Passengers’ choices in multimodal public transport systems

A study of revealed behaviour and measurement methods

Berggren, Ulrik

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ULRIK BERGGREN
FACULTY OF ENGINEERING | LUND UNIVERSITY

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The demand for public transport is increasing, both from passengers in terms of mobility needs and in terms of expectations from society as a whole. However, because public transport services are publicly financed to a significant degree, there is a need to prioritise wisely when distributing the limited resources. However, this prioritising should be based on the needs of the passengers. The findings presented in this thesis contribute to the literature regarding the preferences of public transport passenger and are based on passively recorded trip data including real trade-offs made in a network that contains multiple travel options. Key results indicate the importance of providing departure information and minimising the need for transfers or making transfer points attractive by providing auxiliary services. The thesis illustrates how new sources of mobility data may be used to enable improvements of forecasting model relevance both in terms of timeliness and geo- and demographical specificity.

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Abstract

The concept of individual choice is a fundamental aspect when explaining and anticipating behavioural interactions with, and responses to, static and dynamic travel conditions in public transport (PT) systems. However, the empirical grounding of existing models used for forecasting travel demand, which itself is a result of a multitude of individual choices, is often insufficient in terms of detail and accuracy. This thesis explores three aspects, or themes, of PT trips – waiting times, general door-to-door path preferences, with a special emphasis on access and egress trip legs, and service reliability – in order to increase knowledge about how PT passengers interact with PT systems. Using detailed spatiotemporal empirical data from a dedicated survey app and PT fare card transactions, possible cross-sectional relationships between travel conditions and waiting times are analysed, where degrees of mental effort are gauged by an information acquisition proxy. Preferences for complete door-to-door paths are examined by estimation of full path choice models. Finally, longitudinal effects of changing service reliability are analysed using a biennial panel data approach. The constituent studies conclude that there are other explanatory factors than headway that explain waiting times on first boarding stops of PT trips and that possession of knowledge of exact departure times reduces mean waiting times. However, this information factor is not evident in full path choice, where time and effort-related preferences dominate with a consistent individual preference factor. Finally, a statistically significant on-average adaption to changing service reliability is individual-specific and non-symmetrical depending on the direction of reliability change, where a relatively large portion of the affected individuals do not appear to respond to small-scale perturbations of reliability while others do, all other things being equal.

Key words Public transport; Travel behaviour; Revealed preferences; Travel survey

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To Ellen (into eternity) and Anya (into the future)

Table of Contents

Foreword

The work behind the book that you are now about to read did not start at the onset of my PhD education, but long before that. Perhaps at my internship at the public transport authority of Stockholm during the early 2000's and my first encounter with transport modelling, cost-benefit analysis, and Sverker Enström and Mats Hansson. I then, and later during the work with my master's thesis, realised the power of statistics and quantitative methodology. In addition, I realised I could combine two of my greatest interests – maps and public transport planning. However, during my subsequent transport modelling career, as a consultant with public transport providers as clients, I realised that many of the theoretical and empirical foundations behind the forecasting and simulation tools used to appraise planning schemes lacked local grounding and that the tools thus were almost regarded as black boxes by both planners and decision makers.

That was why the PhD position of an evaluation project which explicitly targeted effects from public transport measures supported by the Swedish environmental agreement grant scheme suited me perfectly. The position offered me an ultimate opportunity to explore the theoretical and empirical roots behind the tools and models I had used for more than a decade, using the demand impacts from the construction of the Lundaexpressen tramway as a point of departure. As a lucky coincidence, I came across a new surveying tool based on smartphones that most people already carry. Before that I had the ambition to use a quite traditional computer-aided pen-and-pencil on-board survey, which would not have contributed to method development of surveying in any particular sense. But using the quite novel survey approach I was able to successfully explore passengers' revealed preferences vis-à-vis a substantial portion of public transport trip phenomena. This effort included a detailed analysis of access and egress trip legs – a principal component that serves as one of the major rationales behind my detailed exploration and analysis of door-to-door trips in this thesis, also including other passenger trade-offs such as the choice of stops for boarding, alighting, and transfer. The methodological decision to apply the concept of explicit choice sets in the application of the discrete path choice modelling framework was substantially facilitated by my professional background in transport modelling.

In addition, I was offered the quite unusual opportunity, in Sweden at least, to access detailed farecard transaction data and thus follow the movement of individual cards through the public transport network in both space and time. Combining the transaction data with real-time vehicle movements I could also both generate complete trip chains and compare trip patterns across two periods, one year in between. Analysing the differences together with corresponding differences in service reliability, I could also study longitudinal responses to changes in a path choice context. However, it required a non-negligible effort to process the raw empirical data and enrich it with other data sources in order to obtain a useful point of departure for the statistical analyses reported in this thesis.

Before starting the presentation of my research, it may be worth reflecting on my intrinsic motives behind it – both those that are expressed openly in the final, reflective, part of the thesis and those of a more implicit nature related to me as a researcher and a person. The latter more fundamental motives may have been relevant both to my choice of research topic and to the methodologic approach. Almost 20 years of working with the planning and analysis of public transport as well as forecasting of passenger demand has surely taught me that there is not just one way to approach tasks involving trade-offs across possible paths of action with a common goal to improve the level of service in public transport.

Malmö in October 2021

Ulrik Berggren

Summary

Public transport is considered to be an important instrument by planning authorities of cities and regions in their efforts to accommodate sustainable and thriving communities. Appraising and forecasting passenger demand for public transport is fundamental in order to provide an attractive service and still make the best use of limited resources.

However, many of the currently existing tools and models used to forecast demand suffer from deficiencies in empirical grounding of the “true” preferences of public transport passengers due to often resource-inefficient and cumbersome surveying techniques. In addition, conventionally used survey techniques involve an inherent risk of bias through under-reporting due to the reliance on time-consuming self-reporting by survey subjects.

The aim of this doctoral thesis is to address the above-mentioned empirical issues by focusing on daily trade-offs made by public transport passengers across the different travel options that exist in regional public transport networks with multiple optional travel paths. Thus, this thesis, which consists of a cover essay, four published papers and one unpublished manuscript, presents new and modified empirical approaches that include at least a certain degree of autonomy and passiveness in the recording of trips by public transport passengers. These approaches enabled the collection of a sufficient quantity of data covering elements that are usually under-reported in travel surveys, such as access and egress trips to and from the public transport system and measures of service reliability (variability) of the public transport connections, to enable model estimation and statistical analyses.

A smartphone-based semi-passive data collection approach was applied in order to contribute to the research aim by collecting revealed trip data at a sufficiently disaggregated level to enable analysis of specific elements of door-to-door public transport trips. One way to approach the issue of whether passengers apply strategies when planning and performing their public transport journeys is to study their waiting times at the first stop of a public transport trip, and this issue is addressed in Papers 1 and 2 of this thesis. The empirical strength of the waiting time trip element, in terms of it being an indicator of “downstream” features such as headway and service reliability as well as of how different passengers strategise and prioritise, makes it particularly useful as an indicator of behaviour. Results from statistical

analyses of waiting time variance patterns indicate a significant difference in behavioural patterns across individuals and groups of individuals and depending on the character and purpose of the trip. Strategic pre-trip planning is performed more for non-routine discretional and long trips than for habitual and short trips, as reported in Paper 2. Usage of information may be associated with a higher degree of travel time optimisation than when not using or having access to such information.

Combining the survey data with scheduled and realised public transport vehicle trajectory data enabled an intricate model approach, presented in Paper 3, with the purpose of estimating complete door-to-door path choice preferences using a discrete choice modelling framework with pre-defined choice alternatives. The alternatives included available transport modes for access and egress in addition to the complete array of public transport mode combinations deemed feasible in a constrained enumeration choice-set generation procedure. Estimation results from multinomial logit and mixed logit models indicate the high relevance of the proposed model and empirical data framework when validating the generated marginal rates of substitution to models based on conventionally collected trip data, but with a low efficiency in terms of the number of alternatives needed to reproduce the observed trips. Transfers entail a particular discomfort alongside the waiting time at the first stop of a trip (in this case used as a proxy for hidden wait time or adjustment discomfort). In addition, further results indicate a premium for certain transferring stops, all other things being equal. As shown when trading off the magnitudes of common trip attributes against bicycle access distance, the attributes may also have an impact on the willingness to travel by this access mode to the PT system.

As with the waiting time study, the choice preference estimates indicate heterogeneity across population groups and across individuals who often exhibit preferences in a consistent manner, and this is also the case when trip characteristics and personal traits are controlled for as was done in the analysis presented in Paper 5. A common trait is that young and male travellers optimise to a higher degree using information and that older passengers dislike transfers more than younger travellers. Information is used more for urban services with high service reliability than for other services.

By applying a panel-based data collection approach based on farecard transactions, the long-term influence of service reliability on the choice of public transport paths was surveyed in a study presented in Paper 4. Because service reliability is difficult to define, measure, and analyse, it is rare to include it in forecasting models. Results from regression analyses indicate a low but significant impact from changed departure regularity i e, the evenness of departures – on the marginal change in relative usage of public transport services over time. The effect is particularly pronounced for high-frequency services in terms of attracting riders as the headway regularity is improved.

The results presented in the thesis have important implications, foremost to public transport planning practitioners, in that they suggest ways to facilitate the generation and updating of planning tools. Thus, the findings of the thesis have the potential to improve the validity and reliability of demand forecasting models to the advantage of decision makes and planners.

Populärvetenskaplig sammanfattning

Vad påverkar hur kollektivtrafikresenärer väljer att resa, och hur kan sådana val mätas så att kollektivtrafikbolagen kan anpassa utbudet och därmed göra resan så angenäm som möjligt? Dessa är de två övergripande frågorna som har studerats i detta avhandlingsarbete. Det visar sig att byten är det som resenärerna helst vill undvika när de väljer resväg, men även gångtid och turtäthet rankas som mycket viktiga när man betraktar hur resenärerna väljer, liksom avgångstidernas pålitlighet.

Genom att mäta resenärers avvägningar mellan reella alternativ går det att jämföra olika egenskaper med varandra. Ett exempel är turtäthet i förhållande till gångsträcka. Resenärer är beredda cykla uppemot 200 meter extra för att nå en kollektivtrafiklinje med en extra tur i timmen, och därmed minska väntetiden. Men det finns andra sätt att minska denna än att sätta in fler turer. Avhandlingens studier visar att även tillgång till detaljerad och uppdaterad avgångsinformation sänker den genomsnittliga väntetiden vid den första hållplatsen. Denna är dessutom generellt ganska kort – fem till sju minuter oavsett turtäthet – men längre för långväga resor och resor som kräver förplanering (t ex för att de är ovanliga för resenären). Väl förberedda och informerade resenärer tenderar alltså att behöva vänta kortare. Dessutom tycks benägenheten att undvika byten minska om bytespunkten är en större station välförsedd med olika typer av service. Väntebenägenheten liksom värderingen av olika företeelser vid val av resväg skiljer sig dock åt mellan olika åldersgrupper och mellan män och kvinnor. Äldre är mindre benägna att välja förbindelser med långa gångvägar och många byten än yngre, och skillnaden är störst för män. Även benägenheten att nyttja information skiljer sig åt – yngre män använder sig av avgångsinformation innan resa i högre grad än andra grupper vilka delvis i högre grad förlitar sig på vana eller utantillkunskap. Vidare tenderar individers genomsnittliga resval att skilja sig mer åt sinsemellan jämfört med hur varje individ väljer över tid, även om man kontrollerar för saker som start- och målpunkt samt tidpunkt för resan.

För att kunna prioritera mellan åtgärder när kollektivtrafik och infrastruktur planeras är människors verkliga preferenser viktiga att ta höjd för då de har stort inflytande på hur människor handlar och i förlängningen hur resandet påverkas av olika åtgärder. Detta är viktigt att veta för att kollektivtrafikmyndigheter ska få ut så mycket nytta som möjligt till resenärerna för de pengar som satsas på trafiken. Det är då inte minst viktigt att prognoser över resandet anses som tillförlitliga och relevanta. Ett problem med många befintliga prognosverktyg är att de ger aggregerade och övergripande förutsägelser för resandet på linjenivå över tid. Det är då svårt för planerarna att veta i förväg hur många resenärer en viss åtgärd ger på en viss linje, något som är extra viktigt i nuläget då toleransen för trängsel kan ha sjunkit i och med covid-19-pandemin. Att ha tillgång till uppdaterade och detaljerade data över människors beteende, och därmed preferenser, i relation till olika åtgärder är av största vikt för att kunna skatta samband till prognosverktyg så att de uppnår tillräcklig upplösning och noggrannhet. Avhandlingens studier har nyttjat ny metodik för att mäta och modellera resenärers beteende under hela resan dörr till dörr i, kollektivtrafiksystemet men även vid anslutningsresan till och från detta. En mobiltelefonbaserad resvaneundersökning genomfördes med 287 deltagande kollektivtrafikresenärer, vilkas resor utgjorde grunden för såväl analysen av väntetider samt för skattningen av valpreferenser. Utöver detta nyttjades en databas med 2,8 miljoner kortregistreringar i sydvästra Skåne (minns ni JoJo?) insamlade under två tvåveckorsperioder, 2016 respektive 2017. Med hjälp av dessa, och Skånetrafikens punktlighetsdatabas, utvärderades resenärernas (kortinnehavarnas) benägenhet att ändra val av linje mellan de berörda åren för några hållplatsrelationer med många resande.

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Surely, the work behind this thesis has been a tremendous, tiresome, and annoying, but also enormously awarding, interesting, and formative effort for me as a researcher and writer. Nonetheless, it would not have been made possible without the devotion and expertise of a number of supportive people, whose assistance and contributions I can never truly express my gratitude for.

First of all, I would like to express my warmest gratitude to Anders and Helena, who obtained the funding and employed me as a PhD in the first place. I will never forget the phone call I received in the middle of a training course regarding the national transport model! I would also like to express my great appreciation to Karin and Carmelo – Karin for excellent supervision in the daunting jungle of quantitative methods, and discrete choice modelling in particular, and Carmelo for introducing me to the handling of vast data materials using SAS software. Fredrik K deserves credit for coming up with the idea behind my fourth paper, linking service reliability to path choice. For the juggling and jolting of data – I owe the pleasure of succeeding in finding my way through it to a number of people. Foremost, my former roommate Carl – thank you so much for our discussions in the initial phase of my analyses of travel data! And, of course, for helping me with coding scripts in MatLab and Python, and later in Biogeme. I would also like to thank Carl-William for introducing me to the world of sql and for showing me how it may be used to manage huge quantities of data. My warmest thoughts of gratitude also go to you, Thomas and Mikkel, for, seemingly on your free time, introducing me to the world of path choice modelling, helping me to specify, manage, and process my empirical data, and for giving excellent input into my writing efforts!

I also wish to express my general gratitude to K2, including John, (formerly) Ellen, Sofie, (formerly) Maria, Hanna, and Andrea for supporting me during the completion of my PhD and for facilitating the dissemination of the results that I actually produced. Here, I also take the opportunity to thank the PhD community of K2 (especially you who spent the most time in parallel with me – Alfred, Elias, Erik J, Erik R, Jean, Jens, Joel, Malin, Sergej, …) for providing an excellent environment for mutual exchange of knowledge, thoughts, and reflections regarding my papers. And, not least, for sharing so much knowledge and experience from their own endeavours. Also, thank you Mia, Thomas, Helena, and Astrid of the administrative team at Transport & Roads for your practical support during my time at the department.

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A special thank you goes to the municipal archive of Malmö for their swift processing of my application to access an image from the picture archive for the cover of this thesis.

And thank you Emeli, Leif, and other employees at Trivector who helped me to implement and use the TRavelVU app. I would also like to express my warm gratitude to Sofie, Andreas, and the "Exreseföreningar" of 2016 and 2017 who endured the cold and mist of November when helping me to recruit participants to the app-based survey!

I'd also like to thank Erik, Anders, Lars, Anna-Karin, Therese, Oskar, Adeyemi, and other colleagues at Ramboll who generously let me use their software, without which I would have never been able to generate the data that I needed on time. And thank you Hamid, for expressing your support for my idea of having a PhD and for showing me trust during my early years of employment as I learned the art of transport modelling.

Finally, my warmest thoughts to my family - perhaps especially to my father Christian. "The apple never falls far away from the tree"… And all my love and gratitude to Anya and, posthumously, to Ellen – forever in my heart. I would never have applied for, nor been able to finish the PhD, without your support. And thank you Lizzie for always staying by my side.

List of appended papers

Paper 1

Berggren, U., Johnsson, C., Svensson, H., & Wretstrand, A. (2019). Exploring waiting times in public transport through a semi-automated dedicated smartphone app survey. Travel Behaviour and Society, 15, 1-14. doi:10.1016/j.tbs.2018.11.002

Ulrik Berggren: Conceptualisation, Data curation, Formal analysis, Methodology, Writing - original draft

Carl Johnsson: Conceptualisation, Methodology, Software and Formal analysis

Helena Svensson: Funding acquisition, Project administration, Supervision, Validation, Writing - review & editing

Anders Wretstrand: Supervision, Validation, Writing - review & editing

Paper 2

Berggren, U. Brundell-Freij, K; Svensson, H & Wretstrand, A. (2019). Effects from usage of pre-trip information and passenger scheduling strategies on waiting times in public transport: an empirical survey based on a dedicated smartphone application. Public Transport. doi:10.1007/s12469-019-00220-1

Ulrik Berggren: Conceptualisation, Data curation, Formal analysis, Methodology and Writing - original draft

Karin Brundell-Freij: Methodology, Supervision, Validation and Writing - review & editing

Helena Svensson: Funding acquisition, Project administration, Supervision, Validation and Writing - review & editing

Anders Wretstrand: Supervision, Validation and Writing - review & editing

Paper 3

Berggren, U., Kjær-Rasmussen, T., Thorhauge, M., Svensson, H., & Brundell-Freij, K. (2021). Public transport path choice estimation based on trip data from dedicated smartphone app survey. Transportmetrica A: Transport Science, 1-34. doi:10.1080/23249935.2021.1973146

Ulrik Berggren: Conceptualisation, Data curation, Formal analysis, Methodology and Writing - original draft

Thomas Kjaer Rasmussen: Conceptualisation, Methodology, Software, Data curation, Supervision, Formal analysis, Validation and Writing - review & editing

Mikkel Thorhauge: Methodology, Software, Supervision, Formal analysis and Validation

Helena Svensson: Funding acquisition, Project administration, Supervision, Validation and Writing - review & editing

Karin Brundell-Freij: Methodology, Supervision, Validation and Writing - review & editing

Paper 4

Berggren, U., D'Agostino, C., Svensson, H., & Brundell-Freij, K. (2021). Intrapersonal variability in public transport path choice due to changes in service reliability. Transportation. doi:10.1007/s11116-021-10218-z

Ulrik Berggren: Conceptualisation, Data curation, Formal analysis, Methodology and Writing - original draft

Carmelo D'Agostino: Conceptualisation, Methodology, Software, Supervision, Formal analysis, Validation and Writing - review & editing

Helena Svensson: Funding acquisition, Project administration, Supervision, Validation and Writing - review & editing

Karin Brundell-Freij: Methodology, Supervision, Validation and Writing - review & editing

Paper 5

Berggren, U; Kjaer Rasmussen, T; Thorhauge, M; Brundell-Freij, K (working paper). Intrapersonal and interpersonal heterogeneity in public transport path choice – an explorative study

Ulrik Berggren: Conceptualisation, Data curation, Formal analysis, Methodology, Writing - original draft

Thomas Kjaer Rasmussen: Data curation, Methodology and Software

Mikkel Thorhauge: Conceptualisation, Methodology, Formal analysis, Software and Supervision

Karin Brundell-Freij: Methodology, Supervision, Validation and Writing - review & editing

Terms and abbreviations

AFC – Automatic Fare Collection: A system for automatic validation and registration of transactions used by fare tokens such as cards. The system used in this thesis registers line, stop, and time stamp at bus boarding validations as well as at validations performed by on-board train staff.

AVL – Automatic Vehicle Location system: A real-time database providing actual trajectories of individual public transport vehicles through the public transport network, including time stamps for all arrivals and departures at pre-scheduled stops.

GTFS – General Transit Feed Specification: Data format for public transport lines, line routes, time profiles, and vehicle journeys originally specified by Google. The Swedish database was provided by Samtrafiken AB via http://www.trafiklab.se.

HLS – High Level of Service. In the analyses of path preferences, HLS stops indicate stops with a particularly high level of passenger service including shops, indoor waiting facilities, etc., mostly associated with major interchanges.

FWT – the wait time at, or ahead of (hidden wait time) the first stop of a public transport trip. May be used as a proxy for the adjustment necessary for the traveller to time specific departure times.

IVT – In-Vehicle Time

MRS – Marginal Rate of Substitution: A measure of the preference of an individual to trade across two different goods, or in the case of this thesis, two different trip attributes.

MU – Marginal Utility; the relative change in utility for each unit of change in the quantity of a good, in the case of this thesis mostly referring to trip attributes such as travel time.

NTR – Number of Transfers/penalty per transfer

PT – Public Transport(ation)

RBT – Reliability Buffer Time: The time a traveller has to account for to reach their destination at a particular time with a certain degree of certainty.

TVM – Ticket Vending Machine: A device by which passengers may validate their farecard before boarding a train. Used for a subset of farecards not containing periodical pre-paid tickets.

TWkT – Transfer Walk Time

TWT – Transfer Wait Time

Activity – a person being stationary, with a spatial tolerance radius of 100 meters, for at least two minutes, e g, being home, at work, waiting, doing shopping, or visiting a friend.

Itinerary – A way to describe the movements, i e, the trajectory of chosen path, of a public transport passenger using leg-type labels such as in-vehicle, wait time, transfer, and access/egress.

Path – a trajectory used by a public transport passenger in order to negotiate the public transport supply available in order to get from point A to point B.

Route/service/line – Different terms for the same basic phenomenon – a spatial and temporal representation of a public transport service comprising vehicles that runs on a pre-defined and pre-scheduled path passing by two or more stops. The following hierarchy is used throughout the thesis, with increasing levels of granularity: Service→Line→Line route→Vehicular run.

Stop (point) – A geographical location and a temporal timetable point where public transport services allow boarding and/or alighting of passengers in a pre-scheduled fashion.

Trajectory – A representation of an agent's (a person or a vehicle) movements in space and time.

Trip – A movement between two activities other than transferring, waiting, or parking.

Trip leg – A movement between events such as boardings, alightings, transfers, and activity points.

Service trip/vehicular run – the trajectory of a specific vehicle conducting a pre-scheduled run in the public transport network and open for passengers.

1 Introduction

This doctoral thesis deals with choice, namely the every-day decisions – be they deliberate or non-reflected – that individuals make when choosing between quite ordinary options. Imagine, for instance, choosing between cashier queues in a grocery store. Assuming that you wish to leave the store as soon as possible and that you do not have an acquaintance in one of the queues, you would probably like to choose the one that results in the shortest waiting time. But which one do you choose, and why?

More specifically, this thesis deals with the measurement and analysis of public transport (PT) passenger behaviour and preferences, as measured through their choices when negotiating the transport system. The empirical foundations of the studies included are the result of two data collection efforts – a smartphone-based travel survey and a compilation of farecard transactions. Both datasets may to some degree be regarded as passive with respect to involvement of the research subjects under study, namely the PT passengers.

Theoretically, this thesis aims at making a contribution to the understanding of how PT passengers face and choose among travel options, by use of quantitative constructs of behaviour and individual choice. The thesis thus draws on the extensive theoretical field regarding quantitative modelling of behaviour, but not without being aware of flaws and insufficiencies due to the necessary formalisation and streamlining inherent in some fundamental axioms that lie behind some of its the fundamental concepts. Thus, and to put these theories in a broader perspective, I will start by introducing the reader to the psychological mechanisms behind different types of individual decision processes, and then gradually move into how scientists, primarily economists and behavioural researchers, have described and analysed these processes through behavioural economics and mathematical models.

In addition, this thesis is a result of an ambition to contribute to the planning practice of PT, by virtue of its new empirical support regarding passengers' preferences regarding different properties of available travel options. Having knowledge of how different measures and properties of the system affect demand serves as a way to facilitate a scientifically grounded prioritising across possible measures aiming to improve the service supply of PT. Ultimately, the business of transport planning deals with management of limited common resources, also beyond purely monetary aspects. Regarding urban space as such a resource, in that it is subject to the 'tragedy of the commons' (Foster-Lloyd, 1833), makes the aspect of its regulation through deliberate planning practices relevant to discuss in relation to human mobility needs. As history, and Ostrom (1990), have shown, public intervention may be successful in taming the self-destructiveness of human self-interest, and the regulation and planning of transport may be regarded as a good example of such (Glover, 2011). Thus, the case for the study of human behaviour, and how individual preferences are expressed in concrete choice situations, ultimately involves the study of how to influence and impact on such choices without the use of brute force, which would entail public outrage and a high political price. In line with this argument, it is essential to study human behaviour as it is, with its flaws and insufficiencies. Not least this is important in order to be able to find ways to curb human behaviour's most destructive elements by taking measures in good time that influence behaviour in a beneficial direction for society as a whole.

This thesis consists of a cover essay and five appended papers – Paper 1 to Paper 5. In the cover essay, the full research effort of the thesis is presented and discussed from different theoretical and methodological aspects, and the implications of the studies' results on society and on the planning of PT are outlined.

In this first chapter of the thesis, I will introduce the reader to why the research presented in this thesis matters for society. I will start by presenting the drivers and motives for engaging in transport-related research in general and subsequently gradually concentrate the focus on the significance of understanding implications on PT planning practices from the behaviour and preferences of individual passengers. The chapter then turns to the rationale behind the choice of approach and the specific research topic applied in this thesis, and it ends with a presentation of research aims and a general overview of the structure of the thesis.

Identification of research needs and motives behind the thesis

As mentioned above, applied theories of individual behaviour and choice naturally come with a substantial formalisation, meaning that reality is simplified in order to be more easily manipulated and structured. Simplistic approaches may not always be completely aligned with theory on psychological choice mechanisms (Van Wee, 2007), but such operationalisations have repeatedly exhibited successful predictive power in at least some aspects of human behaviour. For instance, even though most individuals do not always choose the most advantageous alternative in objective rational terms, due to either imperfect information or biased views associated with the whole choice range or individual options, one can assume that the average individual acts rationally and utility-maximising in the long run (von Neumann & Morgenstern, 1944). Here, this 'long run' perspective may be interpreted as 'when a sufficiently large sample is analysed', this being the number of individuals or various choices made by a single individual and when a sufficient share of these individuals have operationalised their choices into actions. Since first being introduced in the 1940s, the analytic paradigm based on utility maximisation to predict choice has been substantially improved by appending all sorts of model extensions, taking into account an ever-increasing share of human imperfections associated with choice processes. One very important aspect is how individuals choose when options are uncertain, unreliable, or associated with a varying degree of risk. There is no wonder, then, that the issue of risk and uncertainty has drawn the attention of at least one Nobel laureate (e g, Kahneman, Knetsch, & Thaler (1991); Tversky & Kahneman (1981)).

In the remaining parts of this section, different aspects of the thesis are motivated more elaborately. Starting from the general study of individual choice, I then move on to the case for PT as a phenomenon and why the demand for PT should be studied and forecasted using various forms of models and then wrap up with a concluding paragraph describing the identified research needs addressed in the studies that underlie this thesis.

Individual choice in transport and the case for improvement of data collection techniques

There is an on-going discussion regarding whether being mobile constitutes an intrinsic human need (Salomon & Mokhtarian, 1998) or whether it is just a demand derived from a need to perform spatially segregated activities (e g, Bamford, 2001; Hägerstrand, 1970). As is often the case, the empirical truth might be dependent on the choice context. Because this thesis is both empirically and quantitatively oriented, the analyses presented are based on theories of individual discrete choice within the theoretic framework of Expected Utility Theory (EUT), first coined by von Neumann & Morgenstern (1944), and the related applied research framework of random utility theory (RUT), originally formulated by McFadden (1973). Thus, the theoretical framework of this thesis fundamentally depends on a positivistic paradigm that may be related back to the neo-classical economic theory of the rational 'economic man' (Smith, 1776). In its purest form, this paradigm reduces each individual to act like a molecule in a pipe, and similar metaphors associated with classical scientific theory of fluid mechanics (an elaborate critique of neo-classical economic assumptions and applications regarding individual and collective human behaviour is provided by Raworth, 2018). Although recent psychological and behavioural economic research has nuanced this picture substantially (a good synthesis is provided by Mattauch, Ridgway, & Creutzig (2016)), the basic building blocks of discrete choice theory have been shown to hold to an extent sufficient for them to work as tools for forecasting of transport demand, as long as the scope is kept reasonably limited (Ben-Akiva & Lerman, 1985; Ben-Akiva et al., 1999; McFadden & Train, 2000).

It may be viewed, therefore, as given that these tools do their job in making decent predictions of aggregate human behaviour, at least when applied at a macroscopic level – i e, for large populations and at a generalised and descriptive level (like countries, regions, or large metropolitan areas) – and in the 'long run'. And thus far, this level of resolution has been well-aligned with the data available for the estimation and calibration of transport demand models. However, as mobility data have become more abundant (Z. Wang, He, & Leung, 2018) and disaggregate (Chen, Ma, Susilo, Liu, & Wang, 2016; Kurauchi & Schmöcker, 2017), there is now a strong case for the review and significant improvement of the existing models, if we, for now, stick to some of the neo-classical assumptions (although recent research has indicated that some of them may be relaxed somewhat – see, e g Fonzone & Bell, 2010; Gigerenzer & Goldstein, 1996; Watling, Rasmussen, Prato, & Nielsen, 2018). This brings us to one of the key claims of this thesis, that the ever-increasing abundance of mobility data makes an increasingly strong case for using non-, or low-degree, intervention techniques to study individual mobility. Here, I define an intervention as an encounter between a researcher and the subjects such as interviews and enquiries. Returning briefly to physics, there may be a trade-off between the intrusiveness of the study and the risk of unintentionally influencing, and thus biasing, the subject's responses (like the metaphor of Schrödinger's cat). This trade-off is one of the main vantage points for the data collection efforts carried out to support the key claim of this thesis mentioned above.

At present, and since the last fifty years or so, immense improvements in knowledge have been gained in how to understand and predict a subset of the discrete choices and decisions facing users of transport systems. In this space, both long-term location and lifestyle (Verplanken & Roy, 2016), attitude (Verplanken, Aarts, van Knippenberg, & van Knippenberg, 1994), and personal and social values have been shown to be involved in decision processes of individuals on a long-term superior level, while inertia (van Exel, 2011), habit (Kurz, Gardner, Verplanken, & Abraham, 2015) and practical considerations may direct our short-term everyday choices of action.

Current trends and the case for PT

To date, increasing global wealth and economic globalisation has entailed a rapid increase in personal mobility as measured in distance travelled annually per inhabitant in industrialised countries (Memmott, 2007), regardless of classifying this mobility as an intrinsic need or a derived demand. This is also the case in Sweden (Trafikanalys, 2020), which is the country of focus for this thesis. A large share of this increase in personal mobility has been accommodated by an increased dependence on fossil-fuelled individual trips, mainly by car (OECD, 2019; UN, 2017). Globally, the transport sector in the year 2010 contributed to roughly one quarter of all carbon dioxide emissions (IPCC, 2014) and 61 percent of petroleum consumption, and the share of total emissions is growing (IEA, 2020) and is expected to continue to grow (International Transport Forum, 2019). In addition, the World Bank has estimated that 800,000 fatalities and 3 trillion dollars in direct cost to the global economy may be directly associated with urban air pollution (World Bank, 2014). In Sweden, the current share of CO2 emissions associated with transport is even greater at one third of all domestic emissions (Naturvårdsverket, 2020). The dependence on combustion-propelled individual vehicles is responsible for a large part of the carbon emissions in Sweden related to transport[1]. Despite an accelerating increase in electrification, and assuming that at least Swedish electricity supply is virtually emission-free (Energimyndigheten, 2020), there is still a substantial need for an auxiliary, or in many cases primary, system for the provision of general mobility in order to provide for adequate sustainable, safe, affordable, and accessible transport for all (UN, 2015, 2016). This system is PT, and the case for its study is discussed at large in the next subsection of this thesis. The on-going trends of electrification and increased vehicle autonomy of motorised individual mobility may be regarded as both a blessing, in terms of reduced emissions, and a curse, especially as personal vehicles may be gradually less dependent on a physical driver. At the extreme point where cars may run completely independent of human interaction, and also at virtually no distance-based cost, densely populated areas are facing extreme conditions of congestion as well as spatial accommodation issues, as shown by scholars such as Millard-Ball (2019). This potential problem, along with the need to economically incentivise a rapid decrease in the demand for carbon-emitting fuels, adds to the case for PT (The Governmental Commission on Congestion, 2013), especially given the commonly expressed need to maintain geographical accessibility in an urban and regional context (see e g, in the Swedish national infrastructure plan, Trafikverket, 2017b).

Motives for the study of PT demand

The case for investing in PT may be strong, but dire economic realities entail that the ability to rank possible efforts is a key factor for success in order to enable informed selection of efficient measures. In countries such as Sweden with a relatively dispersed urban population and high car ownership rates, all existing PT networks require public subsidies to ensure provision of equitable transport service levels. To be politically justifiable, the PT system must therefore benefit a sufficiently large share of the population to make it a legitimate cost to society. Although isolated or subsets of PT lines may be strictly economically profitable, in

[1] According to the Swedish transport administration, an average car trip affects the climate more than four times as much per passenger kilometre than a bus ride. For train trips, the climate impact is even lower per passenger kilometre (Trafikverket, 2017a).

Sweden, only about half of the funding for PT operations in total emanates from passenger revenue (Trafikanalys, 2020a). In addition, many operation contracts between PT authorities and their contracted operators are, at least to some degree, based on boarding incentives.

As these arguments clearly show, there is a joint interest from both authorities and operators to be able to forecast and predict PT demand. In addition, local planning authorities such as municipalities, cities, and national planning bodies for transport infrastructure need information on tentative future transport demands in order to make trade-offs between different political goals that entail economic as well as environmental and social implications. To facilitate an enlightened and fact-based discussion in society regarding desirable future scenarios, which may be essential in order to arrive at fact-based decisions regarding transport projects (as discussed by, e g, Lyons and Davidson, 2016), development of accountable means to provide decision support that take account of all potential impacts of planning scenarios, involving trade-offs across transport technologies and land use options, is paramount. Here, the successful prediction of demand for transport constitutes a significant part.

The development of modelling methods to analyse PT passenger behaviour and choice preferences

Viewing the need to base a personal transport service backbone on PT (Florida, 2018) in order to support urban and regional development also highlights the issue of individual needs and behavioural patterns, for what is transport demand but a myriad of individual decisions and trade-offs across time, space, and transport technology? The preferences of individual passengers shape behaviour and thus the demand for specific services, and such preferences affect the usage rates of line routes and stations and how such usage varies over time, in part as a response to changing properties of the system. A useful way to derive the demand for such discrete services is by analysing how the demand is distributed across paths. In order to derive this distribution, the underlying choice preferences of the PT passengers must be obtained. A simple example of such path trade-offs of a passenger is presented in Figure 1. In this example, trade-offs are made between service frequency, access distance, and travel time, ultimately originating from the preferences of the passenger for the elements of each trip alternative (path).

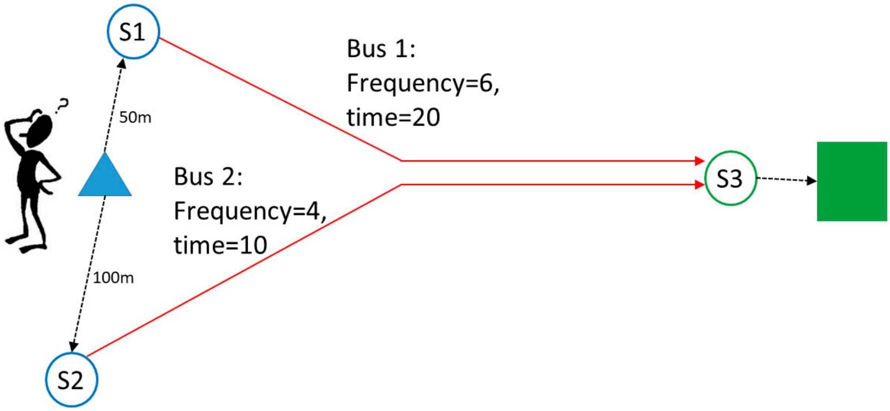

Figure 1 Simple example of PT path trade-off resulting in a path choice. S1-S3 represent PT stops.

However, as Liu, Bunker, and Ferreira (2010) indicate in their review of state-of-the-practice methods to predict path-based demand for PT, current methods to predict demand partly suffer from insufficient empirical underpinning of the underlying preferences due to the lack of detailed data on revealed behaviour by PT passengers. Thus far, the need to manage and cater for increased demand for private transport has directed major efforts into the description, modelling, and forecasting of car traffic. Fortunately, a small, but substantially growing, strain of research effort has also been invested in the estimation of PT passenger behaviour (see, e g, Xu, Xie, Liu, & Nie (2020) or in Gentile, Florian, Hamdouch, Cats, & Nuzzolo (2016) for an overview). However, at least in Sweden, there is a general discontent among professional planners regarding the perceived usefulness (Johansson, Anund, & Koglin, 2019) and validity of current state-of-the-practice infrastructure appraisal tools in which trip forecasting is an essential component. Part of the explanation for these perceived flaws may be related to the higher spatiotemporal disaggregation required for PT demand models compared to those of individual transport modes, in order for them to entail a useful and theoretically appealing representation of the complexity of the PT system with respect to the potential action space open to each passenger (see, e g, Gentile et al., 2016; Nurul Hassan, Hossein Rashidi, Waller, Nassir, and Hickman, 2016; Nassir, Hickman, and Ma, 2015). In addition, but likely related to this lack of perceived validity, there is an empirical knowledge problem in how to appropriately account for detailed human spatiotemporal movements, especially in complex PT networks. Fortunately, and as noted by Liu, et al. (2010), an emerging abundance of detailed mobility data enables new opportunities to revise existing models and to make them more empirically grounded.

Personal integrity and privacy put natural restraints on the intrusiveness of any survey approach, but in recent years a general trend of survey fatigue (Karlberg, 2015) has also manifested itself in an increasing difficulty in gaining sufficiently large samples using traditional survey and interview techniques (Trafikanalys, 2016). Fortunately, this has brought aggregate mobility data from passive data sources to the forefront, not least during times when human movements need to be closely monitored due to health risks to society that are conditioned on human mobility patterns.

Concluding remarks on research needs

To conclude the last four subsections from a PT planning perspective, in this thesis the main existing research needs within the choice-theoretic field have been identified as: (1) To find ways to improve the granularity of demand predictions within PT networks and thus increase the validity and reliability of transport models, and thus (2) to develop and facilitate data collection and management methods in order to enable this high level of granularity and thereby facilitate an up-to-date record of passengers' preferences. This thesis should thus be regarded as another building block in the daunting task of describing, understanding and predicting human behaviour and thus the demand for PT. A special focus has been on waiting times, access and egress trip legs and service reliability due to a perceived lack of stable empirically grounded relationships describing their impact on passengers' preferences and thus for their revealed PT demand patterns. Moreover, recent developments in data collection, sharing, and management described in 1.1.1 have themselves created a need for a kind of data-driven research concerning passenger demand patterns.

Chapter 2 will elaborate more on how both theory and methodology development have evolved alongside this surge in data availability. But first, a conclusive description of the aim and scope of the thesis are presented in the following section.

Scope and overarching aim of the thesis

The attainment of a comprehensive understanding of human preferences and behavioural patterns in terms of revealed choices within PT systems requires a proper empirical representation of relationships in the interface between users and the system. The overarching research aim of this thesis has been to contribute to the knowledge base used in PT passenger demand forecasting. Thus, it aims to facilitate making necessary trade-offs during decision-making regarding the design and review of PT networks, but also within transport infrastructure as well as land use planning in general.

This aim has been addressed by validating existing and developing new empirical methods in order to improve the empirical grounding of forecasting models. Thus, this thesis has sought to deepen, review, and update existing knowledge of why and how (groups of and individual) passengers prefer and behave in different ways, contingent on contextual factors related to the PT system. This has included the evaluation of revealed preferences for commonly analysed trip attributes as well as the study of additional trip components such as access modes and how the sensitivity to service reliability influences behavioural changes over time. Interactions of passengers with features of the service provision in the transport have been studied using methods with a high degree of passive data collection of travel patterns. For most of the analyses on behaviour and preferences of PT passengers contained in this thesis, a semi-passive empirical approach has been applied that is based on a dedicated smartphone-prompted recall survey app, a method that has benefitted from advances in mobile telephone technology and computer science. In addition, a nowadays relatively mainstream approach of using passive data collection based on farecards for PT trips has been applied to specifically analyse the influence of service reliability on path choice.

