect the activity system. In the last few years, the world has witnessed an unprecedented challenge related to the COVID-19 pandemic and a growing exposure to social unrest that demands societal changes. These events, usually associated with a drop in ridership levels, may also be associated with a change in how travellers schedule their activities. In this regard, the proposed methodology can be used to understand how commuters allocate their activities during external disruptions in different scenarios. Peak spreading, congestion pricing and the analysis of time-varying transport demand flow patterns are other applications of this approach. The framework also has the potential to test a broader range of attributes when the data quality and availability allow it, such as travel time uncertainty, in-vehicle occupancy, monetary cost, and the inertia of travelling at a particular time of the day. Including those attributes in the analysis would generate a more comprehensive understanding of the trip-timing decision process of PT commuting. This work, then, offers the potential to open up a research line for more applications of smart card data on PT time-varying demand analysis, given the solid evidence we provide here of the validity of this data source for estimating DTCMs.

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Chapter 5

Investigating the potential of aggregated mobility indices for inferring public transport ridership changes

Abstract

Aggregated mobility indices (AMIs) derived from information and communications technologies have recently emerged as a new data source for transport planners, with particular value during periods of major disturbances or when other sources of mobility data are scarce. Particularly, indices estimated on the aggregate user concentration in public transport (PT) hubs based on GPS of smartphones, or the number of PT navigation queries in smartphone applications have been used as proxies for the temporal changes in PT aggregate demand levels. Despite the popularity of these indices, it remains largely untested whether they can provide a reasonable characterisation of actual PT ridership changes. This study aims to address this research gap by investigating the reliability of using AMIs for inferring PT ridership changes by offering the first rigorous benchmarking between them and ridership data derived from smart card validations and tickets. For the comparison, we use monthly and daily ridership data from 12 cities worldwide and two AMIs shared globally by Google and Apple during periods of major change in 2020-22. We also explore the complementary role of AMIs on traditional ridership data. The comparative analysis revealed that the index based on human mobility (Google) exhibited a notable alignment with the trends reported by ridership data and performed better than the one based on PT queries (Apple). Our results differ from previous studies by showing that AMIs performed considerably better for similar periods. This finding highlights the huge relevance of dealing with methodological differences in datasets before comparing. Moreover, we demonstrated that AMIs can also complement data from smart card records when ticketing is missing or of doubtful quality. The outcomes of this study are particularly relevant for cities of developing countries, which usually have limited data to analyse their PT ridership, and AMIs may offer an attractive alternative.

Keywords: public transport, aggregated mobility indices, ridership, disruptive events.

5.1 Introduction

5.1.1 Public transport demand data

The availability of suitable data is critical for city planners to tackle the current and future challenges in urban mobility. This need is amplified when there is a disruptive change in urban mobility at any scale, ranging from local short-term events such as natural disasters, social unrest, and transport supply breakdown to global long-term events such as pandemics/epidemics, economic crises and conflicts. In this context, a continuous monitoring of public transport (PT) demand changes is essential for authorities and PT operators (UITP, 2018; Milne & Watling, 2019). In spite of the growth in the availability of higher quality data in many parts of the world, still there remain many cities that do not have access to proper data for a constant characterisation of the PT demand; or even if they have it, the available data present limitations in terms of the quality and coverage. In cities without automated data collection systems to passively record ticketing levels, traditionally, the information related to PT demand has come from datasets that have been manually collected on a small population sample. Such data, despite providing granular information, has been criticised for the lack of feasibility to be steadily applied during long periods (Welch & Widita, 2019). This makes them unsuitable to analyse dynamic PT demand changes and to quantify the impacts of unexpected disruptions (Demissie et al., 2016; Saha et al., 2020; Padmakumar & Patil, 2022). By contrast, cities that have already adopted automated fare collection (AFC) schemes have had the advantage of analysing their PT demand information from smart cards and digital transactions (Pelletier et al., 2011; Zannat & Choudhury, 2019; Lizana et al., 2023). However, some limitations on the fare collection system may affect the quality of these data (Lee et al., 2022). For example, ridership data may be lower than the actual one when ticketing are missing or incomplete, such as in the cases of ticket-free riding days or when there are special periods where fare evasion is potentially higher. Additionally, AFC systems may only cover a limited number of the PT modes present in a city (e.g. metro rails only), capturing ridership data only of those modes (Arellana et al., 2020; Wang & Noland, 2021). In these cases, even cities with AFC systems can benefit from secondary data sources to complement traditional ones.

5.1.2 Aggregated mobility indices

The increasing penetration of Information and Communication Technologies (ICT) in society has allowed several emerging datasets to be harnessed to face urban mobility challenges (Budd et al., 2020). Call detail records (CDRs) (Demissie et al., 2016), social media data (Itoh et al., 2014; Spyratos et al., 2019; Shepherd et al., 2021), Wi-Fi and Bluetooth traces (Bjerre-Nielsen et al., 2020), and web-based ticket records (Wei et al., 2017) are some of the technologies explored in the last decade to understand the behaviour of PT passengers. Despite the effort to leverage these data to study different characteristics of PT demand, their adoption has been mainly limited to research purposes and a few case studies, as such data availability remains largely restricted (Welch & Widita, 2019). Less attention, however, has been paid to the usage of data sets associated with GPS traces collected by global mobile phone apps or the level of queries in travel planner apps in the PT sector (Welch & Widita, 2019; Finazzi, 2023). This situation changed in 2020, following the urgent need of health authorities, local governments, transport agencies, and the public for continuously updated and easily accessible data to deal with the COVID-19 pandemic.

Aggregated mobility indices (AMIs) based on ICT were globally provided by tech companies during the COVID-19 pandemic to describe human mobility patterns in cities. AMIs were based on data collected from the regular use of mobile devices associated with GPS and apps, technologies that were already part of tech companies' products and services (Strzelecki, 2022). The information was aggregated to describe human mobility behaviour within cities, offering a near-complete coverage of the urban grid and a large proportion of the population. AMIs were used to analyse mobility trends and scenarios, and assess the effectiveness of mobility restrictions on human mobility (Konečný & Brídziková, 2020; Saha et al., 2020; Yilmazkuday, 2021; Hamidi & Zandiatashbar, 2021; Wen et al., 2021; Wu & Shimizu, 2022). AMIs were also employed in studying COVID-19 transmission (Noland, 2021), pandemic indicators (Kartal et al., 2021; Noland, 2021), air quality (Venter et al., 2020; Rowe et al., 2022) and economic recovery (Zhang et al., 2022), among other topics. Big Tech companies such as Google and Apple shared reports on the aggregated mobility changes of the population at a city or regional scale between 2020 and 2022 (Apple; Data). Other companies, such as Moovit and Citymapper, which run travel planner apps, also offered similar mobility indices (Beck & Hensher, 2020; Fernández Pozo et al., 2022).

Among the AMIs proposed, Google COVID-19 Community Mobility Reports (GCMR) and Apple Mobility Trend Reports (AMTR) were the most popular. GCMR were based on the variation of human movements across different categories of locations (residential, workplace and public transport stations, among others) (Google, 2023). To measure the mobility changes related to PT, GCMR considered the access frequencies and the time spent on PT hubs (bus stops, train stations, etc.). The relative change was estimated by comparing a mobility level with a pre-pandemic baseline value.

The aggregation and anonymisation process followed by Google and Apple to generate the mobility indices presents some particularities. In the case of Apple, the company explicitly states that every Map Apps query used was assigned a random, rotating identifier that continuously reset (Apple, 2023). Thus, data processing removes any possibility of identifying individual user profiles at any moment, i.e., it is not possible to associate two queries with a particular user (Kurita et al., 2021). Apple's indices are then estimated based on the simple comparison of query volumes between a particular day and a single baseline day for a given spatial granularity. On the other hand, The indices provided by Google employed the information provided by the location history of users retrieved from devices that use Google's apps and services. The process allows for daily user profiles in terms of visits to different category places (of a total of seven) (Aktay et al., 2020). This data characteristic makes it possible to impose bounds on how much each unique location history user can contribute to each of the seven place categories 'recognised by Google by randomly selecting only four. In the case of daily visits to public transport hubs, data is obtained by counting the number of users with unique location history who visited a public transport hub at different granularity levels. The aggregate mobility index was then computed as a percentage change by calculating the ratio between the metric for a given day and the same metric computed for the baseline period (Sulyok & Walker, 2020). Conversely to Apple, the methodology implemented by Google also included the utilisation of scaling factors to improve the accuracy of its metrics over time (Aktay et al., 2020). Nonetheless, what those scaling factors account for is not explicitly described by Google, limiting the information available to indicate how those scaling factors were applied to the different metrics provided.

Some uses of the GCMR’s PT index were the characterisation of the use of PT, the clustering of cities with similar PT demand change levels, and the assessment of the effectiveness of mobility restrictions (Arellana et al., 2020; Wen et al., 2021; Angell & Potoglou, 2022; Padmakumar & Patil, 2022; Manout et al., 2023; Seifert et al., 2023). On the other hand, AMTR reported indices estimated based on navigation data from the Apple Maps app service to describe its users’ mobility trend (Apple, 2023). AMTR showed daily relative changes for three transport modes (PT, walking and driving) by estimating the quotient between the volume of direction requests for a specific day and pre-pandemic baseline (Strzelecki, 2022). The characterisation of the change in mobility was one of the main uses of this data set (Beck et al., 2021; Hasselwander et al., 2021; Wen et al., 2021; Padmakumar & Patil, 2022; Drummond & Hasnine, 2023).

5.1.3 Ridership data versus AMIs

Despite the widespread use of the AMIs provided by tech companies during the last three years, it is surprising that limited evidence of the reliability of these indices to represent actual PT demand shifts is available. As the importance of mobility data availability transcends the COVID-19 pandemic, a proper assessment of the potential of AMIs in PT is desirable for wider applications. So far, comparisons between AMIs that offered proxies for PT and ridership data have been provided tangentially by a few studies that analysed both data sources when characterising COVID-19's impact on PT demand. These studies preliminarily reported that AMI captured the generalised drop in ridership during the pandemic outbreak and that after it, they overestimated PT demand recovery (Jenelius & Cebecauer, 2020; Fernández Pozo et al., 2022). For instance, using ridership data, a study conducted in Sweden (Jenelius & Cebecauer, 2020) reported a reduction in PT demand of 40% in Skåne, 50% for Västra Götaland and 60% for Stockholm at the end of June 2020. By contrast, using the PT index of GCMR, the same study observed only a 0%, 10%, and 20% reduction in ridership, respectively. When they explored the PT index of AMTR, they obtained a reduction of around 20% with no noticeable difference between those areas. A smaller difference was observed in New York, where a 50% ridership decrease was observed using the PT index of AMTR when a 70% reduction was reported by the subway transactions (Wang & Noland, 2021). In a study conducted on the Community of Madrid also for 2020, the authors contrasted smart card records with the Moovit mobility index. They found that during the recovery stage, the Moovit index reported a drop of only 5% compared to a reduction of 50% recorded for the ridership data (Fernández Pozo et al., 2022). Despite this evidence, several limitations in the existing studies lead to inconclusive findings about the level of accuracy of AMIs in terms of replicating PT ridership changes and their potential for wide-spread use in PT planning and operational decisions:

- Early comparisons overlooked differences in the methodological approaches used to estimate AMIs. Therefore, the benchmarking required for properly comparing the datasets is yet to be conducted.
- As the primary goal of the above-mentioned studies was to describe PT demand changes and not to assess the similarity between ridership data and AMIs, they did not conduct a formal quantitative comparison, limiting the current evidence to point-temporal comparisons and visual inspections of the trends only. In addition, as these early insights are based on data from the first half of 2020 and a few isolated contexts, there is a significant gap in the literature in studying a more comprehensive period and a wider sample of cases.

- To the best of our knowledge, attempts to leverage the complementary role of AMIs on traditional ridership data have yet to be done (e.g., fill in temporal gaps in the data, identify supplementary information, etc.).

To address these gaps, this study aims to conduct a comprehensive similarity evaluation between the changes reported by AMIs for PT demand and ridership data. Monthly ridership data from 12 cities worldwide from eight countries and daily ridership for three case studies (London, New York and Santiago de Chile) were used for the analysis. Similarity metrics assessed the agreement between AMIs and ridership data for the period 2020-2022. Seasonal ARIMAX models were also employed to test the capacity of AMIs to predict PT demand changes in periods where ridership data did not record the actual demand. The results of this study provide a more comprehensive understanding of similarities and differences between the two data sources and reveal the potential role of AMIs in PT demand characterisation, particularly in developing countries.

The remainder of this paper is structured as follows. The methodology of this study is provided in Section 5.2, including a description of the data and a definition of the metrics used to measure the degree of similarity between ridership data and AMIs. Section 5.3 shows the results of the similarity comparison and Section 5.4 presents the complementarity analysis between AMIs and ridership data. Finally, the implications of the findings and future perspectives are discussed in Section 5.5.

5.2 Methodology

This study investigates the reliability of using aggregated mobility indices (AMIs) for inferring PT ridership changes. **Figure 5-1** shows the methodological procedure followed in this study. First, we retrieved data on AMIs and ridership data between 2020 and 2022 for several cities. Then, a common baseline was defined and adopted, allowing the comparison between data sets. AMIs and ridership were then analysed, and practical applications were explored. A detailed definition of each step is presented next.

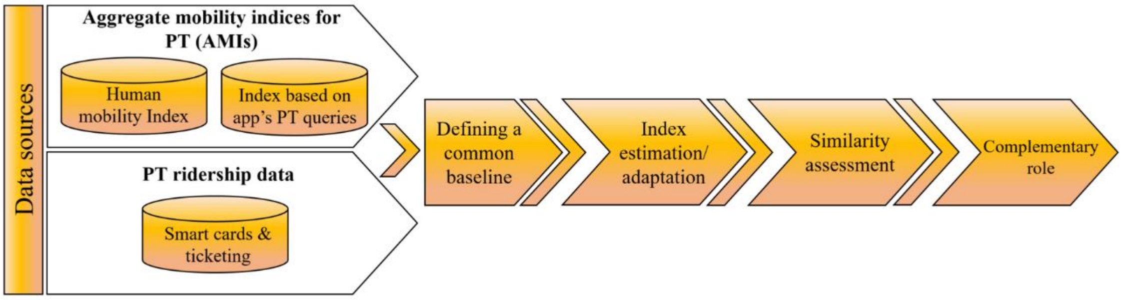

Figure 5-1. Methodological approach followed in this study.

