K2 WORKING PAPER 2019:13

Insamling och analys av väntetider och ruttval - en del i utvärderingen av stadsmiljöavtalet i Lund

Ulrik Berggren

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Ulrik Berggren

Innehållsförteckning

Förord

Den här rapporten är en del av K2:s arbete med att utvärdera stadsmiljöavtalet, ett styrmedel för att främja hållbara stadsmiljöer. K2:s arbete har syftat till att öka kunskapen om stadsmiljöavtalet som medel för att främja hållbara stadsmiljöer där en större andel persontransporter sker med kollektivtrafik och, för vissa avtal i senare omgångar, även med cykel. K2:s arbete har haft två inriktningar, en processutvärdering och en effektutvärdering av avtalens åtgärder och motprestationer. Inom processutvärderingen har studier genomförts kring hur kommuner, landsting och regioner, statliga myndigheter, m.fl. agerar och samarbetar och hur detta har påverkat avtalens inriktning och genomförande. Effektutvärderingen å sin sida har framförallt behandlat resande, förändringar i styrande och vägledande dokument, satsningar på hållbara transporter samt bostadsbyggande och bebyggd miljö. Projektet har avgränsats till de avtal som slöts mellan åren 2015 och 2017 (dvs i de fyra första ansökningsomgångarna), vilka sammanlagt utgör 65 stycken. Arbetet har främst bedrivits inom ramen för två doktorandprojekt, ett med utgångspunkt i processutvärderingen (doktorand från samhällsvetenskaplig fakultet) och ett inriktat på att studera effekter (doktorand från teknisk fakultet). Dessutom har seniora forskare och civilingenjörsstudenter medverkat i projektet.

Denna rapport innehåller text som låg till grund för det mittseminarie som genomfördes inom doktorandprojektet på tekniska fakulteten LTH, Institutionen för Teknik och samhälle, avdelningen Trafik och väg. Texten består av en sk mittseminariekappa som beskriver forkningsområdet samt binder ihop detta med resultat från artiklarna och de två artiklar som hittills blivit publicerade inom doktorandprojektet. Dessutom inleds rapporten med en introduktion till doktorandprojektet på svenska där detta arbete sätts i relation till arbetet med att utvärdera stadsmiljöavtalet. Mittseminariet ägde rum den 25 oktober 2019. Handledare för detta doktrandprojekt är Anders Wretstrand, Karin Brundell Freij och Helena Svensson, alla på Institutionen för Teknik och samhälle, Lunds tekniska högskola.

Lund, oktober 2019

Ulrik Berggren

författare

Helena Svensson

projektledare K2

Introduktion till doktorandprojektet

Denna text syftar till att ge en kort bakgrund samt redovisa metodologiska erfarenheter och hittillsvarande resultat från ett av de doktorandprojekt som ingår i K2:s projekt med att utvärdera stadsmiljöavtalens effekter.

Syftet med utvärderingsprojektet

Under åren 2016 till 2018 slöts sammanlagt 65 stadsmiljöavtal[1] med kommuner och regioner med syfte att, genom riktade stadsbidrag till kollektivtrafikåtgärder (och i sista ansökningsomgången även cykelåtgärder) kopplade till kommunala motprestationer inom hållbar samhällsplanering och bostadsbyggande, öka andelen persontransporter med dessa färdmedel. K2 har i uppdrag av Trafikverket, inom ramen för projektet *Hållbara stadsmiljöer med ökad andel kollektivtrafik – ett forskningsprojekt om stadsmiljöavtalen* att utvärdera bland annat effekter av dessa åtgärder och motprestationer i förhållande till syftet med avtalen. I den beviljade ansökan om forskningsmedel anges att i projektet ska genomföras en ”effektutvärdering med fokus på effekter av avtalen med avseende på t.ex. resande, energieffektivitet, emissioner, bostadsbyggande och bebyggelsemiljö”. Projektet syftar även till att bidra med ny kunskap på mer generell nivå kring effektsamband av åtgärdspaket och ska med detta adressera Trafikverkets målområde om att bidra till förbättrad kapacitet och tillförlitlighet i kollektivtrafiken. Projektet ska även enligt beviljad ansökan ”söka efter kunskap med vetenskaplig metod och med bestämd tillämpning i sikte, i första hand för att användas vid efterföljande utveckling[sarbete]”.