Thus, the scope of the thesis encompasses three main research themes, each containing separate aspects of the interaction of passengers with the PT system: (1) The measurement of waiting times and how they may be used as an indicator of passengers' travel strategies, (2) the use of semi-passively collected trip data to obtain door-to-door path preferences of PT passengers, and (3) the use of a panel approach to measure the impact of service reliability on path choice. The thesis also includes an exposition regarding practical implications for future planning of PT service provision, and transport infrastructure that may be endorsed by the findings in the studies included in this thesis as well as the included validation of mobility-sensing techniques. This validation is achieved through analyses of the outcomes from subsequent model estimation approaches, which in turn are based on the empirical data obtained. Thus, an ambition of the thesis is that it will increase the accessibility of material for decision support by making such material less cumbersome to produce.

Intended research contribution and its operationalisation into research questions

The intention of this thesis is to make a significant contribution to the knowledge base regarding preferences of PT passengers towards different phenomena and features in PT systems. This has been approached through the usage of semi-passive and passive mobility-sensing techniques to study the systematic impact from the PT system on the behaviour of its users, but also to study when individual-specific behavioural patterns may be found. These empirical approaches have been selected based on their potential advantages in terms of detailedness and comprehensiveness, as further elaborated in Section 1.5 below. As a theoretical vantage point for the thesis, theories of basic human cognitive and social processes have been considered, while more specific theories regarding the modelling of discrete choice of individuals have been applied for each specific research question as discussed in the following.

Thus, a quantitative aspect of behavioural research has been applied throughout the empirical effort that forms the foundation for the findings generated in this thesis. This has been a deliberate decision, although I had initial ambitions to somewhat broaden the spectrum of understanding by including in-depth interviews regarding the decision mechanisms at play during path choice. The opportunity to include multiple sources of data that had not been explored in this particular regional setting before has served as a sufficient motivation behind the choice of scope for the thesis, in addition to the perceived shortcomings associated with the assumptions underlying existing path choice models of previous research (Nassir, Hickman, & Ma, 2015) and existing practice.

The first research theme of the thesis is how the waiting times of PT passengers can be used as an indicator for the impact on passengers from various service attributes within the PT system. An underlying ambition here has been to delve more into one of the axioms behind RUT – that behaviour may to some degree be explained by exogeneous conditions.

In order to enable these analyses, data from a smartphone-based travel survey were combined with PT supply data from GTFS (published timetables) and a regional AVL system (a database with all realised service trips and stop departure times). The overarching research question of Paper 1 was formulated as:

RQ1: Can the travelling strategies of PT passengers be discerned from revealed PT waiting times, and, if so, what passenger or system-intrinsic factors might influence such behavioural patterns?

In addition, Paper 2 includes an analysis of the possible impact from passengers' pre-planning and usage of information on their travel patterns, measured as waiting times. The overarching research question may thus be phrased:

RQ2: Is there an influence of stated pre-trip planning strategies and information usage among PT passengers on their revealed travel patterns in terms of waiting time effects?

The issue of how to estimate and validate revealed and expressed preferences during trade-off situations involving joint choices across the multiple PT trip attributes of distinct door-to-door path alternatives, with a special focus on access and egress modes (papers 3 and 5), is addressed in the second research theme of the thesis. Paper 3 is thus based on a careful adaptation of observed trip data from the smartphone-based travel survey in conjunction with pre-defined choice alternatives generated from GTFS timetables for PT legs and from OpenStreetMap© paths for access and egress legs. In addition to the access and egress mode issue, special effort has been spent in this paper on exploring the significance of attractiveness of specific transfer points (in the same spirit as the analyses made by Eltved, 2020). The overarching research question for the study of this paper may be formulated as:

RQ3: What are the main determinants for PT path choice when revealed preferences are measured using a semi-passive surveying instrument?

In Paper 4, which contains analyses based on farecard transaction data in two panel waves merged with AVL data for the corresponding panel time frames, the third research theme is addressed in a specific research question:

RQ4: Can longitudinal change in PT path usage be related to changes in path-specific service reliability?

However, as the heterogeneity in choices has revealed, additional analyses have had to be included (Paper 5), based on the same datasets used in Paper 3 in order to explore the significance of how different individuals might differ systematically in their decision preferences. In accordance, the associated research question, also being part of the second research theme on path preferences, may be formulated as:

RQ5: Is there, all other factors being equal, an unexplained preference element related to PT paths that may be attributed to the taste of individual passengers?

Data sources used in the thesis

Two kinds of data have been used in the studies forming the empirical ground of this thesis – data describing the mobility behaviour of individuals and data describing the PT system in detail. For the analysis of individual mobility, two sources of data were used:

1. Smartphone-based travel survey data obtained from a survey devoted to the studies belonging to this thesis
2. Farecard transaction data from the regional PT provider Skånetrafiken

To extract detailed information about the provision of PT services in terms of vehicle trajectories, two sources of data were used:

3. Scheduled fixed timetables (GTFS) that also included the geographic location of each serviced stop
4. A database of reported real-time locations (AVL data) for regional PT line routes and stops within the study area

Table 1 associates each research question to each of the papers included in this thesis. In addition, the sources of data used in the analyses of each paper are indicated. These associations, along with a full description of the strengths and motives behind the choice to include each dataset, are discussed further in Chapter 3.

Table 1 Research questions targeted in each paper, and the data sources used per paper

Paper	Research theme	RQ1	RQ2	RQ3	RQ4	RQ5	Data source	
							Passenger-related	PT service supply
1	1. Expressed wait times and travel strategies	X					Survey	GTFS+AVL
2		X	X				Survey	GTFS+AVL
3	2. Full path choice preferences			X			Survey	GTFS+AVL
4	3. Reliability and longitudinal path choice				X		AFC data	AVL
5	2. Full path choice preferences	X				X	Survey	GTFS+AVL

Thesis structure

The remaining part of the thesis (cover essay) is structured according to a hierarchical framework, starting from a theoretical psychological and economic perspective on individual choice and decision making, and then gradually moving into more applied (‘narrow’) theoretical and eventually empirical approaches with which to describe and forecast individual behaviour, with a strong focus on PT systems (Figure 2). As mentioned in Section 1.2, the papers making up this thesis may be subdivided into three research themes based on the principal studies underlying the findings presented in each of the papers, where Papers 1 and 2 explicitly analyse waiting times as a proxy variable for strategic passenger behaviour (first theme) and Papers 3 and 5 analyse path choice preferences using a discrete choice analysis framework (second theme). Finally, Paper 4 presents a study of the connections between marginal changes in service reliability and path choice (third theme).

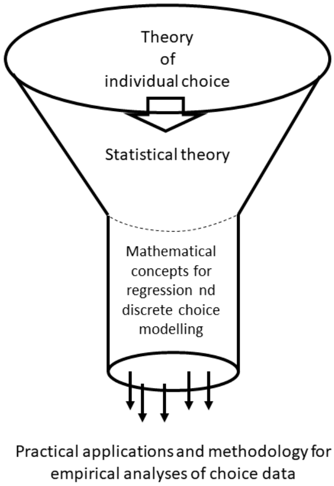

Figure 2 Generalised hierarchical representation of theoretic concepts within this thesis

Chapter 2 frames the thesis by providing a record of relevant theoretic foundations of choice and decision theory as well as by presenting a sample of previous research into choice modelling. In the choice modelling subsection 2.3.4, the selection of earlier work has focussed on studies that have inspired and instructed the design and approach that I have applied in the studies of this thesis. This theory and literature chapter is followed by Chapter 3, in which each research question is addressed based on the data and methodological approaches applied throughout the research work, and it also includes an account of the empirical setting and the assumptions made during the research process. Considerations and shortcomings of each method are also discussed in association with the presentation of each methodological step. Chapter 4 is devoted to addressing the five research questions of the thesis by presenting and discussing the associated findings from each of the corresponding studies. This is followed by a separate Chapter 5 in which I present my conclusions regarding expected implications for the practice of PT planning and demand forecasting as well as the thesis's relevance to society as a whole. Finally, the thesis is concluded in Chapter 6 in terms of reflections on the empirical approach and a general discussion regarding how the findings of the thesis contribute to the research fields of PT planning and demand modelling.

2 Theories of choice, and how to model choice

The ontology of the drivers and motives behind individual choice and decision making may be viewed as being placed somewhere on a scale between two extremes, represented here by two metaphors: As a means for the individual to achieve a certain end (instrumental metaphor) or as a means to attain or maintain a sense of personal subjective wellbeing (intrinsic metaphor). The latter (and also the former, but in an indirect sense) may be rephrased as the concept of *utility* – a concept that was originally introduced by Jeremy Bentham in the context of moral philosophy during the Enlightenment. To Bentham, utility was considered as the “property, in any object, whereby it tends to produce benefit, advantage, pleasure, good, or happiness...[or] to prevent the happening of mischief, pain, evil, or unhappiness to the party whose interest is considered." This definition, as it was later operationalised in classical economic theory (cf. Smith, 1776), has been adopted extensively in the theoretical paradigm that underlies the assumptions used in modelling and forecasting of individual behaviour. This is also the point of departure for the studies forming the basis for this thesis. However, in the exposé on choice and decision theory provided in this chapter, I will somewhat complicate the theoretic foundations of individual choice by also introducing a more complete scope of theories that have been explored by scholars, especially during the last 30-40 years. The rationale behind this expansion is to further motivate my choice of methodological scope, but also to formulate the limitations that the available data and methods put on research practice. Thus, endorsing the theoretical conceptualisation of this thesis deserves an overview of the epistemological landscape, before I focus on theories directly supportive of my own research efforts.

In this chapter, Section 2.1 first introduces the empirically grounded theories of human individual decision processes and how these have been adopted and adapted to economic contexts in the field of behavioural economics. This theoretical overview is relevant for the understanding of the findings in all of the empirical studies presented in this thesis, especially the distinction between automatised habitual versus more elaborated and planned behaviour depending on the type of choice situation and the capabilities associated with the agent – i e, the individual passenger. Section 2.2 narrows the scope somewhat to some applied theories on choice, specifically those associated with the specific characteristics of the transport environment that are relevant to the studies of this thesis. After that, in 2.3, I will describe how economic theory has been operationalised in the mathematical and statistical analytic approaches and methods for the prediction of human actions and preferences represented in path choice behaviour due to their relevance to the study of PT passenger's preferences included in this thesis. Finally, Section 2.4 is devoted to other research efforts relevant to the methods that I have used in the processing of the empirical data that were collected.

Psychology and economics of individual choice

First of all, it is fruitful to orientate the reader into the universe of choice and decision theory by starting with an account of the basic human mechanisms that take place during decision-making processes. These processes have been investigated using different empirical settings using approaches with varying degrees of contextual control. Kahneman and Krueger (2006) discuss the methods by which to survey both instrumental and intrinsic portions of utility, in other words different individual valuations of *subjective wellbeing*. However, if we return to the fundamentals and the ontology of choice for a moment, the context and boundaries in each choice situation must be established.

Freedom of choice versus strategies to ease mental taxation

When elaborating on the relationship between option space and subjective wellbeing and happiness, it is worth mentioning the theories formulated by Sen (1988) in his yoking of freedom of choice and (economic) capabilities. On the other hand, and focussing on a specific situation for an individual, the intrinsic positive value that can be attributed to this "freedom" is not always obvious in light of its merits to induce well-being. In situations of *uncertainty and risk* (Bonsall, 2010; Heiner, 1983), but also in situations of time pressure and other forms of mental taxation (Hodgson, 1997; Wendy Wood, Quinn, & Kashy, 2002; W. Wood & Runger, 2016), people tend to adhere to heuristics, habits, and other strategies that aim to reduce the cognitive burden in complex choice situations. Thus, limiting the scope of choice (the set of available options) may be preferrable to some degree. In line with this need for simplification, Hodgson (1997) introduces seven different decision or action situations in a succinct way, not all mutually exclusive, where habits and rules are employed: (1) *Optimisation*, where the choice set is known and it is possible to employ procedures and decision rules to find an optimum; (2) *Extensiveness*, where the information may be readily accessible and comprehensible but the search for it requires the application of substantial time and resources; (3) *Complexity*, where there is a gap between the complexity of the decision environment and the analytical and computational capacity of the agent (cf. Heiner, 1983); (4) *Uncertainty*, where crucial information and probabilities in regard to future events are essentially unavailable (see also Bonsall (2010)); (5) *Cognition*, the general problem of dealing with and interpreting sensory data; (6) *Learning;* and (7) *Communication* with others. Uncertainty in choice situations may trigger coping strategies (cf. Bagozzi, 1992) that may include procrastination (O'Donoghue & Rabin, 2001), adherence to default and status quo alternatives (Samuelson & Zeckhauser, 1988), or anchoring of beliefs to some information or cue that is regarded as trustworthy. (Chapman & Johnson, 1999)

Habit formation and reformation

In the context of transport, if we for now adopt the assumption that the demand for it is determined by external factors, a significant portion of all choice situations may be classified as being of a routine nature and thus subject to all of the above-mentioned conditions, but perhaps most importantly to inertia related to habit formation (van Exel, 2011). As shown by, for example, Aarts & Dijksterhuis (2000) and discussed by W. Wood and Runger (2016), habitual behaviour can be described as originally being goal-directed but over time, by repetition, becoming detached from the original motives. Habit strength is especially pronounced in acquired action sequences, where each action triggers the subsequent action in a series (Dezfouli & Balleine, 2012).

Breaking habits, on the other hand, requires the incentivising of new repetitious behaviour, as shown in multiple experiments carried out by Bamberg and Schmidt (2003). But, as discussed by Marsden et al. (2020), the introduction of uncertainty (or rather, knowledge insufficiency) as a result of "disruptive events" may be the most efficient driver for shaping new behavioural strategies in order to attain pre-defined individual goals. Because temporary outcomes or *state-related instances of confusion* cue the subject to re-evaluate the choice options perceived as being available and to gather information regarding other alternatives (Monosov, 2020), there is a strong behavioural link that also may manifest during life stage transitions (Fatmi & Habib, 2016; Guthrie & Fan, 2016) or just when having to establish new routines after having changed residential location – a feature also corroborated by the findings by Bamberg (2016). As Bamberg, Ajzen, and Schmidt (2010) showed, this cue may be amplified by additional incentivising facilitators, thus supporting a theory of goal-directed behaviour called *theory of planned behaviour* that links behaviour to intentions and contextual factors. Here it is worth mentioning that individual goals may have an instrumental function in order to attain a satisfactory level of well-being, a behaviour termed as "satisficing" (Kaufman, 1990).

The formation of coping strategies, including the use of information

Elaborating on the topic of decision process typology, strategic, long-term choices are usually made during radical changes such as relocation of residence and/or place of employment and study (Bamberg, 2016; Ralph & Brown, 2017). Due to their potential consequences, such choices need to be elaborated and well-founded more or less by definition, while more tactical and ad-hoc responses regarding, for example, path choice in transport networks may be sub-characterised according to their degree of routineness or novelty. The formation of habits and heuristics to ease the mental effort of choices during trips that are subsequently made in a recurring pattern may include trying different alternatives and thus forming strategies to cope (Bonsall, 2010) or consulting any form of external source of information (friends, fellow passengers, or formal information channels, (Lyons, 2006)). As experience is accumulated, the response to a certain stimulus (e g, cancellation of train services, an accident on the usual road to work), mediated either from fellow passengers or through digital communication media, might trigger habitual or script-based actions or more deliberate and conscious behaviour and searching for information depending on the commonness of the event (Verplanken, Aarts, & van Knippenberg, 1997) and the level of distraction, stress, and taxation of the individual (Wood & Runger, 2016). Or, as found by Mazursky (1998), the search for information may be induced by flaws or errors either in the system itself or in other sources of information that were used previously. Bonsall (2010) suggests a strategic sequence of cognitive events when travellers seek information to deal with perceived uncertainties (p. 52):

(1) "Devote a predetermined amount of resource to the search and then stop (e g, by spending ten minutes studying train timetables)."

(2) "Continue seeking extra information until a predetermined goal" [e g, price] "is met. A satisficing strategy of this kind may lead to an endless search."

(3) "Continue as long as there is a reasonable prospect of reward from continuing. This strategy appears logical, and allows for decreasing rates of return, but requires a reliable method of predicting the likelihood of a successful outcome if the search is continued."

Choice modelling concepts - exogeneous explanatory factors and choice processes

The findings reported in the studies of behavioural interventions mentioned in 2.1 clearly indicate that external – and internal – factors do have significant impact on the choices we make, even though several factors may be at play that cause biasedness and imperfections. From a practical point of view, being able to explain human choice by exogeneous attributes has very important implications for our ability to forecast demand in the transport system. However, although it is plausible to state that human actions may be triggered or moderated by external factors, the relationships may be bounded and partly biased depending on individual (or sometimes just typically human) characteristics (Fonzone & Bell, 2010). To this end, it is worth mentioning the most significant theories on goal and purpose-derived decisions originally developed in psychology to discriminate between different mental and social mechanisms.

Perception and measurement of time

Droit-Volet & Gil (2009) discuss biologically derived behavioural and perceptual implications resulting from the emotional state of the individual as well as ambient conditions. Thus, perceptions of time are not constant for an individual, but rather are contingent of the level of emotional stress, fatigue, and other conditions that affect the level of awareness. To conclude, factors that induce a higher level of awareness and stress, such as lack of security or uncertainty, result in time being perceived much longer than if one is occupied with cognitive efforts associated with more pleasant connotations. In the field of transport research, much effort has been put into time as the basic building block of passenger behaviour, and in addition to monetary measures time is usually used as a reference for different elements of travel discomfort. Diab & El-Geneidy (2014) offer empirical evidence for the over-estimation of onerous trip segments during PT trips, where passengers have been shown to value waiting times – particularly those under uncertainty (Wardman, Chintakayala, & de Jong, 2016) – as particularly stressful. As pointed out specifically by Rahimi, Shamshiripour, Shabanpour, Mohammadian, & Auld (2019) in their explorative survey into aspects of waiting time, the possibility to avoid unreliable travel alternatives is regarded as highly valuable. They conclude that captivity to single unreliable alternatives may prevent one from regarding PT as a viable mode of travel, and that system resilience, i e, network and mode complementarity, is crucial. This is particularly important for constrained trips such as commuting associated with employment with fixed working hours.

Expected Utility Theory (EUT) and its operationalisation as Random Utility Theory (RUT)

EUT has dominated the field of predicting individuals' choices within economic consumer theory from von Neumann & Morgenstern (1944) and onwards. As the authors carefully and thoroughly underlined, using mathematical analogies from physics was a way to make the admittedly extremely complex field of economics simple enough to allow for quantitative analysis, and thus "attempt to simplify all other characteristics" [than the measurement of preferences and utilities] "as far as reasonably possible". Underlying this attempt was the postulates of preference completeness and transitivity as well as the underlying principle of utility-maximising rational economic agents.

However, virtually every word in the last sentence of the previous paragraph has subsequently been questioned on numerous grounds within fields such as psychology, behavioural economics (cf. Mattauch et al. (2016) for an overview) and, as is relevant for this thesis, within transport research. Excellent introductions to this critique relevant for transport mode choice are given by van Exel (2011) and Bonsall (2010) regarding path choice under conditions of uncertainty. Some critics will be mentioned below, most of whom address the dilemmas of choice theory mentioned above (rationality, transitivity, omniscience, etc.) from a psychological and behavioural point of view.

As mentioned in Chapter 1, the analysis framework of this thesis ultimately relies on the mathematical operationalisation of EUT, called RUT, that has come to dominate the field of quantitative behavioural studies. Although based on the somewhat simplistic assumptions regarding human nature of microeconomic theory echoing from von Neumann & Morgenstern (1944), the range of mathematical developments and adjustments to the original model of choice theory has seen a significant proliferation, particularly since the introduction of conditional logit procedures within RUT by McFadden (1973), gradually taking account of an increasing portion of behavioural complexity. Thus, different probabilistic approaches (see, e g, Ben-Akiva et al., 1999; McFadden & Train, 2000) have been assigned to cater for taste variation – e g, attitudes and norms, unobserved heterogeneity, and other cognitive and behavioural complications to the original utility maximisation theory of choice (cf. the list by Hodgson, 1997, referred to in subsection 2.1.1 above).

The role of information – an extension of RUT

As outlined in subsection 2.1.3, Bonsall (2010) elaborates on his proposed extension of the EUT regarding *information acquisition* by introducing the important aspects of perception, knowledge, and experience in the passive or active utilisation of information in decision making under conditions of uncertainty. Bonsall's main argument is that purely probabilistic models confuse purely random events and measurement error with the subjects' individual perceptions and reactions to the uncertainty caused by this seemingly random variability. Thus, his arguments are somewhat in line with the critique against the section of the von Neumann & Morgenstern (1944) approach according to which behaviour can be explained and predicted by optimisation within the framework of perfect access and utilisation of information and the microeconomic postulate of utility-maximising behaviour. Instead, and this is his main argument, the variability of the random component of transport attributes may form certain patterns in space and time caused by, for instance, the periodicity of congestion or other phenomena that affect the perceived reliability. These phenomena may be taken advantage of by experience (one's own or as told by others), successive learning, and eventual habit formation.

Bonsall also mentions the increasing importance of "information and advice provided by system managers or other agencies" because the uptake of information is not a straightforward issue. A classical example, outside the transport sector, was provided by Nelson (1970) in his study of consumer behaviour when searching for information on product quality, where he distinguished between experience goods and search goods. Thus, quality information on experience goods must be purchased in order for consumption to gain this experience, while search goods may be evaluated using available information sources. In my view, transport may be regarded as both an experience and a search good depending on where in the decision process the individual is placed. Lyons (2006) elaborates further on this matter and argues that perceived needs limit the search for information among (prospective) travellers. In contrast to Bonsall, he has found that cognitive limitations and habits determine the search range and that the search may be designed to confirm already made choices (anchoring). However, he agrees with Bonsall that uncertainty is a key motivation for information searching.

Empirically (Lyons, 2006), unusual and complex public transport trips, and trips when the available information is perceived as trustworthy, have been shown to impact on the use of pre-trip information. In studies of information use in the planning phase of PT trips, empirical findings show that the demand for PT may be triggered by situations where (1) the trade-off between options is obscured by some degree of uncertainty (Chorus et al., 2006; Farag & Lyons, 2008) and (2) the consumer is not sufficiently acquainted with the options in order to have developed habitual behaviour (as convincingly shown by Aarts, Verplanken, & van Knippenberg (1997) in an experimental and hypothetical test with students' judgment of travel options). In addition, Lyons (2006), who subdivides the use of information into the planning and the execution phase of a trip, underlines the importance of taking the mental effort of pre-trip planning and associated information searching into consideration. He was subsequently able to foster these arguments in the findings of a qualitative study on the search for pre-trip travel information (Farag & Lyons, 2008) where he found no evidence for a modal shift as a behavioural response to information – instead, information is mainly sought ahead of performing complex or unfamiliar journeys and/or where there is uncertainty due to service disruptions. In the case of uncertainty during a trip (e g, in the absence of pre-established strategies or habitual routines), the decision process may be aided by the obtaining of information at particular decision points, or diversion nodes, in time and space. Thus, the type of information passengers possess – be it past experience of perceived disutility or through an electronic aid – and where this is acquired may determine their course of future action (Gentile et al., 2016). In line with this, Fonzone & Schmöcker (2014) showed with a simulation example how different search (and modelling) strategies when using real-time information regarding departure times can affect total travel times – and waiting times – quite differently, due to different strategies adopted by the passengers.

The use of RUT in discrete choice transport modelling

From here on, I will focus on applications used in the modelling of PT passenger behaviour and preferences in order to somewhat restrict and narrow down the theoretic complexity and to relate to my choice of thesis scope. However, first some general principles for discrete choice modelling will have to be briefly introduced as a backdrop. As Ben-Akiva & Lerman (1985) state in their influential textbook (p. 31), a useful theory of choice should fulfil the following three conditions: (1) Descriptiveness – that it postulates empirically observed human behaviour, (2) Abstraction – "in the sense that it can be formalised in terms which are not specific to particular circumstances", and (3) Operationality – "in the sense that it results in models with parameters that can be measured or estimated". In order to comply with these principles, discrete choice models account for aggregate individual behaviour. Based on its mathematical and statistical consistency and computational efficiency, the random utility model, in particular the multinomial logit (MNL) has been the most extensively applied operationalisation of RUT in order to describe and predict discrete choice, although there are examples of other theoretic frameworks like prospect theory (Kahneman & Tversky, 1979; Z. Li & Hensher, 2011) and random regret theory (Chorus, Arentze, Molin, Timmermans, & Van Wee, 2006; Loomes & Sugden, 1982) being used – all within the so-called expected utility framework. The latter theories pay special attention to the asymmetry of perceived utility depending on the perceived uncertainty and risk associated with a change. I will come back to this topic in the discussion of my results in Chapter 6 in light of alternatives to RUT.

Modelling of network behaviour and path choice

This section contains an account of a few specific theoretical and practical challenges that I have encountered when applying EUT within modelling of path choice and strategic behaviour by PT passengers.

Individual versus “mean” behaviour and taste/preference

Inter- and intra-personal heterogeneity in behaviour and taste may be propitiously accounted for in a discrete choice context such as path choice. As pointed out by Bovy (2009) as well as, more recently, by Hong, Kim, Byeon, & Min (2017), the actual sets of path alternatives perceived by the traveller in each choice situation may be regarded as latent and thus unknown by the analyst. However, the actual choice of a preferred path is also affected by the extent of these “consideration sets”. The variation across individuals, but also across choice situations for the same individual, is normally accounted for in the error term of the random utility model (Ben-Akiva & Lerman, 1985). McFadden & Train (2000) introduce the mixed logit model to account for stochasticity in the coefficients of the utility function in order to enable estimation of the impact of heterogeneity on choice probabilities. Bhat (1998) uses it for mode choice but, as is most relevant in the context of this thesis, Hess & Rose (2009) delve into the issue of correlation between repeated path choices made by each individual by applying a random coefficient mixed logit model on stated choice data in order to estimate values of time for motorists in Sydney. By using a bi-layered correlation structure in their model specification, they were able to estimate, by simulation, separate coefficients for inter versus intra-individual correlation and found that the main variation in tastes could be attributed to differences in individual preferences, but that a significant variation remained even within an individual across choices. Bolduc & Ben-Akiva (1991) instead applied an alternative specification of randomness in the error term (the so-called error component logit), an approach that has been used by some authors and that also may take path correlation into account. Hong et al. (2017) conclude that taste variables can be referred to by empirical Cobb-Douglas distributions based on utilising inverse optimisation from revealed preference smart card records of the Seoul metro system, and they conclude that this assumption results in more realistic path choice models than when using pre-defined distributions of taste variables.

Controlling for path correlation

The state-of-the art in approaches that deal with the correlation in trip attributes that results from overlapping of paths, and the resulting model estimation implications from each approach, is comprehensively presented by Prato (2009). As noted by the author, for road networks the degree of overlap has a significant effect on choice probabilities for the overlapping paths. C-logit (Cascetta, Nuzzolo, Russo, & Vitetta, 1996), path size logit (Ben-Akiva & Bierlaire, 1999), and path size correction logit (Bovy, Bekhor, & Prato, 2008) are all expansions of the basic logit model, while paired combinatorial logit (Prashker & Bekhor, 1998), cross-nested logit (Vovsha, 1997), and generalised nested logit are approaches based on the generalised extreme value correlation functions that account for similarities within the stochastic part of the utility function and that relate the network topology to the specific coefficients that characterise their tree structure but do not allow the consideration of taste variation or correlation over time of unobserved factors. Finally, multinomial probit (Sheffi, 1985) and different variants of the mixed logit concept using pre-defined distributions of the error component or the model coefficients have the advantage of allowing for both taste variation (as mentioned above) and correlation in unobserved factors over time, but they lack closed form expressions and the estimation thus requires time-consuming simulation of the stochastic component.

Modelling uncertainty in PT service provision

In the literature cited so far in this theoretical overview, service attributes of the transport system such as travel times and the intervals of PT departures have been assumed to be more or less pre-defined and relatively stable. When relaxing this quite strong restraint, at least for urban networks using infrastructure shared with other traffic and with services running close to passenger capacity, a stochastic component to the service level should be included in some way. There is strong behavioural support to also, in addition to McFadden's mixing functions related to expressed behaviour, include a probabilistic view on both the perceived level of service provision itself and on the preferences of the agents – namely the travellers (the doubly stochastic concept proposed by Askegren Anderson (2013) is an interesting example of this). One may thus discern between perceived *service reliability* (cf. Chapter 4), while the stochastic components related to individuals and their perceptions may be regarded as inter-individual *heterogeneity in preferences* (the latter often interpreted from revealed behaviour). The operational aspects of PT service stochasticity have been studied excessively, as have measures to mitigate it (Barabino, Di Francesco, & Mozzoni, 2015; Cats, 2013; Cats & Jenelius, 2015; Durán-Hormazábal & Tirachini, 2016; Fadaei & Cats, 2016; Gibson, Munizaga, Schneider, & Tirachini, 2016; Tirachini, 2014). Also, there have been countless efforts to model it in terms of its impact on service quality and demand (Cats, 2013; Hamdouch, Szeto, & Jiang, 2014; Nuzzolo, Russo, & Crisalli, 2001). The increased use of contactless farecards ("smartcards", Kurauchi & Schmöcker (2017)) has enabled a closer study of the impact on demand and ridership from service reliability, and it has reduced the dependency on intrusive survey methods that rely on posing hypothetical statements to the subjects – surveys that also have been shown (Bates, Polak, Jones, & Cook, 2001; Noland & Polak, 2002) to result in exaggerated valuations of travel time uncertainties compared to those revealed by actual behaviour (Raveau, Guo, Muñoz, & Wilson, 2014). Although it may be regarded as behaviourally tractable to include a full account of the empirically identified revealed asymmetry in behavioural responses to risk and uncertainty (i e, prospect theory of regret theory) in behavioural models, applied research by, for example, Avineri & Prashker (2004) found the initial reference levels to be critical for obtaining useful modelling results. Instead, there is the alternative to apply different proxy variables to uncertainty, such as reliability buffer time (RBT) (Bagherian, 2016) and various measures of regularity and punctuality (Currie, Douglas, & Kearns, 2011; Furth & Muller, 2006; Trompet, Liu, & Graham, 2011). When doing so, the stochasticity of service, being seen "objectively" or from a passenger's point of view, has been reduced to operational measures for modelling and benchmarking convenience.

Longitudinal investigation of mobility patterns

To describe and study the spatiotemporal dimensions of human life, Hägerstrand (1970) introduced the term time geography in the ambition to derive the demand for travel from "the needs and desires to participate in various activities at different times and locations" (as cited in Chowdhury, La Paix, & Geurs (2020)). In a classical investigation of the repetitiveness and habituation of trip and activity patterns, Hanson & Huff (1988) conclude, based on data from a one-week large-scale travel and activity survey from Uppsala, Sweden, that individual's activity patterns are characterised by both repetition and variability. However, they also realised that longer measurement periods than a week are needed to fully understand long-term changes in human mobility patterns. Consequently, Thomas, La Paix Puello, & Geurs (2019) conducted a four-week mobility survey with 432 participants using a dedicated smartphone application. They found significant difference in individual travel patterns and mode choice over time depending on trip purpose and trip distance. In addition, Chowdhury et al. (2020) found that mode choice and departure time choice were highly consistent for each individual for routine trips while discretionary trips and trips to less frequently visited locations displayed significantly higher choice heterogeneity over time for these attributes.

Methodological applications in the literature

As emphasised in the introduction, the combination of increasing survey fatigue among the general population and a gradual improvement in the availability of passively collected mobility data from mobile phones and PT fare tokens – be it physical cards or virtual tickets – has facilitated a shift in the approaches within travel surveying. The passively collected trip data have been shown to offer advantages in terms of granularity and precision previously not experienced from travel surveys, and this higher level of detail has enabled a closer analysis of some important trip segments such as waiting times and transfer times. In addition, developments in context sensing and notification prompting may enable closer analyses of choice situations involving uncertainty in the provided level of service, where the level of available information may be an important factor to minimise travel discomfort.

The next subsections account for doctrinal literature knowledge in the following five aspects of the measurement and modelling of choice that are relevant to the topic of this thesis: Travel surveying; the processing and enrichment of empirical trip data; the study of aggregate waiting behaviour; using the data for detailed path model estimation; and, finally, the use of farecard data in order to study longitudinal responses to changes in PT service reliability.

Surveying of travel behaviour

In order to gain knowledge regarding travel habits, patterns, and modal split for planning and forecasting purposes, many countries, regions, and cities carry out travel surveys. The traditional ways to study the preferences of travellers ever since the 1960s (Wardman, cited in Iseki and Taylor, 2009) are based on *revealed preferences* according to travel diaries (Clifton & Muhs, 2012), where a sample of the population are asked to record their trips for a particular or "average" period, usually a day (e g, the National Travel Surveys of Sweden (Trafikanalys, 2017), Denmark (Transportvaneundersøgelsen, 2020) and the region of Scania (Region Skåne, 2014)). Regardless of whether they rely on telephone interviews or self-administered questionnaires, this kind of self-reported means of trip recording has been shown to face a number of problems, including declining sample sizes (Stopher & Greaves, 2007), increased reluctance to complete surveys (TRB, 2003), issues related to representativity (Stopher & Greaves, 2007), missing activities, and under-reporting of short trips (Allström et al., 2016; Wolf, Oliveira, & Thompson, 2003) as well as imprecise records of travel time (Stopher, Jiang, & FitzGerald, 2005). For surveying of route choice in dense road or PT networks, the task may be even more intimidating both for the designer of the survey and for the respondent (Ramming, 2002). In addition, the one-day approach raises issues regarding representativity and omits important aspects of long-term intrapersonal behaviour (Buliung, Roorda, & Remmel, 2008; Hoogendoorn-Lanser, Schaap, & OldeKalter, 2015).

Because many of these shortcomings may be related to response burden, several approaches have been tested in order to facilitate survey participants. One such approach is to use web interfaces (Alizadeh et al., 2019; Anderson, Nielsen, & Prato, 2014; Fonzone et al., 2010; Frestad Nygaard & Tørset, 2016; Harmony & Gayah, 2017; Prato & Bekhor, 2006) that enable flexibility and user-friendliness. However, in order to provide trip and activity data with sufficient granularity to enable their successful use in the increasing number of activity-based transport models (Cottrill et al., 2013), several methods and applications have been developed that are more or less based on the passive recording of mobility data. Greaves et al. (2015) used stand-alone GPS tracking devices distributed among survey participants to complement a web-based travel survey. Marra, Becker, Axhausen, & Corman (2019) used a completely passive approach to collect PT trip data that were validated using vehicular trajectories from timetable and AVL data, but with limited information on activities and access and egress trip legs. However, as found by Chang, Paruthi, Wu, Lin, & Newman (2016) and by Seo, Kusakabe, Gotoh, & Asakura (2017), involving the participant to some degree improves the validity and accuracy of the recorded trip data. The technological solutions with which to accomplish this participation differ somewhat across approaches. In contrast to most similar survey efforts, the TRavelVU survey app (Clark, Adell, Nilsson, & Indebetou, 2017) only utilises GPS and the accelerometer as input devices, unlike MoveSmarter (Geurs, Thomas, Bijlsma, & Douhou, 2015), for instance, which also uses WLAN and GSM networks for positioning (Verzosa, Greaves, and Ellison, 2017). In most existing survey applications, the tracing of movements in space and time, and the detection of travel modes and activities, are achieved by utilising phone-based timing and positioning (geolocation) facilities such as GPS and WiFi receivers as well as telemetry based on communication with nearby base transceiver stations supplemented by accelerometer readings. This kind of autonomous sensing process runs in the background once the related functionality has been enabled in the app (such as is the case in both TravelVU and in another example – SmartMo – described by Berger & Platzer (2015)), and it detects starts and ends of trips as well as changes in transport mode for the active modes of walking, cycling, and running as well as the motorised modes of bus, train, tram, and car. The FMS app (Cottrill et al., 2013) uses raw data from these sources in order to improve detection accuracy through a machine learning algorithm. The prompted recall functionality usually contains some element of map-matching, such as those used in FMS, SmartMo (Berger & Platzer, 2015), and MoveSmarter (cited above), but not in TRavelVU, in order to facilitate mode recognition and the performing of trip corrections by the user.

To summarise, as done by F. Zhao et al. (2019), using smartphones as the basic platform for surveys entails advantages related to the ease of use and quality of the recorded data. In addition, Assemi, Jafarzadeh, Mesbah, & Hickman (2018) underline the need for user adaption in their evaluation of a smartphone-based survey, where they conclude that usefulness and ease of use, as well as the added value for the participant, are most important in order to minimise participant attrition and non-responses. Combining data collection and journey planning services was proposed by Schmitt, Harris, & Currie (2014) and applied by Davidson (2016) & Ghahramani (2016) in order to obtain detailed and valid trip data in PT systems. Most of these prompted recall approaches (Stopher, Shen, Liu, & Ahmed, 2015) use web interfaces (e g, FMS, Cottrill et al. (2013), MoveSmarter, Geurs et al. (2015)) while others like SmartMo (Berger & Platzer, 2015) and TRavelVU (Clark et al., 2017) include all respondent interactions in the smartphone application itself.

Processing of trip data and PT network data

As found by Allström et al. (2016), Geurs et al. (2015), Prelipcean, Gidófalvi, & Susilo (2018), Lopez Aguirre (2018), and other authors validating the new smartphone-based collection techniques, a successful interaction with survey respondents in order to maximise accuracy in the recall prompting of the survey app user interfaces requires data from auxiliary sources. Thus, as specifically mentioned by Vij & Shankari (2015), raw GPS data are not enough to reproduce trips, especially if those involve complex intermodal trajectories. Being one of the major facilitators to the recalling of trips, there is a need for auxiliary data in order to pre-infer modes and activities. Some applications, like MEILI (Prelipcean et al., 2018), use geographical databases in order to reproduce maps in the user interface, while others, like Move Smarter (Geurs et al., 2015), ETH-IVT Travel Diary (Marra et al., 2019) and FMS (Cottrill et al., 2013), include matching of trips to actual PT vehicle trajectories in order to identify line routes and associated properties of the PT service network.

Using passively collected data such as farecard transactions has the benefit of enabling large-scale travel patterns to be explored over time. However, each and every transaction is useless unless the medium used for multiple transactions can be identified and traced across time and space. Approaches in the literature to obtain this trip chaining feature hinge strongly on the configuration of the automatic fare collection (AFC) system. For systems that require only on-board card validations at boarding or en route, two main problems must be overcome in order to obtain complete trip chains from the origin boarding to the destination alighting location – the inference of alighting locations and the discrimination between activities and transfers (Gordon, Koutsopoulos, Wilson, & Attanucci, 2013, who assume an activity-based mobility framework such as that defined by Hägerstrand (1970)). The first problem is usually approached by using some kind of mirroring of the boarding profile (Navick & Furth, 2002; Trépanier, Tranchant, & Chapleau, 2007), with slightly different approaches for potential transfers and other activity destinations. Trépanier et al. (2007) reported an 80 percent success rate in peak hours for their approach to infer alighting locations (bus stops). Barry, Freimer, & Slavin (2009) used a schedule-based shortest path algorithm to infer trip paths, thereby generating complete origin-destination (OD, i e, door-to-door) trips when no explicit location information was available for the intermediate trip points. Exact information on locations is sometimes available in contemporary AFC systems, but when it is lacking locational data of vehicular trajectories may be combined with travel card validations in order to obtain full trip itineraries, one example of which has been reported by Farzin (2008). Different approaches have been reported regarding how to distinguish between and measure transfers, among other kinds of activities, in trip itineraries from travel cards. Different kinds of distance cut-offs have been utilised (Munizaga & Palma, 2012; J. Zhao & Rahbee, 2007), as have scheduled headways of line routes boarded after transfer (Jason B Gordon, 2012; W. Wang, Attanucci, & Wilson, 2011). Seaborn, Attanucci, & Wilson (2009) take bus in-vehicle time (IVT) into account in their calculation of transfer time thresholds from travel card transactions at bus boardings and station gate passings, while Chu and Chapleau (2008) include a maximum transfer walking distance to distinguish transfers from activities. Finally, clustering of PT stops and stations has been introduced by Goulet-Langlois, Koutsopoulos, & Zhao (2016) in their approach to infer activities based on likely activity locations.

Statistical approaches to studying aggregate waiting behaviour

As emphasised by several authors (e g, Ingvardson, Nielsen, Raveau, & Nielsen, 2018), a consistent analysis and prediction framework for waiting times at the first stop (henceforth termed First Waiting Time, or FWT for short) of a PT trip enables an enhanced level of accuracy and validity of behavioural predictions. This may be related to the fact that this trip segment is more subject to the travel strategy of each individual than others (cf. the mental construct of hyperpaths described further below), strategies that are contingent on properties of the network to a large extent (Frestad Nygaard & Tørset, 2016). In many commonly applied transport models, the duration of the FWT trip segments is determined based on headway alone according to the simple half-headway ratio (based on seminal work by, e g, Dial, 1968) assuming complete randomness in passenger arrival to the first stop of a PT trip (henceforth denoted *passenger incidence* as defined by Frumin & Zhao, 2012). To enable the study of potential determinants of FWT, Ingvardson et al. (2018) suggest an empirical approach based on farecard data, as applied for local train trips in the greater Copenhagen area, where cards are validated upon arrival at each boarding station. They were thus able to identify a functional relationship between service frequency and waiting time distributions, regardless of whether the PT departures were presented as scheduled exact departure times or as mean headways. However, and which is inherent in this approach, the behavioural discrimination between passengers who time their arrival to scheduled departures from the first boarding location of a trip and passengers behaving according to a more random arrival pattern in response to pure frequency-based services is not straightforward, as is discussed by Eltved (2020). This is due to the quite common occurrence of delays and disturbances in many PT networks despite being based on fixed schedules.