5.2.1 Data

Two AMIs that offered proxies for PT were retrieved to be tested in their alignment with ridership changes. We selected Google COVID-19 Community Mobility Reports (GCMR) and Apple Mobility Trends (AMTR) as they offered global coverage and the most prolonged availability (Apple, 2023; Google, 2023). Additionally, they present proxies for PT use based on different ICT sources: GCMR used GPS traces from smartphones, and AMTR employed the queries for PT made in the Maps application of Apple devices (a further description of these indices is provided in Section 5.1.2). In this work, we will use the term Human Mobility Index (HMI) to refer to the particular index in the GCMR that measured the changes in human mobility in PT hubs (train stations, bus stops, etc.). Analogously, we will use the term Apple Query Index (QI) to refer to the category of AMTR that compared the level of queries for PT directions in Apple Maps. Both indices were updated daily from 2020 to 2022. Specifically, HMI was provided from 15 February 2020 to 15 October 2022 and QI from 13 January 2020 to 12 April 2022 (AMTR data for 11-12 May 2020, 12 March 2021 and 21 March 2022 were unavailable). On the other hand, ridership data came from validations made by smart cards and paper or digital tickets and were directly retrieved from the official portals of several PT operators. The inclusion criteria for selecting an urban area as a case study considered the availability of ridership data and AMIs. A total of 12 different case studies were selected (considering a monthly temporal resolution of ridership), aiming to include different contexts and increase the generalization of the similarity assessment. In only three of them, daily ridership data were publicly available (London, New York and Santiago de Chile). Both, monthly and daily ridership data were used in the similarity analysis (See **Table C-1**). **Table 5-1** specifies the case studies included in the analysis, indicating the availability of AMIs as well as the temporal and spatial resolution of the retrieved ridership data. This work employed publicly available data, whose use complied with the terms and conditions for each source. Further details of the terms and conditions can be found directly in the web pages of each source using the links provided in the Appendix (**Table C-1**).

Table 5-1. Case studies for the comparison between AMIs and ridership data.

Country	City	Ridership PT authority	Google's Index (HMI) Spatial definition	Apple's Index (QI) Spatial definition
Case studies with daily ridership data				
U.K.	London	Transport for London (TfL)	City of London/ Sub-region 2	London/ City
U.S.	New York	MTA New York	New York County/ Sub-region 2	New York/ City
Chile	Santiago	Met. Public Transport Agency (DTPM)	Santiago Province/ Sub-region 2	-

Country	City	Ridership PT authority	Google's Index (HMI) Spatial definition	Apple's Index (QI) Spatial definition
Case studies with monthly ridership data				
Australia	Sydney	Transport for NSW	City of Sydney/ Sub-region 2	Sydney/ City
Canada	Toronto	Toronto Transit Commission	Toronto/ Sub-region 2	Toronto/ City
Colombia	Bogotá	Transmilenio*	Bogota/ Sub-region 1	-
U.S.	Dallas	Dallas Area Rapid Transit	Dallas County/ Sub-region 2	Dallas/ City
U.S.	Denver	Regional Trip District	Denver County/ Sub-region 2	Denver/ City
U.S.	Salt Lake	Utah Transit Authority	Salt Lake County/ Sub-region 2	Salt Lake/ City
U.S.	Chicago	Chicago Transit Authority	Cook County/ Sub-region 2	Chicago/ City
Taiwan	Taipei	Metro Taipei**	-	Taipei City/ Sub-region
Hong Kong	Hong Kong	MTR Hong Kong**	Hong Kong / Country-region	-

* Only BRT ridership available. ** Only metro ridership available.

5.2.2 Establishing a common definition

To generate comparable datasets, a common basis for estimating mobility changes was adopted. This common basis was required due to differences in how AMIs were reported and the absolute nature of the ridership data (i.e. the total number of transactions), aspects that were ignored in early comparisons. The GCMR and AMTR reported daily relative changes by estimating the quotient between the mobility volume for a specific day and a baseline mobility volume defined for the pre-pandemic. The proportion obtained was reported as a percentage, and a positive value indicated the percentage of increase with respect to the baseline, while a negative one specified the degree of reduction. However, the baseline definition adopted by each index was different. As the QI employed as a baseline the number of queries of only one day, this index was more susceptible to high variability due to the lack of inclusion of weekly mobility cycles. In the case of ridership data, a normalisation of their values respecting a baseline was also required to obtain a relative scale. A review of the criteria employed in the literature for estimating relative changes with aggregate PT demand supported the baseline definition adopted by the HMI (Fernández Pozo et al., 2022; Jiang & Cai, 2022), and for this reason, it was employed as the consistent basis in the current paper. The definition includes the choice of a pre-COVID-19 period, the recognition of demand variability within the week and a way to deal with potential outliers. As no AMIs were available before 2020, using data from 2019 to describe the pre-pandemic period was not possible. Both ridership data and the QI were adapted according to the HMI's baseline definition. We present the details of the baseline definitions adopted for the case studies where daily ridership was available in **Table 5-2**. **Table 5-2** also explores the consistency of daily values for ridership and the QI in the baseline period. Coefficients of variation smaller than 6.0% were observed, revealing high stability in the mobility trends of the same days of the week for the period that characterised the pre-pandemic. It was interesting to observe also for this period that the QI depicted the highest demand for PT information on Fridays and Saturdays, contrasting with the typical daily variability of ridership data (see **Figure C-1**).

Table 5-2. Details of the common baseline adopted to estimate relative changes in ridership data and the QI.

		Apple's Index[1] (QI)		**Ridership Data**		
		London	**New York**	**London**	**New York**	**Santiago**
Period data		13 Jan 2020 to 12 Apr 2022		01 Jan 2020 to 31 Oct 2022	01 Mar 2020 to 31 Oct 2022[2]	01 Jan 2020 to 31 Oct 2022
Baseline definition (pre-pandemic)						
Original reported values		AMTR		Recorded subway and bus ridership, nominal values	Recorded subway and bus ridership, nominal values	Recorded subway and bus ridership, nominal values.
Common baseline definition applied		The median value for each day of the week over the three weeks between 13 January and 2 February 2020		The median value for each day of the week over the five weeks between 3 January and 6 February 2020	Average value for January 2020 for weekdays, Saturday and Sunday	The median value for each day of the week over the five weeks between 3 January and 6 February 2020
Consistency of baseline values						
Coeff. Var. baseline values	Mon	1.7%	5.5%	3.9%	-	1.9%
	Tue	1.8%	1.4%	3.3%	-	2.3%
	Wed	2.2%	2.3%	2.7%	-	4.6%
	Thu	2.4%	2.4%	2.3%	-	4.3%
	Fri	3.2%	2.6%	1.0%	-	4.8%
	Sat	1.4%	3.2%	6.2%	-	5.0%
	Sun	2.9%	4.9%	5.0%	-	5.0%

[1] The category of PT of the AMTR was not available for Santiago de Chile. [2] No bus ridership data collected directly from a smart card or ticketing validation was available between 1 Mar and 30 Sep 2020.

The expressions used to apply the common basis on ridership data and the QI are presented in Equation (5-1) and Equation (5-2). We call these new indices relative ridership change index (RRC) and Apple query modified Index (QMI). The RRC at a time t (RRC_t) was defined as follows:

$$RRC_t = \left(\frac{r_t}{R_{f(t)}} - 1\right) \cdot 100 \tag{5-1}$$

Where r_t is the ridership on day t (t=1, 2, …, T) and $R_{f(t)}$ is the baseline ridership for each day of week f, whose value in Equation (5-1) depends on the day of the week corresponding to t. If both r_t and its corresponding $R_{f(t)}$ were the same, the quotient is one and the RRC_t is equal to zero (i.e. 0% change). The RRC takes a negative value if the ridership in the time t is smaller than the one existing in the baseline period for the corresponding day of the week. For instance, if the ridership were half compared with the baseline value, the index would be equal to -50 (%). The same interpretation apply for the HMI. In the case of New York, daily ridership was not available for January. Therefore, we use the reported average value of ridership for weekdays, Saturdays and Sundays during January 2020 as baseline values. To estimate RRC for the case studies where only monthly ridership was available, we first estimated the average daily ridership for each month, dividing monthly ridership by the number of days of each month. Then, the RRC was estimated analogously, employing the average daily ridership of January 2020 as a baseline value.

In the case of the QI, its original values were reported as percentage changes relative to one particular day. Apple provided these values on a base of 100, assigning a value of zero to the QI of 13 January 2020. Then a value of 5.0 would indicate that for a particular day, the number of queries was five percent higher than the base day. The adoption of the common baseline for estimating relative changes for this index was addressed by proposing the Apple's query modified index (QMI):

$$QMI_t = \left(\frac{QI_t + 100}{QIB_{f(t)} + 100} - 1\right) \cdot 100 \tag{5-2}$$

Where QI_t is the Apple's query index on day t (t=1, 2, …, T) and $QIB_{f(t)}$ is the Apple's query index baseline for each day of the week f, whose value in Equation (5-2) depends on the day of the week corresponding to t. Each QIB was estimated as the median QI value for the same day over the three weeks between 13 January and 2 February 2020 (as there were no earlier values). In this way, the QMI overcomes the original limitation of the QI, comparing query levels of the same days of the week and controlling for outliers if they were present. The QMI shares the same interpretation with HMI and RRC. Monthly QMI and HMI were obtained by averaging their daily values for each month.

5.2.3 Similarity assessment

The degree of similarity between the values reported by AMIs (HMI and QMI) and RRC was assessed by applying metrics under a time series approach. For the monthly analysis, we included the mean Euclidean distance (MED), the cosine distance (COS) and a trend similarity index (STI). The Dynamic Time Warping distance (DTW) and the Granger Causality test were included for the daily similarity analysis where a higher granularity in the data was available. The MED is recommended when a straightforward interpretation of the differences is required. In our case, as the time series values are all relative changes (%), the MED interpretation is the average distance in percentage points between the relative change reported by the AMIs (HMI or QMI) and RRC. The COS is a similarity measurement between two vectors defined in an inner product space (Han et al., 2011). Their values are always between -1 and 1, where 1 means perfect alignment and -1 indicates the opposite. DTW is an alignment-based metric that estimates the Euclidean distance between two time series that may not be aligned (Han et al., 2011). We included DTW for the daily analysis to deal with potential shifts in the times series, particularly present in the QMI. The Granger Causality test determined whether AMIs could be used to forecast the RRC values (Eichler, 2012). This statistical hypothesis test uses Student's statistic and F-statistic tests to determine whether values of a certain variable provide statistically significant information about the values of Y. The trend similarity index (STI) was estimated as the proportion of slopes with the same sign for the same pair of consecutive months/days between the RRC and AMIs. The sign of the slopes for two consecutive times was obtained by observing the direction of the change between the values of each index. The STI between RRC and an AMI (HMI or QMI) was defined as:

$$STI_{RRC,AMI} = \frac{\sum_t s_t^{RRC,AMI}}{T-1} \tag{5-3}$$

$$s_t^{RRC,AMI} = \begin{cases} 1, \; \Delta RRC_{t,t+1} \cdot \Delta AMI_{t,t+1} \geq 0 \\ 0, otherwise \end{cases} \tag{5-4}$$

Where Δ indicate the difference between two consecutives values for the respective index, and T is the length of the time series. STI metric ranges between 0 and 1, where the value one means that the AMI replicated exactly the same direction of change of the RRC and zero the case of a complete disagreement.

5.2.4 Complementary role of AMIs

We also explore the complementary role of AMIs in contexts where ridership data did not capture the actual PT demand and on atypical days where mobility demand was extraordinarily high. Hence, the next situations helped illustrate the role that AMIs may play in complementing ridership data:

- Free bus travel period in London during the pandemic outbreak: From 20 April to 30 May 2020, Transport for London introduced middle/rear-door-only boarding in bus services to take care of drivers. AMIs were used here to reveal an approximation of the actual PT demand in this period where ridership was under-reported.
- Partial ridership data in New York MTA: No bus ridership data collected directly from a smart card or ticketing validation was available for the New York MTA between 1 March and 30 September 2020. Using AMIs, an approximation of the actual RRC in this period was estimated.
- High mobility demand day for Santiago: The day of the national referendum in Chile (Sunday, 4 September 2022) was marked by an extraordinarily high mobility, resulting in the highest recorded RRC for Santiago in the study period. We assessed the discrepancies between the predicted RRC (based on the AMIs) and the recorded RRC.

Autoregressive Integrated Moving Average (ARIMA) models were employed to calibrate the relationship between the recorded RRC and the AMIs. For this, we selected the AMI that exhibited the highest similarity with RRC, while the calibration was made on periods with the most stable conditions available. ARIMA models are particularly efficient and appropriate when successive observations show serial dependence (e.g. in this case, daily observations), and therefore, the assumption of independent errors typically made for cross-section regression data is violated. At the same time, this modelling approach allows testing whether the AMI contribution to explain RRC is statistically significant. As a weekly periodicity was also found in the descriptive analysis (see **Figure C-2**), an appropriate model specification may consider both, daily and weekly autocorrelation. To consider both correlations, a multiplicative seasonal ARIMA model is specified, where one component (p, d, q) captures the daily correlation, and a second component (P, D, Q) explains the weekly correlation in the data. If s is the seasonal period of the time series (considering weekly seasonality s=7), then the seasonal ARIMAX $(p, d, q) \times (P, D, Q)[s]$ (Montgomery et al., 2015) can be written as follow:

$$\Phi_P^*(L^s)\Phi_p(L)(1-L^s)^D(1-L)^d y_t = \mu + \Theta_Q^*(L^s)\Theta_q(L)\varepsilon_t + \omega AMI_t \qquad (5\text{-}5)$$

where y_t is the value of the RRC time series for the time t. ε_t is the white noise process (i.e. random error, i.i.d. Gaussian (0, σ_ε^2)) and L is the backshift or Lag operator, defined as $Ly_t = y_{t-1}$. d represents the differences that can be applied on the dependent variable to obtain a stationary time series for the non-seasonal model. $\Phi_p(L)$ is the polynomial of order p that contains the marginal contribution of the auto-regressive (AR) component and $\Theta_q(L)$ the polynomial of order q of the moving average (MA). $\Phi_P^*(L^s)$ is the operator of the seasonal AR component with order P, D is the seasonal differences number and $\Theta_Q^*(L^s)$ is the operator for the seasonal MA with order Q. Note that we have added in the last term of Equation (5-5) the AMI, which is an exogenous variable in the modelling with coefficient ω.