Doktorandprojektets fokusområde, angreppssätt samt motiv till dessa

Mot bakgrund av syftet med utvärderingsprojektet, men med beaktande av doktorandens bakgrund och kunskapsområde, har betoningen i doktorandprojektets forskning legat på att ytterst studera effekter på resmönster i kollektivtrafiken som resultat av ny infrastruktur med åtföljande trafikala utbudsförändringar. Angreppsättet har varit att introducera och utvärdera nya, eller i sammanhanget oprövade, metoder för insamling av data över resmönster. Dessa metoder, dels en mobiltelefonbaserad undersökningsapplikation och dels data från valideringar av färdbevis, har ett större inslag av automation än traditionella resdagboksbaserade undersökningar och syftar

[1] Här begränsar vi oss till de avtal som slöts inom det första, tidsbegränsade, försöksupplägget mellan 2015-2017.

därmed till att öka såväl kvantitet och kvalitet/detaljrikedom i den insamlade resdatan jämfört med resdagboksdata.

Valideringen av insamlingsmetodiken har skett i flera steg, där första steget har varit att jämföra resultat i termer av aggregerade data kring resfrekvens och reslängd med en konventionell resvaneundersökning för motsvarande geografiska område (Resvaneundersökning i Skåne, Sweco Rapport 2014-06-04). Vidare har, ur det insamlade materialet, indikatorer tagits fram och validerats som visar på resenärsbeteende kopplat till kollektivtrafikens utbudsnivå på olika resrutter där det finns ett reellt val mellan olika rutter per start- och målpunkt. De valda indikatorerna, *väntetid vid första hållplats* och *bytesväntetid*, har vidare utvärderats utifrån olika resenärsgrupper och attribut kopplade till aktuell resa, men även till hur varje resenär säger sig planera och informera sig inför och under respektive resa. Syftet med det senare har, utöver att validera metodiken, även varit att relatera till annan forskning och teorier kring individuella val- och beslutsprocesser i varierande grad av informationstillgång och osäkerhet. För att samla in uppgifter om individens planerings- och informationsstrategier har frågor med fasta svarsalternativ skickats ut till respondenterna direkt efter det att de avslutat ett reselement med kollektivt färdmedel med hjälp av kontext-beroende push-notiser i den mobilapp som nyttjats för att samla in resvanedata.