In addition to studies of waiting times based on passive farecard data, a number of survey approaches have been applied as well. Frestad Nygaard & Tørset (2016) performed a manual waiting time survey at peak times along seven bus lines in Trondheim, Norway. These observational studies were supplemented with a web-based questionnaire where the subjects were to describe their most common PT trip. They found that FWT was generally shorter than the halved headway of the relevant service that was awaited, and they suggested a non-linear, convex relationship between FWTs and departure headway. A behavioural interpretation of this made by many authors (e g, Carrel, Halvorsen, and Walker (2013) is that passengers adapt more strongly to published departure times as service frequency decreases, while routes having an expected headway of at most 10–12 minutes induce a higher degree of randomness in passenger arrivals to the first boarding stop (also supported by findings by Ingvardson et al. (2018)). Longer headways, on the other hand, induce a higher degree of hidden waiting time spent elsewhere than at the boarding stop (Eltved, 2020). Moreover, Frestad Nygaard & Tørset (2016) found that trip purpose did not have a significant impact on waiting times, while service reliability and whether the trip was undertaken regularly using a particular (sequence of) line route(s) were important factors. Luethi (2007), also basing his study on field observations and supplementary interviews with waiting passengers at 28 tram and bus lines in Zürich, Switzerland, concluded that the very short mean FWTs (grand mean of five minutes) found in their survey probably were highly pivoted on the high level of perceived and actual reliability of the Zürich PT network and an associated high share of departure-timed passenger arrivals to the first stop. Salek & Machemehl (1999) filmed passengers waiting for buses in Austin, Texas, and found that scheduled departure frequency explained less than a quarter of the variation in FWTs. Like Frestad Nygaard & Tørset (2016), they found that inter-individual heterogeneity was also a significant factor explaining FWT, which puts the focus on interpersonal vs. intrapersonal heterogeneity in behavioural patterns, an issue that is further addressed by Csikos & Currie (2008).

Passengers' potential feelings of anxiety and stress related to unreliability and bad schedule adherence are an important aspect pointed out by many authors (Brakewood & Watkins, 2018) as a crucial aspect in reducing perceived discomfort associated with FWT. However, the provision of accurate and reliable information regarding actual departure times has been shown to reduce this anxiety substantially, and thus the perceived wait times. Empirical studies, comprehensively reviewed in Brakewood & Watkins (2018), state that the provision of real-time travel information (RTI) may entail average waiting time gains of two minutes and perceived waiting time reductions by up to 30 percent, although this was subject to self-selection in the quoted surveys. Currently, most providers of PT infrastructure offer some kind of road or rail-side fixed information screens displaying likely waiting times for future departures (Harmony & Gayah, 2017). In addition, the rapid proliferation of journey planning applications for smartphones, which nowadays include updated information also regarding departure and arrival times of connecting services at transfer points to an increasing degree (for example, as described by Cats, West, and Eliasson (2016)) has facilitated the use of this information regardless of stop or station layout and location. In Sweden, for instance, 90 percent of all PT authorities provide RTI through smartphone journey planning apps, according to the Swedish Public Transport Association (Svensk kollektivtrafik, 2017). The means of gaining information on actual departure times differ across situations and depend on the topology and complexity of the set of alternatives considered by the passenger. Fonzone (2015) found widespread use of stationary RTI media such as signs (three out of four trips) and on-line journey planners accessed via computer or mobile phones (one half of trips), mainly with the aim of reducing waiting times or determining an appropriate departure time from the trip origin. According to that study, the choice of path was the stage of the trip that was most affected by information messages. Thus, it was used more in advance of or during trips in which multiple PT lines or stops were available in the perceived passenger choice set. According to Brakewood & Watkins (2018), only analytical studies have analysed the overall effects on total travel time from the provision of RTI. One such example is provided by Cats, Koutsopoulos, Burghout, & Toledo (2011) in the results from their mesoscopic dynamic model of the Stockholm metro. They arrive at a 3–4 percent total gain in travel time, chiefly related to optimised passenger waiting times as an effect of RTI provided at the platform, station, or network level, with the higher figure for the latter level.

PT path choice modelling – practical applications

The knowledge field of discrete choice modelling has gradually developed and expanded during the last forty-odd years in order to enlarge the scope of analysis and associated understanding regarding travel preferences of PT passengers. An important application of discrete choice modelling lies within the study of path choice in transport systems. Empirical studies of path choice have thus far chiefly relied on either direct observation in the field (P. Bovy & Stern, 1990; Ramming, 2002) or in simulated environments (Bonsall, Firmin, Anderson, Palmer, & Balmforth, 1997; Frejinger, 2008). However, the task to set up and interpret these choice experiments has rarely been straightforward, and for what is regarded as an optimal option space may not only be contingent on the context and the decision-maker themself, but the sheer size of the option set may itself imply a cognitive burden that induces severe discomfort (Hodgson, 1997). van Exel (2011) found, based on surveys and interviews, empirical evidence for a substantial discrepancy between actual and perceived sets of options in the context of mode choice. For the even more complex problem of route, or path, choice in complex PT networks, Kim, Corcoran, & Papamanolis (2017) found that frequent PT passengers, to a higher degree than occasional travellers, tended to stick to specific paths (combinations of lines and stops), especially when pursuing routine trips such as commuting, when there were relatively few options and the difference in terms of travel time across alternatives was high. The size of this consideration set of viable options may be viewed as being related to the optional value (Smith, 1983) of having many possible alternatives (possibly in analogy with Sen's concept of freedom of choice). In fact, empirical findings based on discrete path choice modelling with an MNL formulation using path size (M. Ben-Akiva et al., 1999) to cater for the correlation – or overlap – between paths generally indicate a positive effect of overlap for PT paths but a negative one for motorist paths (see, e g, Anderson et al. (2014) or more thoroughly in Hoogendoorn-Lanser & Bovy (2007)). Thus, for PT there seems to be a premium, or optional value, for routes involving many at least partially overlapping variants (e g, several bus lines mutually servicing a corridor).

A partly overlapping theoretical feature that deals with attractive set(s) of connections in a given OD pair is provided by the concept of *hyperpaths* (a term originally introduced by Nguyen & Pallottino, 1989), i e, sets of paths with varying degrees of mutual heterogeneity but perceived as equally attractive and with significantly higher perceived utility compared to paths outside this attractive set (see Figure 3). With an objective to explore the existence of such imaginary mental structures, Fonzone et al. (2010) surveyed PT passengers (with an over-representation of "expert users") by asking the subjects – subsets of engineering students and transport experts from six countries – to report on their most recent and most frequently undertaken trip in order to elucidate behavioural traits and attitudes to path change (utilisation of mental hyperpaths), usage of different information channels pre-trip and en route, and pre-trip planning incidence. Interestingly, they found that only twelve percent of the subjects knew the departure frequencies of the most used lines and eight percent knew the timetable. Furthermore, 80 percent made use of pre-trip and/or en route information systems, with the most common source of information being a home-based digital journey planner. In line with the argumentation presented by Heiner (1983) and reported in the studies on habit and effects of experience accumulation mentioned above, attitude to change was inversely related to pre-trip information usage because "information and day-to-day learning tends to lead to a rather fixed, simpler route set considered by travellers. In other words, information and reinforcement could lead to a reduction of the complexity of the actually considered choice set, i e, the sub-set of the optimal lines which is taken into consideration by the traveller for a specific trip, rather than to its enlargement." (p. 19)[2].

[2] The issue of consideration vs. the mathematically complete choice set available to the decision maker is also fruitfully addressed and investigated by Gigerenzer and Goldstein (1996). Although the inclusion of explicit alternatives has spurred auspicious alternative approaches lately (cf. recursive logit applied by Meyer de Freitas et al., 2019 and Nassir et al., 2018), this has not been within the methodological scope of this thesis.

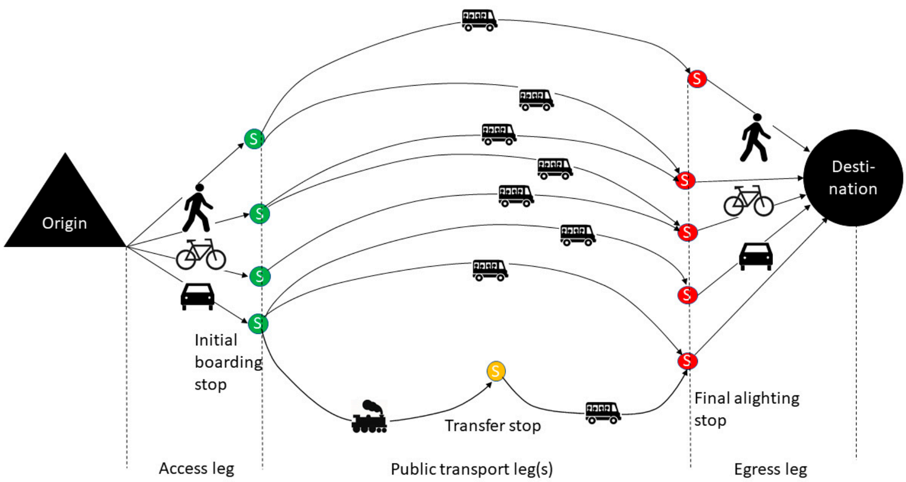

Figure 3 Schematic illustration of a hyperpath, i e an attractive (sub)set of connections in space and time between an origin and a destination. In the figure, each arc represents a specific line variant or departure.

In most traditional path choice models for road networks, the set of paths is implicitly generated through user equilibrium assignment algorithms applying the Wardrop criteria[3] (Sheffi, 1985). Raveau, Muñoz, & de Grange (2011) extend the advantage of not having to pre-define choice sets somewhat by using topological attributes of the network of the Santiago metro as the basis for the estimation of a pure metro path choice model. However, as previous research has noted (Fiorenzo-Catalano, van Nes, & Bovy, 2004, Prato, 2009, Hoogendoorn-Lanser, Bovy, & van Nes (2007), Marra & Corman (2020)), the explicit pre-enumeration of choice sets offers many favourable practical implications and is also behaviourally more realistic than the implicit approach. Choice set enumeration can be performed using deterministic methods, with pre-determined assumptions of link costs, such as K-shortest path (van der Zijpp & Fiorenzo Catalano, 2005), link elimination (Rieser-Schüssler, Balmer, & Axhausen, 2013) and link penalty (de la Barra et al, 1993), or approaches where a range of link labels are used to define the shortest paths (Ben-Akiva et al, 1984). A recent application for a multi-modal network is presented in the work by Tan (2016) as she successfully estimated a multi-modal route choice model based on smart card data from Singapore. In her thesis, Tan (2016) compares the performance of the above-mentioned choice set generation techniques and also includes a restrained enumeration method (Branch and bound, as originally proposed by Friedrich, Hofsaess, & Wekeck (2001)) and concludes that the labelling

[3] At user equilibrium in a flow-dependent network, no single traveller can reduce their travel time by unilaterally changing path, and this implies that the travel times are equal across all used paths at user equilibrium.

approach outperforms the other methods with reference to estimation and processing performance. Hoogendoorn-Lanser, Bovy, & van Nes (2007) and Marra & Corman (2020), on the other hand, conclude that the branch-and-bound approach is particularly suitable for performing estimation of revealed path choice preferences on run-based and time-expanded (dynamic) multimodal networks, considering the issue of concatenation of trip legs in the choice set. Tan (2016) supplemented the AFC data with trip patterns from a national household travel survey, where origins and destinations were identified on the building (postcode) level. She utilised the detailed trip data thus obtained for estimation of PT path choice models that involved access and egress trip legs. Ton et al. (2020) also approached the problem of representing access and egress trip legs in the choice set by using an elimination-by-aspects approach. They emphasise the importance of the thorough estimation of access mode preferences in order to enable the enlargement of PT network catchment areas.

Measurement of longitudinal consistency in sensitivity to service reliability

There are few large-scale studies regarding long-term passenger behavioural responses to uncertainty in transport provision. For a start, and if focussing on PT, there is no consensus as to how uncertainty, when derived from reliability related to departure time variability, should be defined and measured, although several attempts have been made to identify theoretically appealing and operationally feasible measures. First of all, however, one has to distinguish between the substantial range of uncertainties that affect all travelling. As discussed by Heiner (1983), successive learning from experience may affect the adaptability to uncertainty – ultimately to minimise mental stress and disutility. The amplitude (severity) of the disruption may have a more adverse effect on behaviour than "everyday" schedule deviations (common, minor departure perturbations) – a notion[4] supported by both prospect theory (Kahneman & Tversky, 1979) and empirical results (Börjesson & Eliasson, 2011; Diab, Badami, & El-Geneidy, 2015; Yap et al., 2017).

A useful approach to defining travel uncertainty is provided by Bates et al. (2001) who found that this uncertainty itself has a particularly high discomfort factor in addition to additional travel time associated with delays. They also put the spotlight on common methods to survey travel time valuation and travellers' responses to travel uncertainty, methods mostly based on stated preference surveys and particularly for the valuation of travel time uncertainty per se - most frequently for car trips (Abdel-Aty, Kitamura, & Jovanis, 1995; Avineri & Prashker, 2004). Here, they point out that a number of framing-related issues unfortunately cloud the

[4] Referred to by some authors as the "peak-end rule".

validity of the presented results to some extent. Noland & Polak (2002) discuss these framing dilemmas extensively in terms of individuals' sensitivity, or perceptual limits, vis-a-vis travel time uncertainty (what deviations from schedules are actually perceived as delays and how do passengers respond?). According to these authors, significant issues concern, on the one hand, how these dilemmas are presented in terms of trade-offs between probabilities and absolute magnitudes of different delays in stated preference surveys and, on the other, how they depend on context, which, in the PT realm, essentially includes network structure and service frequency. The magnitude of travel time deviation has been empirically shown to have non-linear effects on PT demand measured as PT path choice (Yap, Cats, van Oort, & Hoogendoorn, 2017). In experimental settings, subjects tend to over-sensitise the phenomena under study, generating biased valuations. This has proven particularly problematic when finding a way to characterise uncertainty in ways understood by survey subjects unaccustomed to mathematical representations of probability (Bonsall, 2010).

Fortunately, the increasing availability of spatiotemporal data has facilitated a proliferation of studies during the last decade or so within the domain of longitudinal behaviour in transport systems. One example is the detailed study of revealed PT path choice using passively collected farecard transaction data from ticketing systems (like AFC systems (Kurauchi & Schmöcker, 2017)). By avoiding the low response rates and survey fatigue associated with most "active" (conventional) mobility surveying methods, sufficiently large and long-term datasets have thus been collected to enable the estimation of demand patterns and path choice (Nurul Hassan et al., 2016; Nassir et al., 2015; Tan, 2016). This is particularly relevant for studies of behavioural change over time, i e, longitudinal analysis utilising panel data (Greene, 2014) due to the need for immensely large samples to control for attrition and other causes of data loss. Many authors have applied clustering of longitudinal card transaction data in order to explore mobility patterns. Egu & Bonnel (2020) used a random sample of 40,000 cards and metadata fused with discrete passenger groups in order to correlate these with different mobility patterns, and they applied a classification framework introduced by Hanson and Huff (1988) in order to structure these patterns. They thus found a significant inter-individual variation in travel patterns that was obscured as a seemingly stable travel demand at an aggregate level.

An empirical account of the relationship between perceived reliability and path choice in PT networks is presented by Carrel et al. (2013) in their survey pf PT passengers, in which they found that departure regularity is the most important path-specific feature. As discussed by Carrel et al. (2013), the (expected) departure frequency in conjunction with timetable adherence – departure punctuality – may have implications for revealed behavioural response as expressed in waiting times by PT passengers. Deterministic passenger arrival tendencies may thus be expected for punctual but infrequent services while a more random arrival pattern characterises high-frequency and/or unpunctual, and thus less reliable, services. Thus, as noted (Furth & Muller, 2006; Trompet et al., 2011), passenger responses to PT service reliability are conditional on expected waiting time, which itself is a function of both scheduled headway and its variability.

To measure travel time uncertainty within PT systems, Currie et al. (2011) conducted a qualitative evaluation of ten different service reliability indicators based on international expert judgement and found that excess wait time for high-frequency services and customer journey time delay for services with lower frequency intervals than 10–13 minutes were best suited in terms of availability and information value – the latter measure being conditional on the availability of PT vehicle location data. In an even more extensive review and evaluation of reliability measures, Gittens & Shalaby (2015) list 20 different metrics for which both theoretical and empirical underpinning were presented. They arrived at the conclusion that a useful reliability index should include both in-vehicle and wait time variation and that its specification should differ depending on service context such as the distribution of headways. Thus, they support the differentiation between chiefly stochastic behaviour at "short" headways and mostly deterministic behaviour at "long" headways.

Other researchers have proposed adjusted or completely new indicators of perceived uncertainty in PT service levels in order to cater for advances in data capture methods. Jenelius (2018) used PT vehicle trajectory and automatic passenger count data to extract perceived travel time during periods of congestion and crowded conditions based on disaggregate boarding and alighting figures on a stop and trip level. Bagherian (2016) used scheduled timetables and AFC data to calculate the RBT needed by passengers to compensate for uncertainty during daily PT journeys.

3 Research design

In general terms, the research approach deals with two fundamental dimensions of the PT system: The passengers and the transport system. The first dimension is accounted for by studying passenger behavioural and preferential heterogeneity on the group as well as the individual level. The latter dimension is studied by the inclusion of attributes that are intrinsic, physical parts of the PT system, such as bus stops and train stations, or outcomes of the system, such as travel time, transfers, and service reliability.

This third chapter is introduced in Section 3.1 by a recap from Chapter 1 of the association between the research questions and the studies contained in each constituent paper as well as of the data sources used. Further on, in 3.2, the empirical research setting of the regional PT network of Scania is described followed by a through description in 3.3 of the empirical methods and resulting datasets that formed the basis for subsequent analyses. This section also includes an account of how these data were processed and is followed by Section 3.4, which contains a full record of the analytic methodology.

Approaching the research questions in the papers

As briefly introduced in Chapter 1, each paper of the thesis corresponds to a research question (RQ) that relates to the individual scope of each paper, i e, the measurement and explanation of waiting times (Paper 1/RQ1), The additional impact from travel strategies and travel information on waiting times (Paper 2/RQ2), Path choice preferences from a smartphone travel survey (Paper 3/RQ3), Impacts on path choice from changes in systematic service reliability (Paper 4/RQ4), and Intra vs inter-individual heterogeneity in revealed path choice preferences (Paper 5/RQ5). The naming of each specific research question relates to the papers by their numbering. In addition to graphically relating each research question with the papers, in Figure 4 the contribution of each data source is indicated by an arrow coloured according to the colour of each paper. Thus, survey data, GTFS timetable data, and AVL data were used in the studies outlined in Paper 1, Paper 2, Paper 3 and Paper 5 while the study in Paper 4 was based on a combination of farecard transaction data and AVL data.

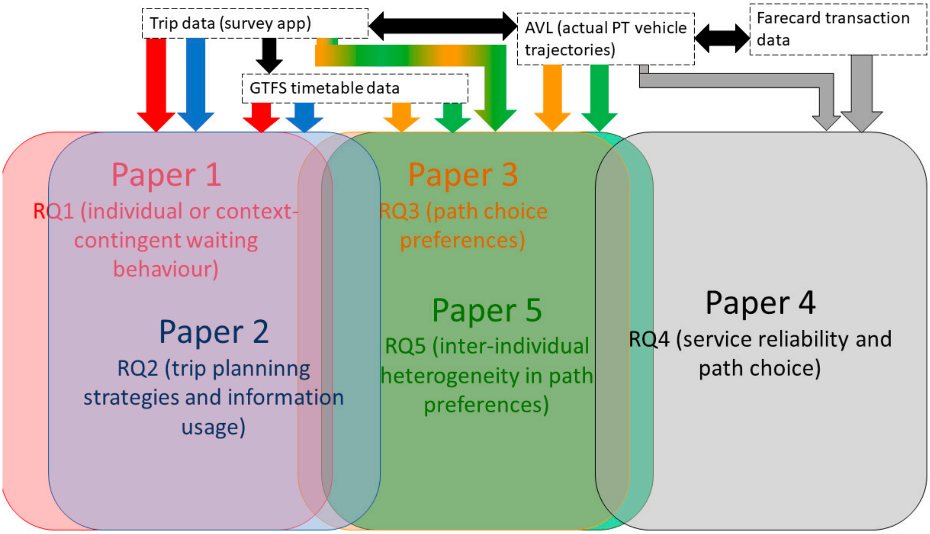

Figure 4 Schematic representation of data usage and associations across the papers that make up this thesis. This diagram thus develops the dataset-paper association established in Table 1. The degree of overlap among the rectangles, representing the papers, the more data usage they have in common. Coloured arrows represent the contribution of each data source (cf. Table 1), and black arrows indicate the joint contribution of multiple data sources.

In the remaining parts of this subsection, each research question is discussed in connection with the research topic of each paper, as well as with a brief description of the data sources used. The purpose of the text is to acquaint the reader with the rationales of each analytical approach in relation to the research questions, as reflected in each heading, and to the data sources.

RQ1: Can hyperpath strategies be discerned from revealed PT waiting times, and, if so, what passenger or system-intrinsic factors might influence such behavioural patterns?

As the original definition reads, hyperpaths may be regarded as sets of particularly attractive PT paths connecting an origin stop with a desired destination stop in a context of stochastic departure times. In the context of Papers 1 and 2 of this thesis, I have interpreted this concept as path sets that may have an elevated level of perceived utility in comparison with alternative paths connecting the same OD pair. Thus, passengers' hyperpath strategies may be manifested in revealed waiting times (primarily ahead of the first PT leg of a trip) because this trip segment is a decisive component of the trip chain in terms of its perceived disutility. In Paper 2, this issue is studied more explicitly than in Paper 1 by introducing the stated use of travel strategy in relation to each PT trip. On the other hand, in Paper 1 the gauging of hyperpath behaviour is confined to how it may be revealed in FWTs and how these times may be related both to properties of the PT network (the "context") and to personal characteristics of the passengers. Note that the concept of "path" partially overlaps the "hyperpath" concept, and the individual-specific preference patterns with respect to paths are further analysed in Paper 3 and Paper 5 (see below).

The more specific issue of parallel routes may also be somewhat related to the definition of hyperpaths and how this theoretical mental concept relates to PT network features such as "service", "line", and "line route". In the context of this thesis, these features are represented by the concept of PT paths. However, it is not always clear whether PT passengers even perceive all possible (combinations of) line routes as viable paths. The approach to this research question aims to shed some light on how passengers, revealed by their waiting times, behave depending on whether the (hyper)path is made up of single or multiple line routes, in the most restrictive definition of the line route concept. The analysis of the potential impact of overlapping paths is further approached in RQ 3 below.

As the basis for the analyses in both Papers 1 and 2, revealed waiting times were retrieved from a semi-passive smartphone-based travel survey. For Paper 2, a subset of the trips (observations in the survey) included stated behavioural responses regarding pre-planning and usage of departure information. By matching observed trips in the survey with corresponding service trips from GTFS and AVL supply data, auxiliary attributes of the PT network were associated to each observed trip in the survey (cf. subsection 4.1.2).

RQ2: Is there an influence of stated pre-trip planning strategies and information usage among PT passengers on their revealed travel patterns in terms of waiting times?

This research question may be regarded as a specific aspect of RQ1 in that stated planning and information use strategies are studied in relation to the PT network context and how behaviour, as indicated by revealed waiting times, may differ depending on these (stated) strategies. The study presented in Paper 2 enabled a comparison of this explicit interpretation of stated travel strategies with the implicit approach to hyperpaths targeted in RQ1.

RQ2 also digs deeper in order to understand the underpinnings of strategic choices among PT passengers and their tentatively systematic differences in revealed waiting time behaviour across strategies targeted in Paper 2 by subdividing them into gender and age groups as well as trip frequency during the survey period. In addition, the contingency of their behaviour on PT network and trip context is studied in Paper 2 by introducing service levels and trip durations and trip purposes.

RQ3: What are the main determinants for PT path choice, when revealed preferences are measured using a semi-passive surveying instrument?

In Paper 3, I leave the concept of hyperpaths to turn to the estimation of passengers' preferences in relation to full PT trip paths. Observed choices were based on survey results in terms of chosen PT stops and line routes, whereas the choice set used for discrete choice estimation was pre-generated based on GTFS data for stop-stop PT trip alternatives and OpenStreetMap access paths for access and egress legs.

The first aspect here is to validate the approach as a whole, both the choice set generation procedure and the application of a smartphone survey to collect observational trip data for the estimation of PT path choice models. Three different coverage metrics were utilised to evaluate both the efficiency and validity of the choice set generation procedure as such, and this included analysing the ability of the choice set generation procedure to reproduce the observed trips. The validation of the choice sets was accomplished by comparing descriptive statistics of the choice set to those of corresponding attributes from the recorded trip observations. Revealed preferences for specific trip attributes, derived from coefficient estimates from a basal MNL model in terms of marginal rates of substitution (MRS) in relation to bus IVT, have been obtained to validate the method as a whole, including the data processing and model estimation framework. Thus, standard state-of-the practice outcome measures have been utilised in this validation.

Being able to predict influence, or catchment, network radii (here generalised by the "range" term) has important implications when structuring the mesh of a PT network and the spacing of stops along PT line routes. The second aspect of the research question aims at shedding light on the impact from en route path properties and phenomena on the revealed willingness to reach a PT stop by bicycle as the access and egress mode, as measured in distance units, e g, what a reduction in travel time or waiting time (as a proxy of headway) may have on the acceptable catchment range. This is targeted in Paper 3 by matching revealed trips to pre-defined complete activity-based OD paths and estimating choice preferences based on network-congruent access and egress distances per access/egress mode.

Having validated the empirical approach and the basal models, the third aspect of RQ3 aims at exploring the possible extra contribution in PT passenger path trade-off preferences from service attributes not directly inherent to the transport system, but rather to the environment and perceived non-transport-related service level associated with en route PT stops, here operationalised as transfer points for multimodal PT trips. This is made possible in the analytic approach presented in Paper 3 by a simplistic binary pre-classification of the stop-adjacent environments, where major interchanges and terminals with adjacent major commercial or public services available have been flagged (as inspired by Dyrberg et al., 2015).

RQ4: Can longitudinal change in PT path usage be related to changes in path-specific service reliability?

Being an attractive path may not be stable over time despite constant service levels because the perceived reliability of the PT service of the path may change. By controlling for origins and destinations and features of the PT network and service level that may change simultaneously, this research question formulates an overarching context of revealed responses to changed service reliability. Because there is no way to directly measure utility, RUT entails that either stated or revealed behaviour may be seen as direct outcomes of individual perceptions and preferences, as discussed in Chapter 2.

Here, in Paper 4, the empirical approach to measure perceived utility caused by changes in service reliability by PT path is operationalised by using a fixed effects revealed preference panel model based on transaction data from the AFC system of the Scania PT network. Two specific measures of reliability – headway regularity and schedule punctuality, computed from AVL data – are introduced in order to quantify service reliability. Moreover, binary logistic regression is applied in order to relate changes in relative path choice probabilities to changes in service reliability, as gauged by the two reliability measures, across a panel span of one year. It is noteworthy that, unlike the other studies of this thesis, Paper 4 applied revealed path choice data from farecard transactions in order to achieve the data richness and quantity needed in order to conduct longitudinal modelling of behaviour.

RQ5: Is there, all other factors being equal, an unexplained preference element related to PT paths that may be attributed to the taste of individual passengers?

Finally, RQ5 expands on the topic of RQ1 and RQ3 by means of an elaborate approach, presented in Paper 5, to dive deeper into the issue of unobserved heterogeneity among PT passenger preferences for path-related trade-offs. Using the same discrete choice data structure as in Paper 3 and applying the analytic framework proposed by Hess & Rose (2009), this issue is analysed in terms of intra and inter-respondent heterogeneity in preferences to access/egress, FWT, and IVT attributes by applying a mixed MNL discrete choice modelling approach.

Empirical setting, methods, and data

Studying passengers' decision making with respect to path trade-offs requires a PT network with enough complexity to provide multiple options for a sufficient number of OD pairs. In addition, data availability and their usability put restraints on the range of optimal study areas[5]. The geographical and typological scope of this thesis has come to focus specifically on regional PT trips in order to include as many PT trips as possible in the behavioural analysis, local as well as regional, that occur within commuting distance from the specific area of interest described in Section 3.2. As defined by Hansson, Pettersson, Svensson, & Wretstrand (2019), regional PT services target passengers travelling between separate urban areas or rural areas, and the trips within this system are made on a regular basis. Because the geographical setting of my research involved not only one city, but rather both Malmö and Lund and their commuting hinterland, this delimitation has appeared plausible. The periods of data collection, November 2016 and 2017, were chosen in order to obtain evidence related to an expected difference in perceived travel uncertainty related to changed service reliability between a "control" period in 2016 and a period during the construction of the Lundaexpressen tramway affecting the area of study in 2017. Moreover, the two empirical datasets, the travel survey and farecard transaction datasets, were collected jointly to enable combined analyses using both datasets. More details regarding the empirical data are presented in Section 3.3. First, however, the demographic features of the study area are described in the following.

Scania and the Malmö-Lund metropolitan area

In 2015, Scania had a total population of 1.28 million inhabitants in an area of 11,302 square kilometres, yielding a population density of roughly 113 persons per square kilometre. The Malmö–Lund corridor, including the villages of Åkarp and Hjärup, housed 400,247 of these inhabitants. However, to enable a relevant validation of the sampled individuals and trips analysed in the studies of this thesis, this section presents descriptive statistics of an intended *target population*, from which the individuals who participated in the survey, described in subsection 3.2.3 below, constitute the sample. More directly, the target population for the studies of this thesis may be defined as the individuals who travelled to and from a tentative catchment area associated with the Lundaexpressen tramway during the study periods.

[5] Originally, the intention was to use the data for ex-ante and ex-post evaluation of both the construction and inauguration of the Lundaexpressen tramway, and this influenced the choice and delimitations of the study areas and survey periods.

To get a reference for the target population, figures from on-board surveys carried out during the period 2016 – 2019 were obtained from Skånetrafiken, and these are presented in Figure 5. The statistics represent trips made by bus lines servicing the study area, i e, the catchment area of the Lundaexpressen tramway in Lund. The rationale behind this particular selection of lines was that it may capture the target population well. When comparing to the composition of the survey sample, in terms of ages and gender split, they are in reasonable mutual agreement, at least for the 2017 survey round (cf. Figure 13 below). Thus, the share of passengers below 35 years of age was roughly 60 percent. For gender, the share of females was 56 percent among the passengers. For stated trip purposes among the passengers, "Commute" and "Business" made up roughly 60 percent of trips if put together, while "Education" amounted to about one third of the trips of the passenger survey.

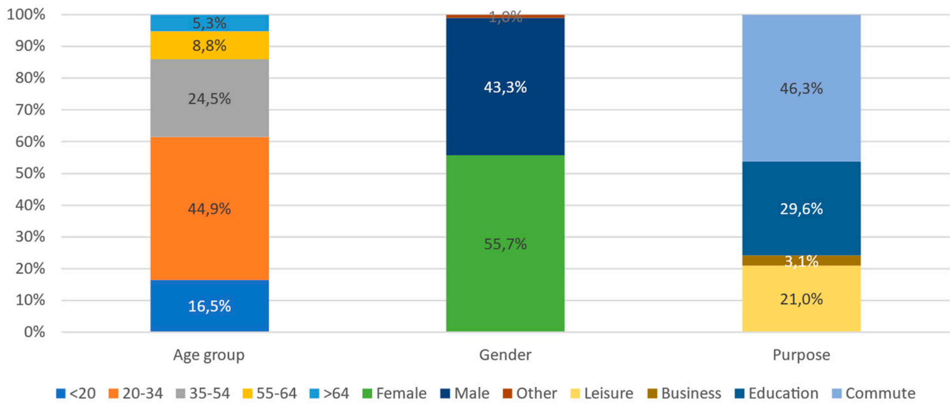

Figure 5 Composition of the bus passengers, in terms of age, gender and stated trip purpose, according to on-board surveys during 2016–2019. N = 7,000 (Source: Skånetrafiken, 2020). No corresponding information was available for train riders in the study area.

For characteristics other than gender, age and trip purpose, such as occupation and education level, a different approach was used to give an idea about the relationship between the target population and the sample given that there were no exact descriptive statistics regarding the target population. Because the locations of all activities were known from the travel survey, the population statistics of the "areas" associated with work and home activities could be retrieved. Distributions of demographic groups were defined based on available data sources (Statistics Sweden, 2020) and locations for the activities "home" vs. "work" and "education" based on information provided by the participants of the survey. The demographic source data consisted of 1,000 by 1,000-metre squares for data on gender and age distributions valid at New Year's Eve 2018 while education level was obtained for

250 by 250-metre squares and concerning the year 2016. For employees, data covering the public–private split of employers were provided based on a geographical precision level called SAMS[6].

Turning to demography for the areas of residence of the survey respondents, the gender balance was quite even, while the survey attracted a larger share of female respondents compared to the corresponding share among the residents, as indicated in Figure 6.

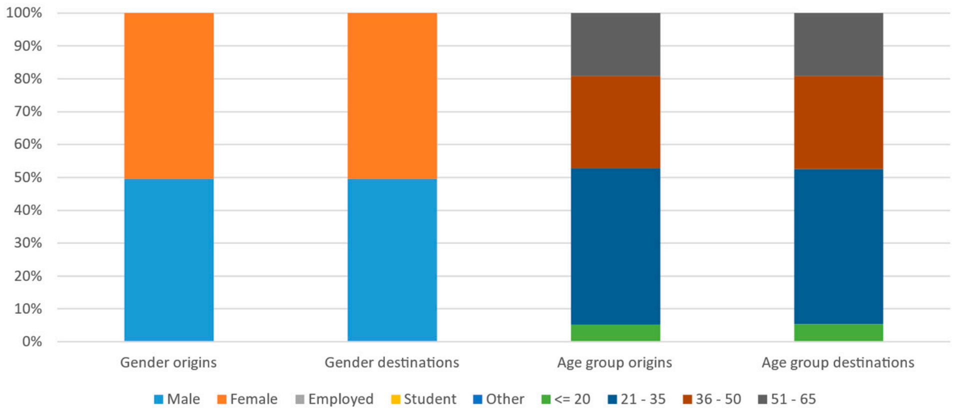

Figure 6 Gender and age distribution of residents and employees in the areas targeted by the respondent recruitment for the survey. Origins correspond to residential locations ('nattbefolkning') while destinations correspond mostly to occupational locations ('dagbefolkning') Source: Statistics Sweden, 2020

The education level was relatively high within the residential locations where the survey respondents indicated living – about 60 percent had an undergraduate degree or higher while about 40 percent had at most a senior high school degree. These figures are quite representative for the situation in Lund municipality, while the corresponding shares for Malmö and the rest of Scania are roughly the opposite, with 60 percent high school degree holders and 40 percent undergraduates (Statistics Sweden, 2019).

Employment statistics could be retrieved as a split between public and private employers. The rationale behind using this to characterise the target population was to indicate the potential weight of people employed in academia compared to other sectors, because the study area included a number of academic institutions. As indicated in Figure 7, the SAMS areas where survey respondents reported work or education activities were largely filled by public employers – 66 to 73 percent

[6] Small Areas for Market Statistics, a definition formerly used by Statistics Sweden to report demographic statistics.

depending on survey year. As a reference, the share of public employers in Scania is 31 percent, in Malmö it is 28 percent and in Lund it is 43 percent. Thus, our target population was obviously employed by public employers, many of which are likely to be academic institutions, to a higher degree than the general population (Statistics Sweden, 2020).

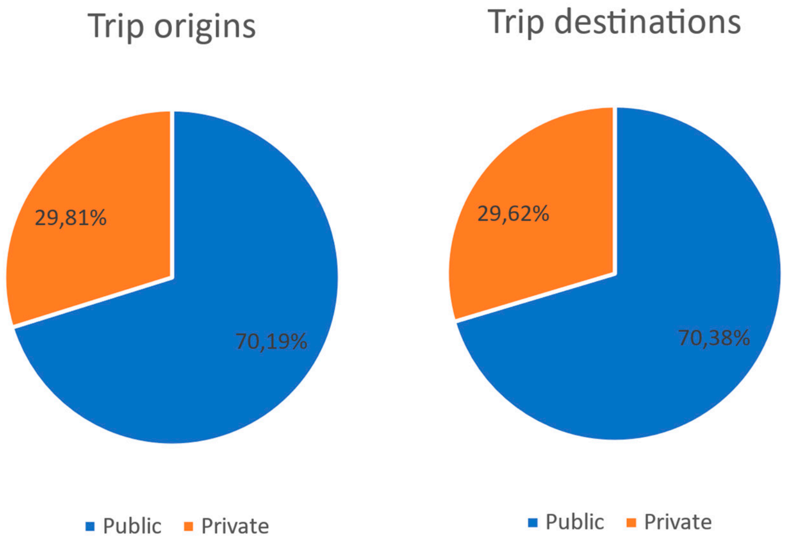

Figure 7 Split of private and public employers in the areas targeted by the respondent recruitment for the survey. Average for years 2016 and 2017, i e, the survey period. Trip origins correspond to residential locations ('nattbefolkning'), while trip destinations correspond mostly to occupational locations ('dagbefolkning') Source: Statistics Sweden, 2020

Skånetrafiken and the PT network of Scania

The regional PT network (illustrated in Figure 8), which is operated by different contractors on behalf of the regional PT authority Skånetrafiken, consisted of roughly 250 lines of which ten were train lines and the others were operated by buses during the periods of data collection in 2016 and 2017. Bus lines are categorised into city buses, regional buses, and express buses depending on their function in the network topology. During the survey period, roughly 14,500 service trips were operated on an ordinary weekday, running 268,500 kilometres, while the corresponding figure on Sundays and public holidays was 6,900 and 153,500 kilometres, respectively (figures retrieved from the GTFS database for Scania county), and 3,500 stops were served. During the survey period, the AFC system was based on smart contactless farecards (JoJo card), where the traveller could either upload cash or periodic zonal validity for a variety of (combinations of) fare zones. Single tickets could be purchased in ticket vending machines (TVMs) and by credit cards on regional buses. Skånetrafiken applies a tap-on-only system for buses, while train tickets must be purchased in advance and are validated on-board by itinerant staff. In 2019, 465,000 boardings were made during an average weekday (Skånetrafiken, 2020).

Figure 8 Network representation of the regional PT supply of Scania. Yellow lines represent regional bus services and green circles indicate urban centres that are serviced by dedicated city buses. Gray lines represent regional train services (© Skånetrafiken).

The survey – methods and properties of the collected data

As introduced briefly in Chapter 1, the main part of this thesis is empirically based on a prompted-recall smartphone travel survey that used a dedicated application (app), including a degree of crowd sensing (Chang et al., 2016). The survey was semi-automatic in the sense that it passively recorded some aspects of movements, such as paths, but required the participant to actively contribute through a user interface in the “training” of the survey algorithms associated with mode and activity recognition. Participants were also asked to state personal characteristics in the app upon registration. The survey was carried out in two waves during November 2016 and 2017 where, for each wave, passengers recruited at bus stops and on-board vehicles were offered to download, register and use the smartphone app TRavelVU (Clark et al., 2017) for two weeks each year in order to collect all movements during each two-week period. A separate recruitment effort was made ahead of each survey wave, but participants in the 2016 survey were contacted ahead of the 2017 survey wave. The resulting sample of respondents for each survey wave is presented in Figure 9. Given the recruitment method, i e, convenience sampling made by student recruitment staff and a relatively modest participation incentive (participants were offered a raffle draw of 10 (in 2016) and 20 (in 2017) farecards pre-charged with 200 SEK each), the resulting number of participants was comparable to or better than similar contemporary survey efforts (e g, Berger & Platzer, 2015; F. Zhao et al., 2019; Marra et al., 2019). Thus, a total of 279 PT passengers participated by sharing their mobility by PT during the full survey period. Out of these, 223 contributed during the 2016 survey wave by downloading and installing the app, while 172 joined the 2017 survey wave. A total of 203 persons ultimately used the survey app in 2016 and 144 in the 2017 wave, and their phones were registered for the survey in order to deliver trip data. Only eight participants from the 2016 survey wave volunteered to join the 2017 wave (Figure 9).