5.3 Exploratory analysis

5.3.1 Monthly analysis

A monthly analysis of 12 cities worldwide from eight countries showed that HMI and QMI were capable of replicating the RRC with different degrees of accuracy. **Figure 5-2** presents the monthly variability of each index for the entire study period per case study, while **Table 5-3** presents the results for the similarity metrics. Overall, AMIs correctly mimicked the main direction of changes depicted by RRC. In all the cases considered, AMIs properly replicated the drop in PT demand during the pandemic outbreak. However, in most cases, AMIs reported higher PT demand recoveries than the RRC. The average MED for the HMI and QMI were 11.9 and 11.6 for 2020 and 14.4 and 26.6 percentage points for the entire period, respectively. Cities like London and Sydney exhibited the greatest match between HMI and RRC, with small MED obtained (5.1 and 4.0). However, common MED were between 10 and 20 percentage points for most studied cases. Regarding the QMI, this index exhibited a similar adjustment to HMI until April 2021. After this date, QMI showed a general increase until August 2021, when the index stabilised around 60 percentage points above RRC values. The Similarity Trend Index (STI) ranged from 0.71 to 0.94 for the HMI and 0.73 to 0.92 for the QMI, revealing a high capability to replicate the direction of change of the monthly ridership trends by the AMIs. The cosine distance values supported these results showing magnitudes that indicate high similarity. Case studies where only partial ridership information was retrieved showed higher differences compared with the general trends. For instance, the greatest difference between HMI and RRC was observed in Bogota. This may be explained as ridership data for Bogota only describes the BRT system's demand and does not consider the local bus system. Moreover, contrary to the remaining case studies, AMIs in Taipei and Hong Kong reported lower

PT demand recovery than the RRC. This difference may be explained by considering that only metro ridership was available for these two cities.

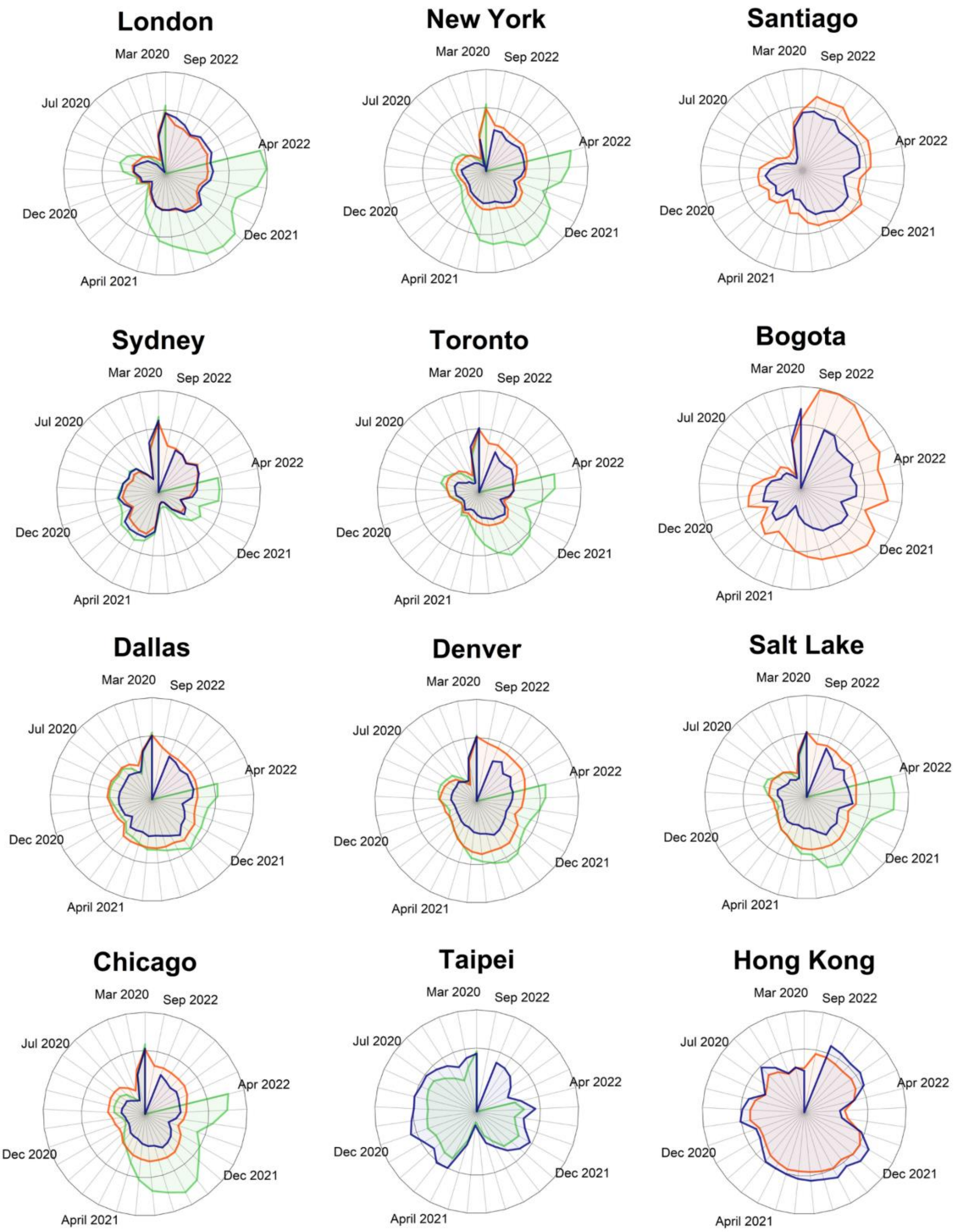

Figure 5-2. Average monthly changes in HMI (orange), QMI (green), and RRC (blue). Centre of the graphic indicates -100% change, central grid circumference 0% change and external grid circumference +60% change (all compared with baseline values). Data from February 2020 to October 2022 (for some case studies, available ridership data end in July 2022).

Table 5-3. Monthly similarity metrics between AMIs and RRC.

Google's human mobility index (HMI)						
	MED				**STI**	**COS**
Location	**All years**	**2020**	**2021**	**2022**	**All years**	**All years**
London	5.8 ●●●	8.3 ●●●	3.0 ●●●	6.5 ●●●	0.87 ▲▲△	0.99 ▲▲▲
New York	9.2 ●●●	12.5 ●●○	8.2 ●●●	7.0 ●●●	0.93 ▲▲▲	0.99 ▲▲▲
Santiago	18.1 ●●○	14.2 ●●○	18.6 ●●○	21.8 ●●○	0.90 ▲▲▲	0.94 ▲▲▲
Sydney	4.1 ●●●	5.3 ●●●	4.3 ●●●	2.1 ●●●	0.94 ▲▲▲	0.99 ▲▲▲
Toronto	10.1 ●●○	13.9 ●●○	8.1 ●●●	8.1 ●●●	0.90 ▲▲▲	0.99 ▲▲▲
Bogota	35.2 ●○○	14.6 ●●○	43.0 ●○○	49.8 ●○○	0.84 ▲▲△	0.52 ▲△△
Dallas	13.4 ●●○	13.2 ●●○	16.7 ●●○	9.4 ●●●	0.71 ▲△△	0.99 ▲▲▲
Denver	18.1 ●●○	10.3 ●●○	23.9 ●●○	20.0 ●●○	0.77 ▲△△	0.96 ▲▲▲
Salt Lake	15.7 ●●○	12.4 ●●○	21.4 ●●○	12.2 ●●○	0.71 ▲△△	0.97 ▲▲▲
Chicago	18.0 ●●○	18.8 ●●○	20.3 ●●○	13.8 ●●○	0.90 ▲▲▲	0.99 ▲▲▲
Taipei	-	-	-	-	-	-
Hong Kong	10.3 ●●○	7.4 ●●●	11.9 ●●○	11.8 ●●○	0.94 ▲▲▲	0.81 ▲▲▲
Average	14.4	11.9	16.3	14.8	0.86	0.92
Std. Deviation	8.1	3.6	10.8	12.4	0.08	0.14
Median	13.4	12.5	16.7	11.9	0.90	0.99
Apple query modified index (QMI)						
	MED				**STI**	**COS**
Locations	All years	2020	2021	2022	All years	All years
London	36.2 ●○○	13.4 ●●○	44.6 ●○○	73.3 ●○○	0.81 ▲▲△	0.61 ▲△△
New York	37.6 ●○○	14.8 ●●○	47.7 ●○○	64.3 ●○○	0.88 ▲▲△	0.67 ▲△△
Santiago	-	-	-	-	-	-
Sydney	11.2 ●●○	2.8 ●●●	10.9 ●●○	35.3 ●○○	0.81 ▲▲△	0.96 ▲▲▲
Toronto	28.4 ●○○	13.1 ●●○	33.3 ●○○	56.0 ●○○	0.88 ▲▲△	0.83 ▲▲△
Bogota	-	-	-	-	-	-
Dallas	18.6 ●●○	10.1 ●●○	19.9 ●●○	38.0 ●○○	0.77 ▲△△	0.90 ▲▲▲
Denver	27.0 ●○○	12.1 ●●○	33.5 ●○○	48.1 ●○○	0.92 ▲▲▲	0.83 ▲▲△
Salt Lake	30.1●○○	12.0 ●●○	35.3 ●○○	64.6 ●○○	0.73 ▲△△	0.67 ▲△△
Chicago	33.5 ●○○	7.6 ●●●	47.1 ●○○	64.2 ●○○	0.85 ▲▲△	0.66 ▲△△
Taipei	16.8 ●●○	18.7 ●●○	13.5 ●●○	14.4 ●●○	0.85 ▲▲△	0.91 ▲▲▲
Hong Kong	-	-	-	-	-	-
Average	26.6	11.6	31.8	50.9	0.83	0.78
Std. Deviation	8.7	4.2	13.3	17.7	0.06	0.12
Median	28.4	12.1	33.5	56.0	0.85	0.83

AMIs: aggregate mobility indices, RRC: ridership relative change index, MED: mean Euclidean distance, STI: similarity trend index, COS: the cosine distance. ●●●: MED ≤ 10, ●●○: 10<MED ≤25, ●○○: MED>25. ▲▲▲: STI/COS ≥ 0.90, ▲▲△: 0.90>STI/COS≥0.80, ▲△△: STI/COS <0.80.

5.3.2 Daily analysis

The daily analysis compared HMI and QMI with RRC for the cities of London, New York and Santiago. **Figure 5-3** provides a graphical illustration of the aggregate PT demand shifts depicted by each index. The HMI was found to match surprisingly well with the daily RRC time series. At the same time, the QMI displayed a reasonable fit in terms of the magnitude of the PT demand recovery until the first half of 2021. For that period, the main trends of peaks and troughs of the RRC time series were also depicted appropriately by HMI and QMI, including short sharp reductions during holidays. A particular concurrence of the values of all indices was observed during the periods where the stricter mobility restrictions were in place (pandemic outbreak and from November 2020 to February 2021).

To identify changes in the pattern of the dissimilarity between the AMIs and RRC, **Figure 5-3** also presents the differences between them for each day. A positive distance indicates that the AMIs observed a lower relative drop or a higher relative increase than the RRC. The difference between HMI and the RRC showed relatively constant values, whilst the difference between QMI and the RRC exhibited greater variability. In general, mostly positive differences were observed, except for London, where the HMI generated negative differences from May 2021 onwards. This situation coincides with changes in the fare scheme for children, which involved removing free travel for some ages. The highest dissimilarities in the London case between HMI and RRC were observed from April to May 2020, when mandatory payments in London's buses were suspended. In the case of New York, a change in the trend of the differences was observed during the first half of 2020, where RRC was represented only by the subway ridership. In the case of Santiago, the most remarkable observed differences were associated with sharp peaks in the HMI during special events (e.g. national elections and referenda). For the QMI, the highest differences with the RRC were observed during the first recovery period (June to November 2020) and during the second recovery (April 2021 onwards, where QMI was considerably higher). A ratio of increase in the number of PT queries greater than the recovery in the actual ridership during the first half of 2021, when many restrictions were eased, would explain these discrepancies. This interpretation is supported by the results of Sydney (see **Figure 5-2**), where its QMI experienced a similar increase when a similar ease of mobility restrictions started in that city at the end of 2021.

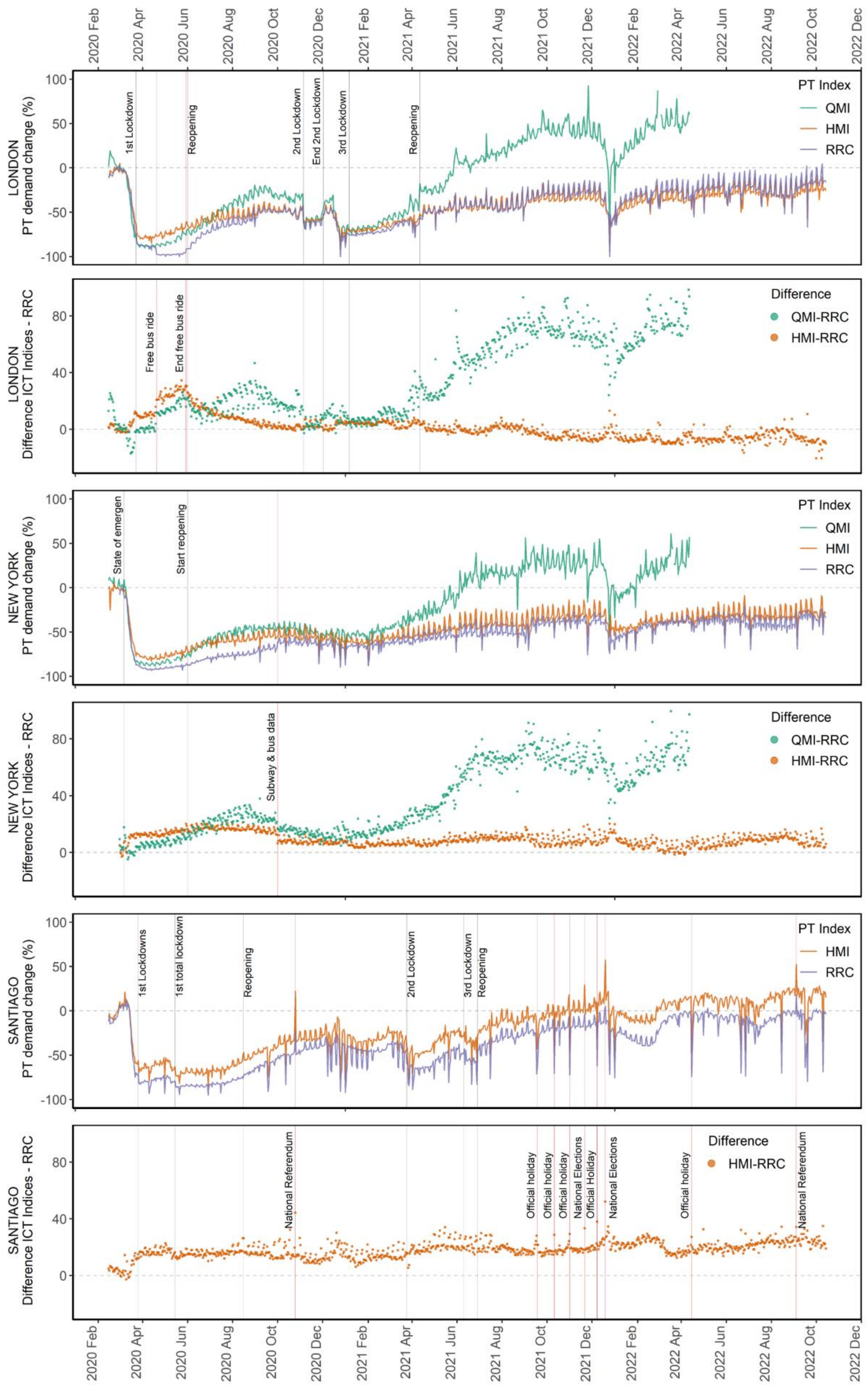

Figure 5-3. Daily variation of PT mobility indices. HMI, QMI and RRC for the case studies of London, New York and Santiago.