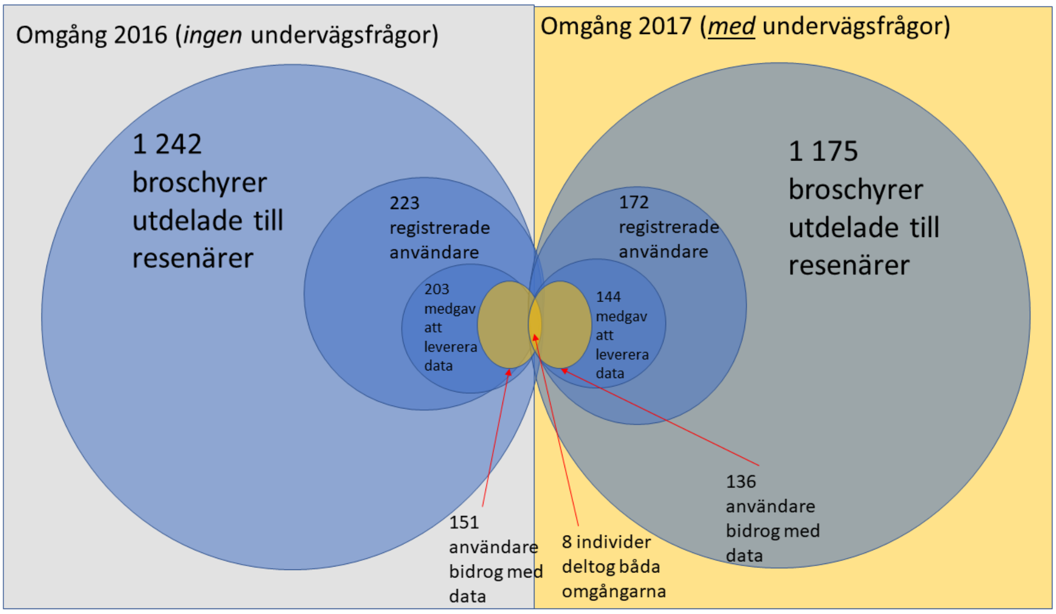
Det övergripande motivet till val av forskningsområde har varit svårigheten att empiriskt belägga och härleda de samband och tumregler mellan utbud och ruttval i kollektivtrafiken som bland andra Trafikverket, men även kommersiella trafikanalysverktyg, anger som standard. Det har således funnits ett upplevt och reellt behov av att utveckla metodik för att samla in detaljerad resdata för kollektivtrafikresor, inklusive anslutningar, byten och väntetider, liksom att utforska effektsamband mellan kollektivtrafikutbudets utformning och resenärers beteende med utgångspunkt i denna data. Då de befintliga resvaneundersökningarna inte erbjuder denna typ av data har nya grepp tagits, vilka jag utvecklar mer i nästa avsnitt.

Metodologiska erfarenheter

Metodiken för insamling av individers resmönster med hjälp av en särskild undersökningsapplikation i smarta telefoner bygger på aktivt deltagande av den enskilde respondenten, som varje dag uppmanas att gå in och korrigera/revidera de automatiskt genererade sekvenserna av aktiviteter och färdmedel. Den nyttjade applikationen (”resvaneappen”), TRavelVU[2], använder sig av maskininlärning av tidigare angivna aktiviteter och färdmedel i kombination med hållplatskoordinater och accelerometerdata för att föreslå aktiviteter och färdmedel, där aktiviteter alltid har en tidsmässig men även kan ha en rumslig innebörd - t ex ”hemma”, ”arbete” men även ”väntetid” och ”parkering”. En aktivitet definieras som när telefonen är stationär i minst två minuter, och med ”stationär” menas då att telefonen inte rör sig utanför en kvadrat med 100 meters sida.

[2] Kommersiellt tillgängligt verktyg som utvecklas och marknadsförs av Trivector.