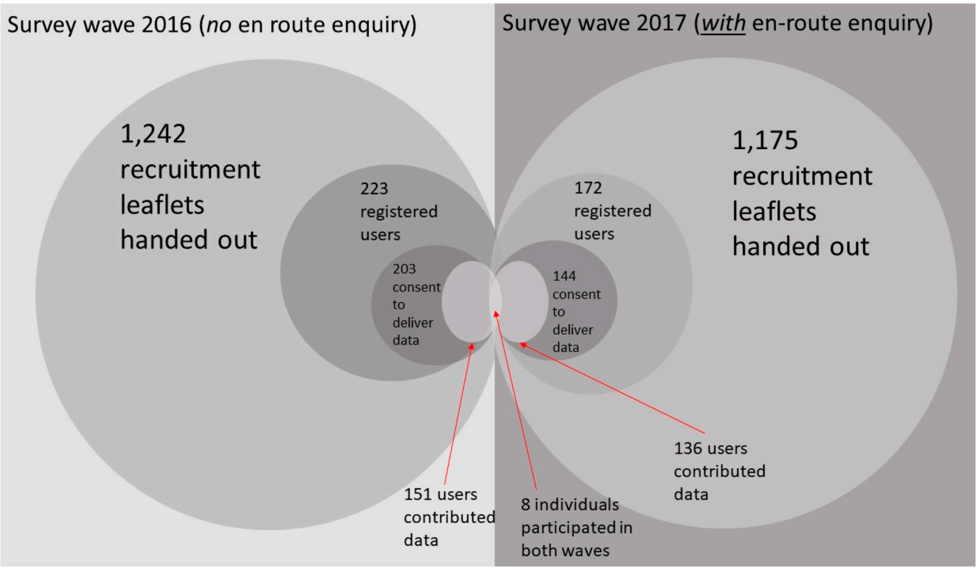

Figure 9 Schematic illustration of attrition during the recruitment of survey participants. Each potential participant was handed a recruitment leaflet informing about the survey. The en route enquiry in the 2017 wave asked passengers about planning strategy and information use.

An additional element was included in the 2017 survey wave, namely en route notification-prompted questions regarding trip planning strategies and information usage (Turner, Allen, & Whitaker, 2017) (Table 2). The purpose of this element was to investigate whether being in possession of a tentative strategy and/or information during trip execution, in terms of planning ahead using any type of planning aid, had an impact on the ability by the traveller to optimise travel time, thus relating back to the discussion of Fonzone & Schmöcker (2014) and the findings of Fonzone et al. (2010).

Table 2 Questions prompted to survey respondents after each PT trip segment. In the statistical analysis, the aggregates indicated in the rightmost column were used.

Topic	Question	Options (only one response possible)	Aggregation
Stated planning strategy	What best applies to this bus/train journey?	i) I planned the journey prior to departure (journey planner, timetable, [know the] timetable by heart) ii) I went to the bus stop without checking information beforehand iii) I don't know iv) This wasn't a journey by bus/train	i) – Planned ahead ii) – Did not plan ahead iii), iv) –
Stated information use	What source did you use for the information?	i) I know the timetable by heart ii) Travel planner in my phone/computer iii) Timetable in pdf/paper format iv) Other	ii) I i) No info/planning aid ii) – iv) – Info/planning aid
Stated pre-knowledge of timetable	Did you know the timetable by heart?	i) Yes ii) No	–
Stated optimization strategy	Did you specify a preferred arrival or departure time in the travel planner?	i) Arrival time ii) Departure time	–

To infer transport mode, the TRavelVU app uses rule-based fuzzy logic algorithms for machine learning, exploiting data from previously submitted itineraries and data on PT stops as well as estimated modes from accelerometer readings. On average, development tests have shown that this method results in a transport mode detection accuracy of around 80 percent (Linse, 2016). To further enhance this accuracy, as well as to classify the kind of activity being pursued, the user is prompted by the end of each day of the survey to log in to the app and 1) rectify and/or confirm inferred travel modes, 2) specify activities, and 3) submit trips in this reviewed form.

As reported by other authors (Verzosa et al., 2017), battery drainage is the main reason for participant attrition during smartphone travel surveys. In the case of this study, according to email correspondence with persons registered in TRavelVU for the survey but not delivering trip data, the main reason for not using, or even uninstalling, the app was high battery consumption, and to some extent difficulties when post-correcting the daily trip itinerary. This is in line with results reported by Greaves et al. (2015) regarding survey fatigue and as discussed by Assemi et al. (2018) in their model for categorising negative perceptions toward smartphone surveys among respondents. In order to address the energy issue in TRavelVU, all processing related to the inference of transport mode, filtering, and cleaning, was performed back-end on a central server with which the phones of survey participants exchanged data only on a limited number of occasions (when there was a sufficient amount of data and there was a WiFi Internet connection) in order to save energy. There is, however, always a trade-off between power consumption and spatial accuracy – especially during this kind of long-term data collection. To minimise battery drainage, GPS sensing was turned off if the accelerometer or telemetry revealed no movements, and the phone was thus regarded as being “static”. Spatial accuracy was determined by a two-meter distance-based filter (cf. subsection 3.2.7) at low traveling speed and a desired sampling frequency of 0.5 Hz.

The total raw data collected by the app consisted of 27,047 trip segments (13,553 from the 2016 survey and the rest from 2017), making up 7,579 trips in the 2016 survey and 5,600 trips in the 2017 survey. In total, roughly half of the trip segments were walking trips, while segments performed in PT vehicles made up one fifth of the trip segments (5,363 in total). Of the PT trips, 61.6 percent were stated by the respondents as being planned ahead. For 48.3 percent of these trips, pre-existing timetable knowledge was used, and the remaining 51.5 percent of trips were based on journey planner information. For trips that were not planned ahead according to respondents, 23.8 percent used existing timetable knowledge instead. In this context, one should note that there was no dependence in the sequence of prompted questions, and all of them were asked regardless of any previous replies.

On average, and regardless of travel mode, each participant made 3.6 and 2.9 trips[7] per day in the 2016 (Figure 10) and 2017 survey waves, respectively (standard deviation: 3.4 trips in 2016 and 2.7 in 2017). For PT modes, the average trip rate was 0.98 trips per day in the 2016 wave and 1.01 trips per day in the 2017 wave. These figures are not significantly different from the Swedish national travel survey (Trafikanalys, 2017), thus providing some support for the validity of our data despite it being a small, and potentially biased, sample. Figure 10 illustrates the variation in trip rates throughout the survey period of 2016 among all respondents, and per day for the number of respondents travelling on that particular day. Interestingly, the number of trips seems to peak on Fridays or Saturdays. As Figure 11 illustrates, the distributions of trip segment start times are of the expected shapes regardless of transport mode. PT modes have a somewhat more concentrated peak on weekdays, and a peak around closing time for many shopping centres around 5 p.m. on weekend days. A corresponding illustration is found below in Figure 16 for farecard transactions during the same period, with similar shapes.

[7] See definition of a “trip” in subsection 3.2.7 below

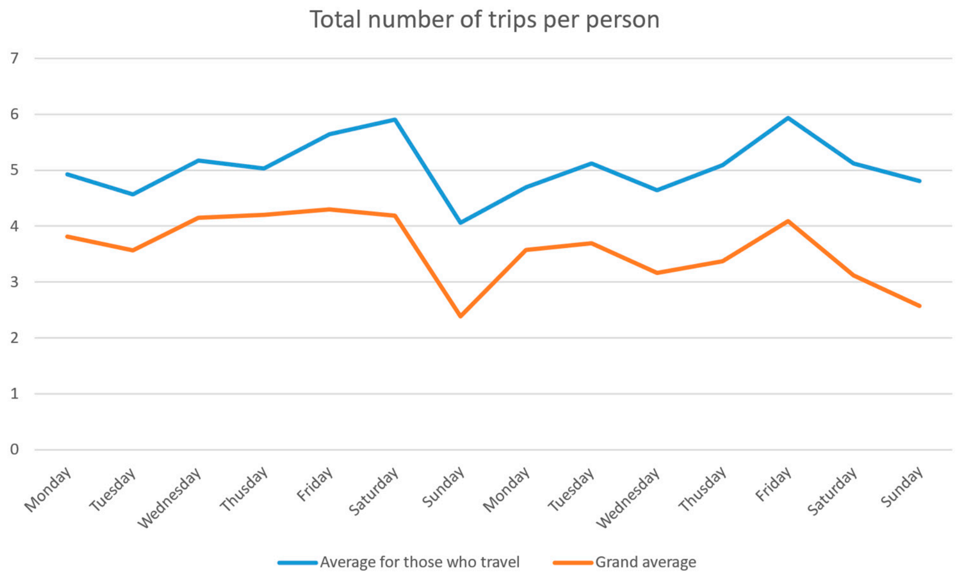

Figure 10 Trip rate in the 2016 survey wave. Grand average refers to the mean trip rate for all survey respondents.

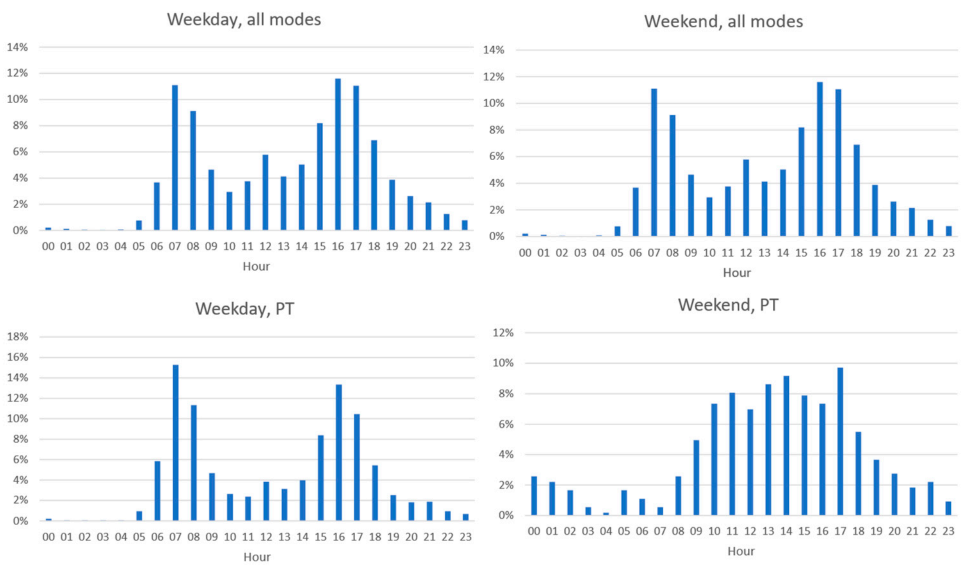

Figure 11 Distribution of trip start times for all modes, PT modes, and day type, respectively, in the survey

The average duration and length per transport mode is presented in Table 3 for both survey waves. The last row of Table 3 indicates the average number of transfers (NTR) and waiting times during PT trips in the survey (for trips in which the main mode was a PT mode), both being classified as activities and thus being at least two minutes long. Trip distances and the distribution of activities somewhat differed across survey waves. Thus, trips recorded during the 2017 wave were somewhat longer and more complex than those from the 2016 survey wave. This may have been a result of marginally different participant recruitment strategies in 2017 where an additional on-board recruitment effort was added to the stop-based recruitment of the 2016 survey wave, which appears to have attracted some passengers performing a higher degree of multimodal trips than the 2016 sample. This may also be part of the explanation for lower disutility values for transfer-related trip attributes from the 2017 observations compared to those from 2016 in the estimation of choice preferences (further presented in Chapter 4). In Figure 12, the distribution of pure transfers across trips is presented for the full survey sample. At most six transfers were recorded for a single trip. NTR for bus trips (n = 3,889) averaged 0.8, and the corresponding figure for train trips was 0.9 (n = 1,445). This could serve as an indication of the stronger acceptance – and need – for transfers when trains are used as the main transport mode.

Table 3 Descriptive statistics of trip segment characteristics from the surveys of 2016 and 2017

Mode	Mean distance (km)	Mean duration (mm:ss)
Walk	0.60	14:01
Bicycle	1.80	11:23
Car	13.90	19:39
Bus	10.00	18:17
Train	37.80	37:02
Transfer movement and wait time	0.15	09:07

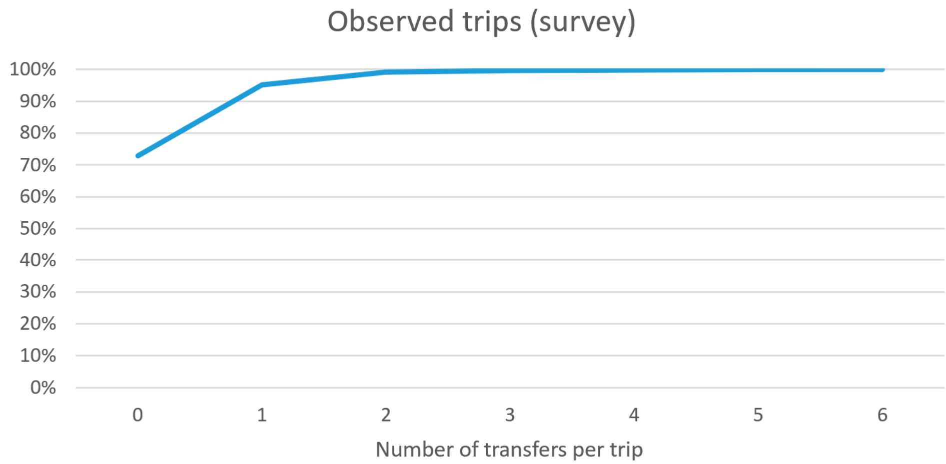

Figure 12 Cumulative distribution regarding NTR per trip in the app survey

Each survey participant was prompted upon registration to fill out a short set of questions. There, the participants were asked to specify gender, year of birth, occupation, access to a private car, access to a pre-paid monthly smart card on regional PT, the option of flexible working hours, and personal contact information. Responses to this questionnaire revealed a slightly higher share of female than male users, and young adults (ages 20–35 years) were seemingly overrepresented in relation to the age distribution of the inhabitants of Lund in general (Figure 13). In this context, it is relevant to note that the general share of the Swedish population that had access to smartphones was 85 percent in 2017 (Internetstiftelsen, 2017). However, internet usage through smartphones was significantly higher (93-99 percent) in the cohorts below 55 years of age while older cohorts had a significantly lower usage, as measured in terms of having used a smartphone to access the internet during the past year. For 56–65-year-olds, this share was 84 percent, among 66–75-year-olds it was 71 percent, and for people above 76 years it was only 30 percent. There should be no doubt that older age groups are difficult to reach when recruiting to smartphone-based travel surveys. However, in my case the negative implications may have been relatively limited due to the relatively young target population (see subsection 3.2.1). On the other hand, there is no support in the literature for a gender divide in the usage rates of smartphones (Ghahramani, 2016; Velaga, Beecroft, Nelson, Corsar, & Edwards, 2012). The somewhat larger share of females in the survey than in the resident target population may be related to a generally higher inclination among women to participate in surveys (Smith, 2008), but both the age and gender composition among respondents corresponded quite well to the target population when viewed in terms of PT passengers (Figure 14).

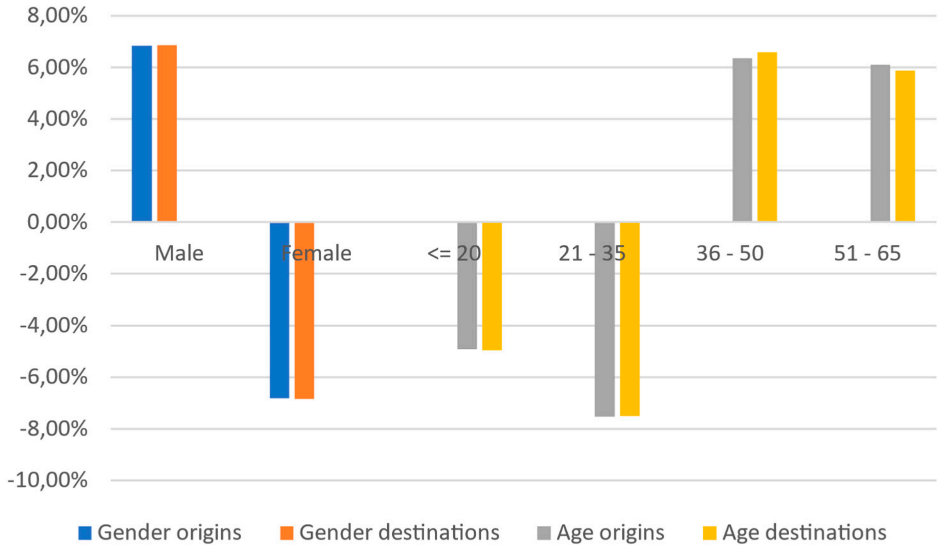

Figure 13 Comparison of the target population (at origins and destinations) and survey sample regarding age (in years) and gender. Mean values across survey waves. Differences are expressed in percentage points. Sources: Statistics Sweden and Berggren et al, 2018.

In terms of occupation, most of the survey respondents were employees, and the largest occupational group consisted of graduate and post-graduate students. According to the regional travel survey of Scania from 2017 (Region Skåne, 2018), 13 percent of respondents reported being students, but in this survey they amounted to nearly half of the respondents. The distribution of occupations in the survey thus indicates a disproportionately large share of students in this sample of the population. When stated trip purposes among the passengers are compared between the PT passenger target population and the occupations stated by survey respondents, there is a reasonable alignment of roughly 60 percent share of trips if "Commute" and "Business" are made equivalent to being employed, while "Education" is made equivalent to "Student" in the survey, although the composition in the 2016 sample is somewhat more skewed towards students compared to 2017.

As concerns age distributions, given the large share of students in the survey respondent group an expected elevated level of young respondents was found among survey respondents compared to the population areas of their residence. This was particularly evident in the 2016 survey round, while the recruitment of respondents managed to engage a somewhat older group in the 2017 round.

However, compared to the general population in Malmö and Lund, where the share of inhabitants that are below 35 years in Malmö is 45 percent and in Lund 49 percent (Statistics Sweden, 2019), the corresponding shares in the target areas are somewhat comparable.

Roughly a third stated always having access to a car, a third having access at times, and a third never having access. More than two thirds of the users stated having access to a prepaid monthly smart card for PT, constituting a strong indicator of commuting by PT. The shares of passengers using these periodical fare cards were roughly equal among students and employees, although the share of passengers always having access to a card was higher among employees. Three out of four employees had access to flexible working hours, which may enable an adjustment of working hours to PT supply and timetables.

Description of auxiliary data sources

As mentioned in Sections 1.4 and above, one important rationale behind the geographical scope of the studies reported on in this thesis was the availability of data, including auxiliary sources that could be used for enrichment purposes. Timetables and line routes in Scania were obtained from a dataset in the GTFS format covering scheduled network and associated timetables collected jointly for all PT providers in Sweden and provided as open access through an API[8] on Samtrafiken AB's website trafiklab.se. Secondly, access was granted by Skånetrafiken to an AVL database covering actual stop-to-stop trajectories for all PT vehicles in the network. From this database, deviations from scheduled departures and arrivals for all PT lines and stops were obtained. Thirdly, two separate excerpts of farecard transaction data were obtained from the AFC system by a special agreement with Skånetrafiken. Note that the AFC data were used only in the study of service reliability, and the other databases were used for all studies included in the thesis.

The two major databases used for auxiliary information regarding the service supply – the GTFS timetable database and the AVL vehicular trajectory database – were both more or less ready for research, but they both had specific properties and limitations that had a significant influence on their analytic potential. The AVL database was used for calculation of reliability metrics and for the spatiotemporal matching of trips from the survey with real vehicle trajectories, as well as for matching of the observed trips with the generated choice sets in the discrete choice modelling of path preferences. Here, the time-consuming procedure for extracting the data meant that only a subset of 20 PT services out of 250 (cf. subsection 3.2.2), as specified in Table 4, could be included. However, as the matching of observed

[8] Application Programming Interface – a means to access external data repositories

trips to the datasets of scheduled and realised vehicular trajectories, respectively, revealed, 78.6 percent of the trips that were successfully matched to scheduled GTFS timetables also had a corresponding match to the realised vehicular runs of the AVL data. Because the AVL database provided both planned and actual arrivals and departures for every stop used for boarding and alighting along each route, missing data regarding actual times (occurring for 13.53 percent of all stop departures) could be replaced by the corresponding scheduled (departure) times. Because the matching to observations itself ensured that the trip was actually made, this action did not introduce errors involving cancelled services. However, the temporal accuracy of the matching may have been affected somewhat.

Table 4 Characteristics of the 20 line routes from which AVL data were obtained that were included in the studies of this thesis. U – local city route, S/R – suburban or regional bus route, T – train route

Line route ID	Line type	Line route length (km)	Number of stops served	Minimum headway (minutes)
3	U	11	31	6
33	U	19	43	10
160	S/R	36	20	15
166	S/R	24	39	10
169	S/R	24	15	10
170	S/R	26	20	20
171	S/R	21	12	5
731	U	8	33	15
733	U	11	39	7
736	U	9	29	10
750	U	5	9	10
802	T	289	27	60
803	T	326	17	60
804	T	299	16	60
805	T	79	5	60
806	T	65	5 or 6	37
812	T	114	15	60
815	T	173	28	30
817	T	98	17	30
827	T	58	4	60

The GTFS database was obtained from trafiklab.se based on text files for routes, stops, and trip and stop times as well as operator info and pre-defined transfer times. However, in order to obtain useful formats for matching to survey observations as well as for the generation of choice sets for the subsequent discrete choice modelling of path preferences, the raw GTFS data were imported into the proprietary network analysis tool VISUM using a dedicated add-in script[9]. This enabled a close scrutiny and overview of the data, and easy customisation of the format used for matching. During the course of this data review, unrealistically long pre-defined transfer times and distances were adjusted toward shorter default values that were based on empirical data from the survey[10]. Because the GTFS data could only be imported one day at a time, a "representative" weekday, Saturday, and Sunday were used, where a "representative" weekday was chosen to avoid temporary replacement buses and other (planned) disruptive events related to infrastructure maintenance. However, what could not be avoided was the temporary, but major, disruptions of the cross-border regional train services between Sweden and Denmark, which were caused by temporary but strict border controls, imposing extra transfers on every train connection from Denmark to Sweden during 2016.

Collection of farecard transaction data

A separate farecard transaction dataset was needed in order to attain a sufficiently large sample to study longitudinal changes in travel behaviour. The choice of farecards as the source of travel behavioural indicators for PT passengers was made due to its richness, accuracy, and relative ease of access – properties emphasised in relevant literature (Kurauchi & Schmöcker, 2017). The AFC farecard transaction database consisted of all card validations on the stop and line level in the regional PT network. To enable comparisons, the same collection periods as for the travel survey were selected – two weeks during November 2016 and 2017, respectively, and covering trips made with the same 20 selected PT line routes as selected for AVL data extraction (described above) – and these two 2-week periods constituted the two waves of the panel dataset. For both panel waves, the data comprised a time stamp, stop name, and line route name as well as a card identifier for each boarding event on the selected routes. In addition, data from stationary TVMs were used with the same temporal extension. However, the line route used for the actual trip was not specified in the TVM data but was inferred from subsequent on-board validations. The raw data thus obtained contained only boarding information and had to be further processed in order to infer full trip chains using a procedure outlined in Section 3.3 below. Figure 14 presents an example of fully inferred trips in terms of scheduled headways according to GTFS timetable data for each line route identified in the AFC data (as matched on line route number).

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[9] The choice of tool for editing and, ultimately, choice set generation from PT timetables was motivated by my experience of using the tool for PT network analysis.

[10] These were a result of pre-defined "guaranteed" transfer times used as input to journey planners, because the GTFS source data were originally intended only for such use. This issue is elaborated further by Eltved (2020).

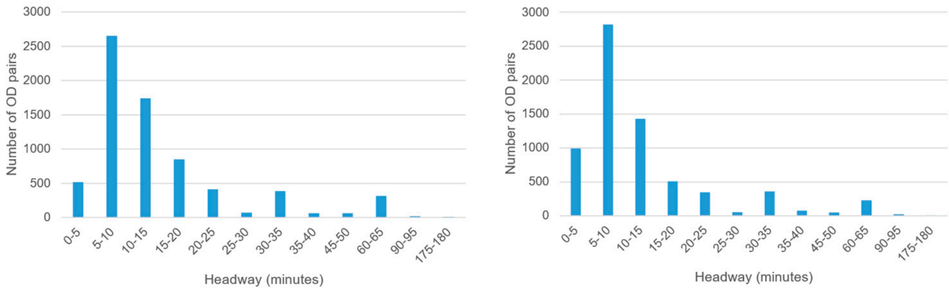

Figure 14 Distribution of the number of observed (travelled) OD-pairs per scheduled headway in the time frames (panel waves) in 2016 (left) and 2017 (right), respectively, of the AFC dataset

In total, transaction data from 244,790 cards were collected from the 2016 wave while the corresponding figure for the 2017 wave was 205,880 cards, of which 58,346 cards were identified in both waves from their ID[11]. Roughly a sixth of these remained after filtering out the cards that had been validated fewer than ten times in each wave. The refinement and processing of this data is outlined in Section 3.3 below. Due to the fact that exact door-to-door origin and destination locations were missing, there was no information available regarding the target population of this study, although it is fair to assume that it may have resembled the characteristics presented in Figure 14 above.

Figure 15 depicts a corresponding trip pattern over the course of different days of the week for the farecard transactions as is indicated from the survey trip record in Figure 11 above.

[11] The cards used in the models were assigned random IDs that were consistent across panel waves but not directly traceable to the specific card numbers used in the AFC system.

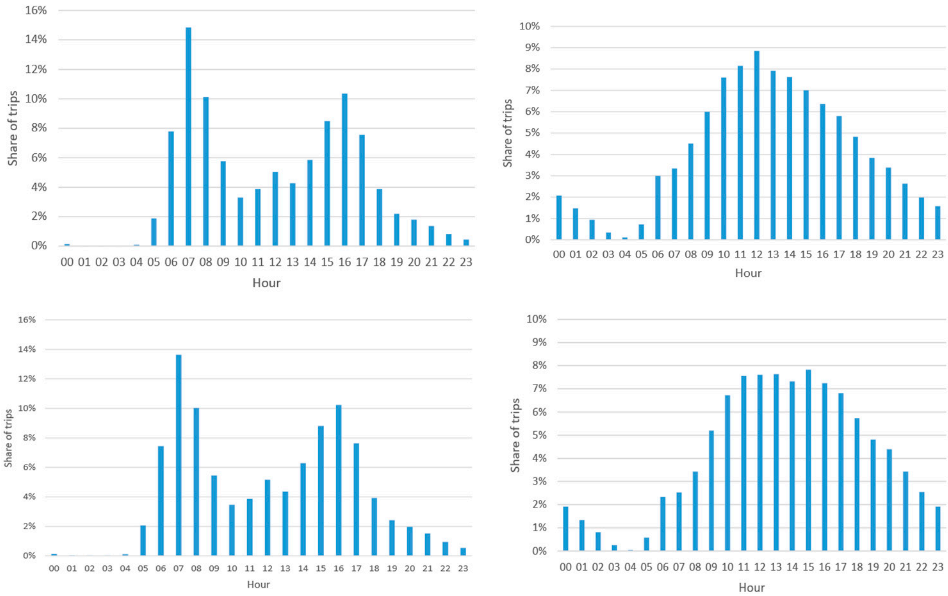

Figure 15 Time distribution of farecard transactions per day type. Upper and lower left: Weekday; Upper and lower right: weekend day. The upper diagrams display data from the 2016 wave while the lower diagrams display data from the 2017 wave.

Motives behind the choice of data sources

The intention for the choice of empirical approach was to enable a fine level of granularity in the observed travel patterns, including a longitudinal dimension – features usually not achieved using conventional survey approaches – in order to approach the overarching research questions regarding preferences and travel patterns of PT passengers as described in Section 3.1. Table 5 describes some general traits of the two empirical datasets that were utilised in the analyses of this thesis – the survey and the farecard dataset – and thus illustrates the different strengths inherent to them.

Table 5 Properties of each dataset that resulted from the two applied empirical approaches of the thesis

Empirical dataset	Survey	Fare transactions
Number of observations	279 individuals, 3,930 PT trips	1,293 cards/individuals, 18,828 transactions, 2,076 analysis cases (line route*cardID*origin-destination).
Sampling strategy	All trips regardless of PT line route made by specific individuals recruited at specific stops and on-board buses on one particular line route	All PT trips made with 20 specific lines during four weeks in total
Data properties	Full door-to-door trips for a limited sample of travellers during four weeks in total	Only boarding transactions (bus) and pre-purchased + on-board validations (train)
Contribution	Detailed information on full trips	Large-scale longitudinal information on use of specific PT lines

Each source of data was carefully chosen based on its inherent information value and potential contribution to the analyses in each study. Because the survey was conducted as part of the empirical data collection devoted to this thesis, it was considered with particular care due to the inherent potential to customise it favourably with respect to the research framework intended for the thesis. This customisation included a detailed approach to study travel patterns, including the obtaining of detailed data regarding transfers, travel modes, and mode-separated access and egress durations and distances in order to enable the subsequent estimation of path preferences. For the survey approach, data were thus obtained on trip leg level with a high degree of geographic specificity for full door-to-door trips including details regarding each leg type. A contributing aspect that motivated the use of this source of detailed survey data was that it would open for an exploratory approach to personal mobility patterns in PT networks, including access and egress. In addition, the survey instrument in itself enabled collection of personal data regarding each participating respondent such as age, gender, etc.

However, the raw data from the survey had only a weak association with the PT network. This insufficiency made it necessary to supplement the survey data with detailed information regarding scheduled and real-time vehicular trajectories of the PT supply that could be appended to the observed trips of the survey. GTFS timetable data were selected due to the comprehensive scope of the regional PT network of Scania – which was the area of study. This enabled it to be used to generate the explicit sets of alternatives needed for the estimation of path preferences, but also to provide a more aggregate description of the PT supply such as travel times, transfer times and service and path-based headways.

The survey data were highly valuable due to their richness and to the possibility to customise the data collection procedure and geographic scope according to the desired framework of the thesis. However, the challenging task of recruiting participants limited the possible quantity of recordable trip data to a quite restricted subset of the total range of trips made within the assigned geographic and temporal extent of the study. In order to expand the quantitative aspects of travel pattern analysis within the PT system to a more inclusive trip selection, farecard transaction data were collected from the AFC system of the regional PT provider Skånetrafiken, providing card-based travel patterns including each bus boarding and on-board validation on regional trains. From these data, it was therefore possible to trace the movements of each card (not necessarily but likely associated with a specific individual per card ID) through the PT network, including transfers. The data source enabled a large quantity of trip trajectories (nearly 600,000 registered cards for about 2.8 million transactions that entailed a total of 19,000 trips meeting the inference criteria) to be inferred for a subset of 20 PT services.

Despite its comprehensiveness, the GTFS source lacked information regarding the actual provision of PT services. The actual whereabouts of each PT vehicle was important in the studies of this thesis for two main reasons: (1) In order to associate each observed trip in the survey to a PT service, which needed a detailed and relevant account of actual departure times, and (2) to connect each boarding and card validation event in the AFC data to actual PT services. This association, which was attainable from the AVL data, was necessary in order to obtain full trip trajectories in the PT system, including the inference of alighting stops and the distinguishing between intermediate transfers and activities. Moreover, the AVL data were also used to generate the reliability performance data used in the studies of explanatory factors of waiting times (papers 1 and 2) as well as in the longitudinal analysis of passengers' sensitivity to changes in service reliability in terms of their choice of PT path (Paper 4).

Practical assumptions and operational definitions regarding PT trips

In order to structure the use of the data sources, and their mutual combinations, it is propitious to give an account of their relationship to each other. In order to make these relationships comprehensible, a short account of the data structure of each dataset is provided below.

First of all, the survey data were structured based on trip segments between natural discontinuities such as activities, boardings, alightings, and other changes of transport modes or activities. In the survey, activities were teased out based on heuristic rules regarding durations of stationary events and allowances for how much movement was permitted in order to be defined as being stationary. In my case, the temporal activity threshold was two minutes while the spatial restraint was set to 100 metres. Events fulfilling both of these restrictions, not moving more than 100 metres for at least two minutes, were thus categorised as activities. Trips, per definition, were defined as movements in time and space leading from one activity, other than transfer, waiting, and parking, to another activity, with the same exceptions. The key features, later used as reference points to combine and match trip itineraries from the survey with GTFS and AVL data, were thus trip segment IDs and boarding and alighting stop GTFS IDs. Hence, OD trip chains were defined as originating in an activity, tagged by the IDs of the first and last trip segments. These activity points were subsequently used to generate alternative access and egress legs, a procedure described in detail in Section 3.3 below.

However, and this is important – there was no information regarding stop IDs provided from the survey itself because the data obtained from it lacked a pre-defined PT network. Thus, in order to enable the successful matching between observed PT trip segments and timetable and AVL data, respectively, which was needed in order to obtain the attributes of each PT line, stop point information was joined spatially onto the trip itineraries from the survey.

Waiting time durations were identified in the enriched survey data by discriminating between waiting times at the first stop of a PT trip – FWT – and wait times at transfers (TWT). The FWT trip components were defined based on two main criteria: 1) The subsequent trip segment must be a PT segment and 2) the previous trip segment must be an activity or access mode (walk, bicycle, or car). For TWT, both the preceding and subsequent mode with respect to the transfer wait event had to be a PT mode and all three trip segments (PT mode #1 – TWT – PT mode #2) had to belong to the same trip ID. Here it should be noted that some of the thus recorded FWT and TWT events were segments of their own if the waiting time lasted for at least 2 minutes, which was the app threshold value for recording an activity, and these were to be coded as “Transfer/Wait” by the survey participants. Yet other FWT or TWT events, where the duration was less than 2 minutes, were in a sense fictive because they consisted only of the change of mode. These FWT or TWT events were assigned a random value in the interval of (0,2) minutes.

A consistent definition of time periods has been used throughout the analyses based on the survey data in order to explore differences in behaviour during different times of the day and week (Table 6). This subdivision was based on an approach to identify consistent service patterns in the PT network – a useful feature in the subsequent generation of explicit choice sets for the path choice model (cf. subsection 3.4.2), but also used as a proxy for different trip types. For example, commuter trips were expected to dominate during the morning and afternoon peaks. The interaction between time and trip purpose is further discussed in subsection 3.4.1, where the wait time analysis setup is outlined.

Table 6 Time periods applied throughout the survey-based analyses of travel behaviour in this thesis

Time period and definition		Time interval
1	Afternoon peak	Weekdays 15–19
2	Morning peak	Weekdays 06–09
3	Weekday off peak	Weekdays 19–24
4	Weekday daytime	Weekdays 09–15
5	Saturday evenings	Saturdays 17–24
6	Saturday daytime	Saturdays 09–17
7	Sunday	Sundays and public holidays 09–24

The farecard dataset had to be enriched in order to enable successful trip chaining, a procedure outlined in subsection 3.3.3 below. This enrichment was accomplished by merging with information from the AVL dataset for the same 20 PT services/line routes as discussed above. In order to discern inter-trip activities from transfers between PT services, the headway in the peak period of the line route used for post-transfer/activity boarding was considered. Thus, if an intermission (“time gap”) between an alighting and a boarding event – occurring on the same day and meeting the spatial constraints – lasted longer than the maximum weekday headway of the line route used for the subsequent boarding, it was regarded as an activity and the alighting stop was the trip’s destination, otherwise the intermission was regarded as a transfer event that was to be included in the trip. A random sample of trip intermissions is shown in Figure 16. As indicated in the scatterplot, a large portion of gaps were less than 60 minutes. Although the median (and mode) headway in Figure 16 is as low as 14 minutes, most events (95 percent) were classified as activities because trip intermissions also include date changes, leaving just five percent of them being transfers. This was also attributable to the relatively small selection of line routes in the data, making possible transfers between routes somewhat limited. Consequently, the mean number of trips (trip legs) per farecard ID and day was as low as 1.7 during both panel waves. The second "peak" in Figure 16 is located around the nine-hour mark (400-650 minutes), suggesting that these time gaps corresponded to work or education-related activities. Negative trip intermissions were associated with inconsistencies between boarding time stamps and previous trip alighting stop arrival times that originated from the process of inferring alighting stops or stations in which the observed trips in the travel card data were matched with the service trips in the AVL data.

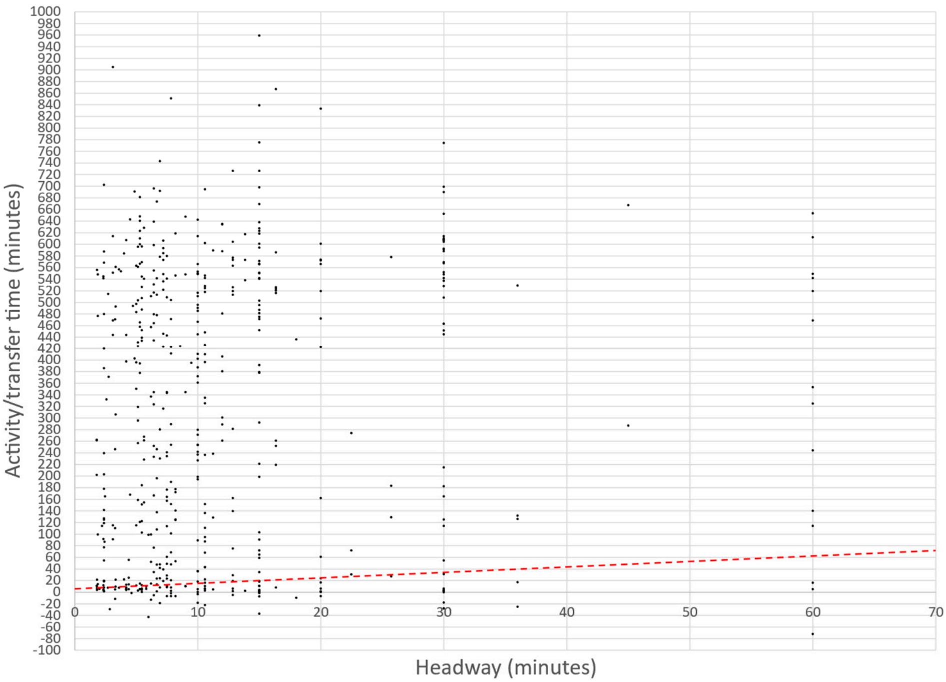

Figure 16 Trip intermissions (10 percent random sample of all weekday observations) between trip segments in minutes, plotted against headways (also in minutes) of the line route used for a subsequent trip, on days with multiple trip segments. The red line, and the area between the line and the x axis, indicates events categorised as transfers.

To control for the use of different stop points for the same ultimate origin or destination (e g, home or work), street network-congruent walk time matrices for neighbouring stops within 600 metres were applied to increase the flexibility of OD pair definition (inspired by the work of Goulet-Langlois et al. (2016) and with the cut-off distance value based on the empirical findings from the smartphone app survey). Thus, only stops within the cut-off network walking distance to neighbouring stops and present on at least one occasion in the card transaction data were included in order to rule out irrelevant stops.

As discussed in subsection 3.2.5 above, the temporal adjustment behaviour among PT passengers appears to be contingent on both service reliability and expected headway of the critical trip leg, i e, the PT leg with the lowest service frequency of a trip trajectory. As suggested by Carrel et al. (2013) and stated in the American Transit Capacity and Quality of Service Manual (TCQSM), and for highly reliable services, this adjustment is most prominent at 10–13-minute-headways and above. Thus, in order to investigate the potential importance of service frequency in addition to reliability, I have set the inflection point between short and long headways to 12 minutes, reflecting the midpoint of the interval [10,15] minutes mentioned in the TCQSM. Thus, above this value, the majority of PT passengers are assumed to start consulting timetables and scheduling becomes the most important factor. On the other hand, shorter headways should imply a higher level of random arrivals of PT passengers at origin boarding points and one would expect a stronger focus on headway regularity in order to minimise expected wait times.

Post-processing of empirical data

As noted in 3.2.6 above, auxiliary data were needed in order to obtain information regarding the PT system by matching observed trips from the survey with individual vehicular trajectories – scheduled or realised – in the PT network. In addition, auxiliary information was needed to obtain full PT trips from the farecard transactions. This section first outlines the processing steps that I applied to match observed trips with the PT network – necessary steps both for the wait time analyses of Papers 1 and 2 (research theme 1) and path preference analyses of papers 3 and 5 (research theme 2). It then moves on to the process by which full PT trips were obtained from the AVL data in order to analyse line route usage – which was the purpose of the study in Paper 4 and the subject of the third research theme.

Enrichment of the survey data

In order to enrich the survey data with attributes of PT lines such as headway and route course, a matching procedure had to be applied between trip segments of the survey with timetable GTFS data as well as actual vehicle trajectories from the AVL database. In order to achieve the first matching task, and provided that stop points of boarding and alighting for each PT trip segments were identified, a series of search scripts were used to find likely line routes based on two cases – single or multiple line routes, respectively – servicing the travelled OD stop pair (Figure 17). For single line routes, only the geographical constraints (stop points and line routes) were accounted for, while for multiple line routes, temporal constraints (departure times of individual service trips) were also included. Thus, for each trip segment performed along a path serviced by multiple line routes, departure times of passenger trips were matched with service trip data in the form of a) scheduled departure times from GTFS and b) actual departure times from AVL data.