Table 5-4. Similarity metrics between AMIs and RRC, daily analysis.

Period	Similarity Index	Google' human mobility Index (HMI) London	New York	Santiago	Query modified index (QMI) London	New York
Distance between AMIs and RRC (in percentage points)						
All	Mean	6.2	9.1	18.2	35.7	36.1
2020	Euclidian	8.8	12.0	14.7	13.6	14.5
2021	distance	3.5	8.2	18.6	44.9	47.9
2022	(MED)	6.6	7.1	21.2	72.0	61.9
Dynamic Time Warping distance (DTW)						
All	DTW	5.0	5.8	9.6	24.5	24.2
2020		4.7	5.2	6.6	7.4	6.3
2021		3.8	6.1	9.4	30.5	24.2
2022		6.9	6.4	16.8	64.6	60.3
All	MED Std.	5.8	4.5	5.7	28.5	25.2
	MED	5.8	8.3	17.5	37.3	36.5
	MED	7.1	11.2	20.1	31.6	35.2
Similarity Trend Index (STI)						
All	STI	0.80	0.83	0.75	0.61	0.73
2020		0.80	0.82	0.68	0.59	0.70
2021		0.77	0.83	0.76	0.63	0.73
2022		0.85	0.83	0.83	0.54	0.74
Cosine distance (COS)						
All	COS	0.99	0.99	0.94	0.62	0.69
2020		0.99	0.99	0.99	0.98	0.99
2021		0.99	0.99	0.94	0.37	0.30
2022		0.98	0.99	0.81	-0.78	-0.55
Granger Causality Test						
2020-	Test F	4.8	11.5	19.4	44.8	45.6
2022	*p*-value	0.03	<0.01	<0.01	<0.01	<0.01

Similarity metrics presented in **Table 5-4** support the descriptive analysis based on **Figure 5-3**. Considering the entire period, the MED for the HMI were 6.2, 9.1 and 18.2 for London, New York and Santiago, respectively. In the same order, standard deviation values of 5.8, 4.5 and 5.7 were calculated, indicating consistency among the case studies in terms of the differences between the HMI and the RRC. For each case study, the MED of HMI was seen to be relatively constant across the three years, showing great stability in its capabilities of replicating the changes reported by ridership data. In the case of the QMI, an overall MED of 35 percentage points was estimated for London and New York. Contrasting with the HMI results, the QMI showed an increasing difference along the time series with the RRC. Moreover, the standard deviation of the MED of QMI ranged from 26 to 28 percentage points, considerably higher than the one estimated for HMI. The analysis based on the DTW distance offered a similar interpretation for the AMIs. The Similarity Trend Index (STI) showed that the HMI replicated correctly between 75% and 85% of the RRC trend change directions; in the case of the QMI, the STI dropped to values from 54% to 74%. This may be explained considering that RRC and HMI depicted higher PT demand recovery on weekends, while QMI reported greater values on Fridays and Saturdays (see **Figure C-2**). The cosine distance indicated that QMI only presented a high similarity with RRC during 2020 and the Granger Causality Test indicated that both HMI and QMI could be used to predict RRC.

5.4 Modelling results

Based on the results of the similarity analysis, the HMI was selected as the best candidate for exploring the capability of AMIs to complement ridership data. Seasonal ARIMAX models were used to calibrate the relationship between HMI and RRC and then to forecast RRC for three particular cases (which have already been described in detail in section 5.3.4): a free bus travel period in London, a partial ridership data period in New York (both during the first half of 2020), and the day with the highest recorded RRC in Santiago during late 2022. A seasonal component of seven days was considered as the correlograms of the time series identified weekly periodicity. The periods used to fit and validate the models were selected considering the nearest interval to the research periods with homogeneous differences between the HMI and RRC. Two models were fitted for London, one with data located before the research period and a second with data after it. For fitting and validation purposes, the selected data were split into two segments considering a proportion 5:1. Details of the fitting, validation and research periods, as well as the modelling results, are shown in **Table 5-5**.

Table 5-5. Seasonal ARIMAX time series modelling results.

	London		New York	Santiago
Period details				
Forecasting	backward	forward	backward	forward
Fitting period	01 Dec 2020 to 30 Sep 2021	15 Feb to 07 April 2020	01 Dec 2020 to 30 Sep 2021	10 Mar to 10 Aug 2022
Validation period	01 Oct 2020 to 30 Nov 2020	08-14 April 2020	01 Oct 2020 to 30 Nov 2020	11 Aug to 03 Sep - 05 Sep to 11 Sep 2022
Research period	15 April to 30 Sep 2020	15 April to 30 Sep 2020	01 March to 30 Sep 2020	04 Sep 2022
Modelling results				
Variable	Coef (t-stat)	Coef (t-stat)	Coef (t-stat)	Coef (t-stat)
Exogenous variable – Google human mobility Index (HMI)				
HMI ($\boldsymbol{\omega}$)	1.15 (54.25)	1.12 (64.86)	0.97 (57.26)	1.14 (51.14)
Model specification				
$(\boldsymbol{p},\boldsymbol{d},\boldsymbol{q})(\boldsymbol{P},\boldsymbol{D},\boldsymbol{Q})$	(1,0,1)(1,1,1)	(1,0,0)(1,0,0)	(1,0,2)(1,0,1)	(1,1,1)(2,0,0)
Non-Seasonal Component (p,d,q)				
Intercept ($\boldsymbol{\mu}$)	-	-0.52 (0.40)	-9.31 (2.29)	-
AR1 ($\boldsymbol{\phi_1}$)	0.84 (15.21)	0.64 (5.80)	0.96 (43.43)	0.24 (2.28)
MA1 ($\boldsymbol{\theta_1}$)	-0.38 (4.22)	-	-0.40 (6.47)	0.89 (15.41)
MA2 ($\boldsymbol{\theta_2}$)	-	-	-0.22 (3.82)	-
Seasonal Component [s=7] (P,D,Q)				
SAR1 ($\boldsymbol{\phi_1^*}$)	0.23 (3.02)	0.27 (1.98)	0.99 (204.37)	0.27 (3.26)
SAR2 ($\boldsymbol{\phi_2^*}$)	-	-	-	0.23 (2.98)
SMA1 ($\boldsymbol{\theta_1^*}$)	-0.87 (22.28)	-	-0.88 (23.67)	-
Goodness-of-fit				
LL	-506.67	-101.2	-496.62	-358.02
AIC	1025.13	210.4	1009.24	728.03
BIC	1047.3	218.28	1038.98	746.22
Residuals – Fitting sample				
Ljung-Box (*p*-value)	0.51	0.79	0.56	0.45
MED	0.96	1.31	0.90	1.72
RMSE	1.30	1.62	1.21	2.48
Mean Error	0.04	-0.04	0.02	0.2
Residuals –Validation (out-of-sample data)				
MED	0.97	1.19	1.02	2.08
RMSE	1.30	1.46	1.37	2.55
Mean Error	0.50	0.37	0.82	-0.63

The results highlighted the statistical significance of the HMI in the model estimation of RRC (t-statistic higher than 50.0), whose relationship with the actual RRC (ω) was estimated between 0.97 and 1.15. Both, the non-seasonal (daily correlation) and the seasonal (weekly correlation) components were statistically significant in the modelling. In the non-seasonal component, coefficients ϕ of the Autoregressive model (AR) were significant in the first order (p=1). This means that the RRC on a day before (t-1) only was relevant to explain the RRC value of the next observation (t). AR coefficients were all positive, ranging from 0.24 to 0.96. In the case of the Moving Average (MA) coefficients (θ), those associated with the MA of orders 1 and 2 were statistically significant. This implies the prediction benefited from correcting the error term of the lagged RRC prediction t-1 and t-2. Analogous results were observed for the seasonal component but related to observations of consecutive weeks (e.g. ϕ_1^* indicates a statistically significant effect of the RRC value of the previous week to the prediction of RRC of the next, considering the same day). The residual of the fitted models satisfied white noise properties, i.e. no evidence of autocorrelation was found, and the *p*-values of the Ljung-Box statistical test were all greater than 0.05. Results indicate an exceptional capability of the models to replicate recorded RRC using the HMI. RMSE values in the fitting stage fluctuated between 1.21 and 2.48 only, while MED ranged between 0.90 and 1.72 percentage points. Moreover, the quality of the predictions for the validation data was as high as the fitting stage, also obtaining remarkable goodness of fit. Once the models were validated, we employed them to predict RRC values on previously defined research periods.

5.4.1 London case study

The fitted and forecasted RRC for the London case study are shown in **Figure 5-4**. Modelling results suggest a substantial under-reporting in ridership due to the free-bus policy enacted from 20 April to 24 May 2022 (see **Figure 5-4B**). The difference between recorded and predicted RRC was at least 20 percentage points when the free-bus trip policy started on 20 April 2020. The predicted RRC (using forward and backward forecasting) coincided with the under-reporting magnitude, showing only that the forward forecasting generate a slightly more conservative prediction of the RRC. Predicted RRC suggested that the actual PT demand started to recover at the end of April 2020, not at the end of May, as the recorded RRC shows. Thereby, the dissimilarity between recorded and predicted RRC increased as PT demand started a slow and gradual recovery that ridership data did not take into account. The results also revealed that even when the free-bus policy finished on 24 May, the under-reporting in ridership continued for several months, gradually decreasing. In fact, according to **Figure 5-4B** it took at least two months after the end of the free bus policy to observe the unification between the recorded and predicted RRC. This finding revealed a gradual adaptation process of PT users to return to normal payment behaviour after experiencing a free bus ride policy, which ridership data was unable to observe.

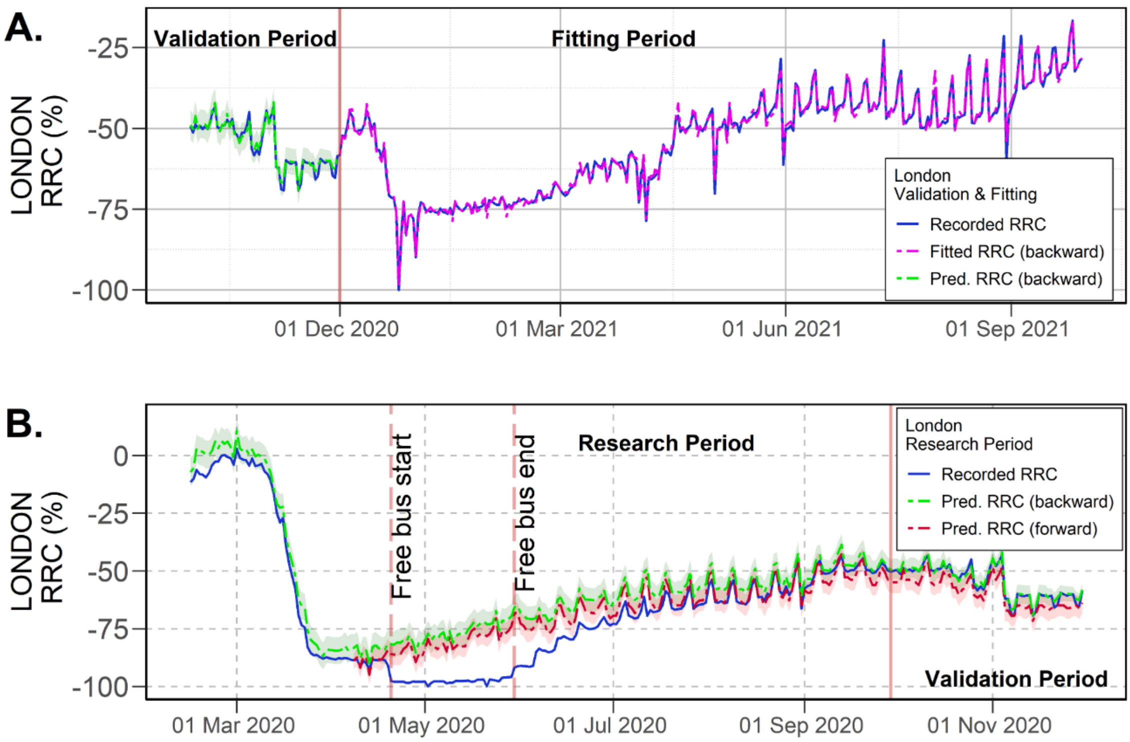

Figure 5-4. Predicted RRC using calibrated HMI for London. (A) Results for the fitting and validation period, (B) Forecasting for the research period (95% confidence intervals).

5.4.2 New York case study

Graphical results for the New York case study are provided in **Figure 5-5**. Here, using HMI, it was possible to obtain an approximation of the actual ridership change in the city during the research period (see **Figure 5-5B**). To understand these results, two facts may be recalled from the New York data description: a) recorded RRC from 1 March to 30 September 2020 are based only on subway validations, and b) data from 1 October onward contain both bus and subway ridership data. Thereby, as the calibration between RRC-HMI is made when the complete data are available, the predicted RRC illustrates an approximation of the actual ridership in the New York MTA, as both bus and subway ridership would have been available. The results suggest that the actual changes in ridership in the system were lower in magnitude than the only-subway changes. Therefore, bus ridership should have experienced lower changes than the subway during the research period. In fact, the estimation showed that bus ridership was, on average, about 20 percentage points above the recorded relative subway changes for the period. It is interesting to notice that, as the predicted RRC is depicted below the recorded RRC on the first weeks of March 2020, the backward forecasting of RRC should be seen as a conservative approximation of the true RRC in terms of actual ridership recovery.