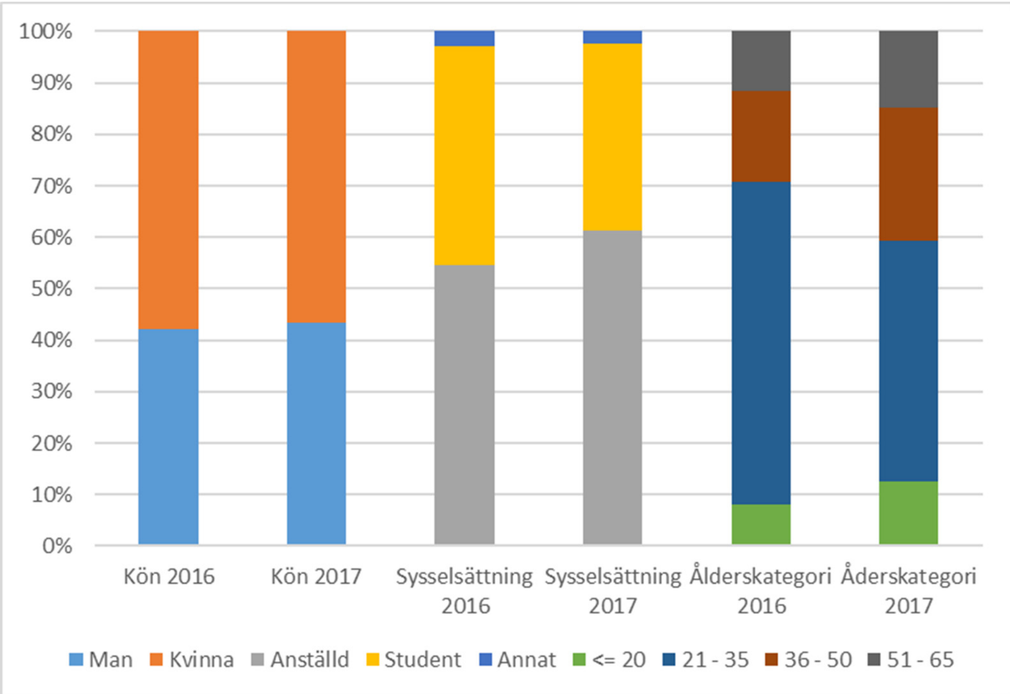
I Figur A redovisas resultatet av deltagarrekryteringen till resvaneundersökningens båda omgångar (två veckor under november 2016 och motsvarande period 2017). Rekryteringen gjordes genom direkt förfrågan, i samband med utdelning av en informationsbroschyr om undersökningen, till kollektivtrafikresenärer vid hållplatser i Lund och Malmö och, inför 2017 års undersökning, ombord på bussar. Målpopulationen utgjordes av resenärer som kunde tänkas bli påverkade av tillkomsten och anläggandet av den nya spårvägslinjen mellan Lunds C och Brunnshög, och således gjordes deltagarrekryteringen i anslutning till 20 buss- och tåglinjer som trafikerar spårvägens tilltänkta influensområde i nordöstra Lund samt i den viktiga pendlingskorridoren mot Malmö. I samband med registreringen angav deltagaren även kontaktuppgifter i form av e-postadress, vilket möjliggjorde en uppföljande studie. Resultaten av denna, samt en pilotanvändarstudie på K2, visar båda på två huvudsakliga orsaker till bortfall mellan registrering i appen och deltagande i studien fullt ut genom att leverera rättade resdata: (1) Kraftigt ökad energiåtgång i telefonen och (2) att rättningen medförde en orimligt stor arbetsbörda. Vissa förbättringar i appen mellan undersökningsångångarna kan dock ha bidragit till att bortfallet mellan medgivandesteget och steget där användaren börjar leverera resdata minskade från 52 till åtta.



Figur A. Rekrytering och antal slutliga deltagare i respektive undersökningsomgång. Undervägsfrågorna utrönade planeringsstrategi och informationsanvändning hos deltagarna kopplat till varje kollektivtrafikresa. Registrerade användare uppgav vid rekryteringen att de skulle ladda ner och installera appen, de som också medgav att leverera data genomförde verkligen installationen.

Med tanke på att målpopulationens sammansättning strikt sett är okänd är det svårt att säkert uttala sig om representativiteten i studien. Andelen studenter, och åldersfördelningen, rimmar dock ganska väl med det faktum att rekryteringsområdet rymmer flera utbildningsverksamheter, främst inom ramen för Lunds universitet. Sett till hela populationen kollektivtrafikresenärer i Skåne, är urvalet dock sannolikt tämligen skevt sett till åldrar och sysselsättning (**Figur** B), även om andelen förvärvsarbetande och personer över 35 år ökade något när särskilda rekryteringsinsatser riktades mot en viss busslinje, linje 20 mellan Lunds C och ESS, inför undersökningens andra omgång.