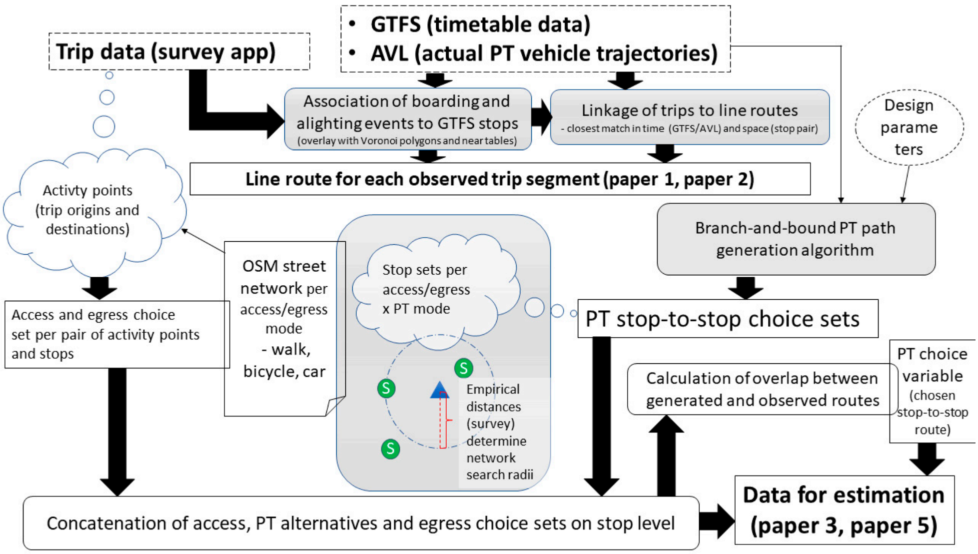

Figure 17 Schematic representation of the workflow for matching trip segment data from the survey with PT supply data from GTFS and the AVL system (Papers 1-3 and Paper 5), generating explicit choice sets from GTFS timetable and access+egress mode-specific path options, and identifying chosen paths (Papers 3,5). Square boxes represent datasets, while rounded boxes indicate processing steps, with the grey boxes representing processes performed in external software (ArcGIS and VISUM, respectively). Clouds indicate data features extracted from the referred datasets.

This was accomplished in two steps, where the first step used Voronoi[12] polygons around stop point locations (as illustrated in Figure 18) extracted from the GTFS data described above. All locations, defined as endpoints of trip segments in the survey and being within each polygon, were defined as starting or ending, depending on metadata from the survey, from the stop belonging to that particular polygon.

[12] Sometimes also termed Thiessen polygons and originally defined by Georgy Voronoi, 1908

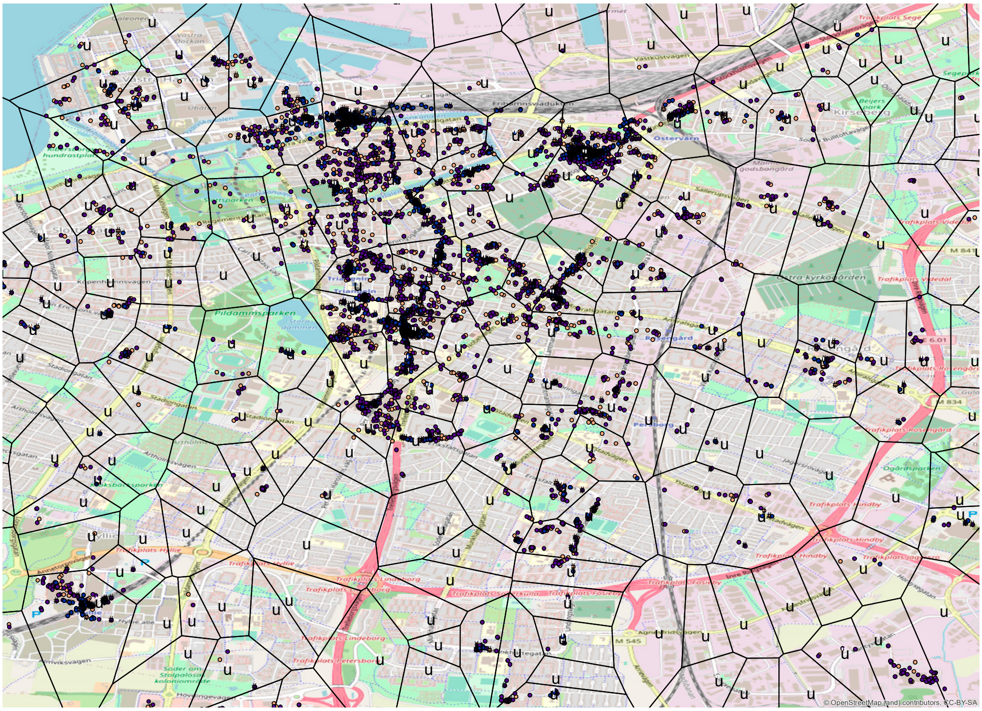

Figure 18 A subset of the GPS points collected by the survey participants using the survey app. The map indicates starting points (black triangles and hollow circles) and end points (filled circles) of trip segments belonging to trips where at least one PT mode was involved. Polygons represent Voronoi surfaces of each stop point (denoted by “H”) from the GTFS data and were used to identify origin and destination stops for each trip segment.

During the subsequent scrutiny and comparison of the results from the first step with aggregate survey data, the precision of the location information from the survey GPS data was found not to be sufficient to accurately infer correct stops for some boarding and alighting events. Thus, the second step of the stop inference included the search for line routes connecting auxiliary, neighbouring stops with the destination stops. This search was based on geographical information regarding detailed stop-based line route courses from the GTFS data as well as locational data regarding up to 10 nearest neighbouring stops within a radius of 2,000 metres (Euclidean distance) to each boarding and alighting stop inferred in the first step. If a direct line route connection was missing for a particular trip segment, a script calculated possible stops based on a list of neighbours ranked in order of distance from the originally inferred stop from the Voronoi analysis of the first step.

Thus, all boarding and alighting events occurring within Scania were successfully matched to stops. However, there was a share of trips also originating in, or having their destination, in Denmark, where GTFS and AVL data were only available for regional trains connecting Copenhagen and Elsinore with Scania. This resulted in stop polygons not taking account of auxiliary services such as buses and the metro, observations from which were recorded during the survey. The trip segments associated with these auxiliary PT modes thus had to be removed from the trip itineraries.

In the process of inferring line routes and service trips for each trip segment, there were a number of segments that had to be removed from the data set for various reasons. Origin and destination stops were identified as identical for a few segments, and some had stops or line routes that were not identified due to trips commencing and ending within very large Voronoi polygons – the size being explained by a location outside the study area of Scania and thus having few neighbouring stops. Most of the other missing data were caused by erroneous location registration – where origin and destination coordinates were very close to each other (within metres, although with substantial time differences). The dilemma with reduced GPS coverage in tunnels became evident for the 2016 survey data when using the line route search script for paths with multiple line routes to search for possible connections for survey trip segments between Copenhagen and destinations in Sweden. In this direction, passengers were required to change trains at the Copenhagen Airport station[13], but this transfer was rarely recorded.

The resulting trajectories thus consisted of three datasets (headway cases) – one for trip segments performed along paths serviced by single PT line routes (headway case 1), one based on departure times from GTFS timetable data (headway case 2), and one set with trajectories based on AVL departure time data (headway case 3). The two latter cases had the possibility to include multiple line routes. The three datasets and associated headway cases were used to analyse waiting times and possible explanations for these in the study for Paper 1. For the subsequent discrete choice modelling of Paper 3, the AVL-matched data were preferred due to the highest level of accuracy. For trips with missing service data from the AVL dataset, timetable-matched PT line route data were used instead.

Full PT trips from AFC data

Returning to the AFC farecard database, it was necessary to identify recurring trips, likely primarily involving commuting of any kind, in order to obtain trip types that were subject to changes in line route properties and hence to enable analysis of possible habit re-formation through longitudinal effects of changes in service attributes. This was achieved by applying two main criteria (the first criterion also applied by Chu & Lomone (2016)): (a) The same card was used to make at least ten trips in both time frames (panel waves), and (b) OD pairs and line routes recurred at least three times per time frame (panel wave). Figure 19 outlines the successive

[13] During the survey period, all passengers travelling to Sweden from Denmark by train were required to pass through an ID checkpoint at CPH, which resulted in an inevitable transfer in this subterranean rail station.

filtering of the number of cards involved in the transaction data and by which the number of transactions of the final estimation dataset was reduced to 9,211 and 9,617 transactions per panel wave, respectively.

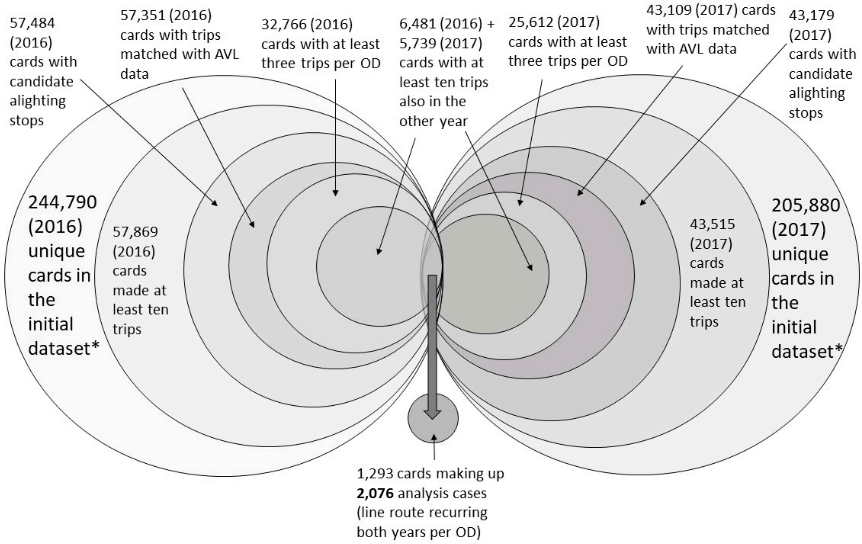

Figure 19 Data refinement procedure of the analysis cases to be included in the final farecard panel data set. One analysis case comprised the attributes of Line route (L), $RI_{L,2016}$, $RI_{L,2017}$, $P_{L,2016}$, $P_{L,2017}$, CardID, Number of trips in $2016_{L,OD}$, Number of trips in $2017_{L,OD}$, Trip $proportion_{L,OD,2016}$, Trip $proportion_{L,OD,2017}$, Origin stop, and Destination stop. *Unique cards that may be found in both panel waves

The final dataset ready for analyses was made up of relative frequencies, wave by wave, for each case of travel card ID, line route ID, and OD pair – i e, the revealed preference of each farecard holder to choose a particular line route (included in their revealed personal consideration set) for each OD trip during each panel wave.

In addition to the AFC data, reliability data, in the form of scheduled and actual departure times at all stops, was obtained from the AVL system for the same line routes as the card transaction data and merged with the dataset of analysis cases based on line route ID and time frame identifiers (Figure 21), including separate identifiers for weekdays and weekends, respectively. Thus, two primary datasets were prepared for analysis.

1. Relative line route frequencies by panel wave regardless of day type
2. Relative line route usage frequencies per weekday and weekend day, respectively

A procedure to infer alighting stops was implemented to enable the generation of full OD trips for subsequent behavioural studies. This was accomplished through a series of steps merging and combining datasets using sql, which are roughly outlined in the upper part of Figure 20 and largely inspired by the work of Jason B Gordon (2012). For train trips for which the fare was pre-paid using TVMs, the line route was inferred by sorting all transactions per travel cardID and time stamp.

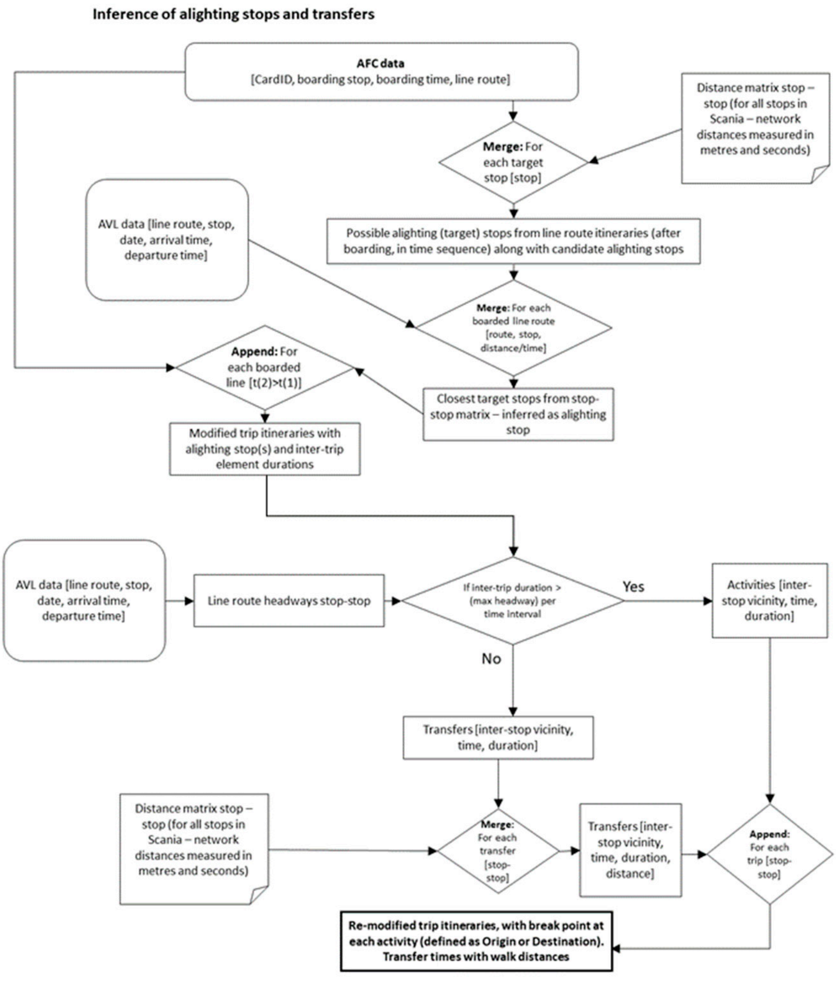

Figure 20 Schematic diagram of the procedure by which OD matrices were generated from farecard transaction data

Like Gordon (2012) and a number of other authors, I used subsequent boarding stops as candidates for alighting stops at a particular leg of a trip (mirroring). Candidate alighting stops were attained using a network-congruent search radius based on maximum acceptable access walk distances (4,000 metres) attained from the smartphone travel survey. From the attained array of possible alighting stops per trip, one of them was selected that was on the same line route as the boarding stop of that particular trip in the AFC data. Because this matching was based on both spatial (boarding stop and line route) and temporal criteria (the most likely departure according to the minimisation problem expressed in Equation 1), each passenger (farecard ID) trip had a corresponding vehicle movement determined from the AVL data.

$$t_{diff,opt} = \min_{i} \left| t_{boarding,AFC} - t_{dep,AVL,i} \right| \quad (1)$$

where $t_{diff,opt}$ is the optimal time difference, $t_{boarding,AFC}$ is the time of boarding according to the AFC dataset, and $t_{dep,AVL,I}$ is the departure time relevant to trip i. Figure 21 illustrates the inference of transfer events when different stops were used for alighting and subsequent boarding.

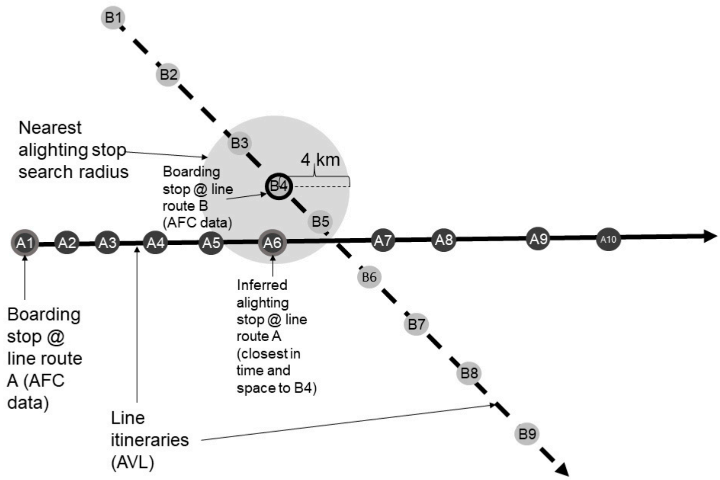

Figure 21 Schematic representation of the inference of alighting stops from transfers with walk links (adapted from Gordon (2012)).

Data analyses

This subsection outlines the analytic approaches chosen to deal with the research questions specified above and is subdivided according to the research themes formulated in Chapter 1. In this context it is worthwhile to highlight that paper 5 essentially builds upon methods and findings made in Paper 3, which describes the path choice estimation framework, but with some extensions that are also included in subsection 3.4.2. In this section each analytical approach is presented and explained, starting with the regression, ANOVA, and cross-tabulation approaches used in the waiting time analyses of Papers 1 and 2, moving on to the discrete choice modelling of Papers 3 and 5, and ending with the logistic regression approach of Paper 4.

Wait time analyses

Analysis of inter-individual variation in FWT, assuming it to be a good proxy for hyperpath strategizing among passengers, was performed using two different approaches, of which model 1:0 represents the most simplistic model using univariate ANOVA. A more elaborate approach, applied in models 2:5–2:8 and based on behavioural archetypes with respect to FWTs, is described further in the next paragraph below.

A total of 3,930 observed trip segments from the survey were successfully matched to GTFS timetabled line routes for stop pairs with one (headway case 1) or more (headway case 2) possible line routes, while a subset of 2,974 trip segments were successfully matched to line routes in the AVL data (headway case 3, cf. subsection 3.3.1). The smaller number of matches in the AVL-matched survey data may be explained by the fact that AVL data were only available for a subset of 20 line routes, presented in Table 4 above, compared to the complete county-wide GTFS line route dataset. Linear regression models (1:1–1:3 in Table 7) were specified in order to analyse the specific relationship between FWT and total OD headway at boarding stops, one for each of the three headway cases and based on the FWT definitions stated in subsection 3.2.7.

To explore possible interactions and impacts on waiting times from variables other than service frequency, passenger-stated planning strategy, and information usage, ANOVA model 1:4 was specified, which included categorical explanatory variables related to the respondent as well as the trip and the transport system (Table 7). Scheduled headway was introduced as a continuous variable, and the time periods were defined according to the seven classes discussed previously in subsection 3.2.7. As indicated in Table 7, most of the potentially explanatory variables for FWT were extracted from the survey data. From the survey questionnaire, personal data such as gender and age were obtained. Trip purpose was derived from the activity at the end of each trip, other than waiting and transfer, and activity before each trip[14] was obtained in a similar manner but was derived from the activity recorded ahead of each trip. Day type (weekday, Saturday, or Sunday) was derived from time stamps, and access mode (walk, bicycle, or car) emanated from the mode recorded in the app just before the FWT event (if being at least 2 minutes) or PT mode (for "fictive" FWT events below two minutes). Finally, stop type was defined according to the characterisation made by Dyrberg, Christensen, Anderson, Nielsen, & Prato (2015) and applied by Ingvardson et al. (2018), but in addition to the stop type "interchange", "terminus" (addressing the different waiting times at termini reported by Csikos & Currie, 2008) and the context variables "urban" and "rural" were added. These additional stop context variables were based on the land use surrounding each stop and were based on the land use types CBD/central; Hospital; Commercial; Residential; Industrial; Retail; Education; and Other.

Models 2:1–2:3 and 2:9 of Table 7, belonging to the study of Paper 2, include two additional variables, beyond the ones mentioned above, related to stated planning strategy and the use of information en route. These models were based only on 2017 survey wave data, in contrast to models 1:0–1:4 that are based on the full survey dataset. Using a chi square approach, indicated in Table 7, possible relationships between personal characteristics, trip attributes, and stated strategy and information usages, respectively, were explored in models 2:5–2:9. Included in this approach, as manifested in models 2:5–2:8, was an additional analytic dimension associated with individual behavioural consistency, as manifested in the four different wait time archetypes first proposed by Csikos & Currie (2008): "Like clockwork", with minimal FWT of, at the most, a few minutes; "Consistent within a wider window"; "Consistent plus outliers"; and "Largely random". Here, respondents were grouped into four equally large archetype groups based on median differences between the upper and lower quartiles of their revealed FWT as a measure of inter-individual FWT variability. The four archetypes were defined by using the four quartiles of these medians. The last model, 2:10, analysed TWT with respect to trip duration in order to analyse this relationship explicitly.

[14] Selectable activity types were Home, Temporary overnight, Work, School/education, Business, Drop off/pick up, Shopping, Healthcare, Other errand, Visit friends and relatives, Sports/outdoor, Restaurants/café, Hobby, Entertainment and culture and Other activity, respectively

Table 7 Model framework for the analysis of possible explanatory factors of waiting time (FWT – wait time at first stop of PT trip, TWT – transfer wait time). Note that the table continues on p 101.

Paper	Model type	Model number	Dataset	Dependent variable	Independent variables
1	Univariate ANOVA	1:0	Full survey	FWT	Phone ID (proxy for survey participant)
1	Linear regression	1:1	Full survey, GTFS	FWT	Scheduled headway, single line route
1	Linear regression	1:2	Full survey, GTFS	FWT	Scheduled headway, single or multiple line routes
1	Linear regression	1:3	Full survey, AVL	FWT	Actual headway, single or multiple line routes
1	Univariate ANOVA	1:4	Full survey, GTFS, AVL	FWT	Respondent: Gender, age; Trip: Purpose, previous activity, access mode, access distance, day type, time period; PT service attributes: Scheduled headway; Boarding stop: Context, stop type; Respondent gender*Trip purpose, Respondent gender*Stop type; Respondent gender*Stop context; Trip purpose*Stop type; Access mode*Trip duration
2	Univariate ANOVA	2:1	2017 survey wave	FWT	Stated planning strategy*Stated information use; Stated planning strategy; Stated optimisation strategy
2	Univariate ANOVA	2:2	2017 survey wave, GTFS	FWT	Stated planning strategy*Stated information use; Stated planning strategy; Stated optimisation strategy; Day type; Time period; Gender; Trip purpose; Stop type; Previous activity; Occupation; Flex time
2	Univariate ANOVA	2:3	2017 survey wave	TWT	Stated planning strategy*Stated information use; Stated planning strategy; Stated optimisation strategy
2	Univariate ANOVA	2:4	2017 survey wave, GTFS	TWT	Stated planning strategy*Stated information use; Stated planning strategy; Stated optimisation strategy; Day type; Time period; Gender; Trip purpose; Stop type; Previous activity; Occupation; Flex time
2	Chi square test	2:5	2017 survey wave, GTFS	Stated planning strategy	Stated information use; scheduled headway; service reliability; trip duration; trip purpose; previous activity; respondent occupation; respondent gender; respondent age; time of day; day type; first boarding stop type; respondent trip rate during survey; FWT archetype
2	Chi square test	2:6	2017 survey wave, GTFS	Stated information use	Scheduled headway; service reliability; trip duration; trip purpose; previous activity; respondent occupation; respondent gender; respondent age; time of day; day type; first boarding stop type; respondent trip rate during survey; FWT archetype
2	Chi square test	2:7	2017 survey wave, GTFS	Stated pre-knowledge of timetable	Scheduled headway; service reliability; trip purpose; previous activity; respondent gender; respondent age; FWT archetype
2	Chi square test	2:8	2017 survey wave	Stated optimisation strategy	Trip purpose; previous activity; respondent occupation; activity vs home end of trip; respondent work time

Paper	Model type	Model number	Dataset	Dependent variable	Independent variables
					flexibility; respondent gender; respondent age; Time of day; Day type; First boarding stop type; FWT archetype
2	Chi square test	2:9	2017 survey wave	FWT archetype	Trip purpose; previous activity; trip duration; service reliability; respondent occupation; respondent work time flexibility; respondent gender; respondent age; respondent trip rate during survey
2	Linear regression	2:10	2017 survey wave	TWT	Trip duration

PT path choice modelling

Choice set generation – access and egress legs

Motivated by earlier research efforts discussed in Section 2.3, a process was set up in order to generate explicit choice sets between activity points from the survey. Thus, the empirical anchor features for the generation of path alternatives for the choice sets were the recorded origin and destination locations of the trips in the survey (Figure 23). For each OD pair, a tree structure of path alternatives was generated where sets of unique PT stops were associated with each origin or destination location using pre-defined search criteria related to maximum distance (walk and bicycle) or time (car) as well as a cut-off value for number of stops. The former criteria were based on empirical observations in the survey (Table 8) while the latter were established using trial-and-error with an overarching aim to maximise the overlap with observed trips.

The reader should note that the procedure for choice set generation used here may not correspond to a true choice process of an individual as described in behavioural psychology literature. For instance, it is not possible for the researcher to observe the actual considered choice set for each individual, and thus some form of heuristics and assumptions have to be applied in order to represent all choice sets for multiple individuals and to enable modelling of behaviour (Bovy, 2009). The methodology to generate explicit, deterministic path alternatives may thus be regarded as a practical way to entail a sufficiently varied and versatile choice set, regardless of how the actual decision process is actually manifested in real-life situations (cf. the discussion of decision points in Section 2.2). For modelling purposes, decisions are often assumed to be sequential and/or hierarchical if the feasible alternatives contain combinations of underlying choice dimensions (Ben-Akiva & Lerman, 1985). However, in this thesis I have chosen to assume an implicit element in joint decisions, e g, the joint decision to choose a specific access mode to a specific stop in order to catch a specific PT service at that stop. In other words, the constituent trip legs were so tightly associated with each trip path alternative that the full joint decision was assumed to be made ahead of the trip. The outcome in terms of actually caught PT connections may be a result of this decision, or a consequence of properties of trip legs “upstream” of the diversion node in question (e g, alternative travel times or headways before a transfer stop).

Table 8 Cut-off restraints applied in the generation of access and egress choice sets. The maximum choice set restraint was higher ranked than the spatial and temporal constraints, which were set to include 96–98 percentile levels of the empirical distributions from the survey

Access/egress mode	PT mode	Spatial or temporal constraint (meters/hours)	Maximum choice set size
Walk	Urban bus	2 km	20
	Regional bus	2 km	10
	Train	2 km	10
Bicycle	Urban bus	5 km	10
	Regional bus	10 km	10
	Train	10 km	10
Car	Urban bus	N/A	N/A
	Regional bus	2.8 h	10
	Train	2.8 h	10

In order to limit the number of alternatives and to account for relevance in terms of availability of the access and egress modes of bicycle and car for each individual, an additional restriction was applied. Travellers who did not explicitly state in the survey to have used a bicycle or car for specific non-home-based access or egress trips were simply assumed to not have them as tentative choice options. Thus, alternatives with car or bicycle as access (egress) mode for trips with activity at an origin (destination) other than home were removed from the choice set if there was not a successful match for these combinations of access and egress modes with observed trips (see also Figure 23).

Choice set generation - PT modes

To maximise the output of attractive paths in the choice set (Bovy, 2009), a branch-and-bound approach (Friedrich et al., 2001) was applied in the enumeration of explicit PT choice sets for each time period and stop pair in the access+egress stop sets, here interpreted as origin and destination stops for PT trip legs. Thus, separate choice sets were generated for the 14 different time periods (seven per survey wave) indicated in Table 6 in subsection 3.2.7. The seven indicated time periods per survey wave (year) formed the basis for extracting GTFS timetables for the 2016 and 2017 survey waves, respectively. The generation of paths was performed in the proprietary software VISUM in an all-to-all manner between the selected stops in each timetable stop set (Table 9). The final joint PT path choice set thus generated included variables indicating time period and survey year. In Figure 22, the complete choice set generation procedure is outlined schematically, including the concatenation of access, PT, and egress alternatives, for door-do-door (activity to activity) trips.

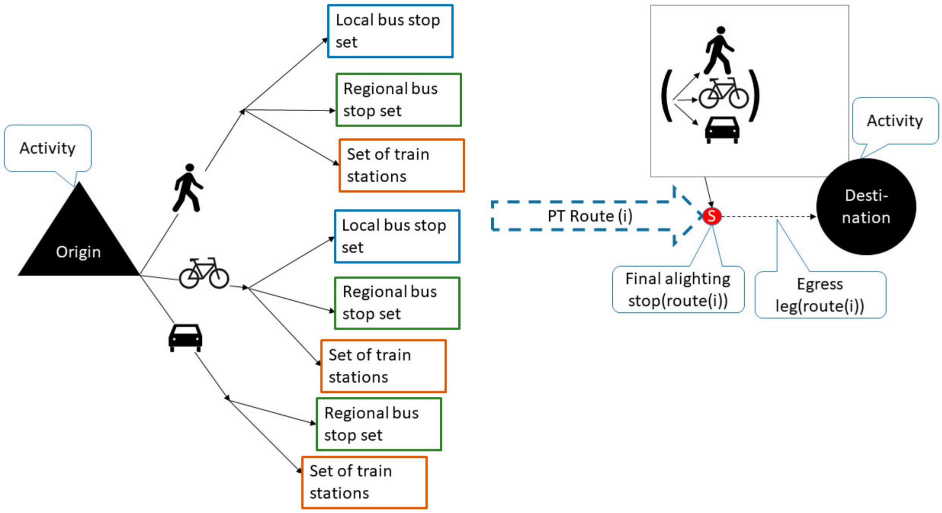

Figure 22 Process structure of choice set generation – i e, concatenation of access, PT, and egress legs – based on a tentative choice process from trip origin to destination (activity points in the survey). Note that a separate access and egress choice set was generated for each combination of PT mode and access/egress mode (as indicated by coloured boxes). Route (i) represents PT paths. The set of access/egress modal options was contingent on the activity type. Thus, only access and egress trip legs that were associated with the "home" activity offered all three modes (walk, bicycle, and car), while, for all other activities path alternatives that included car as a driver and bicycle were omitted from the choice set.

Table 9 Stop set and timetable (tt) hierarchy in relation to the time periods used for choice set generation and subsequent matching with observed trips. Time period IDs are according to Table 6. The stops were defined as traffic assignment zones (centroids) for each timetable when generating PT paths.

Time period (Year-ID)	Stops set weekday tt	Stops set Saturday tt	Stops set Sunday tt
2016-1	943	-	-
2016-2	943	-	-
2016-3	943	-	-
2016-4	943	-	-
2016-5	-	654	-
2016-6	-	654	-
2016-7	-	-	654
2017-1	1,048	-	-
2017-2	1,048	-	-
2017-3	1,048	-	-
2017-4	1,048	-	-
2017-5	-	806	-
2017-6	-	806	-
2017-7	-	-	806

Choice set evaluation

The choice set generation procedures for access+egress and PT legs were evaluated according to a framework originally proposed by Rieser-Schüssler et al. (2013), i e, by size, reproduction rate of observed paths, path diversity, and the plausibility of the hierarchical path sequence. However, except for the second property, there are – to my knowledge – no objective benchmark values as to when satisfactory levels of these conditions are met. For instance, the reproduction rate of actual observed paths may be measured in a number of ways. In the setup used in this thesis, a measure of path coverage suggested by Ramming (2002) was used in conjunction with the measures *passenger journey coverage* (Cov_r), *efficient coverage* (Cov_e), and *passenger path coverage* (Cov_{lv}) proposed by Tan (2016) to measure this reproduction rate. The definitions of each measure are presented in Table 10 along with a short description. Put succinctly, the passenger journey coverage measures the efficiency of the choice set generation procedure in representing the trips of each passenger, the efficient coverage measures the usefulness of the generated paths, and passenger path coverage measures the ability of the choice set to reproduce each observed path. In all definitions, i represents the individual passenger, R represents the generated choice set, N represents the total number (individuals, observations, etc.), and $I(\cdot)$ is an indicator function equal to one if the relevant condition is fulfilled. For passenger path coverage, the threshold value for path overlap was set to 0.8 based on findings by Anderson et al. (2014). This means that at least 80 percent of the link length of a choice set path (l of link v) must be overlapped by an observed path in order for it to be considered for matching, and the path with the maximum overlap for a particular OD pair may be considered a successful match to the observed path.

For the full estimation dataset, the choice set may be regarded as huge in relation to the number of observations, as indicated by the outcome in terms of efficient coverage. The extremely low coverage efficiency of 0.006 percent, necessary to attain a passenger path coverage of 39 percent and thus represent a decent share of observed choices from the choice set, was largely due to the hierarchical tree structure of mode-specific access and egress legs concatenated with PT trip path options. Although most of the survey respondents had at least one trip reproduced in the choice set, only a fraction had all their trips successfully reproduced. For PT trip legs however, the branch-and-bound approach was more successful in reproducing the observed trips than the approach applied to reproduce access and egress trip legs (as seen in terms of passenger path coverage).

Table 10 Definitions and outcome for each choice set coverage measure applied to evaluate the choice set generation procedure.

Path set coverage measure	Definition	Outcome		
		Access+egress	PT	Total
Passenger journey coverage – at least one trip	$Cov_r = \frac{\sum_i I(\delta_{r\in\{R\}})}{N_i}$	91.45%	94.78%	84.76%
Passenger journey coverage – all trips		2.60%	24.16%	2.23%
Efficient coverage	$Cov_e = \frac{\sum_n I(\delta_{r\in\{R\}})}{\|\{R\}\|}$	0.43%	27.59%	0.0057%
Passenger path coverage	$Cov_{lv}(k) = \frac{\sum_{n=1}^{N} I(O_{\max\{r\},lv,r} \geq k)}{N}$	44.88%	82.64%	39.43%

Ultimately, the outcome with respect to the evaluation criteria specified above relied heavily on the successful matching of observed trips with pre-defined choice set paths. The matching was performed separately for access and egress legs and PT trip legs, respectively. For access and egress, activity point and stop IDs were matched, while PT legs were matched by IDs of boarding, transfer, and alighting stops in conjunction with the (sequence of) line route ID(s). GTFS data formed the basis for stop ID, while a combination of GTFS and AVL data was used for line route matching (cf. Figure 18).

In total about half of the number of full door-to-door trips (1,487 of the 3,046) deemed as valid in the observations set were successfully matched to a pre-generated activity-to-activity path alternative. A majority of the mismatches referred to failure to match to a pre-generated access and egress leg, and the most common causes of these failures could be attributed to imperfections in the trip data obtained from the survey, such as missing access and/or egress leg(s), and only a clear minority of the mismatches were related to the matching procedure per se.

Comparing the properties of each trip leg type between the observed trips and the choice set enabled me to both validate the choice set and judge its suitability for model estimation of choice preferences. Particular emphasis was put on access and egress legs because this trip leg type is usually lacking in conventional PT path choice models. Because walk legs constituted about 87 percent of the observed access and egress trip legs, they had a large impact on the validity of the data. On average, walk durations were shorter among the matched observations compared to the choice set, regardless of whether the observational data originated from the survey directly or from the matched choice set alternative. This may be due to longer access and egress legs potentially being more complex to match and thus being over-represented among the observations that were not valid for modelling purposes. For bicycle and car access/egress, the choice set-matched observed trips had average lengths and durations shorter than for the corresponding alternatives in the choice set, thus indicating an expected average preference for shorter legs among the passengers of the survey than the average choice set alternative. For FWT and TWT, observation-matched choice set values were significantly shorter than those of the full choice set. However, TWTs measured in the survey were found to be significantly longer than those from the choice set. It should be noted, though, that the survey values consisted of events that were assigned at least two-minute-long (transfer or wait) activities in the survey app and were thus biased upwards. For transfer walk times (TWkTs), the values were quite similar when the full choice set was compared to the survey data, while the chosen alternatives of the choice set were significantly shorter. The same pattern was found when comparing the observed NTR per trip to the corresponding full choice set and matched choice set means, respectively. The very low NTR in the choice set data of the matched observations had important implications on the model estimates, as discussed further in Chapter 5.

Despite the differences encountered during the comparison of pre-defined path alternatives with the observed counterparts, the differences in their respective composition (duration and length) may not have had a direct impact on the preference estimates as long as the observed paths were represented in the choice set and the included path parameters were of a sufficient variation (see, e g, Bovy (2009) for a related discussion). For access/egress walk and NTR, the variance of the choice set exceeded or equalled the observed variance, while the observed variance for bicycle and car access/egress legs as well as walk and wait times at transfers far exceeded their pre-defined choice set counterparts.

Based on the above validation results, I decided to move on to the model estimation phase of the study. To maximise the sample for the model estimation, two separate datasets were defined depending on whether the observations included a successful match to full door-to-door choice set or just to the PT path choice set. Variables not related to access and egress were specifically targeted in a set of 2,842 observations that had only been matched to the PT stop-to-stop choice set, henceforth referred to as the *'B' estimation dataset.* The subset of these observations with successful matches not only to the PT legs, but also to the full choice set, including access and egress legs, contained 1,487 choice set-matched observations and is consistently referred to as the *'A' estimation dataset* in the remainder of the thesis. All observations of the 'A' dataset were thus also included in the 'B' dataset.

Variables attained from choice set data

As noted above, each observed trip from the survey was matched to a relevant path alternative in the pre-defined choice set based on time period and stop and line identifiers as anchors between the two datasets. Thus, attributes associated with each matched trip were obtained from the choice set data – i e, timetable-derived PT trip attributes and access+egress leg distances and durations from the street network used (Open Street Map). Separate IVT attributes were related to bus, regional train, and commuter train legs, respectively. Average values of transfer-related aspects such as waiting time and walk time per transfer as well as NTR were calculated for each path sequence[15]. Headway of the first PT trip leg and the maximum headway among all PT trip legs of the whole trip were derived from hourly departure frequency by stop pair. These two headway attributes may be viewed as two alternative proxies for (hidden) waiting time and adjustment time associated with the first stop of a PT trip. Frappier, Morency, & Trépanier (2018) motivate the inclusion of this factor by their finding that the departure frequency of a downstream line may affect the propensity to choose a multimodal path that includes a transfer to this line.

In addition, in this step a dummy variable was defined according to whether at least one boarding or transfer was made at a stop classified as being associated with an elevated level of PT passenger-relevant service[16].

Path choice model estimation

Separate model formulations were designed to address each of the research questions RQ3A–C as well as RQ5. For each model formulation, additional covariates were added to the utility specification in order to increase the model fit and to test for the influence of each covariate on utility, and thereby on preferences and behaviour. Utility maximisation of individual travellers was assumed here for simplicity, and a random utility modelling framework (Ben-Akiva & Lerman, 1985) was used to link choice probabilities with expressed utility. This subsection first deals with the conventional MNL specification used in the analyses in Paper 3 targeting RQ3. Subsequently, the mixed logit (ML) formulations (McFadden & Train, 2000) used to target RQ5 in Paper 5 regarding inter-individual choice correlation are specifically described.

The MNL models of Paper 3 were estimated using maximum likelihood estimation, where a log-likelihood function is maximised, using SAS software and the MDC procedure with multinomial logit model specifications. In order to limit the number of alternatives in the estimation procedure, sampling of a maximum of 1,000 alternatives was made for each chosen option from the full choice set using draws from a uniform distribution[17].

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[15] Note that this is a simplification because not every single connection is regarded, but rather average values of TWT and TWkT for all connections of each set of line route and stop sequences. Thus, the temporal dimensions of the path sets are suppressed and only regarded in terms of the *time period* attribute.

[16] This included amenities such as shops, restaurants, and cafés, and the stops denoted with this flag consisted of major train stations and bus interchanges.

[17] The sample size of the choice set was chosen somewhat arbitrarily. However, in doing so I considered the combinatorial potential of including 10*10 access+egress combinations per mode and adding a mean number of PT main trip paths of 37 as reported by Anderson et al. (2013). When comparing parameter estimate values, going from 30,000 (containing the mean choice set size per activity pair) to 1,000 sampled path options did not change these values significantly.

Let $y_{r,i}$ be a matrix of individual choice indicators:

$$y_{r,i} \begin{cases} 1 \; if \; individual \; i \; selects \; alternative \; r, \\ 0 \qquad\qquad\qquad otherwise \end{cases} \tag{2}$$

The log-likelihood function is then given by the logarithm of the product of the unconditional probability $P_{r,i}$:

$$LL = \sum_i \sum_r y_{r,i} ln(P_{r,i}) \tag{3}$$

A series of model specifications were tested for the systematic utility expression ($V_{i,n}$) for alternative r and individual n, as presented in Table 11 below. The objective functions were specified as linear-in-parameters for all models tested, and all of them included the "basic" travel time attributes for PT and access/egress modes as well as transfers. In addition, mode-specific constants were included for bicycle and car, while walk was kept as a reference. Hidden wait time, i e, the time the traveller had to adjust in order to time the departure of the first PT trip leg, was transformed according to ln(60/[number of departures per hour]), while a transformed (logarithmic) path-size (PS) term (Ben-Akiva & Bierlaire, 1999) was included in order to take into account the correlation related to overlap across paths. This path-size correction term was computed as:

$$PS_r = \sum_{a \in \Gamma_r} \frac{L_a}{L_r} \frac{1}{\sum_{s \in \{R\}} \delta_{a,s}} \tag{4}$$

where *a* is a link belonging to the sets of links *Γ* belonging to path *r*, *{R}* is the complete choice set, and *δ* is the link-path incidence dummy.