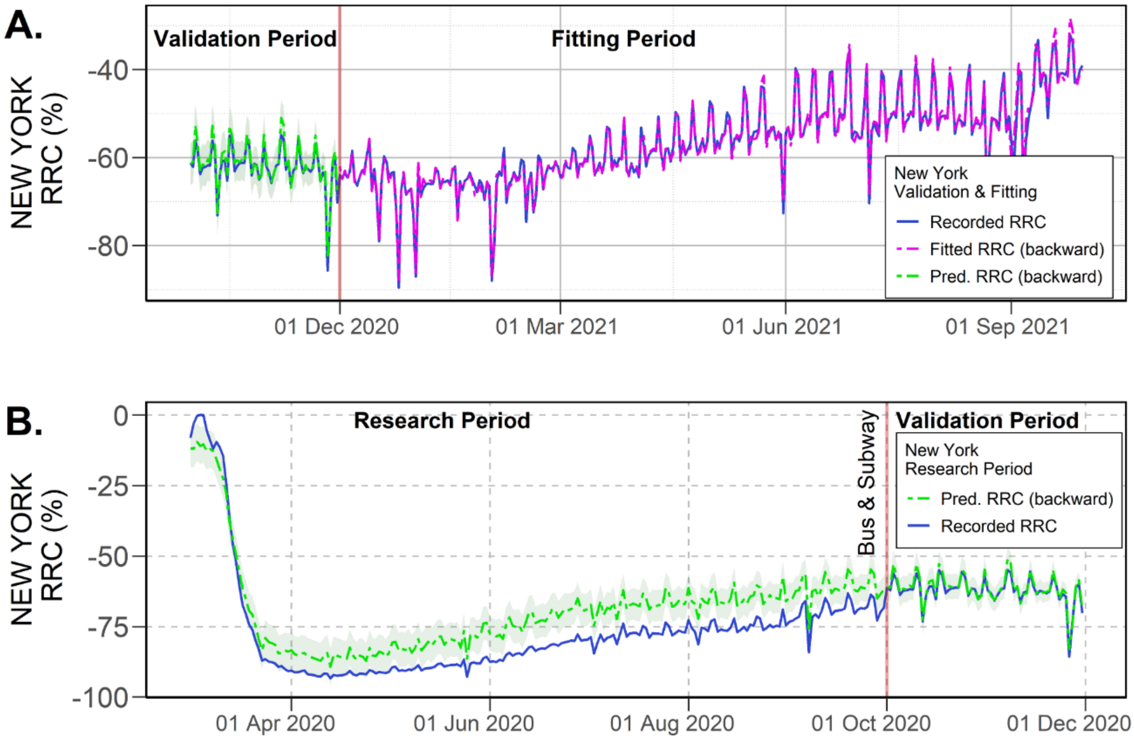

Figure 5-5. Predicted RRC using calibrated HMI for New York. (A) Results for the fitting and validation period, (B) Forecasting for the research period (95% confidence intervals).

5.4.3 Santiago case study

Fitted and forecasted RRC for the Santiago case study are presented in **Figure 5-6A**, while **Figure 5-6B** zooms in on a fraction of the validation period. The results of the RRC prediction for the Chilean national referendum on 4 September 2022 showed that the HMI overestimated the recorded RRC (30.2% vs. 17.2%, see **Figure 5-6B**). This difference was much higher than any other prediction error observed in the validation period, suggesting that the reason for that difference was an exceptional overestimation in the mobility on PT hubs registered by the HMI. Several elements that may have influenced the overestimation in the predicted RRC are hypothesised, related mainly to the nature of the HMI. For instance, a high HMI value may be associated with an increment in the time spent in PT stations due to higher waiting times of PT users caused by either a high demand or a limited PT supply. In fact, on 19 December 2021 (also an election day), Santiago's PT supply was severely criticised for the lack of bus services, low frequencies and unusually long waiting times. Interestingly, that day Santiago's HMI exhibited its highest value (57.1%) and highest difference with the RRC. An additional feasible cause of the HMI overestimation is linked to the exceptional nature of a national referendum, which involved millions of people travelling to their assigned locations. This generalised and exceptional number of people on the street may have affected the MI, for instance, by increasing pedestrian activity near PT hubs. In consequence, even when HMI successfully predicted RRC on regular days (including public holidays), it may be susceptible to registering higher mobility levels than the actual ridership on days with exceptional mobility.

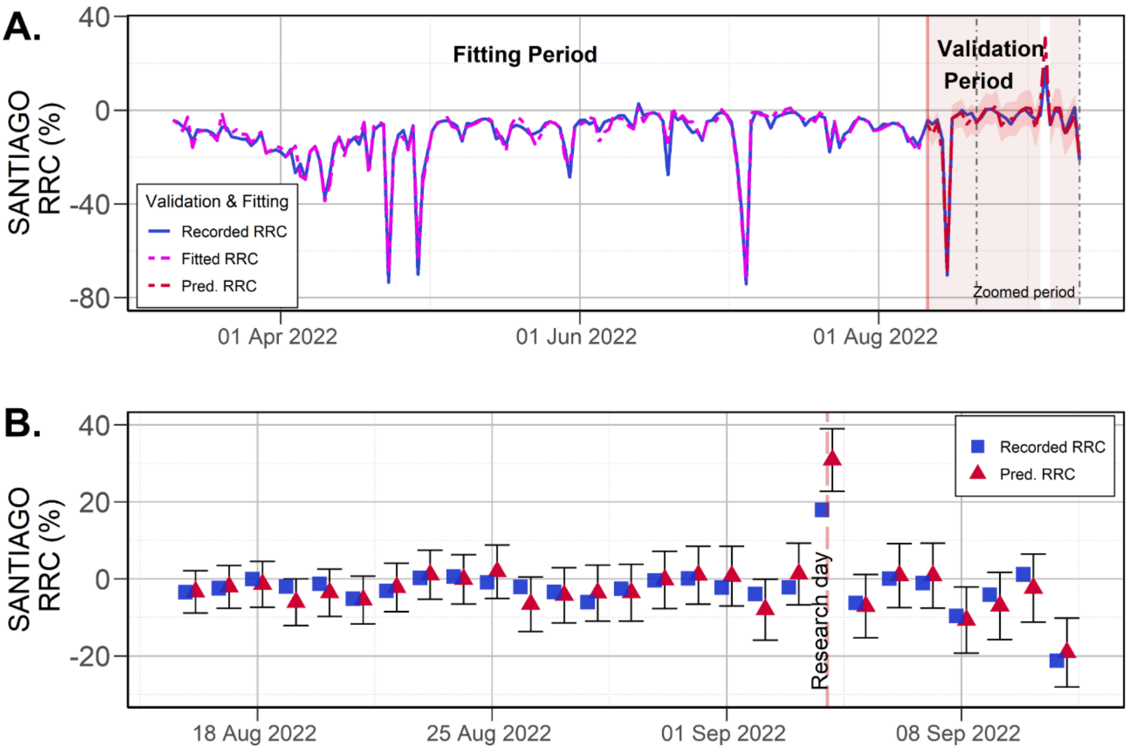

Figure 5-6. Predicted RRC using calibrated HMI for Santiago. (A) Results for the fitting and validation period, (B) Forecasting for the research period (95% confidence intervals).

5.5 Concluding discussion

Despite the extended use of aggregated mobility indices (AMIs) as proxy for the aggregate shifts in PT demand in the last years, existing research is inconclusive as to what extent they could replicate the changes recorded by actual PT ridership. The results reported here provide the first rigorous assessment of the capabilities of such indices to reproduce actual aggregate shifts in PT demand. We conducted such assessment addressing the gaps of previous studies by: 1) establishing a common methodological approach for estimating relative mobility changes with different data sources, 2) considering a larger number of case studies and analysing differences in a more comprehensive study period and 3) exploring the complementary role of AMIs with ridership data. We summarise the result of their performance as follows:

Difference in relative changes between AMIs and ridership data (RRC): AMIs correctly captured the main changes in ridership levels, particularly for the first year of analysis (2020). When compared with ridership data, averages monthly differences of only 11.9 ± 3.6 and 11.6 ± 4.2 percentage points were found for the relative changes provided by Google (HMI) and Apple's Index (QMI) during 2020, respectively. While considering the daily analysis, average differences between 8.8 and 14.5 percentage points were observed. Even though these results suggest that AMIs tend to overestimate relative changes compared with ridership data, they greatly differ from previous studies, which reported differences between 30 to 50 percentage points for the same period (Jenelius & Cebecauer, 2020; Wang & Noland, 2021; Fernández Pozo et al., 2022). The fact that previous studies have overlooked methodological differences between ridership data and AMIs in terms of their collection and definition would explain these discrepancies. For the following years, HMI kept a similar performance for all the study period, whilst QMI showed a substantial overestimation from April 2021.

Accuracy in replicating the direction of change of ridership: The metric varied depending on the temporal granularity of the analysis. Based on the monthly similarity assessment, HMI and QMI correctly replicated as high as 85% of the direction changes. In the daily analysis, only the HMI kept a similar performance; QMI achieved slightly worse (61% to 73% overall). This difference in the QMI performance for the daily analysis has its root in the higher level of recovery in the number of PT queries on Fridays and Saturdays, which contrasts with the patterns recorded by ridership and HMI, which revealed higher recoveries on Saturdays and Sundays (See **Figure C-2**).

Overall consistency: Strong evidence was found supporting a better performance of HMI relative to QMI. HMI showed a lower and more consistent mean distance with the changes reported by ridership data across the entire study period and a higher capability to replicate the direction of ridership change (between 10 and 20 percentage points more accurate). Additionally, the difference QMI-RRC presented five times the deviation observed between HMI-RRC. All these findings may imply that indices based on PT queries would be more prone to generate higher deviation and less accuracy in replicating ridership changes than GPS-based indices, particularly if extended periods are considered.

Different degrees of similarity were observed between the values of HMI and RRC among the case studies, with Sydney and London being the two cities where the highest similarities were found. We hypothesize that the definition of bus stop areas, fare evasion, coverage of PT services integrated into the AFC system and the variation in the PT infrastructure across the study period may have influenced how well HMI mimicked RRC. For instance, in the cases of London and Sydney, having well-established bus stop areas may have increased HMI's accuracy in accounting for changes in PT usage. Similarly, lower fare evasion and higher coverage of PT services in these two cities may have facilitated that ridership data reproduced the actual changes in the entire PT network. In contrast, for cities where only partial ridership was available (i.e. not all PT modes), the observed differences were higher (e.g. the Bogota case) or the differences observed followed different trends compared with other cases (e.g. Hong Kong). Since the characteristics and their effects discussed here remain speculative, further supplementary data collection efforts should be made to establish ground truth associations.

The overestimation in the QMI compared with the recovery in the actual ridership was observed for most of the cities analysed from April 2021, in moments when mobility restrictions were being eased. The reasons for this overestimation were likely the addition of the PT queries made by the new Apple Map app's users and the changes in the users' use behaviour of the Apple Map app. In particular, in this period users may have had a greater need for information on changes made to PT frequencies and services, which may have elevated the number of PT queries. These circumstances may have caused the increase observed in the QMI values immediately after the lifting of travel restrictions since this index was estimated considering a pre-COVID-19 baseline (which implicitly considers a pre-COVID-19 number of users and PT query behaviour). Hence, addressing the natural increase in the penetration of certain technology on which a QMI may be based, as well as the changes in the trend, may be relevant for future practical applications based on query data. This would improve the reliability of query indices for mid- and long-term analyses, especially when fixed baseline periods are considered. Conversely to the QMI, the HMI did not show evidence of an increasing overestimation trend over time. It is speculated that the consideration of daily profiles for users, the inclusion of bounds on how much each unique location history user could contribute to each of the seven place categories and the utilisation of scaling factors to improve the accuracy of its metrics over time (Aktay et al., 2020; Sulyok & Walker, 2020) may have helped to normalise the HMI over time. Contrasting to the provider of the QMI, the HMI also may have benefited from the broader penetration of Google's extensive suite of apps and services among smartphones, which are widely used in Android and iOS. This may have also helped to prevent observing a substantial number of new users that could have affected the index as occurred with the QMI index.

Although both the HMI and QMI were accessible in numerous countries, several limitations regarding their availability should be noted. The HMI of Google was available in 130 countries and their respective sub-regions. In comparison, Apple only covers 60 countries with a more restricted number of sub-regions, primarily focusing on major cities or capitals. Additionally, while Apple's mobility indices include driving and walking alongside transit, the transit data was often missing in many countries. This issue has been noted in cities across India, Thailand, Poland, South Africa, and Chile, among others. The absence or incompleteness of this data may be attributed to the lower adoption of Apple Maps and the limited penetration of Apple smartphones in those places. Overall, geographical areas with less coverage from both Google and Apple mobility indices include many African nations, Central Asia, and Middle Eastern countries. Consequently, these limitations hinder the use of AMIs as a proxy for ridership in regions with low smartphone penetration, many of which are associated with developing countries. However, it is reasonable to anticipate that smartphone usage may increase in the future, potentially expanding access to AMIs in these areas. Furthermore, the availability of AMIs tended to favour larger cities over smaller ones, a trend that was even more pronounced for the Apple Index. This presents another challenge in accurately measuring AMIs for smaller regions and towns. As it stands, the findings from this study primarily reflect larger cities and overlook many geographical regions due to data limitations. Additional research is required to address these shortcomings and validate AMIs in a broader context.

Overall, two directions for potential uses of AMIs were identified: (a) providing a complementary characterisation of ridership changes and (b) providing supplementary information on the quality of PT services. Related to (a), in cities that do not have access to AFC systems, AMIs may play a key role in the analysis of PT systems, helping provide a refined characterisation of mobility trends to face global long-term events such as economic crises, pandemics/epidemics and conflicts, and local short-term events such as natural disasters, social unrest and transport supply disruptions. Such a characterisation is currently unavailable in these contexts, as existing traditional methods rely on information gathered by surveys, which provide restricted insights from small sample sizes and partial coverage of the consequences of the event (temporally and spatially). This contrasts with the capabilities of AMIs, which have the potential to provide continuous monitoring of the mobility over a region, registering the impacts of unanticipated events on PT demand and its resilience. In relation to cities that already have AFC systems, as we demonstrated in this study, AMIs may be useful when ridership data from ticketing is missing or of doubtful quality, such as in the cases of ticket-free riding days or when there are special periods where evasion is higher. In this regard, AMIs may offer a more far-reaching alternative to face this challenge than current methods based on manual passenger counting, motion and weight sensors, and CCTV cameras.