Noterbart är att ingen deltagare var över pensionsåldern 65 år. Totalt samlade deltagarna in 27 047 *reselement* (den kortaste uppmätta tidsgeografiska enheten), varav 5 363 med kollektiva färdmedel, under de båda undersökningsperioderna. Väntetider utgjordes dels av de aktiviteter som kodats som detta i appen, dels i efterhand härledda väntetider utifrån sekvenser som bestod av ett anslutningsfärdmedel (gång, cykel, bil) plus ett efterföljande kollektivt färdmedel. Då de senare saknade varaktighet, till skillnad från de förra, ansattes de ett slumptal mellan noll och två minuter (tröskelvärdet för en aktivitet är som bekant två minuter i resvaneappen).



Figur B. Deltagare i den mobilbaserade resvaneundersökningens två omgångar

Till skillnad mot en undersökning med resvaneapp så kräver insamlande av data från färdbevisvalideringar ingen aktiv handling av respondenter, och datan kan i princip täcka samtliga utförda transaktioner. För att uppnå synergier i datainsamlingen valdes samma två veckor i november 2016 respektive 2017 som för resvaneappen, och även samma 20 buss- och tåglinjer dit rekryteringen av användare till appen koncentrerades. Hittills har transaktionsdata för 2016 analyserats översiktligt ochföljande övergripande uppgifter finns tillhanda; Totalt antal unika kort (periodkort och reskassa) som följts var 244 790 år 2016 och 264 713 år 2017 varav 58 346 återfanns i båda omgångarna. Totalt utförde kortinnehavarna (om vi antar att varje kort motsvarar en person) 1 588 833 respektive 1 246 416 korttransaktioner (”resor”) per undersökningsperiod. Då kortdatan saknade uppgifter om avstigningsplats gjordes en speglingsoperation där påstigningsplatsen på eftermiddagen antogs vara avstigningsplats på förmiddagen och vice versa. Om då samma plats uppträdde både som påstignings- och avstigningsplats inom samma tidsperiod (morgon eller eftermiddag) antogs den vara en plats för byte, och tiden mellan avstigning och påstigning antogs utgöra bytestiden. Vid okulär jämförelse av dessa med bytestider från studien med resvaneappen var typvärdet identiskt (fyra minuter) men spridningen liksom medelväntetiden var kolossalt mycket större i kortdatan jämfört med appdatan (medel i kortdatan var 53 minuter mot nio minuter i appdatan, standardavvikelsen var 1:45 timmar i kortdatan men 18 minuter i appdatan). Således bör det vara lämpligt att tillämpa en snävare tidsdefinition av byte användas i den fortsatta analysen av kortdatan.

Hittillsvarande resultat

Följande avsnitt, som redovisar resultat från den mobiltelefonbaserade resvaneundersökningen, är baserat på de två vetenskapliga artiklar som jag skrivit, varav en har publicerats (Berggren, Johnsson, Svensson, & Wretstrand, 2019) och en är under granskning (Berggren, Brundell-Freij, Svensson, & Wretstrand, *under granskning av tidskriften Public Transport*).

Statistiska analyser visar att varaktigheten på väntetiden vid första hållplatsen är förhållandevis oberoende av turintervallet i den relation som resenären senare färdas i – endast en halv procent av variationen i väntetider kan förklaras av turtätheten, medan ärende i samverkan med kön respektive resans längd förklarar en dryg procent var av variationen. När det gäller bytesväntetider har bytespunktens läge och typ (t ex byteshållplats, ändhållplats, lantlig resp. urban belägenhet) i samverkan med resans syfte den största förklaringsandelen på fem procent medan ärende i samverkan med kön förklarar dryga två procent av väntetidens variation. Väntetiden var signifikant längre för resor över en timme och som skedde i fritidssyfte och från större bytespunkter jämfört med resor från övriga stadsbusshållplatser och för arbetsresor (ingen signifikant skillnad mot landsbygdshållplatser). Observera således att mellan 88 (första väntetid) och 75 (bytesväntetid) procent av variationen förklaras av slumpen (det statistiska felet) vilket visar på de registrerade väntetidernas stora spridning. En intressant slutsats som kunde dras var att det fanns individuell konsistens i väntetiderna, både i genomsnittlig längd och i spridning – vissa individer väntade i snitt längre eller hade större spridning i väntetider jämfört med andra och vissa minimerade tiden i högre grad än andra, oaktat övriga oberoende variabler såsom turtäthet och reslängd. Det fanns få gemensamma drag såsom ålder mellan individer med ett visst beteendemönster, men det kunde konstateras att kvinnor i snitt hade något längre väntetid vid första hållplats, åtminstone för vissa ärenden.