Access and egress times were summed and hence assumed to affect choice preferences in a symmetric fashion. However, the access and egress modes of bicycle and car were treated differently depending on whether the activity associated with the access/egress leg was home or non-home based (see above and in Figure 23).

In congruence with discrete choice modelling theory (McFadden, 1973), error terms were assumed to be distributed extreme-value type 1 errors, and the probability that individual *n* chooses alternative *i* was thus defined as:

$$P_{r,i} = \frac{e^{V_{r,i}}}{\sum_{s=\{R\}_i} e^{V_{s,i}}} \;, \forall r, s \in \{R\}_i \tag{5}$$

For the ML setting applied to address RQ5, a more complex log-likelihood statement was assumed, specified in Equation 6:

$$LL(\Omega) = \sum_{n=1}^{N} ln \left[\int_{\alpha} (\prod_{t=1}^{T_n}(\int_{\gamma} P_{i,t} \quad (j_{n,t}|\alpha,\gamma)h(\gamma)d\gamma))f(\alpha)d\alpha\right] \tag{6}$$

where *t* is a choice task and *Tn* represents the total set of tasks for individual *n*. *α* and *γ* are coefficients to be estimated, where *α* represents the inter-individual panel component and *γ* the intra-individual cross-sectional taste component for each stochastic variable in the specification of the systematic utility *V*. In my case, this specification was applied only on the access/egress walk and bicycle time, the FWT, and IVT trip segments, as described in Paper 5 and indicated in Table 11.

For the estimation of the ML model parameters, a maximum simulated likelihood framework was set up according to Equation 7:

$$SLL = \sum_{n=1}^{N} ln \left[\frac{1}{R}\sum_{r=1}^{R}(\prod_{t=1}^{T_n} P_{n,t}(j_{n,t}|\alpha_{r,n},\gamma_{r,t,n}))\right] \tag{7}$$

where *R* indicates the total number of *r* draws. This operationalisation of Equation 6, originally proposed and validated by Hess and Train (2011), was used in order to enable the use of the ML approach despite the quite complex error structure due to up to 500 choice tasks being available in the path choice set for each individual. As reported by the authors, the performance of this simplification enables the discernment of *inter-individual* heterogeneity (and thus choice correlation for each individual, which was the target for RQ5) while keeping calculation complexity, and hence estimation durations, at a reasonable level. However, the usage of just one draw from the γ distribution for each draw from the α distribution means that there is no recognition of variation in the values of γ for each fixed value of α for a given individual, and thus this model framework will not capture this (cross-sectional) component of variation.

As indicated in Table 11, the first basal model formulation was estimated based on both the ‘A’ and the ‘B’ estimation datasets, respectively (models 3:1 and 3:2 in Table 11). To test the hypothesis that the perceived disutility for transfer was lower at certain transfer points, a path-based dummy, indicating the presence of a stop with an enhanced level of service used for transfer along the path, was interacted with waiting time covariates *TWkT*, *TWT,* and *NTR* based on the ‘B’ dataset in model 3:3. These interaction variables were included in addition to the variables included in the first model.

To test the influence of gender and age on path preferences, personal characteristics dummy variables indicating male gender and age above 50 years were interacted with all travel time and transfer-related variables in models 3:4 and 3:5. These models were estimated based on both the ‘A’ and the ‘B’ estimation datasets.

In models 3:6 and 3:7, presented in Table 11, all access and egress travel time variables were replaced with corresponding distance variables. The ‘A’ estimation dataset was used because it comprised a full OD trip observation-matched choice set, including access and egress legs.

Finally, models 5:1–5:3 of Table 11 account for the model setup where specific parameters for inter and intra-respondent variation in choice preferences were included according to the framework proposed by Hess and Rose (2009). As indicated in the table, the first of these ML models analysed the impact of inter- versus intra-individual heterogeneity in preferences toward access and egress time for walk and bicycle. Here, the 'A' dataset formed the basis for the maximum likelihood estimation of model coefficients. Model 5:2 focused on individual consistency in preferences regarding FWT for all trips and FWT during trips longer than one hour, respectively, and was based on the 'B' estimation dataset. Finally, model 5:3 explored the individual preference consistency for train and bus IVT and utilised the 'B' estimation dataset as well. A full account of the ML modelling approach is provided in Paper 5.

The reason why the ML approach was confined to the model specifications of Paper 5 and not the ones specified in Paper 3 was mainly due to the time constraints put on the study presented in this paper. Running ML models typically requires substantially more computational power and time for the maximum likelihood estimation simulation to converge. I presumed the inter vs. intra-individual variation to be most articulated in the preferences towards IVT, access/egress, and FWT and thus focused the ML analyses on these variables.

Table 11 Model framework for the analysis of possible preferences in path choice. Dataset A includes only survey trips matched with access and egress choice sets, while dataset B also includes unmatched access and egress legs. IVT – in-vehicle time, FWT – hidden wait/adjustment time, TWT – transfer wait time, TWkT – transfer walk time, NTR – number of transfers, PS – path size (overlap) term, HLS – attribute interacted with path dummy for paths including at least one stop with an enhanced level of service.

Paper	Model type	Model number	Datasets	Dependent variable	Independent variables
3	Multinomial logit	3:1	A	Choice probability	IVT bus; IVT train; access+egress time walk, bicycle and car; ln(FWT); TWT; TWkT; NTR; home-based access/egress mode bicycle; home-based access/egress mode car; ln(PS)
3	Multinomial logit	3:2	B	Choice probability	IVT bus; IVT train; access+egress time walk, bicycle and car; ln(FWT); TWT; TWkT; NTR; home-based access/egress mode bicycle; home-based access/egress mode car; ln(PS)
3	Multinomial logit	3:3	B	Choice probability	IVT bus; IVT train; access+egress time walk, bicycle and car; ln(FWT); TWT; TWkT; NTR; home-based access/egress mode bicycle; home-based access/egress mode car; TWkT_HLS; TWT_HLS; NTR_HLS; ln(PS)
3	Multinomial logit	3:4	A	Choice probability	IVT bus; IVT train; access+egress time walk, bicycle and car; ln(FWT); TWT; TWkT; NTR; home-based access/egress mode bicycle; home-based access/egress mode car; ln(PS); Respondent gender*access+egress time walk; Respondent gender*access+egress time bicycle; Respondent gender*access+egress time car; Respondent gender*IVT bus; Respondent gender*IVT train; AgeOver50*access+egress time walk; AgeOver50*access+egress time bicycle; AgeOver50*access+egress time car; AgeOver50*IVT bus; AgeOver50*IVT train
3	Multinomial logit	3:5	B	Choice probability	IVT bus; IVT train; access+egress time walk, bicycle and car; ln(FWT); TWT; TWkT; NTR; home-based access/egress mode bicycle; home-based access/egress mode car; ln(PS); Respondent gender*TWkT; Respondent gender*TWT; Respondent gender*NTR; Respondent gender*IVT bus; Respondent gender*IVT train; AgeOver50*TWkT; AgeOver50*TWT; AgeOver50*NTR; AgeOver50*IVT bus; AgeOver50*IVT train
3	Multinomial logit	3:6	A	Choice probability	IVT bus; IVT train; access+egress distance walk, bicycle and car; ln(FWT); TWT; TWkT; NTR; home-based access/egress mode bicycle; home-based access/egress mode car; ln(PS); Respondent gender*access+egress distance walk; Respondent gender*access+egress distance bicycle; Respondent gender*access+egress distance car; Respondent gender*IVT bus; Respondent gender*IVT train; Respondent gender*TWkT; Respondent gender*TWT; Respondent gender*NTR; AgeOver50*access+egress distance walk; AgeOver50*access+egress distance bicycle; AgeOver50*access+egress distance car; AgeOver50*IVT bus; AgeOver50*IVT train; AgeOver50*TWkT; AgeOver50*TWT; AgeOver50*NTR;
3	Multinomial logit	3:7	A	Choice probability	IVT bus; IVT train; access+egress distance walk, bicycle and car; ln(FWT); TWT; TWkT; NTR; home-based access/egress mode bicycle; home-based access/egress mode car; TWkT_HLS; TWT_HLS; NTR_HLS; ln(PS)

5	Mixed multinomial logit	5:1	A		IVT bus; IVT train; access+egress time walk, bicycle and car; access+egress time walk_cross_section, walk_panel; fmin; TWT; TWkT; NTR; home-based access/egress mode bicycle; home-based access/egress mode car; ln(PS);
5	Mixed multinomial logit	5:2	B		IVT bus; IVT train; access+egress time walk, bicycle and car; ln(FWT); ln(FWT)_cross_section; ln(FWT)_panel; TWT; TWkT; NTR; home-based access/egress mode bicycle; home-based access/egress mode car; TWkT_HLS; TWT_HLS; NTR_HLS; ln(PS)
5	Mixed multinomial logit	5:3	B		IVT bus; IVT bus cross_secton; IVT bus panel; IVT train; IVT train cross_section; IVT train panel; access+egress time walk, bicycle and car; ln(FWT); TWT; TWkT; NTR; home-based access/egress mode bicycle; home-based access/egress mode car; TWkT_HLS; TWT_HLS; NTR_HLS; ln(PS)

A binary logistic analytic approach to studying longitudinal effects of PT reliability changes

In order to analyse behavioural responses to changed service reliability, both with respect to increasing (positive) and decreasing (negative) reliability changes, a fixed effects panel approach was used to model the individual passenger's long-term trade-off between line routes in the given OD pairs. Binary logistic regression models were set up, where the regressand comprised the values 1 for change in relative line route usage and 0 for no change. Separate models were used for positive and negative ridership changes, respectively. A rationale here was that passengers were assumed to perceive, and thus be sensitive to, marginal changes in service reliability/predictability differently conditional on the scheduled departure frequency, as discussed in Chapter 2 (with a departure headway of 10 minutes being a tentative behavioural break point according to, e g, Trompet et al., 2011). To this end, two different dimensions of service reliability were identified as being crucial for the perception, and thus the choice, of PT path, namely the line route timetable adherence and headway variability, where line route timetable adherence is usually assumed to be the most important for long-headway services for which the highest proportion of passengers relies on, and adapts to, exact departure times, while headway variability would be most relevant at short-headway services to which most passengers arrive randomly at the origin stop or station. The most extreme case of headway variability is for services without published timetables, where only mean frequencies are communicated to (potential) travellers (Eltved, 2020). Two measures of reliability were used in the analysis based on these dimensions, namely the punctuality index P, supposedly the most relevant for line route timetable adherence, and the headway regularity index RI_h, which is chiefly attributable to headway variability (Rudnicki, 1997). The latter measure, in my case inspired by the work of Osuna & Newell (1972), is specified according to Equation 8.

$$RI_h = 1/(1 + \frac{var(H)}{E^2(H)}) \qquad (8)$$

The specification of RI_h was made in order to obtain some favourable mathematical and intuitive behavioural properties. Thus, as variation in actual headway approaches zero, RI_h may be approximated by one (for "very reliable services"), while, as the variance in actual headway moves toward infinity (for "very unreliable services"), RI_h approaches zero asymptotically. This is sensible given the notion that schedule adherence becomes more important for long headways, while the interval between successive departures dominates at short headways.

Punctuality, being a measure of timetable adherence, usually refers to an arbitrary tolerance value of permissible deviation from a schedule (Rudnicki, 1997), a tolerance often set to a value of a few minutes (Trompet et al., 2011). After having tested a few tolerance values, a two-minute threshold was applied to exclude errors of measurement and rounding without causing unnecessary data loss (in the AVL system, train departures are measured in whole minutes, while bus departures are measured in seconds). The punctuality index P_L applied in this thesis was defined as the proportion of non-punctual departures for line route L, according to Equation 9:

$$P_L = \sum_{v=1}^{V_L} \sum_{s=1}^{S_L} I_{s,v} / N_{S_L,V_{L,}} \qquad (9)$$

were $\begin{cases} I_{s,v} = 1 \; if \; an \; actual \; departure \\ deviates \; more \; than \\ 2 \; minutes \; from \; the \; schedule, and \\ I_{s,v} = 0 \; otherwise \end{cases}$, s is a stop or station in the set of stops or stations S_L for line L, v_L is a vehicle run of line route L, and $N_{S,L}$ is the total number of stops or stations along line L. The measure thus gauges the share of punctual departures, with the definitions stated above, and thus the likelihood of encountering a particular level of punctuality.

As a measure of in-vehicle time variation, RBT (defined in Equation 10 – Gittens & Shalaby, 2015; Uniman et al., 2010) was included in the model framework in order to test for its impact on PT path choice (or, as for the reliability measures defined above, preferences for specific line routes).

$$RBT_{OD,L} = TT_{95perc,OD,L,\{i\}v} - TT_{median,OD,L,\{i\}} \qquad (10)$$

The travel time for each passenger trip (TT_i) was calculated based on departure and arrival time attributes of the temporally and spatially matched PT vehicle trip from AVL data, and the quantiles $TT_{95perc,OD,L}$ and $TT_{median,OD,L}$ were calculated based on the sets of trips $\{i\}$ for each day type (weekday or weekend day), OD pair OD, and line route L.

A total of 14 different models were tested, presented and specified according to Table 12. Two subsets of data, covering increased and decreased line route ridership across panel waves, respectively, were evaluated using each model specification. The regressor variables (the *Δ* variables in Table 12) were normalised to a full fraction scale of change in each reliability and travel time measure, in which, for example, a 50-percent decrease in travel time or reliability index value was set to -0.5.

To analyse differences in revealed behavioural changes due to different headway regimes and day types, each reliability index was interacted with dummy variables. For headway differences, a dummy indicating cases with short maximum weighted headways[18] (at or below twelve minutes) was applied, while the influence of day type (weekdays versus weekends) on the change responses was tested in a data subset in which the day type for each choice was considered using a dummy variable for weekend days, which was interacted with each reliability measure.

Table 12 Model framework applied in order to analyse the impact on line route choice probabilities resulting from relative changes (Δ) in service reliability, measured as regularity index RI_h, punctuality P, and, for the first two models, mean *travel time TT* and *reliability buffer time (RBT)* – all related to line routes L present in the farecard dataset. *HW1, HW2* – variables interacted with dummies for line routes with headways at or below or above twelve minutes, respectively. *WE* – variable interacted with the dummy for weekend days.

Paper	Model type	Dataset	Dependent variable	Independent variables
4	Log-linear regression	Panel dataset of all farecard analysis cases, regardless or day type	Probability of **increased** line route ridership	$\Delta RI_{h,L}, \Delta P_L, \Delta TT_L, \Delta RBT_L$ $\Delta RI_{h,L}$ ΔP_L $\Delta RI_{h,L},{*}HW1, \Delta RI_{h,L}{*}HW2$ $\Delta P_L{*}HW1, \Delta P_L{*}HW2$
			Probability of **decreased** line route ridership	$\Delta RI_{h,L}, \Delta P_L, \Delta TT_L, \Delta RBT_L$ $\Delta RI_{h,L}$ ΔP_L $\Delta RI_{h,L},{*}HW1, \Delta RI_{h,L}{*}HW2$ $\Delta P_L{*}HW1, \Delta P_L{*}HW2$
		Panel dataset of all farecard analysis cases subdivided by day type	Probability of **increased** line route ridership	$\Delta RI_{h,L}{*}WE$ $\Delta P_L{*}WE$
			Probability of **decreased** line route ridership	$\Delta RI_{h,L}{*}WE$ $\Delta P_L{*}WE$

A measure of sensitivity was used in order to test for the impact of each independent variable on the propensity to change line route –regarding both increased and decreased proportional ridership. The sensitivity, evaluated for each regressor, thus indicates the marginal change in the probability of changing the proportional use of a line route with respect to a marginal change of that specific covariate.

[18] The selection condition for an analysis case was valid only if at least one of the time frames contained a line route with a certain ridership-weighted headway for that case.

4 Findings

This chapter constitutes a summary and brief discussion of the results from the five papers that form the basis for this thesis, and it is organised according to the research themes of the five associated research questions. These themes deal with the two fundamental dimensions aiming to nuance the concept of PT passenger behaviour, namely the individual traveller and the transport system. As emphasised in Chapter 1, the empirical evidence focuses on revealed, rather than stated or claimed, actions. One important exception, reported on in subsection 4.1.2, is the use of planning strategies and departure information, where the findings are based on en route statements by the subjects under study. The theme of this subsection is focused on waiting times in their capacity as an indicator of passenger's choice of PT services on an aggregate level. In 4.2, the outcomes of passengers' perceptions are studied in a more detailed manner in the form of preferences based on revealed trade-offs between exogeneous trip attributes. Finally, in Section 4.3, the third theme, which adds a temporal dimension to the analytic framework, travel time uncertainty is described in terms of its impact on passenger behaviour over time.

Exploratory insights into waiting time behaviour of PT passengers

Key results from each statistical model used to study wait time are presented in Table 13, with references to RQ1 and RQ2, respectively, followed by detailed discussions around the findings of each paper in subsections 4.1.1 and 4.1.2 below.

Table 13 Summary of findings responding to RQ1 and RQ2, addressing analysis issues regarding underlying factors explaining hyperpath strategies in relation to waiting times of PT passengers. FWT – wait time at first stop of a PT trip, TWT – transfer wait time. The analysis issue of each model, indicated in the first column, formulates each model specification verbally in terms of dependent and potential explanatory factors.

Analysis issue	RQ	Model number (cf. Table 7)	Method	Key results	Model properties
Possible inter-individual differences in FWT duration	1	1:0	Linear regression	There is a significant difference across individuals in FWT. The cross-sectional StDev across FWT for all trips is larger (StDev 4.3 minutes) than the mean StDev within individuals (StDev = 2.8 minutes) or the StDev across mean StDevs for all individuals = 2.48)	R^2 = 0.16, Adjusted R^2 = 0.103
Impact on FWT of scheduled headway for one-service paths	1	1:1	Linear regression		R^2 = 0.60
Impact on FWT of scheduled headway for multiple-service paths	1	1:2	Linear regression	Passengers tend to time their arrivals to scheduled departure times of the first PT stop at headways of 6-7 minutes and longer.	R^2 = 0.33
Impact on FWT of perceived headway	1	1:3	Linear regression		R^2 = 0.34
Impact on FWT of trip attributes and personal characteristics	1	1:4	Univariate ANOVA	Men and women wait differently for some trip purposes, where women tend to wait longer than men, but not for others. Wait times are longer for bike and car as access mode for medium and long trip durations but not for short trip durations. Scheduled headway has an impact on FWT, but this impact is less articulate than that of trip purpose and access mode	R^2 = 0.121, Adjusted R^2 = 0.078
Impact on FWT of stated travel strategies and information usage	2	2:1	Univariate ANOVA	No statistically significant relationship (at a 0.05 significance level) could be discerned	R^2 = 0.002, Adjusted R^2 = 0.001
Impact on FWT of trip attributes, personal characteristics and stated travel strategy and information usage	2	2:2	Univariate ANOVA	Wait times are longer, both at first stop (45 seconds on average, statistically significant at the 0.05 significance level) and at transfers (almost three minutes longer TWT) for pre-planned trips because they are more complex and longer than trips not requiring pre-planning. Possession of travel	R^2 = 0.112, Adjusted R^2 = 0.083

Analysis issue	RQ	Model number (cf. Table 7)	Method	Key results	Model properties
Impact on TWT of stated travel strategies and information usage	2	2:3	Univariate ANOVA	information entails 25 seconds shorter FWT than without this information.	R^2 = 0.110, Adjusted R^2 = 0.083
Impact on TWT of trip attributes, personal characteristics and stated travel strategy and information usage	2	2:4	Univariate ANOVA	Transfer wait times are on average 1:45 minutes longer for trips where information has not been used compared to when it has	R^2 = 0.242, Adjusted R^2 = 0.092
Association of stated planning strategy with personal characteristics and trip attributes	1, 2	2:5	Chi square	Strategic planning is positively correlated with previous timetable knowledge, being female and older than 50 years, for off-peak and rural trips, but not consulting with new information. More pre-planning is made for paths with scheduled headways above five minutes than below and less for short work trips in urban areas.	All tests significant at the 0.05 level except for Day type
Association of stated information use with personal characteristics and trip attributes	1, 2	2:6	Chi square	Information use is positively correlated with day type being weekend, off-peak time, for trips starting at urban stops and using services with high reliability, for male and young (below 35 years old) respondents, making less than seven of more than 28 trips during two-week survey period	All tests significant at the 0.05 level except for Scheduled headway
Association of stated pre-knowledge of timetables with personal characteristics and trip attributes	1, 2	2:7	Chi square	Timetable pre-knowledge is positively correlated with being a woman and being above 50 years old, and is over-represented for trips using services with headways at ten minutes and longer,	All tests significant at the 0.05 level except for Responden t gender
Association of stated optimisation strategy with personal characteristics and trip attributes	1, 2	2:8	Chi square	Selecting desired departure time in a journey planner is positively correlated with work trips while school trips are positively correlated with selecting a desired arrival time. Arrival time selection is positively correlated with trips to activities while departure time selection is positively correlated with homebound trips. Not having flexible work hours is positively correlated with arrival time selection	All tests significant at the 0.05 level except for Time of day
Association of FWT archetypes with personal characteristics and trip attributes	2	2:9	Chi square	There are less-optimised waiting times for pre-planned trips, but a larger degree of optimisation when using information. Older employees optimise to a larger extent than students	All tests significant at the 0.05 level
TWT and trip duration	2	2:10	Linear regression	Longer transfer times are associated with longer trips.	R^2 = 0.015

Waiting times as an indicator of PT passengers' travel strategies (hyperpaths) and the role of the transport system

The findings addressing RQ1 may be summarised as follows:

i. There appears to be a difference across individuals in their hyperpath strategies when measured in their variation of revealed FWT (model 1:0 in Table 13), but also in individuals' approaches to paths with different FWTs (model 2:9). However, the character of the trip may be a part of the explanation because shorter trips entail a higher degree of hyperpath strategising, i e, FWT optimisation behaviour, than trips exceeding one hour (model 2:9).

ii. There is scant evidence for a systematic difference in hyperpath strategising between paths serviced by single or multiple line routes when measured by the distribution of FWTs (models 1:1–1:3). Thus, the mean difference in the temporal inflection point at which the linear relationship between headways and FWT starts to bend downwards is only in a magnitude of 30 seconds, where single line route paths have slightly longer revealed FWT values on average than multiple line route paths.

As specified in RQ1 and RQ2 (but also relevant for RQ5), the study of waiting times analysed whether there were traces of consistency in revealed waiting times as an indicator of strategic hyperpath behaviour among the survey respondents. It also analysed to what degree trip and transport system-related attributes such as trip purpose and service frequency could serve as tentative explanations for waiting times. It was found, using univariate ANOVA, that the variation across individuals was indeed significantly larger ($P = 0.000$ at the 95% confidence level) than for each individual. The differences across individuals were possible to detect by using measures of waiting time dispersion and FWT archetypes based on explicitly stated usage of strategies and information, although these factors may be regarded as endogenous to the individual to some extent and thus corroborate the findings by Csikos & Currie (2008). The results also contribute to the line of research represented by Kim, Corcoran, & Papamanolis (2017) who found consistency in passengers' choice behaviour in PT networks and to that of Fonzone et al. (2010) who also discussed the importance of knowledge and attitude to change for such consistency as well as for the extent of perceived choice ranges.

Relevant to the choice range, or the hyperpath size, mentioned above, regression models 1:1–1:3 analysed how FWTs correlated with scheduled and actual headway for the different headway cases referred to above. Thus, I aimed to target the issue of how hyperpaths may be discerned differently depending on PT network path properties (Table 13). However, the immense dispersion of the FWT data (as indicated by substantial vertical scattering of FWT observations for each service headway) led to the conclusion that there should be no significant differences across headway cases 1, 2, and 3 (i e, between the FWT datasets).

As suggested by the results from ANOVA tests of FWT against, among other things, trip duration (model 1:4 in Table 13), FWT may partly be attributed to the length of the trip. In addition, there was inter-individual heterogeneity in trip duration that exceeded the heterogeneity across trips for each individual (inter-individual StDev = 62.8 minutes, mean intra-individual StDev = 40.5 minutes, as obtained from a separate univariate ANOVA). The latter result, similar to that reported by Fonzone et al. (2010), was also corroborated by results from the categorisation into FWT archetypes in Paper 2. Thus, it seems like the answer to the RQ would be a "yes"; there are individual differences in FWT behaviour, but these differences may be explained by trip attributes associated with the type of trip. Thus, scheduled headway had a significant impact on both actual FWT and FWT optimisation (hyperpath strategising) behaviour according to the FWT archetype categorisation approach, because a higher degree of waiting optimisation was found for trips using connections with (combined) headways at or below five minutes compared to longer headways. Also, having fewer restraints imposed by work time flexibility enabled a higher degree of waiting time optimisation, as indicated by the results presented in Table 13.

Influence of planning strategy and information usage on travel patterns

When addressing RQ2, the following findings could be obtained from the analysis of stated responses and revealed waiting time behaviour:

i. There is a small but clear impact of both explicitly stated use of planning strategies and information usage on both FWT and TWT (models 2:2–2:4 of Table 13).

ii.

   a. Strategic pre-trip planning, on the one hand, was pursued at an elevated rate for services with relatively long headways and at times and for purposes of a relatively non-routine nature in rural environments by passengers older than 50 years having pre-knowledge of timetables (model 2:5).

   b. Pre-trip information, on the other hand, was sought in urban areas by young individuals, primarily male, for non-routine trips by accustomed (frequent) and occasional PT travellers (model 2:6).

   c. PT passengers tended to optimise their waiting time, especially TWT, to a greater extent when they had access to information and the line routes had a high regularity index, as a proxy for service reliability. For trip purposes that have restraints on the destination end of the trip, arrival time optimisation was used to a greater extent than for home-bound trips, where departure time optimisation was most common – possibly due to temporal restraints at the origin of the trip (models 2:6–2:9).

The degree of use of external sources of travel information and its impact on behaviour was studied using ANOVA and linear regression models. The results from this, and the subsequent Chi square tests from cross-tabulations of the stated trip-based strategies against a number of categorical variables associated with trip attributes and individual characteristics, thus nuanced the results from ANOVA models 2:1–2:4 by controlling for these additional variables. A pattern seems to evolve with respect to the structure of the PT network in which pre-planning is used more for long and unusual discretionary trips than for short habitual trips (thus elaborating on the findings by Farag & Lyons (2008) if we presume that discretionary trips are associated with less risk-taking and more preparations than habitual ones, including the pre-acquisition of travel information).

Trips that had been pre-planned using timetable or digital journey planners had longer FWT and TWT (statistically significant at the 0.05 significance level) than trips performed without elaborate pre-planning. On the other hand, stated use of information, being through consulting timetables or a digital journey planner, entailed a statistically significant average time optimisation in terms of average FWT reduction and TWT. The first result, regarding the impact from stated pre-planning, was not in a direction that I expected but may be related to the confounding factor of trip duration (as a proxy for trip complexity), as indicated by model 2:10. The optimisation of travel time through the use of information is in line with findings from other studies such as that of Cats, Koutsopoulos, Burghout, & Toledo (2011). Thus the usage of information and pre-planning seems to have an impact on travel time optimisation as measured in waiting time minutes, but it may be confounded by the trip type.

Path choice preferences obtained from the disaggregate survey approach

Outcomes from the empirical approach to collecting mobility data using a dedicated smartphone app are presented from the three aspects of RQ3. First, an account of the validation of the survey method and the procedure to reproduce its trip observations in a set of discrete alternatives – the choice set – is provided. Here, the results themselves may serve as a validation approach of the empirical effort as a whole vis-à-vis other, more established, survey approaches. Second, with the purpose to target the second and third aspects of RQ3 regarding catchment and transfer stop characteristics, respectively, key results from each discrete path choice modelling approach – the conventional MNL models of Paper 3 and the ML models of Paper 5 - are presented in Table 14 below and further discussed in the text.

Overall, the estimated model coefficients and preference values in terms of estimates and marginal rates of substitution (MRS) values, relevant for the method validation described in the first sub-question of RQ3, are reasonable in terms of their order of magnitude and sign. However, the exact marginal utility (MU) values are not transferrable directly across empirical contexts. MRS values, on the other hand, seem to align to a more doctrinal value range, when using IVT bus as the reference. For IVT train, for instance, the basal model of Paper 3 entailed an MRS of 0.6, which is in line with values found by Eltved (2020) (0.77 for s-trains and 0.79 for local trains – both versus bus) and Eluru, Chakour, & El-Geneidy (2012) (0.64 for train versus bus). For TWTs, Eltved, who based his results on the national travel survey of Denmark, attained MRS values of between 0.15 and 0.64 depending on whether the target mode had published timetables or not. The latter figure is comparable to the 0.55 attained by the basal model analysed here. Eluru et al. (2012) obtained a value of 0.35 as a reference. For TWkT, the value 1.38 obtained in the basal model is significantly higher than Eltved's figure of 0.54 but in reasonable alignment with the 1.13 value of the national Danish transport model. For TWT, which has an MRS value of 1.04 in the national Danish model, the value of the basal model is significantly lower at 0.55, while Eltved obtained even lower values of around 0.2. For first/hidden wait time, the value of 3.95 from the basal model is significantly higher than that of the Danish national model and that reported by Eltved (2020) (around 0.5). However, this may be attributed to the definition of the corresponding variable in the model specification.

As discussed extensively in Paper 3, the transfer penalties of 56 minutes for one transfer and 105 minutes per transfer for multi-transfer paths are much higher according to the basal model than in both the Danish national model and as reported by Eltved (2020). However, descriptive statistics of observed choice behaviour do not support the high MRS estimate (which seems intuitively to be unrealistically high) due to the limited number of cases in which a real trade-off is made between travel time and transfer. Instead, the high estimate is the consequence of a steep decline in revealed choice probabilities as NTR increases. This is evident in the many cases in which alternatives within the choice set offer similar qualities in other dimensions but vary in NTR. Longer IVTs also have an observable, systematic, and highly statistically significant impact on choice probabilities, but the relationship is not very steep. A reasonable interpretation would be that there is more variation in unmodelled attributes (larger variance of the error term) between alternatives that differ in IVT than there is between alternatives with varying numbers of transfers. If this assumption is correct, it would imply that a model form allowing for more flexible structure of error components might have been more appropriate than the linear path size logit that was applied to the modelling of path choice in this study. As a side note, though, the figures I obtained are not uniquely high even though they are in the upper span of the range that has been reported for revealed transfer preferences, see, for instance, Iseki and Taylor (2009) in their review of transfer valuations. Unfortunately, the amount of research found in the literature that applies the same population categories in their path choice estimation frameworks as those applied in Paper 3 is very limited so far, precluding validation at this level of aggregation.

The evaluation of the choice set generation procedure indicated a decent coverage of the observed trips when removing incomplete or clearly erroneous cases. Especially the branch-and-bound approach to the PT main trip part displayed a performance comparable to or exceeding efforts in similar research endeavours. However, the disaggregate nature of the access and egress legs made the approach utilised here quite inefficient in terms of the coverage of observed trips and the usage of choice alternatives. Fortunately, the performance of the used approach seems to be sufficient for the purpose of generating a data set for the estimation of access and egress mode preferences, as indicated by the reasonable count of matched observations as well as the estimated preference values.

Turning to the second aspect of RQ3, the results from the inclusion of distance and time attributes referring to access and egress legs in the path choice model of Paper 3 clearly indicate the impact of a number of path attributes and PT passenger characteristics on the catchment range as measured in bicycle access and egress distance. The significant factor with the highest impact appears to be the transfer penalty, as with the IVT-based MRS values discussed above. For transfers, passengers are prepared to bicycle more than four kilometres in order to avoid a transfer, while the corresponding distance for each avoided minute of waiting time ahead of the first trip leg is 396 meters (cf. Table 14). Moreover, for each saved minute of transfer walk time, the average passenger is prepared to cycle 181 meters, although this distance is almost 60 meters less for women 50 years of age or younger.

In order to target the third aspect of RQ3, the possible impact on path choice preferences from the surroundings and properties of specific PT stops and stations has been sought. As suggested by modelling results from model 3:3, in terms of MRS weighted by IVT bus, there is a clear premium for stops with an assigned elevated level of service such as major interchanges and terminals. This was most clearly manifested in the valuation of transfers, where the penalty per transfer was reduced to 40 IVT bus minutes per transfer instead of 56–105 minutes for the average stop or station depending on NTR. As discussed further in Chapter 5, this finding may have significance for further PT path choice modelling endeavours as well as for the forecasting and planning of multimodal PT networks.

As suggested by the results reported in Paper 5 and in models 5:1–5:3 (Table 14), there are significant differences across individuals in their taste patterns with respect to all trip attributes that were tested with a specific random component according to the ML framework – namely, access and egress walk and bicycle time, hidden wait time (FWT), and IVT bus and train. These results thus corroborate the results reported in Section 4.1 because models 5:1–5:3 control for a number of trip-related factors that are not accounted for in model 1:0. However, the individual correlation is weaker for the FWT attribute when associated with trips lasting longer than one hour compared to all trips. Thus, as a response to RQ5, there appears to be significant individual-specific consistency in path preferences as far as access+egress time, FWT, and PT IVT are concerned. Possibly this individual preference consistency across choice situations may be attributable to habituation (Cherchi & Cirillo, 2014) related to more or less conscious learning mechanisms induced by repetitive behaviour (Dezfouli & Balleine, 2012; Evans, 2008) or to some degree of internal consistency of preferences caused by other latent individual factors that may have to do with satisficing (Kaufman, 1990; the option is perceived as "good enough", while the prospect of searching for information regarding other alternative options might induce mental stress).

Table 14 Summary of the results from discrete path choice estimation models, addressing analysis issues contained in RQ3 and RQ5. Key results regarding MRS in time units are weighted in relation to IVT bus, while MRS values in distance units are related to access+egress bicycle distance. TU – time units, DU – distance units, IVT – in-vehicle time, TWkT – transfer walk time, TWT, transfer wait time, s – standard deviation (in models 5:1–5:3). The analysis issue of each model, as indicated in the first column, formulates each model specification verbally in terms of dependent and potential explanatory factors. Note that the table continues on p 125

Analysis issue	RQ	Model number (cf. Table 8)	Method	Key results	Model properties
Trade-offs in path choice situations, mode-specific accces+egress attributes	3	3:1	Maximum likelihood estimation of multinomial logit models with path size term to account for path correlation	MRS Access+Egress walk: **3.51 TU**; MRS Access+Egress bicycle: **2.18 TU**; MRS Access+Egress car: **4.48 TU**, penalties of **3.63 TU** for bicycle and **6.00 TU** for car as access/egress modes	N = 1,487; Null log-likelihood: -8,318; Final log-likelihood: -2,002; Adjusted rho-square (McFadden's LRI): 0.7593
Trade-offs in path choice situations, basic travel time attributes	3	3:2		MRS: **0.62 TU** for IVT train; **3.92 TU** for hidden wait time; **0.55 TU** for TWT; **1.38 TU** for TWkT; penalty of **56,27 TU** per single transfer; penalty of **104.67 TU** per transfer for multiple transfers; path overlap has positive utility	N = 2,838; Null log-likelihood: -10,193; Final log-likelihood: -3,751; Adjusted rho-square (McFadden's LRI): 0.632
Trade-offs involving PT stops with elevated level of service	3	3:3		16 TU less transfer penalty (40.30 TU) for HLS stops than for "ordinary" stops with one-transfer paths	N = 2,838; Null log-likelihood: -10,193; Final log-likelihood: -3,774; Adjusted rho-square (McFadden's LRI): 0.6297
Path choice trade-offs across population groups, mode-specific accces+egress attributes	3	3:4		MRS Access+Egress walk **3.53 TU** and MRS Access+Egress car **2.24 TU** more for men above 50 years old than women 50 years or younger	N = 1,487; Null log-likelihood: -8,318; Final log-likelihood: -1,983; Adjusted rho-square (McFadden's LRI): 0.7616

Analysis issue	RQ	Model number (cf. Table 8)	Method	Key results	Model properties
Path choice trade-offs across population groups, basic travel time attributes	3	3:5		MRS TWT 1 TU less for young men than for young women; penalty per transfer 8.5 times longer for men above 50 years for those at that age or below and 5.4 times longer than for women 50 year or younger.	N = 2,838; Null log-likelihood: -10,193; Final log-likelihood: -3,758; Adjusted rho-square (McFadden's LRI): 0.6313
Path choice trade-offs across population groups, all access+egress and travel time attributes	3	3:6		MRS: **100 DU** access+egress bicycle to avoid 1 TU IVT bus; **82.0 DU** access+egress bicycle to avoid 1 TU IVT train; **396 DU** access+egress bicycle to avoid 1 TU hidden wait time; **4.28 DU** bicycle to avoid 1 DU access+egress walk; **0.32 DU** access+egress bicycle to avoid 1 DU access+egress car; **54.6 DU** access+egress bicycle to avoid 1 TU of TWT; **181 DU** access+egress bicycle to avid 1 TU TWkT; **4,120 DU** access+egress bicycle to avoid a transfer.	N = 1,487; Null log-likelihood: -8,318; Final log-likelihood: -1,981; Adjusted rho-square (McFadden's LRI): 0.7619
Individual consistency in path choice trade-offs, mode-specific acces+egress attributes	5	5:1	Maximum likelihood estimation of multinomial *mixed logit panel* models with path size term to account for path correlation	$\beta_{acc/egr\_walk\_mean}$ = -0.393 (significant) $\beta_{s,acc/egr\_walk\_inter\text{-}individual}$ = 0.131 (significant) $\beta_{s,acc/egr\_walk\_intra\_individual}$= 0.00983 (not significant) $\beta_{acc/egr\_bicycle\_mean}$ = -0.506 (significant) $\beta_{s,acc/egr\_bicycle\_inter\text{-}individual}$ = 0.324 (significant) $\beta_{s,acc/egr\_bicycle\_intra\_individual}$ = 7.07e-36 (not significant)	N = 1,487; Null log-likelihood: -7,290.67; Final log-likelihood: -1,318.592; Adjusted rho-square (McFadden's LRI): 0.817
Individual consistency in path choice trade-offs, hidden waiting time (FWT)	5	5:2		β_{FWT_mean} = -0.719 (significant) $\beta_{s,FWT\_inter\text{-}individual}$ = 0.624 (significant) $\beta_{s,FWT\_intra\_individual}$ = 1.12e-33 (not significant) $\beta_{FWT\_long\_mean}$ = 0.365 (significant) $\beta_{s,FWT\_long\_inter\text{-}individual}$ = 0.752 (significant) $\beta_{s,FWT\_long\_intra\_individual}$ = 0.0137 (not significant)	N = 2,838; Null log-likelihood: -9,288.689; Final log-likelihood: -3,251.83; Adjusted rho-square (McFadden's LRI): 0.648
Individual consistency in path choice trade-offs, basic travel time attributes	5	5:3		$\beta_{IVT\_bus\_mean}$ = -0.0701 (significant) $\beta_{s,IVT\_bus\_inter\text{-}individual}$ = 0.0874 (significant) $\beta_{s,IVT\_bus\_intra\_individual}$ = 0.00402 (not significant) $\beta_{IVT\_train\_mean}$ = -0.0679 (significant) $\beta_{s,IVT\_train\_inter\text{-}individual}$ = 0.0815 (significant) $\beta_{s,IVT\_train\_intra\_individual}$ = 0.00115 (not significant)	N = 2,838; Null log-likelihood: -9,288.689; Final log-likelihood: -3,243.963; Adjusted rho-square (McFadden's LRI): 0.649

Service reliability and longitudinal PT passenger behaviour

As a response to RQ4, from the results of the longitudinal logistic regression models and thus following tendencies from the results of Paper 4, it is possible to discern that there is a slight but clear response among PT passengers, in terms of (line route) path change, to changes in PT service reliability by path. Thus, there is a positive effect from increased regularity on path choice probabilities due to the relative importance of regularity for high-frequency services. There is also a negative impact on path choice probabilities from negative regularity change, but this is somewhat less pronounced.

Because findings addressing the first aspect of RQ4, referring to preferences in terms of perceived disutility, are directly related to the empirical results regarding passenger behaviour referring to the second aspect, the focus of this presentation is on concrete measurements of behaviour because it is more straight forward to target by quantitative findings. The results differ somewhat with respect to the exact measures used, in this case timetable adherence/punctuality or headway regularity, and are subject to the direction of change. Depending on the structure of the data, with an overall increase in regularity and service supply but a decrease in punctuality and travel time reliability (RBT) and a general flux of passengers from low-frequency train services to high-frequency bus lines, it is not surprising to find the most clear-cut impact being from increased reliability. This is even clearer when studying the results from the models separated by a dummy for short and long headways, respectively, where both regularity and punctuality have clear impacts on choice probabilities for paths with service headways of at most twelve minutes, while the impact at longer headways from both regularity measures is ambiguous. Further details of the results from the panel analysis are presented in Paper 4 and in Table 15 below.