For the second category (b), the same raw ICT data used to estimate AMIs may be implemented to retrieve supplementary information on the quality of PT services. For example, GPS time on PT hubs could be analysed to study the time spent by owners of phone devices waiting for a PT service. This practical application has the potential to overcome the limitations of existing methods associated with travel surveys by providing a more dynamic, continuous and spatially richer characterisation of waiting times in PT systems. Regarding indices based on PT queries, there is potential in harnessing the dynamic fluctuations of information requested by travellers. For instance, an app query-based index may eventually be used to represent users' perceived level of reliability of the PT supply. This may help PT authorities take action regarding users' PT information needs. An atypical number of requests between specific O-D could be used to activate an immediate response from PT operators. The same data set could reveal whether there are PT service disruptions that could affect frequencies. PT query data may present advantages in identifying PT disruption compared with other novel approaches based on data from social media (Chan & Schofer, 2014) since PT query data may be easily analysed based on variations in the query volumes. Interestingly, both data sources (PT query and social media platforms) can eventually be employed jointly to crosscheck information related to PT service disruption. In brief, the highest potential of AMIs is either their complementary role with existing smart card data or the provision of supplementary information on the quality of PT services.

The findings of this work indicate that AMIs based on data collected by smartphone apps have the potential to provide a reasonable proxy for the aggregate level shift in public transport (PT), particularly those that retrieve GPS traces, which also have the potential to provide supplementary information for PT. Nonetheless, many aspects of AMIs still need to be addressed in the future. The influence of the increasing number of users needs to be clarified, as well as the penetration rate needed to obtain reliable proxies. Additionally, the existing literature will greatly benefit from more transparency in how future AMIs are estimated. Ethical and privacy concerns are also elements that must be considered, as these data sets may reveal private user information and/or expose identifiable mobility traces. With a proper penetration rate, a ridership characterisation at a neighbourhood or more disaggregate level (e.g. at the level of PT hubs) may be available. These data would also allow observations to be made at a high granular temporal resolution, complementing the spatial heterogeneity in such data, eventually providing a rich representation of PT demand changes across the urban grid. To get to this stage, disaggregate data from ICT companies and App providers related to GPS traces and PT queries would need to be available (considering both temporal and spatial information). The decision of the private sector to make available these data may be motivated by the development of potential applications for the public transport sector. An assessment of the quality of these disaggregated data should be first conducted considering the desired spatial aggregation level (e.g. neighbourhood, census zone or PT hub). Such analyses should rely on a validation process that assesses the match between AMIs and ridership data at the chosen disaggregate level to investigate AMIs' data appropriateness. Special attention should be paid to identifying characteristics of the disaggregate zones that may explain the capability of the AMI to mimic ridership across the city (e.g. availability of PT infrastructure, PT demand characteristics). This analysis would allow the possibility to improve reports on particular zones, increasing the reliability of AMIs to represent the changes of PT demand across the city.

Considering the current and future urban challenges, the importance of mobility data availability transcends the COVID-19 pandemic. With that in mind, the main contribution of this work is having proved that AMIs based on a regular smartphone use may be used to generate a reasonable approximation of the actual aggregate PT demand changes. The results of this paper support the need for replacing discontinued AMIs provided during the COVID-19 pandemic by proposing new AMIs based on similar data sets. For instance, it has been recently demonstrated that it is possible to replicate big tech companies' AMIs using GPS traces collected by an emergency smartphone alert app (Finazzi, 2023). Regarding the level of PT queries, these data are currently collected by many private companies and PT operators that run PT trip planners locally or globally. Additionally, future research should focus not only on validating new proxies for PT demand based on data collected by mobile phone apps, but also on comprehensively integrating these emerging datasets with traditional ones.

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Chapter 6
Discussion and conclusions

6.1 Summary

The study of public transport demand amid disruptive events is more timely than ever, considering the current and future urban challenges, such as climate change, social movements, terrorist attacks and pandemics. The outcome of this thesis contributes in this direction, expanding the understanding of public transport demand amid disruptive events by addressing key research gaps in previous literature. It is demonstrated in this research that passengers' adaptations are more complex than the current 'trip reduction' approach adopted in the literature. Moreover, the role of individual-level factors is disclosed, revealing significant equity issues; this finding suggests that, on disruptive events, public transport agencies and operators should not overlook the needs of the more vulnerable population segments. This research also shows strong evidence supporting the use of passive data sources such as smart card data and emerging aggregated mobility indices to analyse public transport demand change amid disruptive events. Overall, the findings generated in this thesis improve the understanding of how passengers adapt their mobility patterns during external disruptions and demonstrate the crucial role that passive data can play in that process. Next, it is presented how each objective proposed in the Introduction Chapter was addressed. **Table 6-1** is presented to easily cross-reference the linkages between research gaps (RG), objectives (O), chapters and main contributions (C). The chapter ends with an outlook for future research venues.

Table 6-1. Association between research gaps (RG), objectives (O), chapters and main contributions (C).

Research Gap (RG)	**O-1** **Chapter 2** *Meta-analysis*	**O-2** **Chapter 3** *Mobility profiles*	**O-3** **Chapter 4** *Trip scheduling*	**O-4** **Chapter 5** *AMIs*
RG-1		C.1	C.1	
RG-2		C.2	C.2	
RG-3	C.3			
RG-4				C.4

6.2 Revisiting the research objectives

The following section reviews the four research objectives mentioned in Section 1.3 to emphasize the progress made toward achieving them.

O-1 To compile global evidence of how individual-level factors affect public transport usage of passengers during a disruptive event (addressing RG-3).

Objective 1 was achieved in Chapter 2 by conducting a systematic review that identified 36 studies that statistically assessed the contribution of individual-level factors to passengers' decision to keep using public transport during the COVID-19 pandemic. Characteristics of these studies, including their objectives, locations, dates, types of data, sample sizes, dependent variables, individual-level factors, and modelling methods, were collected and organised in a consistent format for comparison. The systematic review identified a total of 15 different individual-level factors: demographics (gender, age, race and ethnicity, education, children and household size), socioeconomic status (income, car availability, teleworking possibilities, and full-time employment), perceived importance to the COVID-19 risk and mitigation strategies, healthcare needs (disability and poor health) and transport-oriented attributes (pre-COVID frequent public transport user, travel distance, and public transport physical accessibility). The direction of the association between these factors and the reduction in public transport usage during the COVID-19 pandemic was examined by merging the empirical evidence of those studies. The analysis helped recognise which individual-level factors presented higher consistency in terms of their effect directions and which had more ambiguous associations. Pooled effect sizes were then calculated through meta-analyses conducted on each of the 15 individual-level factors using random-effect models. To conduct the meta-analyses, 16 comparable studies that considered logistic regression models for their research were selected. The results of the meta-analysis stage were the pooled effect size and direction of the 15 individual-level factors and their statistical significance. The analysis ended with a subgroup examination that determined whether control variables such as geographical region and stage of the pandemic could explain part of the heterogeneity found in some associations.

O-2 To model profiles of passengers based on the recovery in their public transport usage amid a disruptive event employing smart card data (addressing RG-1 and RG-2).

This objective was met in Chapter 3. Chapter 3 aimed to identify and model profiles of passengers based on their public transport usage recovery after a long-term lockdown in Santiago, Chile, during the early stage of the COVID-19 pandemic in 2020. Seven indicators were calculated using information from smart card data records. The indicators measured the intrapersonal variability of passengers' public transport usage between the reopening phase and the pre-pandemic period. These included variation of total weekday trips, trip segments per trip, bus usage, time of the first transaction and three trip similarity indices: day travelled sequence, a temporal similarity index (TSI), and boarding location similarity index (LSI) (Egu & Bonnel, 2020). The K-means clustering algorithm was used to identify the mobility profiles by splitting passengers into classes with more homogenous public transport recovery based on the seven mentioned indicators. Results revealed a heterogeneous recovery of public transport usage among passengers, classifying them into two recognisable classes: those who mainly returned to their pre-pandemic patterns and those who adapted their mobility patterns. A complementary stage deals with smart card data limitations regarding the missing sociodemographic characteristics of cardholders. In particular, to retrieve aggregated level socioeconomic characteristics from Census data, a method to predict the home locations of cardholders using the trip records of smart card data was developed. After this step, the relationships between cardholders' associated characteristics (e.g. travel history, transit card type, demographic characteristics of their residential area) with the membership to the mobility profiles found were investigated. In this analysis, variables such as travel history during the lockdown and the pre-pandemic (e.g. number of weekday trips, number of trips on weekends, days travelled and average travel time per trip), transit card type (which allowed the identification of senior and adult cardholders) and aggregated sociodemographic characteristics of the residential location of the travellers (share of migrants, university level, occupation) were considered. Thus, the class membership of each cardholder was studied using the categorical label assigned to each cardholder as the dependent variable and the cardholders' associated characteristics as the explanatory ones. Gradient Boosting Decision Tree and logistic regression models were employed for this task. As a result, the contribution of the variables considered to explain cardholders' class membership was assessed, shedding light on the most relevant characteristics associated with each mobility profile.

O-3 To model trip scheduling decisions of bus commuters during several episodes affected by disruptive events employing smart card data (addressing RG-1 and RG-2).

Objective 3 was achieved in Chapter 3 by investigating the differences in the trip scheduling decisions of bus commuters across multiple episodes influenced at different degrees by two disruptive events. In particular, it was hypothesised that situational contexts affect passengers' departure time by changing their sensitivity to time-varying attributes such as travel time and schedule delay (i.e. the offset between their actual arrival time and their preferred arrival time). Four characteristic episodes that represent before-disruptions (EP1), post-social unrest (EP2), post-COVID-19 outbreak, and after-disruptions (EP4) periods for Santiago, Chile's capital, were investigated. Smart card data and GPS time stamps of buses for Santiago's bus system were available for analysis. Departure time choice models were estimated for each episode, allowing to assess the changes in the marginal utilities of in-vehicle travel time and schedule delay, and the time valuation of schedule delay (TVSD). In addition, to account for potential differences in the trip scheduling preferences between distinctive passenger groups, bus commuters were segmented into two categories by considering passengers' bus frequency use. Thus, for each episode, in addition to the model specification for the unsegmented bus commuters, a second specification that considers the proposed bus commuters' segmentation was also considered. From a methodological perspective, Chapter 3 deals with the lack of crucial attributes in smart card data, such as the passengers' preferred arrival time (PAT), that so far has restricted the implementation of this data source in DTCMs. The framework adopted to infer PAT for smart card data assumes that the PAT varies randomly across commuters following a statistical distribution, whose parameters are obtained during the model estimation using mixed multinomial logit models. The results confirmed the research hypothesis, finding evidence of multi-temporal differences in the PATs of bus commuters as well as in their TVSD during the disruptive episodes.

O-4 To assess the potential of aggregated mobility indices based on data generated from the everyday use of smartphones to characterise public transport ridership changes in a context of high mobility disturbances (addressing RG-4).

Chapter 5 investigates the potential of employing aggregated mobility indices (AMIs), an emerging data source, as a proxy for aggregate public transport demand change. This was achieved by benchmarking two AMIs shared globally by Google and Apple during a period of major mobility disruptions that occurred between 2020 and 2022, with monthly and daily ridership from 12 cities worldwide. The benchmarking between AMIs and ridership change was conducted by applying metrics that follow a time series approach, including the mean Euclidean distance, the cosine distance, a trend similarity index, the Dynamic Time Warping distance and the Granger Causality test. A criterion to standardise the changes in mobility was established to deal with the differences between how AMIs were reported and the absolute nature of the ridership data (i.e., the total number of transactions). The role of AMIs in complementing ridership data when there are difficulties in capturing the actual demand was also explored by considering three situational contexts: a free bus period in London, partial ridership data in New York and a high mobility demand day for Santiago. The analysis of these cases employed Autoregressive Integrated Moving Average (ARIMA) models to calibrate the relationship between the recorded ridership data and the AMIs. The benchmark findings revealed a notable alignment between the trends in ridership data and the AMI shared by Google based on human mobility. Moreover, the analysis of the three situational contexts confirmed the potential of leveraging AMIs to complement existing data sources for the analysis of ridership changes during high mobility disturbances.

6.3 Contributions to knowledge

This section summarises the four main original contributions made in this thesis to the transport field.

C-1 Extending the scope of modelling passengers' behavioural responses amid disruptive events.

This thesis expands the traditional scope of analysis of passengers' behavioural responses amid disruptive events by examining passengers' mobility profiles and departure time choices. Previous research has adopted a 'trip-reduction' perspective, limiting the examination to either trip frequency reduction or the shift to another alternative mode only (Shires et al., 2018; Rahimi et al., 2020; Das et al., 2021). The results of this research support that behavioural responses are much richer than what is traditionally considered in previous research. The specific contributions can be categorised into two categories: response variables and response heterogeneity among passengers, which are detailed below.

C-1.1 *Extending the examination of passengers' responses during disruptive events by studying passengers' mobility profiles and departure time choices.* By allowing the integration of several behavioural adaptations through the identification of passenger profiles, this work extends the traditional 'trip-reduction' perspective adopted in the literature. In particular, mobility profiles based on passengers' public transport usage recovery following an extended disruption were examined by simultaneously considering seven mobility indicators: total weekday trips, trip segments per trip, bus usage, time of the first transaction and three similarity indices: day sequence, a temporal similarity index (TSI), and boarding location similarity index (LSI) (Egu & Bonnel, 2020). In addition, this research provides the only available modelling of passengers' departure time choices during several episodes affected by disruptions. The analysis adds new evidence on the process underlying passengers' trip scheduling decisions amid disruptive events by finding proof of the changes in passengers' sensitivity to schedule delay and arrival time preferences.

C-1.2 *Providing insights about the relations between distinctive behavioural responses adopted during disruptive events and passenger segments*. The role of several passenger segments was studied by modelling passengers' membership to each mobility profile found and bus commuters' trip timing decisions. Regarding the mobility profiles approach, the results contribute to the literature by demonstrating that more vulnerable passenger segments (elderly, migrants and those with low educational levels) are more likely to recover their pre-disruption mobility patterns following an extended disruption than less vulnerable groups. In addition, it was also demonstrated that distinct passenger groups have different trip scheduling decisions. In particular, the arrival time preferences of recurrent bus commuters were found to be more inflexible to change when facing disruptive events than occasional bus commuters. Besides, the same group showed being more prepared to travel when travel time is higher, allowing them to arrive nearer their PAT than the occasional group. Overall, these findings provide new insights into the relationships between passenger segments and distinctive behavioural adaptations.

C-2 Leveraging smart card data for modelling passengers' behavioural responses amid disruptive events while addressing missing attribute limitations.