När det gäller resbeteende i förhållande till informationsanvändning och förekomst eller typ av planeringsstrategi erhölls en del intressanta resultat. Slumpmässigheten i väntetider var mer uttalad vid resor där information eller utantillkunskap om exakta avgångstider inte nyttjats innan resan jämfört med där detta skett. I relationer med turtäthet på minst fem minuter var förplanering och kunskap om tidtabellen mindre vanlig, men nyttjande av tidtabellsinformation mer vanlig, jämfört med vid lägre turintervall. Kvinnor förplanerade i högre grad än män, vilka å andra sidan nyttjade tidtabellsinformation och reseplanerare i högre grad än kvinnor. Resultaten belyser vikten av att ta höjd för olika beteende och attityder till risk (t ex för missad anslutning, manifesterad genom dimensioneringen av väntetidsmarginaler) och osäkerhet i olika befolkningsgrupper i samband prognoser för resande inför planering och dimensionering av kollektivtrafiksystemet.

Relevans för utvärderingsprojektet

Resultaten och erfarenheterna under datainsamlingen visar dels på användbarheten av nya metoder som minimerar behovet av, eller belastningen på, tillfrågade respondenter. Mot bakgrund av fallande svarsfrekvenser i konventionella resvaneundersökningar som bygger på resdagböcker så är detta tämligen dagsaktuellt och något som efterfrågas av allt fler kommuner och regioner som vill kunna mäta effekter av fysiska och beteendepåverkande åtgärder på ett enkelt och kostnadseffektivt sätt. Den i projektet nyttjade metodiken fungerade väl för sitt syfte och visade generellt på vederhäftiga resultat på en aggregerad nivå, såsom antal resor per person och dag, i jämförelse med konventionella metoder. Svarsfrekvensen är dock fortsatt en utmaning – i härvarande studie svarade drygt tio procent av de tillfrågade. Det fortlöpande arbetet i doktorandprojektet att, utifrån de nya insamlingsmetoderna, empiriskt härleda samband mellan kollektivtrafikutbud och resenärsbeteende har bäring på utvärderingsprojektets syfte att bidra med ny kunskap kring sådana effektsamband.

Slutord

Så här långt har analysen av insamlade data fokuserat på att mäta och förklara väntetider, såsom varande en viktig indikator för resenärers uttryckta val av resväg, och därmed kollektivtrafiklinje, i en given resrelation. Det fortsatta arbetet inom doktorandprojektet kommer att ske utmed tre huvudsakliga inriktningar. I den första kommer en fullständig ruttvalsmodell att skattas utifrån dels den insamlade resdatan och dels fördefinierade ruttalternativ baserade på publicerad tidtabell per resrelation. Syftet är här främst att analysera marginella substitutionskvoter och elasticiteter (benägenhet hos resenären att implicit värdera olika val i förhållande till varandra) mellan olika restidskomponenter alltså även anslutningstid och val av påstignings- och byteshållplatser längs resvägen. Den andra inriktningen handlar om att utifrån en ny insamlingsomgång av resdata, med samma metodik som i 2016 och 2017 års omgångar, ta reda på hur den nya spårvägen i Lund påverkar nyss nämnda substitutionskvoter och elasticiteter. I en tredje inriktningen, slutligen, vidareanalyseras kortdatan för att genom en panelanalys utröna huruvida ändrad punktlighet, eller andra förändringar som påverkat trafikutbudet mellan insamlingsomgångarna 2016 och 2017, påverkar resenärernas val av linjer och hållplatser. Samtliga dessa tre linjer utgör led i arbetet att empiriskt utforska effektsamband mellan resbeteende och utbudsegenskaper i kollektivtrafiken.