Table 15 Summary of the results from the panel analysis of responses to changed service reliability, addressing analysis issues responding to RQ4. (+) and (-) indicate model fit for estimation data including increased and decreased path usage, respectively. The analysis issue of each model, indicated in the first column, formulates each model specification verbally in terms of dependent and potential explanatory factors.

Analysis issue	Method	Key results	Model properties
Long-term response to changed reliability, including travel time uncertainty, controlled for travel time and service supply	Logistic regression	Everything else being equal, it is more common to decrease than to increase line route usage but one unit of increased (decreased) regularity increases (decreases) line route choice probability by 0.9 units (0.05 units). Increased service supply decreases the choice probability of a line route	N = 2,056; McFadden's pseudo R^2 = 0.05(+);0.17(-)
Long-term response to changed regularity		No significant impact from changed regularity on increased line route usage without controlling for changed service supply, travel time and travel time uncertainty (RBT), but negative impact on decreased usage	N = 2,075; McFadden's pseudo R^2 = 0.00008(+);0.12(-)
Long-term response to changed punctuality		Ambiguous impact from increased punctuality on line route choice probabilities	N = 2,076; McFadden's pseudo R^2 = 0.03(+);0.12(-)
The effect of scheduled headway on sensitivity to regularity change		At headways of twelve minutes or below, increased regularity increases line route choice probabilities, while it has ambiguous impact on choice probabilities at longer headways	N = 2,076; McFadden's pseudo R^2 = 0.02(+);0.08(-)
The effect of scheduled headway on sensitivity to punctuality change		At headways of twelve minutes or below, increased punctuality increases line route choice probabilities, while it has ambiguous impact on choice probabilities at longer headways	N = 2,076; McFadden's pseudo R^2 = 0.07(+);0.11(-)
The effect of day type on sensitivity to regularity change		No significant effect	N = 2,124; McFadden's pseudo R^2 = 0.005(+);0.07(-)
The effect of day type on sensitivity to punctuality change		Increased punctuality increases line route choice probabilities on weekdays only	N = 2,124; McFadden's pseudo R^2 = 0.03(+);0.12(-)

5 Implications for policy and practice

The focus of this chapter is on likely and potential implications that the empirical contributions of this thesis may have on demand forecasting and thus on the planning of PT, infrastructure, and land use. By way of introduction, I first introduce each tentative implication briefly, followed by longer expositions of each topic in the following subsections. The expected implications are related to the third aim stated in Section 1.2.

First, the successful application of new empirical approaches based on passively (farecard data) and semi-passively (the survey) collected records of individual mobility suggests that such detailed modelling endeavours may feasibly be applied in order to update preference parameters in contemporary transport models. This may be a way to legitimise the use of such transport models for demand forecasting in local or regional PT improvement projects, especially if population group-specific preferences are included. Specific findings regarding preferences point to a few important results regarding overlapping paths, transfer stop configurations, population group-specific preferences and influence on stop catchment areas. In addition, emphasis is put on the findings in Paper 4 that underline the importance of including service reliability as a path choice preference parameter in PT demand forecasting and the findings in Paper 5 on the inter-individually heterogeneous nature of path preferences (5.1).

Second, the findings in Paper 2 give some support to the idea that planning practices may make use of "soft" measures in order to influence the behaviour of passengers in a desired way through the design of journey planners and the provision of service information (5.2).

Finally, results regarding path choice preferences of Paper 3 support a holistic view of infrastructure and land use planning in that it may include trading off between measures that affect multiple PT path elements (e g, transfer point improvements versus stop spacing), which might therefore significantly affect demand patterns. Thus, the development of coordinated planning practices should be applied in the physical planning of cities and their surroundings (5.3).

Implications for the planning of PT networks

The findings of Papers 1–3 bring important implications for the practice of PT planning to the fore. First of all, the findings in Paper 3 may offer important contributions regarding demand forecasting and might act as input to cost-benefit analyses. Below, I list the most important takeaways that can be identified from the findings of revealed preferences related to PT path choice.

- There appears to be a preference premium for overlapping paths, a notion found by other authors as well (e g, Askegren Anderson (2013) and Raveau et al. (2014)). Neglecting to include this factor in demand forecasting models may underestimate demand on PT services with overlapping segments and thus result in failure to target measures aiming to alleviate crowding along the appropriate PT line route(s).
- There is a significant path choice effect from specific transfer ("HLS") stops. Omitting specific properties of these stops or stations from forecasting models may distort the picture by overestimating the demand for services that do not include these kinds of transfer points. The issue of transfer penalty in transport models, also discussed by Eltved (2020), further underlines the importance of including specific transfer point attributes in demand forecasting models.
- Mode-specific preferences should be included across population groups. Using only the mean preferences may lead to failure to correctly predict demand for certain modes by specific groups, as indicated by the differences across different gender and age groups found in estimated preferences for specific PT modes as well as access/egress modes. For PT modes specifically, this may be particularly problematic in cases of services running at near their passenger capacity and if mode-specific premiums are omitted. For access/egress modes, the differences across groups and modes are important to consider in order to avoid failing to comply with preferences and capacity demands when designing park-and-ride, kiss-and-ride, and bicycle parking facilities. Travel information is also acquired and used differently across trip types. For instance, evidence from Paper 2 indicates that behaviours differ across different types of days, trip types, and trip purposes. Again, this highlights the importance of not relying too heavily on mean values in forecasting and prediction of behaviour.
- Drawing on the findings related to catchment, or influence area, around PT stops as a result of variations in willingness to bicycle, it is important to note the influence from a number of path attributes. Increased catchments may be related to increased departure frequency, reduced IVT and fewer transfers as well as shorter TWkTs. Thus, it may be plausible for PT route planners to trade off the possibility of improving any of these properties of

the PT network against the spacing of stops as well as the mesh size of the PT network, e g, to avoid time-consuming detours that originally aimed to reduce access distances. However, as also pointed out in Paper 3, the preferences may differ across population groups, emphasising the importance of using disaggregate preference estimates when estimating catchment trade-offs in order to include all targeted groups.

It appears that the usually clear-cut relationship between the headway of PT services and passenger behaviour in contemporary transport demand models should be nuanced somehow in order to include the heterogeneity that may depend on trip duration and path complexity. There is some support in the findings presented in Paper 1 that different individuals behave systematically differently. However, the underlying reasons for systematically heterogeneous travel behaviour – such as some individuals consistently making longer trips than others – makes it difficult to point to the individual factors alone. Instead, it is reasonably clear that long and/or complicated trips (in terms of multimodality or number of legs) require more planning and information searching – a notion also corroborated by the findings of Farag and Lyons (2008). Relying too heavily on simplistic aggregate preference valuations may distort the forecasting of passenger demand when broken down into individual (sub) paths, i e, services, line routes and trips, as is discussed in connection with Paper 3.

Although not applying an agent-based approach (Hajinasab, 2018), but rather having relied on a more aggregate analysis framework of mobility, by just including a few more disaggregating dimensions I have found support for the importance of using a sound level of disaggregation in the empirical foundations for forecasting predictors of demand. In this thesis, I have introduced methods of mobility data collection that combine high detail and reasonable representativeness with manageable respondent burden. In addition, and as a way to obtain the desired data disaggregation level, the findings of the first three papers of this thesis support the validity of the methodology used, which included significant portions of passiveness and non-intrusiveness in relation to the individual respondent under study. The latter may be an important aspect for future data collection efforts that must face the issues of survey fatigue and privacy concerns, as expressed by many people, in order to obtain representative population samples. The importance of such representativeness increases both because of the desire to include additional dimensions of personal characteristics that may correlate with transport behaviour, and in order to secure a fully descriptive capacity of the population as a whole. The gradually increasing maturity of the semi-passive approach that formed the empirical basis for Papers 1–3 and 5 may prove the approach to be viable to apply in further contexts than that of my study. Findings from Geurs et al. (2015) and Thomas et al. (2019) support the addition of this survey approach to population groups that are harder to reach with conventional methods. In my view, the semi-passive survey approach should also be used to increase the availability of mobility surveying at large in order to target new demand models to local contexts and (possibly) travel preferences, but also to update and calibrate existing models more frequently. Thus, the approach to mobility data collection applied in this thesis has the potential for bringing state-of-the-practice transport models up to date, to the benefit of their perceived validity among decision makers.

From Paper 4, findings in response to RQ4 underline the importance of including measures of reliability in demand forecasting, for the same reasons as for the other factors presented above. Or, more specifically, to be able to anticipate the trade-offs made by passengers between PT service properties such as travel time and reliability. However, the successful inclusion of the reliability factor in detailed demand prediction efforts may put high demands on the ability to simulate future levels of reliability on PT line route level. Also, as a sub note, future research endeavours need to find methods to feasibly include the path-specific service reliability in the estimation framework for PT path preferences.

Also, as the results of Paper 5 suggest, proper modelling of behavioural preferences in PT should strive to account for inter-individual differences other than those represented by distinct population groups based on age or gender in order to maximise the explanatory power of the models.

Implications for the design of guidance to passengers

Findings in Paper 2 as well as previous research by, for example, Cats et al. (2011), Oliker & Bekhor (2018), and Brakewood & Watkins (2018) indicate that the availability of departure time information, no matter whether being it fixed and based on a schedule or dynamically updated according to real-time conditions, has the potential to affect the degree of optimisation available to the PT passenger. In addition, as indicated by my findings related to stated planning behaviour using digital journey planners, the default settings in these actually have important implications on passenger behaviour, and the construction of itineraries in these digital planning aids may ultimately direct movements of passengers. However, and as shown by, for example, X. Li, Liu, & Yang (2018) as well as Yang, Kitamura, Jovanis, Vaughn, & Abdel-Aty (1993), usage rates of planning aids and pre-trip information services, as well as their perceived reliability, are crucial bits of knowledge needed in order to make use of my findings. This is also supported by the impact that service reliability and headway had on the willingness to use information on departure times, as shown from the analysis presented in Paper 2, with the highest willingness for high-frequency and highly reliably services. Nevertheless, information provision and journey planner design in order to influence passenger flows should be important tools for PT operators dealing with high passenger loads and certain levels of non-adherence to pre-published schedules among their services. Not least, this is important at times of low acceptance rates for crowding. The default setting of desired departure or arrival time may serve as an illustrative example. As pointed out by Mattauch et al. (2016), individuals tend to avoid making active choices and instead favour default options. An interpretation of the results from one of the stated response questions of Paper 2 is that the fact that a majority of trips that the respondents scheduled using digital journey planners were based on the desired departure time as the binding restraint. This option also happened to be the default option in the relevant journey planner at that time. The fact that the itineraries generated in the journey planner were contingent on this choice of restraint – departure or arrival time – thus also imposed a high influence on path choice.

Implications for the planning of infrastructure

In this thesis I have emphasised the importance of using realistic and relevant measures of phenomena that are crucial in order to understand, predict, and evaluate the demand for PT services. As I present in Paper 4, service reliability is one of such factors that are difficult to include in static demand models. Using measures of schedule adherence and departure interval predictability, I showed that it is definitely not impossible to include reliability as a factor in path choice preference estimation. However, as is always the case when estimating and validating transport models, the availability and quality of data (in this case from a vehicle trajectory database on a high-resolution time and stop level) is crucial.

Similar to the way travel time uncertainty is an integral part of assignment approaches of car traffic in response to congested infrastructure, reliability is integral to the realistic ability to forecast path-based PT demand. One important aspect is the ability to ex-ante evaluate infrastructure-based robustness measures in PT systems. Such measures may include alternative routes (in this case being a trade-off to the path overlap premium found in Paper 3) or other measures that entail increased capacity or redundancy aiming to alleviate consequences for passengers, for instance, at line closures. Including travel time variability should be relevant for the evaluation of costly technical infrastructure improvements that need to be justified by a corresponding improvement in passenger utility related to reduced uncertainty.

Finally, and perhaps most importantly, I would like to emphasise the relevance of a few of the findings of Paper 3 to the general practice of the planning of infrastructure, and thus ultimately of the use of land in cities and regions. That factors beyond the amenities of the interchange itself, related to the immediate vicinity to PT transfer points (“HLS stops”, or stops with an elevated level of service in Paper 3), have a significant impact on perceived path utility and thus on the preferences of PT passengers, highlights the importance of integrating the PT system into the urban fabric to create appealing environments around these locations. Such locations should typically be situated in areas naturally frequented by multiple population groups – not just PT passengers – in order to be viable for commercial services. At least this is a feature that the “HLS stops” of Paper 3 have in common – being major interchanges typically close to major commercial and societal facilities in addition to having amenities such as heated waiting rooms and extensive information systems.

Moreover, the discussion of catchment areas, or areas of influence for the PT system in Paper 3, have high relevance to the general practice of infrastructure planning. One important example is how the design of street networks influences not only the direct accessibility of bus stops, but also to the possibilities to optimise their numbers (as discussed, for example, by Hansson, Pettersson-Löfstedt, Svensson, & Wretstrand (2021)) and to place each one of them at an optimal location both in terms of operations and accessibility.

6 General discussion and reflections on the contributions of the thesis

This final chapter of the thesis includes a general discussion of the findings and resulting general contributions to knowledge in the field of individual choice theory within transport systems. In this chapter, I also return to some of the findings and discuss them along with the strategic methodological paths applied when put in the perspectives of relevant previous research.

Moreover, new ideas for future research endeavours – concerning improvements in empirical approaches, methods for data analysis, and further behavioural phenomena to study – are outlined based on dilemmas and shortcomings that were encountered during the studies underlying this thesis. The chapter is finalised with some concluding remarks concerning the scope of the thesis as a whole.

Contributions with respect to the overarching aim and scope of the thesis

As stated explicitly in Chapter 1, the scope of this thesis covers how behavioural phenomena among PT passengers may be explained by objective, factual circumstances related to the trips made, particularly those associated with the PT system as such, and to personal characteristics. This has been achieved by applying new approaches to mobility data collection in combination with comprehensive auxiliary data describing the PT system. From these empirical vantage points, the aim of the thesis has been to gain an understanding regarding how and why passengers behave, and thus likely make preferences, differently depending on contextual factors related to the PT system as well as to heterogeneity among passengers. For the latter, I found that personal characteristics may have an impact, but also that some behavioural differences remain unexplained across individuals. A way to address the aim of the thesis was to show and validate how passive and semi-passive approaches to collect mobility data may be used to find out the revealed preferences of passengers towards features of the PT system. Also, as was discussed in Chapter 5, the findings may be of use for planners prioritising among measures aiming to improve the level of PT service in order to increase PT passenger satisfaction and increase ridership. The new data collection methods introduced in this context have the potential to facilitate more local, context-relevant, PT forecasting models in the future, and this will enhance the accuracy of these models and enable more precise and successful improvement measures for PT systems.

Contributions with respect to choice theory

In terms of theoretical contributions, the findings of this thesis are typically confined to the context of passengers' choices within PT systems. However, in my view, the findings may also be regarded as universal to some degree. A seemingly habitual usage of PT paths is indicated by the results of Paper 4, in that a majority of passengers that had at least one other choice option whose service reliability changed for the better still appeared indifferent to this change as indicated by marginal relative line route usage. Perhaps the net change in reliability, when comparing the existing and the other potential path(s), was not perceived as being substantial enough to encourage a change in (habitual) path. In that case, inertia (van Exel, 2011) in combination with some kind of endowment (Kahneman et al., 1991) or satisficing (Kaufman, 1990) effect may be present in the data. However, the results should be considered with some care due to the relatively low sensitivity to changing service reliability. In addition, the exact psychological mechanisms behind the dynamics of long-term path choice remain to be disentangled through usage of more fine-tuned measures such as latent psychometrical constructs (see, for example, hybrid approaches such as that sketched up by Alizadeh et al. (2019) and Prato et al. (2011), but only for car drivers' path choice). It should be noted in this context that I found no significant impact on path choice from absolute line route-specific reliability in the cross-sectional discrete choice framework used in Paper 3. One possible reason for this preference indifference is the many other attributes that were included in the cross-sectional models, and which may obscure the weak impact from service reliability on path choice.

In Paper 5, inter-individual heterogeneity in path preferences was found for all trip attributes it was tested for, i e, IVT bus and IVT train, access+egress walk time and first/hidden wait times. Because seemingly individual-specific behavioural traits may also be discerned from the findings presented in Paper 1 and Paper 2 with regards to waiting times, this is perhaps the more general takeaway from this thesis (a trait supported by the findings of Thomas et al. (2019) regarding mode choice and Chowdhury et al. (2020) regarding rip destination choice – both using techniques for data collection resembling those used in this thesis). Thus, similar general patterns of significant inter-individual preferences resulted both from simple comparisons of dispersion measures but also through the archetype classifications of Paper 2 and in the complex analyses of Paper 5 that applied ML discrete choice frameworks with an individual-based panel component. There might be elements of individual-specific (reinforcement) learning behaviour involved here, as discussed in Chapter 2 in the context of habit formation as a coping strategy to overcome complexity and uncertainty (Hodgson, 1997), and these might be in combination with some aspect of satisficing behaviour (Kaufman, 1990). In cases like these, the (subconscious) impact from information, as a way of nudging passengers into a desired choice pattern, may become relevant because, as reported in Paper 2, the existence and design of departure time information in digital journey planners did have a slight but statistically significant impact on waiting times.

Contributions to PT passenger preference research

Historically, one major incentive for the development of transport models has been to manage negative aspects of car traffic and to appraise new infrastructure projects ex-ante using cost-benefit analyses based on neoclassical economic theory. For a long time, PT has been one of the measures to alleviate congestion and emission problems. Many PT operators, on the other hand, have shown mixed levels of interest in advanced demand models based on the classical four-step approach, and this is for relevant reasons in many cases (see the discussion in Johansson (2020)). Such reasons may be related to their (perceived) lack of relevance or validity, as they were originally developed to manage movement of individual vehicles – a concept quite different from the doubly constrained (to specific pre-scheduled trips in space and time) and highly dynamic nature of PT trips. This thesis has attempted to bridge the perceived gap between transport analysts and PT service planners by introducing new approaches to the collection of mobility data, and thus facilitating the tailoring of PT demand models to local requirements. However, there is an additional purpose related to the *description* of the PT service supply. Returning to the historical perspective, basic algorithms for the prediction of vehicle flows may directly apply implicit network assignment algorithms based on user equilibrium due to the reasonably simple relationships between volume and flow. However, these relationships do not hold for PT passenger flows and instead require multiple additional dimensions in order to produce a behaviourally and empirically reasonable forecasting framework as operationalised in assignment algorithms. A further discussion of this matter is provided by other authors such as Eltved (2020).

In contrast to the generic contributions to choice theory discussed above, the specific properties of the Scania PT network may have had strong implications on at least some of the results presented in Paper 3 regarding path choice preferences that may thus be regarded as context specific. Most prominently, the extraordinary high transfer penalty compared to other studies and models is likely highly influenced by the limited network size and complexity in the Scania study, especially when compared to most other studies and models that use large metropolises as the basis for the estimation of choice preferences. Both the degree of network complexity and how this affects the need to transfer in order to connect origins and destinations have importance here. That is, complex systems that force a large share of riders to transfer during their everyday trips make these riders more accustomed to the phenomenon and thus less reluctant to paths involving transfers. Moreover, the share of PT choice riders versus captive PT riders in the system may influence these preferences, as indicated by Ha, Lee, & Ko (2020) with reference to PT choice preferences in different passenger groups. This is also supported by the finding of Papers 1 and 2 of this thesis, that passengers exhibit longer wait times for unusual (as measured by trip purpose) and complicated trips (as measured in duration and NTR) compared to trips representing more habitual mobility such as commuting, thus seemingly expressing a "transfer anxiety" by including more safety margins in terms of FWT or TWT. However, in large networks where transfers are common, this anxiety should not be expressed to this extent by commuters that are used to transfers. However, and as indicated by the impact from the "HLS" stop class introduced in the analyses in Paper 3, the particular transfer point may matter here because beginning to use a path including a transfer point never visited before may induce extra disutility with transfers due to an increased transfer anxiety level.

The substantial number of observations from the dedicated smartphone survey that were deemed invalid for inclusion in the path choice model is unfortunate. However, the low detection rate of complete trips may likely be attributable to the fact that the survey instrument, the smartphone app, was previously untested and was in its developmental infancy during the execution phase of the survey waves. The smartphone app had never been used for full-scale surveying of travel patterns ahead of the survey performed to provide the empirical underpinning for this thesis. It has also been found, from the research field taken as a whole, to be quite rare to use data from smartphone surveys to estimate full door-to-door PT path choice preferences. However, when considering the successful utilisation of the survey data for the model estimation performed for this thesis, future improvement of the smartphone-based survey technology should support a promising future for the usage of resulting data for model validation and estimation purposes.

Contributions to discrete path choice modelling research

When going into more detailed results, a focal point of this thesis has been on the methodological approach to using mobility data from a dedicated smartphone survey app in order to estimate path choice preferences in PT. The findings reported in Paper 3 and Paper 5 relied on an explicit pre-generated choice set. This was mainly due to practical circumstances and my pre-knowledge of PT trip assignment software. However, this makes it difficult to directly compare my findings to those of, for example, Tan (2016), who used a combined approach including link labelling–link elimination algorithms, and to those of Anderson et al. (2014) and Eltved (2020), who used a simulation approach. In addition, we have the context-specific factors. However, the relative alignment of the general properties of the mobility data used for the estimation and the general traits of the estimated coefficients such as signs and approximate magnitudes of substitution rates imply that the method sensitivity might not be that important for the end results after all. To this end, the selection of covariates for the basal model was made with reference to these earlier studies. Due to the nature of the empirical data, I found no clear model improvement from the transformation of travel time attributes, for instance, to reflect preference damping. Instead, I used a damping transformation on the hidden/first waiting time element with promising implications on model fit. This also fits well with theory and previous findings (e g, Frappier et al., 2018) regarding waiting time functions that are often included in state-of-the-practice modelling tools.

To conclude, given the data and methodology available for my work on estimation of path choice preferences, my findings support the relevance and validity of the chosen framework, both in terms of data collection and calculations. Nevertheless, there is much to be done in terms of streamlining and structuring of the data management effort, especially when it comes to the efficiency of the choice sets for access and egress trip legs. As reported in Paper 3, the extremely low coverage efficiencies of well below one percent for access and egress, which was required in order to attain a passenger path coverage of around 50 percent of valid observations, meant that the explicit access+egress choice set needed a very large quantity of path alternatives in order to represent a decent share of the observed choices. Some of the obviously irrelevant alternatives were excluded by using assumptions regarding access and egress mode availability, but there is certainly a great potential for reducing this number even further and thus improving the efficiency of the choice set generation process.

Avenues for further research efforts

There is a vast spectrum of potential research endeavours of which a shortlist of the ones that I regard as most intriguing are mentioned in the following. The most natural continued research would be to dive even deeper into studies of choice preferences. Originally included in the synopsis for this thesis were research questions regarding possible mode-specific preferences for PT modes other than train and bus, such as the tram mode that is now (as of spring 2021) in service in the city of Lund. Findings relevant for this research topic are of great relevance for the ex-ante appraisals of PT infrastructure measures, which usually involve trade-offs of whether to invest in capital-intensive high-capacity concepts such as tramways or to rely on less up-front investment-demanding solutions based on buses that run on ordinary streets. A future elaboration of the model framework proposed in this thesis should enable the controlling for factors such as travel time and service reliability, which may confound results from simple comparative cross-sectional experiments (such as ridership per mode before and after the opening of the tramway).

Another possible expansion of the analytic framework would be to include preferences for particular departure and arrival times and the impact from these on valuations related to hidden waiting times. Using a more microscopic approach than the time period-based framework used in Paper 3, and including individual PT departures and connections instead, could be a way forward here. In my view, the issue of hidden wait time, and how the significance of it varies across headway regimes and depending on (perceived) service reliability, is an under-researched issue that is sometimes even omitted or at least considerably generalised in PT assignment algorithms for simplicity.

Speaking of service reliability, in this thesis a quite simplistic approach using static off-line data regarding real PT vehicle trajectories was used to calculate pre-defined values of the reliability measures of punctuality and headway regularity. These values were subsequently used as independent covariates in regression models. However, in order to use these models for demand prediction in ex-ante evaluations of PT measures, it may be non-optimal to use reliability figures of the existing system. Rather, the analyst would prefer values for the scenarios under evaluation. Thus, further research efforts should be put into obtaining simulated reliability measures that may be plugged into path choice models for future network scenarios. The measures proposed in Paper 4 of this thesis may thus be calculated based on simulated vehicle run times instead of the times obtained from actually executed vehicle trajectories. The analytic framework of Paper 4 specifically targeted the issue of controlling for irrelevant factors affecting path choice over time, such as the nature of the network offered between different desired trip origins and destinations, as well as changes in demand patterns. However, as the results revealed, the general change in service reliability for significant parts of the network somewhat complicated the analysis of time-dependent changes for individual cases (including individual line routes and passengers). Methodological improvement should target this issue by separating between minor and major reliability changes, as discussed by Yap et al. (2017). Taking account of the key concept of "relative frequency of negative critical incidents" (Friman, Edvardsson, & Gärling, 2001) could be a reasonable point of departure.

Last, but definitely not least, a short discussion is worthwhile regarding the known deficiency of random utility models that they are based on mean values of, for example, choice preferences, while they typically do not take distributional properties into account. Including dispersion and distributional measures as independent variables of choice utility functions in preference models, and thus including heterogeneity to a greater extent than is common practice, would be an exciting way forward here. Not least, this would be relevant to the above discussion regarding individual differences as well as for other socio-economic factors that were not included in the analyses of this thesis.

Reflections on the empirical approach

At this stage, I suppose it is the time to finally reflect somewhat around my choice of topic and research approach. For, as Plato argued, a knowledge claim can be made if and where beliefs and truths coincide. The truth is then something that is thought of as being intangible and that a scientist can only strive to reach, while the beliefs are what we have in our minds and which serve as points of departure for a research endeavour. Thus, in my view, it is reasonable for every researcher to declare their beliefs and to try to formulate their intrinsic values in order to make a sincere effort to provide a comprehensive backdrop to their choice of research scope and their expectations as to what they will find. This is important, not least in order to attain an acceptable level of credibility.

The ontological view on the empirical approach in this thesis has been that it describes reality "as it is" during a limited time scope and for a limited sample of individuals. Possible generalisations to other places and individuals are not directly possible. However, and this is important, the nature of the modelling framework has made it possible to compare and thus validate findings that are conditional on the data available to my research with findings from other contexts that are based on other methods and definitions. There is a specific value in itself to be able to replicate results generated with quite different methodological and empirical preconditions but applying similar theoretic frameworks. This validation and replication ambition has been the cardinal argument behind my choice of the random utility theoretic framework used to estimate path choice, despite its flaws and shortcomings. In short, given its limitations, the usefulness and the ability to validate the results of a vast range of similar research findings provide a strong rationale for this choice of modelling framework. It should also be emphasised here that a statistical inference paradigm is extensively applied throughout the analyses included in this thesis, which limits the possibilities of drawing extensive conclusions from the empirically analysed population samples. In this context, causal relationships should always be interpreted with utmost caution, and claims regarding such directed connections require theoretical and contextual knowledge from the researcher.

In addition to being quantitative, the perspective in this thesis on human behaviour has been chiefly deterministic. In statistical modelling, one may include a stochastic component aiming to relax assumptions on perfect information and consistent behaviour, but this still assumes a systematic core component that is based on rational foundations, while "irrational" and otherwise unexplained behaviour may be allotted to the random component. This is a practical point of view, but also a deeply metaphysical one – that human behaviour may ultimately be associated with, impacted, or triggered by exogeneous circumstances – directly or by more or less complex indirect psychological processes. These processes may be conscious and deliberate or more or less "automatic" and hence related to previous actions and learning from one's own experiences or those of others. The latter, in turn, may have a variegated likelihood of occurrence or "expression" depending on social or genetic individual preconditions. As always however, there is the non-negligible element of pure chance itself.

Concluding remarks

As a closing exhortation, the most salient ambition of this thesis is that its contribution in terms of validating semi-passive and passive PT mobility collection approaches will lower the thresholds for the collection of locally relevant PT demand and revealed preference data. If so, there is a chance that demand forecasting models may be easier to update with local and contemporary parameter data in order to have a stronger impact on relationships, and thus they can be regarded as more relevant by local planners and analysts thus increasing the critical mass of users, which should increase the quality of the models in the long run. The strength of methods in which complex models are used in order to predict demand is that they require a systematic approach to the description of both the current situation as well as of future scenarios. However, as pointed out in the introduction of this thesis, insufficient access to relevant data may impair the successful application of such models in two ways. Primarily, it may entail a disproportionate workload and resource requirement discouraging their use altogether. Secondly, the resulting predictions may be inferior due to poor alignment of the data used for estimation of key causal relationships with data from the actual (geographical) context for the analysis.

Thus, the development of methods to gather local behavioural data is key to making forecasting models more relevant for local decision makers and planners, and thus for their increased use for scenario analysis. Using scenario planning techniques may be a way to approach the need for decision makers to comprehend the vast range of uncertainties characterising the future. Making forecasting techniques accessible and relevant for local contexts could be a way to enable closer studies of a wider range of possible visions and scenarios compared to what is common practice today due to the relatively resource-inefficient methods currently in use. In Sweden, for example, output from the national transport forecasting model is required by the department of transportation (in this case represented by the Swedish Transport Administration) in order for regional infrastructure projects to be eligible of national funding. However, the national model has been estimated on almost 20-year-old demand data, which was not locally collected but is based on national averages. On the other hand, this means that the potential for local, small-scale data collection efforts should be substantial, given that standards are set in order to streamline data collection and processing. The contributions of this thesis may have a role to play in this important future work.

As a final note, in spite of the research efforts made in conjunction with this thesis and elsewhere, the exploration of human behaviour in the PT system is only in its infancy and there is much more to find. This thesis provides an early account of how new data sources may contribute to the successful insight into this intriguing field of research.

7 References

Aarts, H., & Dijksterhuis, A. (2000). *Habits as knowledge structures: Automaticity in goal-directed behavior.* Journal of Personality and Social Psychology, 78(1), 53-63. doi:10.1037/0022-3514.78.1.53

Aarts, H., Verplanken, B., & van Knippenberg, A. (1997). *Habit and information use in travel mode choices.* Acta Psychologica, 96, 1-14.

Abdel-Aty, M., Kitamura, R., & Jovanis, P. P. (1995). *Investigating Effect Of Travel Time Variability On Route Choice Using Repeated-Measurement Stated Preference Data.* Transportation Research Record, 1493, 39-45.

Alizadeh, H., Farooq, B., Morency, C., & Saunier, N. (2019). *Frequent versus occasional drivers: A hybrid route choice model. Transportation* Research Part F: Traffic Psychology and Behaviour, 64, 171-183. doi:10.1016/j.trf.2019.05.009

Allström, A., Gidofalvi, G., Kristoffersson, I., Prelipcean, A. C., Rydergren, C., Susilo, Y., & Widell, J. (2016). *Experiences from smartphone based travel data collection – System development and evaluation.* Retrieved from Stockholm:

Anderson, M. K., Nielsen, O. A., & Prato, C. G. (2014). *Multimodal route choice models of public transport passengers in the Greater Copenhagen Area.* EURO Journal on Transportation and Logistics, 6(3), 221-245. doi:10.1007/s13676-014-0063-3

Askegren Anderson, M. K. (2013). *Behavioural Models For Route Choice Of Passengers In Public Transport.* (PhD Doctoral disertation). DTU, Copenhagen, Denmark.

Assemi, B., Jafarzadeh, H., Mesbah, M., & Hickman, M. (2018). *Participants' perceptions of smartphone travel surveys.* Transportation Research Part F: Traffic Psychology and Behaviour, 54, 338-348. doi:10.1016/j.trf.2018.02.005

Avineri, E., & Prashker, J. N. (2004). *Violations of Expected Utility Theory in Route-Choice Stated Preferences Certainty Effect and Inflation of Small Probabilities.* Transportation Research Record(1894), 222-229.

Bagherian, M. C., Oded; van Oort, Niels; Hickman, Mark. (2016). *Measuring Passenger Travel Time Reliability using Smart Card Data.* Paper presented at the TRISTAN IX: Triennial Symposium on Transportation Analysis, Oranjestad, Aruba.

Bagozzi, R. P. (1992). *The Self-Regulation of Attitudes, Intentions, and Behavior.* Social Psychology Quarterly, 55(2). doi:10.2307/2786945

Bamberg, S. (2016). *Is a Residential Relocation a Good Opportunity to Change People’s Travel Behavior? Results From a Theory-Driven Intervention Study.* Environment and Behavior, 38(6), 820-840. doi:10.1177/0013916505285091

Bamberg, S., Ajzen, I., & Schmidt, P. (2010). *Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action.* Basic and Applied Social Psychology, 25(3), 175-187. doi:10.1207/s15324834basp2503_01

Bamberg, S., & Schmidt, P. (2003). *INCENTIVES, MORALITY, OR HABIT? Predicting Students' Car Use for University Routes With the Models of Ajzen, Schwartz, and Triandis.* Environment and Behavior, 35(2), 264-285. doi:10.1177/0013916502250134

Bamford, C.G. (2001) *Transport Economics, 2nd edition.* Oxford: Heinemann.

Barabino, B., Di Francesco, M., & Mozzoni, S. (2015). *Rethinking bus punctuality by integrating Automatic Vehicle Location data and passenger patterns.* Transportation Research Part A: Policy and Practice, 75, 84-95. doi:10.1016/j.tra.2015.03.012

Barry, J. J., Freimer, R., & Slavin, H. (2009). *Use of Entry-Only Automatic Fare Collection Data to Estimate Linked Transit Trips in New York City.* Transportation Research Record: Journal of the Transportation Research Board, 2112(1), 53-61. doi:10.3141/2112-07

Bates, J., Polak, J., Jones, P., & Cook, A. (2001). *The Valuation Of Reliability For Personal Travel.* Transportation Research Part E: Logistics and Transportation Review, 37, 191-229.

Ben-Akiva, M., & Bierlaire, M. (1999). *Discrete Choice Methods and their Applications to Short Term Travel Decisions.* In R. W. Hall (Ed.), Handbook of Transportation Science (pp. 5-33). Boston, MA: Springer US.

Ben-Akiva, M., & Lerman, S. R. (1985). *Discrete Choice Analysis - Theory and Application to Travel Demand.* Cambridge, Massachusetts: MIT Press.

Ben-Akiva, M., McFadden, D., Gärling, T., Gopinath, D., Walker, J., Bolduc, D., Rao, V. (1999). *Extended Framework for Modeling Choice Behavior.* Marketing Letters, 10(3), 187-203.

Bentham, Jeremy. [1789] (2009). *An Introduction to the Principles of Morals and Legislation (Dover Philosophical Classics).* Dover Publications Inc. ISBN 978-0486454528.

Berger, M., & Platzer, M. (2015). *Field Evaluation of the Smartphone-based Travel Behaviour Data Collection App "SmartMo".* Transportation Research Procedia, 11, 263-279. doi:10.1016/j.trpro.2015.12.023

Bhat, C. M. (1998). *Accommodating Variations In Responsiveness To Level-of-service Measures In Travel Mode Choice Modeling.* Transportation Reseach Pt A, 32(7), 495-507.

Bolduc, D. and Ben-Akiva, M. (1991). *A multinomial probit formulation for large choice sets.* Proceedings of the 6th International Conference on Travel Behaviour, Vol. 2, pp. 243–258.

Bonsall, P. (2010). *Traveller Behavior: Decision-Making in an Unpredictable World.* Journal of Intelligent Transportation Systems, 8(1), 45-60. doi:10.1080/15472450490437744

Bonsall, P., Firmin, P., Anderson, M., Palmer, I., & Balmforth, P. (1997). *Validating the results of a route choice simulator.* Transportation Research Part C: Emerging Technologies, 5(6), 371-387. doi:https://doi.org/10.1016/S0968-090X(98)00003-5

Bovy, P., & Stern, E. (1990). *Route Choice: Wayfinding In Transport Networks.* Hingham, MA, USA: Kluwer Academic Publishers.

Bovy, P. H. L. (2009). *On Modelling Route Choice Sets in Transportation Networks: A Synthesis.* Transport Reviews, 29(1), 43-68. doi:10.1080/01441640802078673

Bovy, P. H. L., Bekhor, S., & Prato, C. G. (2008). *The Factor of Revisited Path Size.* Transportation Research Record: Journal of the Transportation Research Board, 2076(1), 132-140. doi:10.3141/2076-15

Brakewood, C., & Watkins, K. (2018). *A literature review of the passenger benefits of real-time transit information.* Transport Reviews, 39(3), 327-356. doi:10.1080/01441647.2018.1472147

Buliung, R. N., Roorda, M. J., & Remmel, T. K. (2008). *Exploring spatial variety in patterns of activity-travel behaviour: initial results from the Toronto Travel-Activity Panel Survey (TTAPS).* Transportation, 35(6), 697-722. doi:10.1007/s11116-008-9178-4

Börjesson, M., & Eliasson, J. (2011). *On the use of "average delay" as a measure of train reliability.* Transportation Research Part A: Policy and Practice, 45(3), 171-184. doi:10.1016/j.tra.2010.12.002

Carrel, A., Halvorsen, A., & Walker, J. (2013). *Passengers' Perception of and Behavioral Adaptation to Unreliability in Public Transportation.* Transportation Research Record: Journal of the Transportation Research Board, 2351, 153-162. doi:10.3141/2351-17

Cascetta, E., Nuzzolo, A., Russo, F., & Vitetta, A. (1996). *A MODIFIED LOGIT ROUTE CHOICE MODEL OVERCOMING PATH OVERLAPPING PROBLEMS. SPECIFICATION AND SOME CALIBRATION RESULTS FOR INTERURBAN NETWORKS.* Paper presented at the 13th International Symposium on Transportation and Traffic Theory, Lyon, France.

Cats, O. (2013). *Multi-agent Transit Operations and Assignment Model.* Procedia Computer Science, 19, 809-814. doi:10.1016/j.procs.2013.06.107

Cats, O., & Jenelius, E. (2015). *Planning for the unexpected: The value of reserve capacity for public transport network robustness.* Transportation Research Part A: Policy and Practice, 81, 47-61. doi:10.1016/j.tra.2015.02.013

Cats, O., Koutsopoulos, H. N., Burghout, W., & Toledo, T. (2011). *Effect of Real-Time Transit Information on Dynamic Path Choice of Passengers.* Transportation Research Record: Journal of the Transportation Research Board, 2217(1), 46-54. doi:10.3141/2217-06

Cats, O., West, J., & Eliasson, J. (2016). *A dynamic stochastic model for evaluating congestion and crowding effects in transit systems.* Transportation Research Part B: Methodological, 89, 43-57. doi:10.1016/j.trb.2016.04.001

Chang, Y.-J., Paruthi, G., Wu, H.-Y., Lin, H.-Y., & Newman, M. W. (2016). *An investigation of using mobile and situated crowdsourcing to collect annotated travel activity data in real-word settings.* International Journal of Human-Computer Studies. doi:10.1016/j.ijhcs.2016.11.001

Chapman, G. B., & Johnson, E. J. (1999). *Anchoring, Activation, and the Construction of Values.* Organizational Behavior and Human Decision Processes, 79(2), 115-153. Retrieved from http://www.idealibrary.com

Chen, C., Ma, J., Susilo, Y., Liu, Y., & Wang, M. (2016). *The promises of big data and small data for travel behavior (aka human mobility) analysis.* Transp Res Part C Emerg Technol, 68, 285-299. doi:10.1016/j.trc.2016.04.005

Cherchi, E., & Cirillo, C. (2014). *Understanding variability, habit and the effect of long period activity plan in modal choices: a day to day, week to week analysis on panel data.* Transportation, 41(6), 1245-1262. doi:10.1007/s11116-014-9549-y

Chorus, C. G., Arentze, T. A., Molin, E. J. E., Timmermans, H. J. P., & Van Wee, B. (2006). *The value of travel information: Decision strategy-specific conceptualizations and numerical examples.* Transportation Research Part B: Methodological, 40(6), 504-519. doi:10.1016/j.trb.2005.08.002

Chowdhury, S., La Paix, L., & Geurs, K. T. (2020). *Inter- and Intrapersonal variation in destination choice.* EJTIR, 20(4), 194-213. doi:10.18757/ejtir.2020.20.4.3951

Chu, K. K. A., & Chapleau, R. (2008). *Enriching Archived Smart Card Transaction Data for Transit Demand Modeling.* Transportation Research Record: Journal of the Transportation Research Board, 2063(1), 63-72. doi:10.3141/2063-08

Chu, K. K. A., & Lomone, A. (2016). *Reproducing Longitudinal In-Vehicle Traveler Experience and the Impact of a Service Reduction with Public Transit Smart Card Data.* Transportation Research Record: Journal of the Transportation Research Board, 2541, 81-89. doi:10.3141/2541-10

Clark, A., Adell, E., Nilsson, A., & Indebetou, L. (2017). *Detailed Mapping of Tools and Applications for Travel Surveys (2017:32)*. Retrieved from Lund: https://www.trafa.se/globalassets/rapporter/underlagsrapporter/2017/english-version-trivector-detailed-mapping-of-tools-and-applications-for-travel-surveys2.pdf

Clifton, K., & Muhs, C. D. (2012). *Capturing and Representing Multimodal Trips in Travel Surveys.* Transportation Research Record: Journal of the Transportation Research Board, 2285(1), 74-83. doi:10.3141/2285-09

Congestion, T. G. C. o. (2013). *Mobilitet og fremkommelighed i hovedstaden (English: Mobility and accessibility in the Capital region).* Retrieved from Copenhagen:

Cottrill, C. D., Pereira, F. C., Zhao, F., Dias, I. F., Lim, H. B., Ben-Akiva, M. E., & Zegras, P. C. (2013). *Future Mobility Survey.* Transportation Research Record: Journal of the Transportation Research Board, 2354(1), 59-67. doi:10.3141/2354-07

Csikos, D., & Currie, G. (2008). *Investigating Consistency in Transit Passenger Arrivals: Insights from Longitudinal Automated Fare Collection Data.* Transportation Research Record: Journal of the Transportation Research Board, 2042, 12-19. doi:10.3141/2042-02

Currie, G., Douglas, N., & Kearns, I. (2011, 09/28 - 09/30/2011). *An Assessment of Alternative Bus Reliability Indicators.* Paper presented at the Australasian Transport Research Forum, Perth, Australia.