Despite the broad applications of smart card data in the literature, their use for analysing passengers' behavioural responses amid disruptive events has been minimal. In this regard, this research demonstrates that smart card data can play a crucial role in that characterisation. This is achieved by employing smart cards in disaggregate-level models while addressing some of their missing attribute limitations, such as the missing of passengers' preferences for arrival times and sociodemographic characteristics. This research contributed to the literature in this regard by broadening the application of smart card data in the modelling of public transport demand by addressing research gaps related to data imputation. In particular:

C-2.1 *Employing smart card data for the analysis of disaggregate passengers' travel behaviour.* Currently, most of the existing disaggregate evidence regarding the characterisation of the pre-, during, and post-disruption of passengers' travel adaptations rely on survey-based data, either SP data (based on hypothetical scenarios) or RP data (based on a retrospective approach that relies on respondents’ memories). The advantages of smart card data are then leveraged in this work, extending the perspective of data sources available for analysing passengers’ behavioural responses amid disruptive events.

C-2.2 *Establishing a framework to employ smart card data to estimate departure time choice models*. The study reported here is the first to employ smart card data to estimate departure time choice models. The proposed methodology addresses both challenges of smart card data for this task, imputing bus in-vehicle travel times for the unchosen time intervals and estimating passengers’ preferred arrival time (PAT). Regarding the in-vehicle travel times for the unchosen time alternatives, the methodology proposed a data fusion approach, enriching the trip samples with a GPS bus location dataset. On the other hand, the PATs are calculated by adapting the methodology proposed by Bwambale et al. (2019) to smart card data. The approach was validated by obtaining plausible marginal utilities for travel time and schedule delay, reasonable goodness of fit and valuations of the trade-off between travel time and schedule delay (TVSD) in the range of previous studies.

C-2.3 *Proposing a method to link socioeconomic characteristics spatially aggregated with cardholders by predicting their home locations.* The proposed method uses the DBSCAN algorithm (Ester et al., 1996) applied to the spatial coordinates of each cardholder's first daily boarding transactions to obtain the home location of cardholders. This approach overcomes the limitations of previous methods using residential location for smart card data (Amaya et al., 2018) by explicitly recognising the existence of outliers. Socio-demographics from Census data can then be retrieved at an aggregated level by linking the predicted home location with the desired spatial aggregation of Census data. The aggregate sociodemographic variables can then be estimated as a ratio between a target population and the total population for a particular Census zone. With this method, characteristics related to educational level, employment and migrants can be spatially retrieved and analysed.

C-3 Elucidating how individual-level factors influence public transport usage during a disruptive event.

To the author’s knowledge, the research conducted in Chapter 2 regarding the COVID-19 pandemic provides the only available synthesis of existing literature regarding how individual-level factors affect public transport usage during a disruptive event. The specific contributions can be summarised as:

C-3.1 *Determining the most influential individual-level factors regarding their effect size.* This research presented the only available systematic comparison of the effect sizes of individual-level factors on public transport usage during a disruptive event. The results revealed substantial differences in the effect sizes among the factors analysed. Factors such as car availability, teleworking and high educational level increased the odds of reducing public transport trips by as much as three times. Conversely, a more modest effect on public transport usage (less than 30%) was observed for the other individual-level factors, including COVID-19 risk perception. These findings strongly support the need to not only assess the effect directions in the transport domain but also compare effect sizes, as Parady and Axhausen (2023) recently discussed.

C-3.2 *Revealing heterogeneous levels of consistency in the effect direction of individual-level factors.* Two main groups of individual-level factors were detected: a) factors that showed consistent positive associations with the reduction of public transport usage amid the studied disruptive event, such as car availability, teleworking, high-level income, high educational level and COVID-19 risk perception, and b) factors that showed ambiguous effect directions, such as gender, age, race and ethnicity, and employment. It was also established by doing a subgroup analysis in the meta-analyses that cultural and social differences associated with the location where a study is conducted may explain part of the heterogeneity found in b).

C-3.3 *Verifying the presence of inequality.* The findings shed light on the population segments that continued using public transport modes during the COVID-19 event: women and those with a low educational level, low income, with healthcare needs, without the possibility of teleworking, who travel longer distances and who have no car availability. These findings offer key insights to public transport agencies and operators into understanding specific passenger groups' restrictions and their transport needs during disruptive events (DeWeese et al., 2020).

C-4 Demonstrating the capabilities of emerging data sources to be used in the analysis of public transport ridership changes.

This work reports the only available rigorous assessment of aggregated mobility indices (AMIs), an emerging data source based on regular smartphone use, to be used as a proxy for actual ridership changes. The outcomes of this study are particularly relevant for cities of developing countries, which typically have limited data to analyse ridership levels, and AMIs may offer an attractive alternative. The contributions to the knowledge in this regard are:

C-4.1 *Proving that AMIs can reasonably approximate actual ridership changes*. AMIs correctly captured the main changes in ridership levels and showed high accuracy in replicating the change direction. This supports potential use in cities that do not have access to smart card data. There, AMIs may play a key role in the analysis of aggregate-level public transport demand, helping provide a refined characterisation of mobility trends to face global long-term events such as economic crises, pandemics/epidemics and conflicts, and local short-term events such as natural disasters, social unrest and transport supply disruptions.

C-4.2 *Demonstrating that AMIs can complement smart card data to retrieve actual ridership changes*. These findings highlight the relevance of AMIs even in cities that have already adopted smart cards and digital transactions schemes, particularly when limitations on the fare collection system affect the quality of the information gathered. For example, this may occur when ticketing is missing or incomplete, such as on ticket-free riding days or when there are special periods where fare evasion is potentially higher. Other situations could be when smart cards only cover a limited number of the public transport modes present in a city (e.g. metro rails only), capturing ridership data only for those modes (Arellana et al., 2020; Wang & Noland, 2021). In these cases, even cities with smart card data could benefit from AMIs to better characterise aggregate ridership changes.

6.4 Future research directions

As the research conducted in this thesis focused on a period affected primarily by the COVID-19 pandemic, an evident next step is to undertake additional applications on more diverse disruptive events such as natural disasters, social movements, and operation failure, among others. Moreover, despite Chapters 2 and 5 incorporating global evidence, Chapters 3 and 4 use the same case study to test the applications of smart card data. In this regard, there is a potential to test the methodologies developed here in other case studies where smart card data are also available. Next, more specific avenues for future research are described in detail.

i. Travel behavioural responses of passengers

Considering the progress made in Chapters 3 and 4, future research avenues regarding travel behaviour responses of passengers during disruptive events may consider: a) extending the scope in the analysis of trip scheduling decisions and b) conducting a joint examination of travel responses. Regarding a), as little empirical evidence regarding the investigation of departure time choices on public transport commuting is available in the literature (Habib, 2021), the contribution made in this work offers the potential to extend the analysis to other public transport modes (metro, rail, etc.) and increase the time-varying attributes considered (e.g. travel time uncertainty, in-vehicle occupancy, monetary cost, the habits of travelling at a particular time of the day, etc.). Besides, it would be interesting to consider a broader set of individual-level factors to generate a more comprehensive understanding of the trip-timing decision process. In this regard, a potential avenue to expand the study of the departure time choice of passengers could be adopting a latent class specification (Peer et al., 2016). Related to b), conducting a joint examination of travel responses is another way to recognise the complex set of responses that passengers may adopt during disruptive scenarios. For example, it would be possible to jointly model the shift from public transport to an alternative mode in combination with the departure time choice (Ma et al., 2018). This would shed light on the potential interaction between the two types of responses, which has yet to be addressed in the context of disruptive events.

ii. Challenges in smart card data

Considering the contributions made in Chapters 3 and 4 regarding the use of smart cards in disaggregate-level modelling amid disruptive events, future research avenues may consider a) linking the travel history of new cards with old cards, b) conducting a cross-mode analysis using passive data and c) improving the processes to infer sociodemographic characteristics for smart card data. Related to a), a challenge of smart card data, particularly in systems whose smart cards are not customised, is the impossibility of combining travel history recorded on old and new cards (i.e. when cardholders renew their card, the track of the cardholder is lost). This is particularly problematic when the aim is to track the travel behaviour of passengers over long periods (more than one year), as for that period, it is likely that card expirations or losses happen, limiting the observation of travel behaviours over time. Therefore, a methodology to associate a cardholder’s new ID smart card with their old one may generate a better representation of the dynamics in passengers’ decision-making process amid disruptive events across long periods. With respect to b), a cross-mode impact analysis perspective is another avenue for future research of smart card data to enhance the understanding of passengers’ behaviour amid disruptive events. This can be done by simultaneously considering several passive data sources in a seamless data integration analysis between smart card data records, ride-sourcing, bike-share system and phone data, to name a few. In this way, it would be possible to achieve a better understanding of the interaction between alternative modes during disruptive events which have only been partially addressed (Yang et al., 2022; Borowski et al., 2023). Finally, regarding c), future research should explore new ways to infer the sociodemographic characteristics of cardholders. Although this work demonstrates the advantages of exploring the individual travel behaviour of public transport users using smart card data, it highlights the need to generate a richer dataset regarding the presence of individual-level factors. If suitable data is available, methods to combine traditional surveys with passive data will be an interesting direction for future research (Kusakabe & Asakura, 2014).

iii. Influence of individual-level factors

Possible extensions to the work developed in Chapter 2 are a) examining more generalised types of long-term disruptive events and b) providing a systematic review considering a different dependent variable. Related to a), an interesting research avenue is examining global empirical evidence of how individual-level factors have affected passengers' public transport usage for a wide range of disruptive events. These efforts would help benchmark the conclusion reported in this research related to the COVID-19 pandemic with more generalised events. So far, preliminary evidence suggests that the role of some individual-level factors found in this research would be similar to the one reported for other events. For example, the role of car availability and teleworking in the decision to stop using public transport reported in this research is similar to the one reported by Kontou et al. (2017) regarding the effect of Hurricane Sandy in the US in 2012. With respect to b), future research on this topic may also consider re-evaluating the choice of the dependent variable to be meta-analysed. For example, an alternative perspective to the one considered in Chapter 2 may be meta-analysing demand elasticities (Holmgren, 2007). This approach would also offer an explicit interpretation of the heterogeneity observed between study cases and public transport demand.

iv. Emerging data sources

The benchmarking between AMIs, an emerging data source based on regular smartphone use, and ridership data presented in Chapter 5 provides strong evidence of the capabilities of AMIs to be employed as a proxy for aggregate public transport demand. In this regard, three future research avenues were identified. First, the analysis conducted in this research does not examine the underlying factors behind the different degrees of similarity observed between the values provided by the AMIs and actual ridership data among the cities analysed. In this regard, the role of city characteristics such as the location of bus stops, fare evasion levels, coverage of services integrated into the AFC system, and the variation in the transport infrastructure across the study period could shed light on this. A detailed analysis of these aspects would help calibrate the AMIs for cities with no ridership data to compare. Second, the results of this paper support the need to replace discontinued

AMIs provided during the COVID-19 pandemic by proposing new AMIs based on similar data sets. For instance, it has been demonstrated that it is possible to replicate big tech companies' AMIs using GPS traces collected by an emergency smartphone alert app (Finazzi, 2023). Finally, future research should not only validate new proxies for ridership based on data collected by mobile phone apps, but also comprehensively integrate these emerging datasets with more traditional ones or add new information. For example, the GPS of phones around public transport hubs could help study the time passengers wait for a bus or train service.

6.5 Concluding remarks

This thesis has generated new empirical evidence and methodologies that enhance the understanding of public transport demand change amid disruptive events. By highlighting the importance of analysing several data sources, this thesis offers a unique approach to dealing with existing research gaps. At the same time, new avenues for future research are opening in this work related to the use of passive data sources, such as smart card data in the modelling of disaggregate behavioural responses of passengers, and more emerging data sources, such as the aggregate mobility indices in the modelling of public transport ridership. In this regard, more studies are necessary to continue leveraging these data's advantages and make the proposed methodologies more widely applicable. As the shocks produced by disruptive events continuously contribute to reshaping travellers' consideration of public transport, these research avenues are crucial to secure the availability, trust and readiness of suitable data sources in the future to support policy initiatives based on updated literature. In addition, despite the progress made in this thesis regarding the role of individual-level factors in passengers' behavioural responses, additional research is required to gain better insights into a broader set of disruptions. Addressing all these avenues for future research would continue the effort made in this thesis to shed light on the changes in public transport demand amid disruptive events. The joint effort in this regard has the potential to achieve a better understanding of public transport demand dynamics, particularly regarding current and future urban challenges, where public transport plays a crucial role.

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Appendix A

Table A-1. Summary of studies that characterised the changes in PT demand during the COVID-19 pandemic at an aggregate level.