Mittseminarietext

Texten som följer är den text som låg till grund för mittseminariet som genomfördes inom doktorandprojektet på tekniska fakulteten, LTH, Lunds universitet. Texten är en sk mittseminariekappa som beskriver forkningsområdet samt binder ihop detta med resultat från de två artiklar som hittills blivit publicerade inom doktorandprojektet.

The use of detailed public transport survey data for analysis of waiting times and route choice

Ulrik Berggren

LUND UNIVERSITY

MID-TERM THESIS

Faculty of Engineering, Department of Technology and Society

Presented at K2, Lund 25th of October 2019

Discussant: Trude Tørset

1. Introduction

"Why am I stuck on the bus for work again even though the train goes much faster?" How one can explain choices in routine situations for others or to one-self is not always a straightforward issue to resolve. The choice may be of a habitual kind, made without further consideration, or it may be motivated by beliefs or triggered by actual events, recent or in the past, or deliberate and based on search for relevant information. The choices may seem perfectly rational to oneself, but purely arbitrary or subjective or "silly" from another person's point of view.

Nevertheless, this thesis aims at approaching the kind of choices that can be attributed to a phenomenon common to all humans, although I will restrict the environment where it will be discussed, measured and analysed: Route, or path, choice in public transport. As I will describe in detail in the theory section below, route choice may be conceptualised as being either routine and habitual, or intended and deliberate, and this makes it difficult to measure since both explicit circumstances and inertia and habit come into play in the choice process. The latter may readily be introduced in an objective utility function in a discrete choice model, but the former is usually swept under the carpet (the error term or alternative specific constants) in the most commonly used multinomial models. But how evident are actually the alternatives, and how far does self-control of the individual reach, without being hampered by habit, inertia, bounded rationality, attitudes and beliefs? And is there an obvious advantage having multiple options, or is this rather a particular cause of mental overload or stress for the decision maker, and how do humans react to this kind of situations? These issues will be fully addressed in the theory section, with due references to previous thinkers and scholars. In the next section, however, I will narrow down the perspectives somewhat to methodological and empirical issues of measuring revealed passenger behaviour and to what extent deliberate strategies and pre-trip information collection and utilisation can be shown to be pursued by public transport passengers.

Since the empirical results presented in this thesis is based on two journal papers (Berggren, Johnsson, Svensson, & Wretstrand, 2019) (Berggren, Brundell-Freij, Svensson, & Wretstrand, *under review*), the results section is organised by paper, in this order.

2. Motives

But, why on earth study route choice? Taking the holistic framework of maximising public transport quality of service and resource efficiency as general societal maxim, also as a means to approach a sustainable future, predicting where in the public transport network money makes the most use should be a matter of major concern to policy makers. Regardless of how insignificant each single individual choice may seem; taken together they can have considerable effects on both operational and strategic long-term performance of the transport system as a whole. In systems that are operating close to the capacity limit, small fluctuations in the decisions of passengers can have potentially huge effects. However, measuring actual behaviour and its causes may sound easier than it actually is, taken all the various possible mechanisms that can influence human behaviour. The very rationale behind the topic chosen for this thesis is that, taking the more or less well-known flaws of conventional survey tools and commonly used person tracking techniques, I found that it is time to introduce the hybrid approach of user-mediated semi-automatic survey tools into the route choice estimation field. As yet, however, in this thesis I have had to restrict myself to measurements of a subset of, although important, public transport trip elements – waiting times, which is the kind of element of a public transport trip most travellers are actually able to influence. In addition, I have studies what strategies and information passengers use to minimise or make the most use of this, allegedly onerous, phenomenon. As such, this thesis may be regarded as a prequel to the on-going route choice estimation work that is to be fully covered in a sequence of papers in progress.