Davidson, A. (2016, November 15, 2015). *Big Data Exhaust for Origin-Destination Surveys - Using mobile trip-planning data for simple surveying.* Unpublished manuscript. New York, USA.

Dezfouli, A., & Balleine, B. W. (2012). *Habits, action sequences and reinforcement learning.* Eur J Neurosci, 35(7), 1036-1051. doi:10.1111/j.1460-9568.2012.08050.x

Diab, E. I., Badami, M. G., & El-Geneidy, A. M. (2015). *Bus Transit Service Reliability and Improvement Strategies: Integrating the Perspectives of Passengers and Transit Agencies in North America.* Transport Reviews, 35(3), 292-328. doi:10.1080/01441647.2015.1005034

Diab, E. I., & El-Geneidy, A. M. (2014). *Transitory Optimism.* Transportation Research Record: Journal of the Transportation Research Board, 2415(1), 97-106. doi:10.3141/2415-11

Dial, R. B. B., Richard E. (1968). *Public transit planning system.* Socio-Econ. Plan. Sci., 1, 345-362.

Dixit, M., Brands, T., van Oort, N., Cats, O., & Hoogendoorn, S. (2019). *Passenger Travel Time Reliability for Multimodal Public Transport Journeys.* Transportation Research Record: Journal of the Transportation Research Board, 2673(2), 149-160. doi:10.1177/0361198118825459

Droit-Volet, S., & Gil, S. (2009). *The time-emotion paradox.* Philos Trans R Soc Lond B Biol Sci, 364(1525), 1943-1953. doi:10.1098/rstb.2009.0013

Durán-Hormazábal, E., & Tirachini, A. (2016). *Estimation of travel time variability for cars, buses, metro and door-to-door public transport trips in Santiago, Chile.* Research in Transportation Economics, 59, 26-39. doi:10.1016/j.retrec.2016.06.002

Dyrberg, M. B., Christensen, C. B., Anderson, M. K., Nielsen, O. A., & Prato, C. G. (2015). *Transfer attributes in route choice models for public transport passengers.* Paper presented at the 4th hEART conference, Copenhgen.

Egu, O., & Bonnel, P. (2020). *Investigating day-to-day variability of transit usage on a multimonth scale with smart card data. A case study in Lyon.* Travel Behaviour and Society, 19, 112-123. doi:10.1016/j.tbs.2019.12.003

Eltved, M. (2020). *Modelling passenger behaviour in mixed scheduleand frequency-based public transport systems.* (PhD disertation). Danmarks Tekniske Universitet, Copenhagen.

Eluru, N., Chakour, V., & El-Geneidy, A. M. (2012). *Travel mode choice and transit route choice behavior in Montreal: insights from McGill University members commute patterns.* Public Transport, 4(2), 129-149. doi:10.1007/s12469-012-0056-2

Energimyndigheten. (2020). *Energiläget 2020.* Retrieved from Stockholm, Sweden:

Evans, J. S. (2008). *Dual-processing accounts of reasoning, judgment, and social cognition.* Annu Rev Psychol, 59, 255-278. doi:10.1146/annurev.psych.59.103006.093629

Fadaei, M., & Cats, O. (2016). *Evaluating the impacts and benefits of public transport design and operational measures.* Transport Policy, 48, 105-116. doi:10.1016/j.tranpol.2016.02.015

Farag, S., & Lyons, G. (2008). *What Affects Use of Pretrip Public Transport Information?* Transportation Research Record: Journal of the Transportation Research Board, 2069(1), 85-92. doi:10.3141/2069-11

Farzin, J. M. (2008). *Constructing an Automated Bus Origin–Destination Matrix Using Farecard and Global Positioning System Data in São Paulo, Brazil.* Transportation Research Record: Journal of the Transportation Research Board, 2072(1), 30-37. doi:10.3141/2072-04

Fatmi, M. R., & Habib, M. A. (2016). *Life-Oriented Approach of Modeling Commute Mode Loyalty and Transition Behavior.* Transportation Research Record: Journal of the Transportation Research Board, 2565, 37-47. doi:10.3141/2565-05

Fiorenzo-Catalano, S., van Nes, R., & Bovy, P. H. L. (2004). *Choice Set Generation for Multi-modal Travel Analysis.* EJTIR, 4(2), 195-209.

Florida, R. (2018). *The new urban crisis* (Paperback ed.). New York: Basic Books.

Fonzone, A. (2015). *What Do you Do with Your App?* Transportation Research Record: Journal of the Transportation Research Board, 2535(1), 15-24. doi:10.3141/2535-02

Fonzone, A., & Schmöcker, J.-D. (2014). *Effects of Transit Real-Time Information Usage Strategies.* Transportation Research Record: Journal of the Transportation Research Board, 2417, 121-129. doi:10.3141/2417-13

Fonzone, A., Schmöcker, J.-D., Bell, M., G.H, Gentile, G., Kurauchi, F., Nökel, K., & Wilson, N. H. M. (2010). *Do Hyper-Travellers Exist? Initial Results Of An International Survey On Public Transport User Behaviour.* Paper presented at the 12th WCTR, Lisbon, Portugal.

Fonzone, A. B., Michael G.H. (2010). *BOUNDED RATIONALITY IN HYPERPATH ASSIGNMENT: THE LOCALLY RATIONAL TRAVELLER MODEL.* Paper presented at the TRB Annual meeting, Washington DC.

Foster-Lloyd, W; *Two Lectures on the Checks to Population*. Oxford Univ. Press, Oxford, England, 1833, reprinted (in part) in Population, Evolution, and Birth Control, G. Hardin (ed., Freeman, San Francisco, 1964), p. 37

Frappier, A., Morency, C., & Trépanier, M. (2018). *Measuring the quality and diversity of transit alternatives.* Transport Policy, 61, 51-59. doi:10.1016/j.tranpol.2017.10.007

Frejinger, E. (2008). *Route Choice Analysis: Data, Models, Algorithms and Applications*. (PhD disertation). École Polytechnique Fédérale de Lausanne.

Frestad Nygaard, M., & Tørset, T. (2016). *Waiting Time Strategy for Public Transport Passengers.* Paper presented at the Trafikdage, Aalborg, Denmark.

Friedrich, M., Hofsaess, I., & Wekeck, S. (2001). *Timetable-Based Transit Assignment Using Branch and Bound Techniques.* Transportation Research Record, 1752(1), 100-107. doi:10.3141/1752-14

Friman, M., Edvardsson, B., & Gärling, T. (2001). *Frequency of negative critical incidents and satisfaction with public transport services.* Journal of Retailing and Consumer Services, 8, 95-104. doi:10.1016/S0969-6989(00)00003-5

Furth, P. G., & Muller, T. H. J. (2006). *Service Reliability and Hidden Waiting Time - Insights From Automatic Vehicle Location Data.* Transportation Research Record, 1955, 79-87.

Gentile, G., Florian, M., Hamdouch, Y., Cats, O., & Nuzzolo, A. (2016). *The Theory of Transit Assignment: Basic Modelling Frameworks.* In G. Gentile & K. Noekel (Eds.), Modelling Public Transport Passenger Flows in the Era of Intelligent Transport Systems: COST Action TU1004 (TransITS) (pp. 287-386). Cham: Springer International Publishing.

Geurs, K. T., Thomas, T., Bijlsma, M., & Douhou, S. (2015). *Automatic Trip and Mode Detection with Move Smarter: First Results from the Dutch Mobile Mobility Panel.* Transportation Research Procedia, 11, 247-262. doi:10.1016/j.trpro.2015.12.022

Ghahramani, N. B., Candace. (2016). *Trends in Mobile Transit Information Utilization: An Exploratory Analysis of Transit App in New York City.* Journal of Public Transportation, 19(3), 139-160.

Gibson, J., Munizaga, M. A., Schneider, C., & Tirachini, A. (2016). *Estimating the bus user time benefits of implementing a median busway: Methodology and case study.* Transportation Research Part A: Policy and Practice, 84, 72-82. doi:10.1016/j.tra.2015.07.011

Gigerenzer, G., & Goldstein, D. G. (1996). *Reasoning the Fast and Frugal Way: Models of Bounded Rationality.* Psychological Review, 103(4), 650-669.

Gittens, A., & Shalaby, A. (2015). *Evaluation of Bus Reliability Measures and Development of a New Composite Indicator.* Transportation Research Record: Journal of the Transportation Research Board, 2533(1), 91-99. doi:10.3141/2533-10

Glover, L. (2011). *Public Transport as a Common Pool Resource.* ATRF 2011 - 34th Australasian Transport Research Forum.

Gordon, J. B. (2012*). Intermodal Passenger Flows on London's Public Transport Network Automated Inference of Full Passenger Journeys Using Fare-Transaction and Vehicle-Location Data.* (PhD disertation). Massachusetts Institute of Technology, Boston.

Gordon, J. B., Koutsopoulos, H. N., Wilson, N. H. M., & Attanucci, J. P. (2013). *Automated Inference of Linked Transit Journeys in London Using Fare-Transaction and Vehicle Location Data.* Transportation Research Record: Journal of the Transportation Research Board, 2343(1), 17-24. doi:10.3141/2343-03

Goulet-Langlois, G., Koutsopoulos, H. N., & Zhao, J. (2016). *Inferring patterns in the multi-week activity sequences of public transport users.* Transportation Research Part C: Emerging Technologies, 64, 1-16. doi:10.1016/j.trc.2015.12.012

Greaves, S., Ellison, A., Ellison, R., Rance, D., Standen, C., Rissel, C., & Crane, M. (2015). *A Web-Based Diary and Companion Smartphone app for Travel/Activity Surveys.* Transportation Research Procedia, 11, 297-310. doi:10.1016/j.trpro.2015.12.026

Greene, W. H. (2014). *Panel Data Models for Discrete Choice.* New York.

Guthrie, A., & Fan, Y. (2016). *Weakening Obstacles to Transit Use.* Transportation Research Record: Journal of the Transportation Research Board, 2565, 103-110. doi:10.3141/2565-12

Ha, J., Lee, S., & Ko, J. (2020). *Unraveling the impact of travel time, cost, and transit burdens on commute mode choice for different income and age groups.* Transportation Research Part A: Policy and Practice, 141, 147-166. doi:10.1016/j.tra.2020.07.020

Hajinasab, B. (2018). *A Dynamic Approach to Multi-agent-based Simulation in Urban Transportation Planning.* (PhD Disertation). Malmö University, Malmö, Sweden.

Hamdouch, Y., Szeto, W. Y., & Jiang, Y. (2014). *A new schedule-based transit assignment model with travel strategies and supply uncertainties.* Transportation Research Part B: Methodological, 67, 35-67. doi:10.1016/j.trb.2014.05.002

Hanson, S., & Huff, J. O. (1988). *Systematic variability in repetitious travel.* Transportation, 15, 111-135.

Hansson, J., Pettersson, F., Svensson, H., & Wretstrand, A. (2019). *Preferences in regional public transport: a literature review.* European Transport Research Review, 11(1), 38. doi:10.1186/s12544-019-0374-4

Hansson, J., Pettersson-Löfstedt, F., Svensson, H., & Wretstrand, A. (2021). *Effects of rural bus stops on travel time and reliability.* Public Transport. doi:10.1007/s12469-021-00281-1

Harmony, X. J., & Gayah, V. V. (2017). *Evaluation of Real-Time Transit Information Systems: An information demand and supply approach.* International Journal of Transportation Science and Technology, 6(1), 86-98. doi:10.1016/j.ijtst.2017.05.003

Heiner, R. A. (1983). *The Origin of Predictable Behavior.* The American Economic Review, 73(4), 560-595. Retrieved from https://www.jstor.org/stable/1816559

Hess, S., & Rose, J. M. (2009). *Allowing for intra-respondent variations in coefficients estimated on repeated choice data.* Transportation Research Part B: Methodological, 43(6), 708-719. doi:10.1016/j.trb.2009.01.007

Hess, S., & Train, K. E. (2011). *Recovery of inter- and intra-personal heterogeneity using mixed logit models.* Transportation Research Part B: Methodological, 45(7), 973-990. doi:10.1016/j.trb.2011.05.002

Hodgson, G. M. (1997). *The ubiquity of habits and rules.* Cambridge Journal of Economics, 21, 663-684.

Hong, S.-P., Kim, K. m., Byeon, G., & Min, Y.-H. (2017). *A method to directly derive taste heterogeneity of travellers' route choice in public transport from observed routes.* Transportation Research Part B: Methodological, 95, 41-52. doi:10.1016/j.trb.2016.10.012

Hoogendoorn-Lanser, S., & Bovy, P. (2007). *Modeling Overlap in Multimodal Route Choice by Including Trip Part-Specific Path Size Factors.* Transportation Research Record: Journal of the Transportation Research Board, 2003(1), 74-83. doi:10.3141/2003-10

Hoogendoorn-Lanser, S., Bovy, P., & van Nes, R. (2007). *Application of Constrained Enumeration Approach to Multimodal Choice Set Generation.* Transportation Research Record: Journal of the Transportation Research Board, 2014(1), 50-57. doi:10.3141/2014-07

Hoogendoorn-Lanser, S., Schaap, N. T. W., & OldeKalter, M.-J. (2015). *The Netherlands Mobility Panel: An Innovative Design Approach for Web-based Longitudinal Travel Data Collection.* Transportation Research Procedia, 11, 311-329. doi:10.1016/j.trpro.2015.12.027

Hägerstrand, T. (1970). *What about people in Regional Science?* Papers of the Regional Science Association, 24(1), 6-21. doi:10.1007/BF01936872

IEA (2020). *Tracking Transport 2020.* IEA, Paris, available at https://www.iea.org/reports/tracking-transport-2020

Ingvardson, J. B., Nielsen, O. A., Raveau, S., & Nielsen, B. F. (2018). *Passenger arrival and waiting time distributions dependent on train service frequency and station characteristics: A smart card data analysis.* Transportation Research Part C: Emerging Technologies, 90, 292-306. doi:10.1016/j.trc.2018.03.006

International Transport Forum. (2019). *ITF Transport Outlook 2019.*

Internetstiftelsen (2017), *Svenskarna och Internet 2017. Undersökning om svenskarnas internetvanor.* Version 1.0

IPCC. (2014). *Climate Change 2014: Mitigation of Climate Change: Working Group III Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Retrieved from New York:

Iseki, H., & Taylor, B. D. (2009). *Not All Transfers Are Created Equal: Towards a Framework Relating Transfer Connectivity to Travel Behaviour.* Transport Reviews, 29(6), 777-800. doi:10.1080/01441640902811304

Jenelius, E. (2018, 04/09/2018). *Experienced Public Transport Service Reliability - Integrating Travel Time And Travel Conditions.* Paper presented at the 7th International Symposium on Transport Network Reliability (INSTR), Sydney, Australia.

Johansson, E. (2020). *The Knowledge Problem of Public Transport Policy.* (PhD Disertation). Lund University, Lund, Sweden.

Johansson, E., Anund, A., & Koglin, T. (2019). *Appraisal of a regional public transport project: A document and interview analysis on a light rail case in Sweden.* Case Studies on Transport Policy, 7(2), 196-204. doi:10.1016/j.cstp.2019.04.007

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). *Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias.* Journal of Economic Perspectives, 5(1), 193-206. doi:10.1257/jep.5.1.193

Kahneman, D., & Krueger, A. B. (2006). *Developments in the Measurement of Subjective Well-Being.* Journal of Economic Perspectives, 20(1), 3-24.

Kahneman, D., & Tversky, A. (1979). *Prospect Theory: An Analysis Of Decision Under Risk.* Econometrica, 47(2), 263-292. Retrieved from https://www.jstor.org/stable/1914185

Karlberg, C. (2015). *The survey fatigue challenge: Understanding young people's motivation to participate in survey research studies.* (Master). Lund University, Lund, Sweden.

Kaufman, B. E. (1990). *A New Theory of Satisficing.* The Journal of Behavioral Economics, 19(1), 35-51.

Kim, J., Corcoran, J., & Papamanolis, M. (2017). *Route choice stickiness of public transport passengers: Measuring habitual bus ridership behaviour using smart card data.* Transportation Research Part C: Emerging Technologies, 83, 146-164. doi:10.1016/j.trc.2017.08.005

Kroesen, M., & Chorus, C. (2018). *The role of general and specific attitudes in predicting travel behavior – A fatal dilemma?* Travel Behaviour and Society, 10, 33-41. doi:10.1016/j.tbs.2017.09.004

Kroesen, M., Handy, S., & Chorus, C. (2017). *Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling.* Transportation Research Part A: Policy and Practice, 101, 190-202. doi:10.1016/j.tra.2017.05.013

Kurauchi, F., & Schmöcker, J. D. e. (2017). *Public Transport Planning with Smart Card Data* (F. Kurauchi & J.-D. Schmöcker Eds.). Boca Raton: CRC Press.

Kurz, T., Gardner, B., Verplanken, B., & Abraham, C. (2015). *Habitual behaviors or patterns of practice? Explaining and changing repetitive climate-relevant actions.* Wiley Interdisciplinary Reviews: Climate Change, 6(1), 113-128. doi:10.1002/wcc.327

Li, X., Liu, W., & Yang, H. (2018). *Traffic dynamics in a bi-modal transportation network with information provision and adaptive transit services.* Transportation Research Part C: Emerging Technologies, 91, 77-98. doi:10.1016/j.trc.2018.03.026

Li, Z., & Hensher, D. (2011). *Prospect Theoretic Contributions in Understanding Traveller Behaviour: A Review and Some Comments.* Transport Reviews, 31(1), 97-115. doi:10.1080/01441647.2010.498589

Linse, L. (2016, 16/11/2016).

Liu, Y., Bunker, J., & Ferreira, L. (2010). *Transit Users' Route-Choice Modelling in Transit Assignment: A Review.* Transport Reviews, 30(6), pp 753-769. Retrieved from http://www.informaworld.com/10.1080/01441641003744261, https://trid.trb.org/view/1082792

Loomes, G., & Sugden, R. (1982). *Regret Theory: An Alternative Theory of Rational Choice Under Uncertainty.* The Economic Journal, 92(368), 805-824. Retrieved from https://www.jstor.org/stable/2232669

Lopez Aguirre, A. J. (2018). *Processing Crowdsourced Data for The Analysis of Mobility Behaviour.* (PhD disertation). Gent, Gent, Belgium. (D/2018/10.500/53)

Luethi, M. W., U A; Nash, A. (2007). *Passenger arrival rates at public transport stations.* Paper presented at the Transp. Res. Board 86th Annu. Meet. No. 07-063., Washington.

Lyons, G. (2006). The role of information in decision-making with regard to travel. Retrieved from Bristol:

Lyons, G., & Davidson, C. (2016). *Guidance for transport planning and policymaking in the face of an uncertain future.* Transportation Research Part A: Policy and Practice, 88, 104-116. doi:10.1016/j.tra.2016.03.012

Marra, A. D., Becker, H., Axhausen, K. W., & Corman, F. (2019). *Developing a passive GPS tracking system to study long-term travel behavior.* Transportation Research Part C: Emerging Technologies, 104, 348-368. doi:10.1016/j.trc.2019.05.006

Marra, A. D., & Corman, F. (2020). *Determining an efficient and precise choice set for public transport based on tracking data.* Transportation Research Part A: Policy and Practice, 142, 168-186. doi:10.1016/j.tra.2020.10.013

Marsden, G., Anable, J., Chatterton, T., Docherty, I., Faulconbridge, J., Murray, L., Shires, J. (2020). *Studying disruptive events: Innovations in behaviour, opportunities for lower carbon transport policy?* Transport Policy, 94, 89-101. doi:10.1016/j.tranpol.2020.04.008

Mattauch, L., Ridgway, M., & Creutzig, F. (2016). *Happy or liberal? Making sense of behavior in transport policy design.* Transportation Research Part D: Transport and Environment, 45, 64-83. doi:10.1016/j.trd.2015.08.006

Mazursky, D. (1998). *The effects of invalidating information on consumers subsequent search patterns.* Journal of Economic Psychology, 19, 261-277.

McFadden, D. (1973). *Conditional logit analysis of qualitative choice behavior.* In P. Zarembka (Ed.), Frontiers in Econometrics (pp. 105-142). New York: Academic Press.

McFadden, D., & Train, K. (2000). *MIXED MNL MODELS FOR DISCRETE RESPONSE.* JOURNAL OF APPLIED ECONOMETRICS, 15, 447-470.

Memmott, J. (2007). *Trends in Personal Income and Passenger Vehicle Miles.* Retrieved from Washington D.C:

Millard-Ball, A. (2019). *The autonomous vehicle parking problem.* Transport Policy, 75, 99-108. doi:10.1016/j.tranpol.2019.01.003

Mondschein, A. B., Evelyn; Taylor, Brian D. (2006). *Cognitive Mapping, Travel Behavior, and Access to Opportunity.* Transportation Research Record, 1985, 266-272.

Monosov, I. E. (2020). *How Outcome Uncertainty Mediates Attention, Learning, and Decision-Making.* Trends Neurosci, 43(10), 795-809. doi:10.1016/j.tins.2020.06.009

Munizaga, M. A., & Palma, C. (2012). *Estimation of a disaggregate multimodal public transport Origin–Destination matrix from passive smartcard data from Santiago, Chile.* Transportation Research Part C: Emerging Technologies, 24, 9-18. doi:10.1016/j.trc.2012.01.007

Nassir, N., Hickman, M., & Ma, Z.-L. (2015). *Behavioural findings from observed transit route choice strategies in the farecard data of Brisbane.* Paper presented at the Australasian Transport Research Forum 2015, Sydney, Australia. http://www.atrf.info/papers/index.aspx

Naturvårdsverket. (2020). *Fördjupad analys av den svenska klimatomställningen 2020 Klimat och luft i fokus (6945)*. Retrieved from Stockholm, Sweden:

Navick, D. S., & Furth, P. G. (2002). *Estimating Passenger Miles, Origin-Destination Patterns', and Loads with LocationStamped Farebox Data.* Transportation Research Record, 1799(02-2466), 107-113.

Nelson, P. (1970). *Information and Consumer Behavior.* Journal of Political Economy, 78(2), 311-329.

Nguyen, S., & Pallottino, S. (1989). *Hyperpaths and shortest hyperpaths.* In B. Simeone (Ed.), Combinatorial Optimization: Lectures given at the 3rd Session of the Centro Internazionale Matematico Estivo (C.I.M.E.) held at Como, Italy, August 25–September 2, 1986 (pp. 258-271). Berlin, Heidelberg: Springer Berlin Heidelberg.

Noland, R. B., & Polak, J. W. (2002). *Travel time variability: A review of theoretical and empirical issues.* Transport Reviews, 22(1), 39-54. doi:10.1080/01441640010022456

Nurul Hassan, M., Hossein Rashidi, T., Waller, S. T., Nassir, N., & Hickman, M. (2016). Modeling Transit User Stop Choice Behavior: Do Travelers Strategize? Journal of Public Transportation, 19(3), 98-116.

Nuzzolo, A., Russo, F., & Crisalli, U. (2001). *A Doubly Dynamic Schedule-based Assignment Model for Transit Networks.* Transportation Science, 35(3), 268-285. doi:10.1287/trsc.35.3.268.10149

O'Donoghue, T., & Rabin, M. (2001). *CHOICE AND PROCRASTINATION.* The Quarterly Journal of Economics. Retrieved from https://academic.oup.com/qje/article-abstract/116/1/121/1938917

OECD. (2019). *ITF Transport Outlook.* Retrieved from https://www.oecd-ilibrary.org/transport/itf-transport-outlook-2019_transp_outlook-en-2019-en

Oliker, N., & Bekhor, S. (2018). *A frequency based transit assignment model that considers online information.* Transportation Research Part C: Emerging Technologies, 88, 17-30. doi:10.1016/j.trc.2018.01.004

Ostrom, Elinor (1990*). Governing the Commons: The Evolution of Institutions for Collective Action.* Cambridge, UK: Cambridge University Press. ISBN 978-0-521-40599-7.

Osuna, E. E., & Newell, G. F. (1972). *Control Strategies for An Idealized Public Transportation System.* Transportation Science, 6(1), 52-72. Retrieved from http://www.jstor.com/stable/25767635

Prashker, J. N., & Bekhor, S. (1998). *Investigation of Stochastic Network Loading Procedures.* Transportation Research Record, 1645(1), 94-102. doi:10.3141/1645-12

Prato, C. G. (2009). *Route choice modeling: past, present and future research directions.* Journal of Choice Modelling, 2(1), 65-100. doi:10.1016/s1755-5345(13)70005-8

Prato, C. G., & Bekhor, S. (2006). *Applying Branch-and-Bound Technique to Route Choice Set Generation.* Transportation Research Record: Journal of the Transportation Research Board, 1985, 19-28.

Prato, C. G., Bekhor, S., & Pronello, C. (2011). *Latent variables and route choice behavior.* Transportation, 39(2), 299-319. doi:10.1007/s11116-011-9344-y

Prelipcean, A. C., Gidófalvi, G., & Susilo, Y. O. (2018). *MEILI: A travel diary collection, annotation and automation system.* Computers, Environment and Urban Systems. doi:10.1016/j.compenvurbsys.2018.01.011

Rahimi, E., Shamshiripour, A., Shabanpour, R., Mohammadian, A., & Auld, J. (2019). *Analysis of transit users' waiting tolerance in response to unplanned service disruptions.* Transportation Research Part D: Transport and Environment, 77, 639-653. doi:10.1016/j.trd.2019.10.011

Ralph, K. M., & Brown, A. E. (2017). *The role of habit and residential location in travel behavior change programs, a field experiment.* Transportation, 46(3), 719-734. doi:10.1007/s11116-017-9842-7

Ramming, S. M. (2002). *Network Knowledge and Route Choice.* (PhD dissertation) MIT, Boston

Raveau, S., Guo, Z., Muñoz, J. C., & Wilson, N. H. M. (2014). *A behavioural comparison of route choice on metro networks: Time, transfers, crowding, topology and socio-demographics.* Transportation Research Part A: Policy and Practice, 66, 185-195. doi:10.1016/j.tra.2014.05.010

Raveau, S., Muñoz, J. C., & de Grange, L. (2011). *A topological route choice model for metro.* Transportation Research Part A: Policy and Practice, 45(2), 138-147. doi:10.1016/j.tra.2010.12.004

Raworth, K. (2018). *Doughnut Economics.*

Region Skåne, 2014. *Resvaneundersökning i Skåne 2013.* Sweco rapport 2014-06-04

Region Skåne, 2018. *Så reser vi i Skåne – Resvaneundersökningen 2018, 2019-06-28.* Available at https://utveckling.skane.se/publikationer/rapporter-analyser-och-prognoser/resvaneundersokning-i-skane

Rieser-Schüssler, N., Balmer, M., & Axhausen, K. W. (2013). *Route choice sets for very high-resolution data.* Transportmetrica A: Transport Science, 9(9), 825-845. doi:10.1080/18128602.2012.671383

Rudnicki, A. (1997). *Measures of Regularity and Punctuality in Public Transport Operation.* IFAC Proceedings Volumes, 30(8), 661-666. doi:10.1016/s1474-6670(17)43896-1

Salek, M.-D., & Machemehl, R. B. (1999). *Characterizing Bus Transit Passenger Wait Times* (SVVlrfC/99/167211-1). Retrieved from Austin, Texas:

Salomon, I., & Mokhtarian, P. L. (1998). *WHAT HAPPENS WHEN MOBILITY-INCLINED MARKET SEGMENTS FACE ACCESSIBILITY-ENHANCING POLICIES?* Transport Research, Part D, 3(3), 129-140.

Samuelson, W., & Zeckhauser, R. (1988). *Status Quo Bias in Decision Making.* Journal of Risk and Uncertainty, 1, 7-59.

Schmitt, L., Harris, S., & Currie, G. (2014). *Adapting an Online Transit Journey Planner into a Low-Cost Travel Survey Tool.* Transportation Research Record: Journal of the Transportation Research Board, 2405, 8-15. doi:10.3141/2405-02

Seaborn, C., Attanucci, J., & Wilson, N. H. M. (2009). *Analyzing Multimodal Public Transport Journeys in London with Smart Card Fare Payment Data.* Transportation Research Record: Journal of the Transportation Research Board, 2121(1), 55-62. doi:10.3141/2121-06

Sen, A. (1988). *Freedom of choice, concept and content.* European Economic Review, 32, 269-294.

Seo, T., Kusakabe, T., Gotoh, H., & Asakura, Y. (2017). *Interactive online machine learning approach for activity-travel survey.* Transportation Research Part B: Methodological. doi:10.1016/j.trb.2017.11.009

Sheffi, Y. (1985). *Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods.* Englewood Cliffs, New Jersey: Prentice Hall.

Smith, Adam (1776). *An inquiry into the wealth of nations.* London: W. Strahan and T. Cadell; republished, London: Home University, 1910

Smith, K. V. (1983). *Optional Value: A Conceptual Overview.* Southern Economic Journal, 49(3), 654-668.

Smith, W. G. (2008). *Does Gender Influence Online Survey Participation?*: *A Record-linkage Analysis of University Faculty Online Survey Response Behavior.* Retrieved from San José

Statistics Sweden (2019) The MONA database, available at https://www.scb.se/en/services/guidance-for-researchers-and-universities/mona--statistics-swedens-platform-for-access-to-microdata/

Statistics Sweden (2020) Population statistics retrieved from https://www.statistikdatabasen.scb.se/pxweb/en/ssd/START__AM__AM0207__AM0207Z/NattSni07FoRN/

Stopher, P. R., & Greaves, S. P. (2007). *Household travel surveys: Where are we going?* Transportation Research Part A: Policy and Practice, 41(5), 367-381. doi:10.1016/j.tra.2006.09.005

Stopher, P. R., Jiang, Q., & FitzGerald, C. (2005). *Processing GPS data from travel surveys.* Paper presented at the 28th Australasian Transport Research Forum, Sydney, Australia.

Stopher, P. R., Shen, L., Liu, W., & Ahmed, A. (2015). *The Challenge of Obtaining Ground Truth for GPS Processing.* Transportation Research Procedia, 11, 206-217. doi:10.1016/j.trpro.2015.12.018

Svensk kollektivtrafik (2017). *Svensk kollektivtrafiks årsredovisning 2017.* Available at https://www.svenskkollektivtrafik.se/globalassets/svenskkollektivtrafik/bilder/fakta/publikationer/arsredovisning-2017

Tan, R. (2016). *MODELING ROUTE CHOICE BEHAVIOUR IN PUBLIC TRANSPORT NETWORK.* (PhD dissertation) National University of Singapore

Thomas, T., La Paix Puello, L., & Geurs, K. (2019). *Intrapersonal mode choice variation: Evidence from a four-week smartphone-based travel survey in the Netherlands.* Journal of Transport Geography, 76, 287-300. doi:10.1016/j.jtrangeo.2018.06.021

Tirachini, A. (2014). *The economics and engineering of bus stops: Spacing, design and congestion.* Transportation Research Part A: Policy and Practice, 59, 37-57. doi:10.1016/j.tra.2013.10.010

Ton, D., Shelat, S., Nijënstein, S., Rijsman, L., van Oort, N., & Hoogendoorn, S. (2020). *Understanding the Role of Cycling to Urban Transit Stations through a Simultaneous Access Mode and Station Choice Model.* Transportation Research Record: Journal of the Transportation Research Board, 2674(8), 823-835. doi:10.1177/0361198120925076

Trafikanalys. (2016). *Resvaneundersökningar som indata till persontransportmodeller - problem, möjligheter och framtida behov i Sverige och Norge (2016:21)*. Retrieved from Stockholm, Sweden:

Trafikanalys (2017). The Swedish national travel survey, available at https://www.trafa.se/en/travel-survey/travel-survey/

Trafikanalys. (2020). *Transportarbete i Sverige 2000 - 2019*. In M. f. Trafikanalys (Ed.).

Trafikanalys (2020a). *Regional linjetrafik 2019*- Available at https://www.trafa.se/globalassets/statistik/kollektivtrafik/kollektivtrafik/2019/regional-linjetrafik-2019.pdf

Trafikverket (2017a). *Jämför färdmedel – bil, flyg, tåg och buss (Eng: Compare transport modes – car, air, train and bus).* Available at https://www.trafikverket.se/for-dig-i-branschen/miljo---for-dig-i-branschen/energi-och-klimat/jamfor-trafikslag/

Trafikverket (2017b). *Förslag till nationell plan för transportsystemet 2018–2029, Remissversion 2017-08-31.* Available at http://trafikverket.diva-portal.org/smash/get/diva2:1363916/FULLTEXT01.pdf

Transportvaneundersøgelsen (2020). The Danish national travel survey, available at https://www.cta.man.dtu.dk/transportvaneundersoegelsen

TRB (2003). *Measuring Personal Travel and Goods Movement: A Review of the Bureau of Transportation Statistics; Surveys -- Special Report 277.* Washington, DC: The National Academies Press.

Trépanier, M., Tranchant, N., & Chapleau, R. (2007). *Individual Trip Destination Estimation in a Transit Smart Card Automated Fare Collection System.* Journal of Intelligent Transportation Systems, 11(1), 1-14. doi:10.1080/15472450601122256

Trompet, M., Liu, X., & Graham, D. J. (2011). *Development of Key Performance Indicator to Compare Regularity of Service between Urban Bus Operators.* Transportation Research Record: Journal of the Transportation Research Board, 2216(1), 33-41. doi:10.3141/2216-04

Turner, L. D., Allen, S. M., & Whitaker, R. M. (2017). *Reachable but not receptive: Enhancing smartphone interruptibility prediction by modelling the extent of user engagement with notifications.* Pervasive and Mobile Computing, 40, 480-494. doi:10.1016/j.pmcj.2017.01.011

Tversky, A., & Kahneman, D. (1981). *The framing of decisions and the psychology of choice.* Science, 211(4481), 453-458. doi:10.1126/science.7455683

UN. (2015) *Transforming our world: the 2030 agenda for sustainable development.,* Resolution 70/1 C.F.R.

UN. (2016). *Mobilizing sustainable transport for development: Analysis and policy recommendations from the United Nations Secretary-general's high-level advisory group on sustainable transport.*

UN. (2017). *Global Mobility Report 2017.* Retrieved from Washington D.C:

Uniman, D. L., Attanucci, J., Mishalani, R. G., & Wilson, N. H. M. (2010). *Service Reliability Measurement Using Automated Fare Card Data.* Transportation Research Record: Journal of the Transportation Research Board, 2143(1), 92-99. doi:10.3141/2143-12

van der Zijpp, N. J., & Fiorenzo Catalano, S. (2005). *Path enumeration by finding the constrained K-shortest paths*. Transportation Research Part B: Methodological, 39(6), 545-563. doi:10.1016/j.trb.2004.07.004

van Exel, J. (2011). *Behavioural Economic Perspectives on Inertia in Travel Decision Making.* (PhD disertation). Vrije Universiteit Amsterdam, Amsterdam.

Van Wee, B. (2007). *Large infrastructure projects: a review of the quality of demand forecasts and cost estimations.* Environment and Planning B: Planning and Design, 34, 611-625.

Wang, W., Attanucci, J. P., & Wilson, N. H. M. (2011). *Bus Passenger Origin-Destination Estimation and Related Analyses Using Automated Data Collection Systems.* Journal of Public Transportation, 14(4), 131-150.

Wang, Z., He, S. Y., & Leung, Y. (2018). *Applying mobile phone data to travel behaviour research: A literature review.* Travel Behaviour and Society, 11, 141-155. doi:10.1016/j.tbs.2017.02.005

Wardman, M., Chintakayala, V. P. K., & de Jong, G. (2016). *Values of travel time in Europe: Review and meta-analysis.* Transportation Research Part A: Policy and Practice, 94, 93-111. doi:10.1016/j.tra.2016.08.019

Watling, D. P., Rasmussen, T. K., Prato, C. G., & Nielsen, O. A. (2018). *Stochastic user equilibrium with a bounded choice model.* Transportation Research Part B: Methodological, 114, 254-280. doi:10.1016/j.trb.2018.05.004

Velaga, N. R., Beecroft, M., Nelson, J. D., Corsar, D., & Edwards, P. (2012). *Transport poverty meets the digital divide: accessibility and connectivity in rural communities.* Journal of Transport Geography, 21, 102-112. doi:10.1016/j.jtrangeo.2011.12.005

Verplanken, B., Aarts, H., & van Knippenberg, A. (1997). *Habit, information acquisition, and the process of making travel mode choices.* European Journal of Social Psychology, 27, 539-560.

Verplanken, B., Aarts, H., van Knippenberg, A., & van Knippenberg, C. (1994). *Attitude Versus General Habit: Antecedents of Travel Mode Choice.* Journal of Applied Social Psychology, 24(4), 285-300.

Verplanken, B., & Roy, D. (2016). *Empowering interventions to promote sustainable lifestyles: Testing the habit discontinuity hypothesis in a field experiment.* Journal of Environmental Psychology, 45, 127-134. doi:10.1016/j.jenvp.2015.11.008

Verzosa, N., Greaves, S., & Ellison, R. (2017). *Smartphone-based Travel Surveys: A Review. Working paper.* Institute of Transport and Logistics Studies (ITLS). The University of Sydney Business School. Sydney, Australia.

Vij, A., & Shankari, K. (2015). *When is big data big enough? Implications of using GPS-based surveys for travel demand analysis.* Transportation Research Part C: Emerging Technologies, 56, 446-462. doi:10.1016/j.trc.2015.04.025

Wolf, J., Oliveira, M. S., & Thompson, M. (2003). *Impact of Underreporting on Mileage and Travel Time Estimates Results from Global Positioning System–Enhanced Household Travel Survey.* Transportation Research Record, 1864(1), 189-198.

Wood, W., Quinn, J. M., & Kashy, D. A. (2002*). Habits in everyday life: Thought, emotion, and action.* Journal of Personality and Social Psychology, 83(6), 1281-1297. doi:10.1037/0022-3514.83.6.1281

Wood, W., & Runger, D. (2016). *Psychology of Habit.* Annu Rev Psychol, 67, 289-314. doi:10.1146/annurev-psych-122414-033417 von Neumann, J., & Morgenstern, O. (1944). *THEORY OF GAMES AND ECONOMIC BEHAVIOR.* Princeton, US: Princeton University Press.

World Bank (2014). *Toward Sustainable and Energy Efficient Urban Transport - Energy Efficient Cities (4).* Retrieved from Washington, USA:

Vovsha, P. (1997). *Application of Cross-Nested Logit Model to Mode Choice in Tel Aviv, Israel, Metropolitan Area.* Transportation Research Record, 1607(1), 6-15. doi:10.3141/1607-02

Xu, Z., Xie, J., Liu, X., & Nie, Y. (2020). *Hyperpath-based algorithms for the transit equilibrium assignment problem.* Transportation Research Part E: Logistics and Transportation Review, 143. doi:10.1016/j.tre.2020.102102

Yang, H., Kitamura, R., Jovanis, P. P., Vaughn, K. M., & Abdel-Aty, M. (1993). *Exploration of route choice behavior with advanced traveler information using neural network concepts.* Transportation, 20, 199-223.

Yap, M. D., Cats, O., van Oort, N., & Hoogendoorn, S. P. (2017). *A robust transfer inference algorithm for public transport journeys during disruptions.* Transportation Research Procedia, 27, 1042-1049. doi:10.1016/j.trpro.2017.12.099

Zhao, F., Pereira, F. C., Ball, R., Kim, Y., Han, Y., Zegras, C., & Ben-Akiva, M. (2019). *Exploratory Analysis of a Smartphone-Based Travel Survey in Singapore.* Transportation Research Record: Journal of the Transportation Research Board, 2494(1), 45-56. doi:10.3141/2494-06

Zhao, J., & Rahbee, A. (2007). *Estimating a Rail Passenger Trip Origin-Destination Matrix Using Automatic Data Collection Systems.* Computer-Aided CIvil and Infrastructure Engineering, 22, 376-387.