Authors	Location/ Data source	Base ridership	Pandemic Date/ Study period	Dependent variable	Mode/ level of spatial aggregation	Model/ general model category	Influential factors	Drop in ridership: worst/ end study period
Teixeira and Lopes (2020)	New York, USA/ Smart card validations	Mar 2019 and Feb 2020	Mar 2020/ Mar 2019, Feb and Mar 2020	Daily ridership ratio between subway and bike sharing.	Subway, bike sharing system/ Metropolitan area	Ordinary least squares (OLS)/ CNT	COVID-19 situation	90%/ 90%
Jenelius and Cebecauer (2020)	Three regions in Sweden/ Digital ticket system, automatic passenger counting & paper tickets	The nearest day (weekday or holiday) in 2019	Feb-May 2020/ Feb-May 2019 & Feb-May 2020	Relative change on daily trip ridership	Several PT modes/ Metropolitan area	Descriptive analysis	Ticket types, active cards, PT mode	40%, 50%, 65%/ 35%, 45%, 60%
Qi et al. (2021)	20 Metropolitan areas in the US/ Ticket validation data	Feb 2019 to Jan 2020	Feb 2020 to Jan 2021/ Feb 2019 to Jan 2021	Monthly reduction in ridership	Bus and light rail/ Several metropolitan area	Random effects panel data model/ CNT©	COVID-19 situation, @sociodemographics	60% to 90%/ 40% to 80%
Chang et al. (2021)	Taipei, Taiwan/ Smart card validations	Jan-Mar 2017, 2018 & 2019	Jan-Mar 2020/ Jan-Mar 2017-2020	Daily ridership	Metro/ Station-level	Difference-in-difference (DiD)/ CNT	COVID-19 situation, @socio-demographics, activity and transport supply	48%/ na
Wang and Noland (2021)	New York, U.S./ Smart card validations	Jan-Sep 2019	Jan-Sep 2020/ Jan-Sep 2019-2020	Daily ridership (log)	Subway/ Metropolitan area	Prais-Winsten model/ CNT	COVID-19 situation	90%/ 70%

Authors	Location/ Data source	Base ridership	Pandemic Date/ Study period	Dependent variable	Mode/ level of spatial aggregation	Model/ general model category	Influential factors	Drop in ridership: worst/ end study period
Mützel and Scheiner (2022)	Taipei, Taiwan/ Smart card validations	Jan-Mar 2019	Jan-Mar 2020/ Jan-Mar 2019 & 2020	Station-to-Station metro ridership	Metro/ Station-level	Descriptive analysis	Weekday & day period	25%/ <15%
Padmakumar and Patil (2022)	Six cities, India/ Mobility service providers' indices	Apple Mobility Trend & Google Mobility Report dates	Mar-Sep 2020/ Mar-Sep 2020	Daily change in PT mobility index	Proxy PT/ City-level	Generalized linear mixed-effects (GLME) model/ CNT©	@sociodemographics	90%/ 30%
Fernández Pozo et al. (2022)	Community of Madrid, Spain/ Smart card validations	Avg. daily ridership 10 Feb to 8 Mar 2020	Mar-Sep 2020/ Jan-Sep 2020	Weekly relative change in ridership	PT modes/ System-level	Descriptive analysis	PT mode, ticket types, active card	95%/ 50%
Xiao et al. (2022)	Salt Lake County, U.S./ Station boarding validations	Predicted monthly ridership during COVID-19 pandemic	Mar 2020 to Jul 2021/ Jan 2017 to Jul 2021	Vulnerability as the decline in monthly ridership & resilience as the recovery of ridership	Light rail/ Station-level	Bayesian structural time series (BSTS) & decision tree/ CNT©	@sociodemographics, activity and transport system attributes	80%/ 60%
Gramsch et al. (2022)	Santiago, Chile/ Smart card validations	First two weeks of Mar 2020	Mar-Sep 2020/ Jan-Sep 2019 & Jan-Sep 2020	Ratio daily PT trips over the total population	Bus, Metro & Train/ Municipality-level	Fixed effects regression model/ CNT	COVID-19 situation, @sociodemographics	80%/ 60%
Jiang and Cai (2022)	Beijing & Shanghai, China/ Smart card validations	Avg. ridership of the same day in three	Jan 2020 to Aug 2021/	Daily relative change in metro ridership	Metro/ System-level	Generalized linear model/ CNT©	COVID-19 situation, @sociodemographics	89%, 83%/ 35%, 14%

Authors	Location/ Data source	Base ridership	Pandemic Date/ Study period	Dependent variable	Mode/ level of spatial aggregation	Model/ general model category	Influential factors	Drop in ridership: worst/ end study period
		consecutive weeks in 2019	Jan 2019 to Aug 2021					

CNT: model with a continuous dependent variable; na: information not available.

Table A-2. Data sources visited to characterise public transport (PT) demand in several cities.

PT operator	Location	Link
Los Angeles Country MTA	Los Angeles, U.S.	https://www.apta.com/
Washington Metro Area	Washington DC, U.S.	
MTA New York City Transit	New York, U.S.	
Utah Transit Authority	Utah, U.S.	
Toronto Transit Commission	Toronto, Canada	
Transmilenio (BRT)	Bogotá, Colombia	https://transmilenio.hub.arcgis.com/
Metro Taipei	Taipei, Taiwan	https://english.metro.taipei/
Transport for London	London, U.K.	https://data.london.gov.uk/
Metropolitan Mobility Network (RED)	Santiago de Chile	https://www.dtpm.cl/
MTR Hong Kong	Hong Kong	https://www.mtr.com.hk/
Transport for NSW	Sydney, Australia	https://www.transport.nsw.gov.au/

Table A-3. Details of the modelling specification of the factor COVID-19 risk perception used for the meta-analysis.

LRM	Country	N	Description	Specification	Odds ratio	Signify-cance	Std. error
El Zein et al. (2022)	FRA	1413	If health risks are not satisfactorily addressed in PT - model 1	Dummy, 1: not satisfactorily, 0: Satisfactory	1.08	NS	0.12
El Zein et al. (2022)	FRA	512	If health risks are not satisfactorily addressed in PT- model 2	Dummy, 1: not satisfactorily, 0: Satisfactory	1.32	-	0.11
Zafri et al. (2023)	BAN	804	Perceived risk of COVID-19 transmission in PT	Five-point Likert scale	1.30	-	0.11
Zafri et al. (2023)	BAN	804	Trust in preventive strategies	Five-point Likert scale	1.50	-	0.12
Liu et al. (2022)	CHN	315	Perception of the severity of COVID-19 in adolescents	Latent variable based on 5 factors measured with a	1.43	-	0.11

LRM	Country	N	Description	Specification	Odds ratio	Signify-cance	Std. error
				five-point Likert scale			
Liu et al. (2022)	CHN	315	Perception of the severity of COVID-19 in commuters	Latent variable based on 5 factors measured with a five-point Likert scale	1.33	-	0.09
Palm et al. (2021)	CAN	4710	Perception of the level of risk COVID-19 to them	Dummy, 1: high risk, 0: Otherwise	1.13	-	0.06
Soria et al. (2023)	USA	5648	Prioritize sanitization as mitigation strategy	Dummy, 1: Prioritize sanitation in PT hubs, 0: Prioritize other strategies	1.09	-	0.02
Jiao and Azimian (2021)	USA	88716	Anxiousness induced by COVID-19 or other conditions	Dummy, 1: Several days, 0: Not at all	1.85	-	0.19
Jiao and Azimian (2021)	USA	88716	Anxiousness induced by COVID-19 or other conditions	Dummy, 1: >Half days, 0: Not at all	2.17	-	0.24
Jiao and Azimian (2021)	USA	88716	Anxiousness induced by COVID-19 or other conditions	Dummy, 1: Nearly every day, 0: Not at all	2.55	-	0.28
Abdullah et al. (2020)	WW	1203	COVID-19 risk perception: include a positive correlation among, infection concern, social distance, mode cleanliness, use face-mask	Latent variable based on 5 factors measured with a five-point Likert scale	1.14	-	0.07
Rankavat et al. (2023)	IND	1884	COVID-19 risk perception: include (+) correlation of exposure to infection, importance of physical distancing, health & Hygiene	Latent variable based on 3 factors measured with a five-point Likert scale	1.34	-	0.09
Rankavat et al. (2023)	IND	1884	COVID-19 risk perception: include (+) correlation of health safety perception in PT and PM	Latent variable based on 2 factors measured with a five-point Likert scale	1.30	-	0.09
Das et al. (2021)	IND	840	Perceived importance of Hygiene/cleanliness in PT	Dummy, 1: Very important, 0: not important	2.27	-	0.4

LRM	Country	N	Description	Specification	Odds ratio	Signify-cance	Std. error
Das et al. (2021)	IND	840	Perceived importance of Hygiene/cleanliness in PT	Dummy, 1: Important, 0: not important	1.85	-	0.75
Tan and Ma (2021)	CHN	559	Perceived possibility of being infected in private car	Five-point Likert scale	1.70	-	0.20

'-': statistically significant negative effect on PT use.

Appendix B

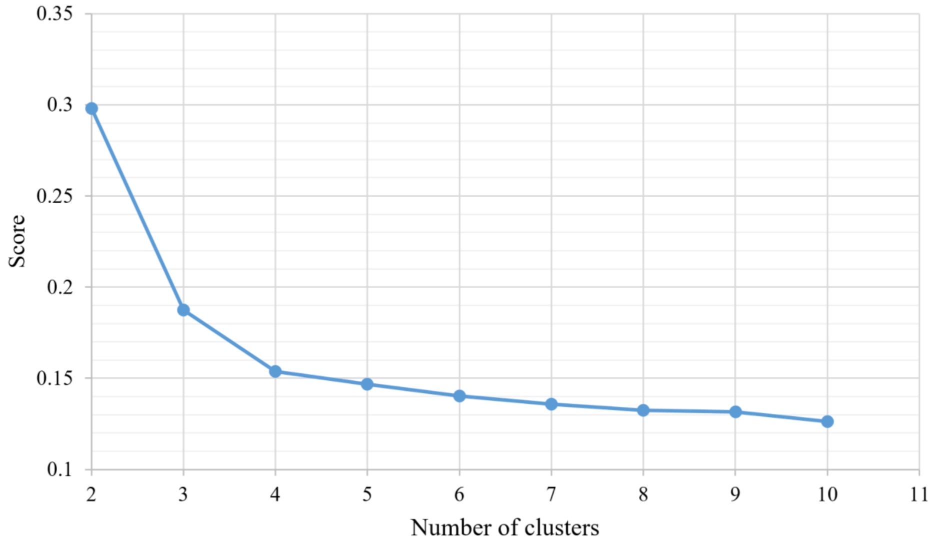

Figure B-1. Silhouette scores for the clustering analysis, indicating that the recommended optimal number of cluster is two.

Appendix C

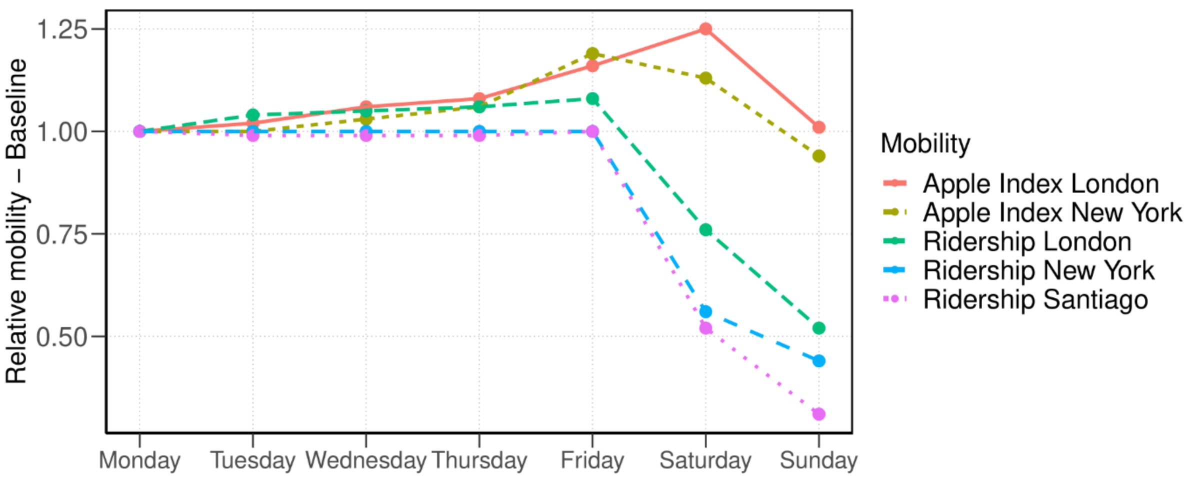

Figure C-1. Average mobility per day of the week by data set, baseline period.

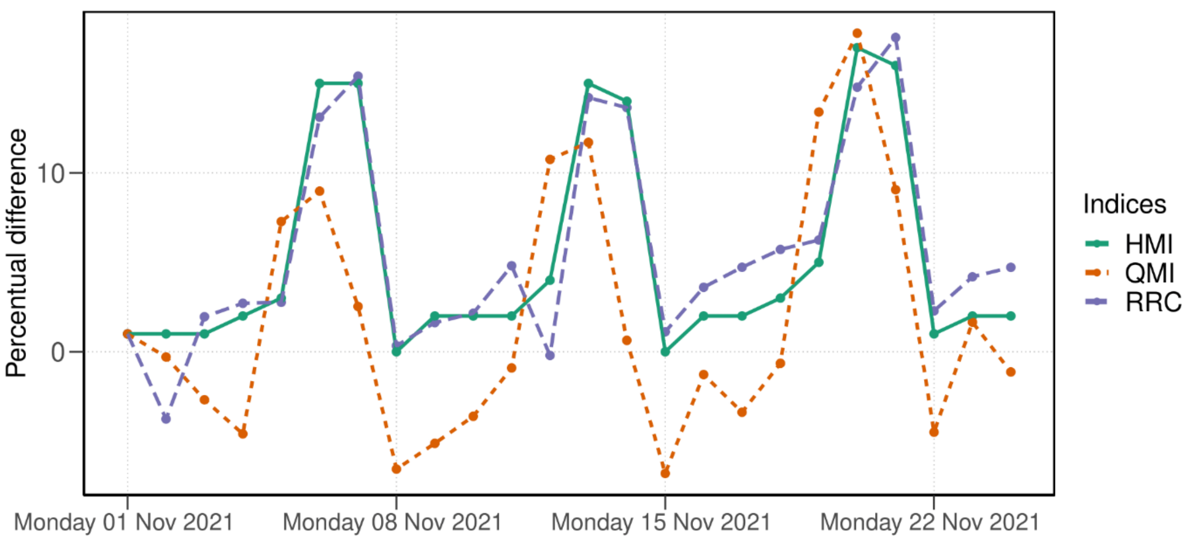

Figure C-2. Weekly periodicity pattern in by index for the London case study.

Table C-1. Monthly and daily dataset sources.

Ridership data	London	Transport for London	https://app.powerbi.com/view?r=eyJrIjoiMjZjMmQwYTktZjYxNS00MTIwLTg0ZjAtNWIwNGE0ODMzZGJhIiwidCI6IjFmYmQ2NWJmLTVkZWYtNGVlYS1hNjkyLWEwODljMjU1MzQ2YiIsImMiOjh9
	New York	MTA New York	https://data.ny.gov/Transportation/MTA-Daily-Ridership-Data-Beginning-2020/vxuj-8kew
	Santiago	DTPM	https://biblioteca.mtt.gob.cl/documento/857f8b86-fe10-4f86-aec3-65ecb746e76f
	Sidney	Transport for NSW	https://www.transport.nsw.gov.au/data-and-research/passenger-travel/train-patronage/train-patronage-monthly-figures
	Toronto	Toronto Transit Commission	https://www.apta.com/
	Bogota	Transmileno	https://storage.googleapis.com/validaciones_tmsa/ValidacionTroncal.html?
	Dallas	Dallas Area Rapid Transit	https://www.apta.com/
	Denver	Regional Trip District	https://www.apta.com/
	Salt Lake	Utah Transit Authority	https://www.apta.com/
	Chicago	Chicago Transit Authority	https://www.apta.com/
	Taipei	Metro Taipei	https://english.metro.taipei/cp.aspx?n=E6F97A6FF9935E98
	Hong Kong	MTR Hong Kong	https://www.mtr.com.hk/en/corporate/investor/patronage.php
AMIs	HMI	Google Covid-19 Community Mobility Reports	https://www.google.com/covid19/mobility/
	QI	Apple Mobility Trends	https://covid19.apple.com/mobility