3. Theory of choice

3.1. Philosophy and psychology of choice

The available opportunity space within which an individual has had possibility to choose between alternatives, as being an act of deliberation and consciousness, has historically hinged on social status and/or wealth, and was by e g Aristotle[3] framed as an intrinsic good and central in order to lead a good life. Sen (1985) further introduces the notion of capabilities and thus puts focus on the individuals' ability to actually make use of different options through functionings. In modern society, however, as technology and both time instances where choices can be made, as well as the available options, approach infinity, 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 at time pressure and other forms of mental taxation (Hodgson, 1997; Woodet al., 2002; Wood & Runger, 2016), people tend to adhere to heuristics, habits and other forms of strategies that aim to reduce the cognitive burden. Hodgson (1997) discusses seven different decision or action situations, 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 of the resources; (3) *Complexity*, where there is a gap between the complexity of the decision environment and 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 sense data, (6) *Learning* and (7) *Communication* with others. Kahneman et al (1991) and Tversky & Kahneman (1981) mean that people approach uncertainty and complexity by often value options differently depending on how they are framed and during what contexts and circumstances they materialise to the decision maker. Here, clearly a process of socialisation and (reinforcement) learning is involved, which is discussed further in the next subsection in the context of the attainment and utilisation of information. Other such coping strategies (cf Bagozzi (1992)) to uncertainty in choice situations that have been suggested include procrastination (O'Donoghue & Rabin, 2001), adherence to default and status quo alternatives (Samuelson & Zeckhauser, 1988) and anchoring (Chapman & Johnson, 1999) of beliefs to some information or cue found trustworthy, or as Kahneman & Krueger (2006) suggest, to some high-intensity affective value, or momentary affect near in time.

[3] See note 1 in Sen (1988)

3.2. Theoretic attempts to explain behaviour

From von Neumann & Morgenstern (1944) and onwards, expected utility theory (EUT) has dominated the field of predicting individuals' choices within economic consumer theory. As the authors carefully and thoroughly underline, 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. Virtually every word in the last sentence has subsequently been questions on a manifold of 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 (van Exel (2011) has an excellent introduction to this critique relevant for transport mode choice, and Bonsall (2010) regarding route choice under uncertainty). Most of these critics will be mentioned below, and most of them address the issues of choice theory introduced in the first subsection in this chapter. However, within psychology, there have also been theories emerging that are at least to some extent concurrent with the postulates of rationality within choice theory. Theory of reasoned action (TRA) (Ajzen & Fishbein, 1969), and the subsequently suggested Theory of planned behaviour (TPB) (Ajzen, 1991), point to "subjective rationality" in decision making of individuals, in that choices are made based rationally on intentions contingent on subjective (social) norm, (individual) attitude and perceived behavioural control (as a function on contextual circumstances). However, both TRA and TPB has been criticised on empirical grounds (see below and also relevant findings by Kroesen & Chorus (2018); Kroesen et al (2017)). The concept of goal-directed behaviour, and how goals interact with and compete with other behavioural traits in the motivational process preceding a decision (Forster et al., 2007), may be viewed as an expansion of TRA and TPB. Goals, or motives, may be obvious and easy to derive from actual circumstances for the individual, or implicit and based on past experiences and perceptions, made by oneself or as told by acquaintances(B. Verplanken & Holland, 2002; Wood & Runger, 2016). Aarts & Dijksterhuis (2000) showed an empirical link between goals and habitual behaviour, and Neal et al (2013) nuance this picture even further when concluding that goals are significant only for moderately habitual behaviour, while strong habits were invariant to goals. Moreover, Neal, Wood, Labrecque, and Lally (2012) show the importance of context cues in the triggering of certain habitual behaviour, characterised by low self-regulation. Interestingly, self-evaluation indicated self-perception of goal-directed behaviour among subjects in the study referred. This tendency might be an example of what Fischhoff (2003) denoted as a kind of outcome bias, and thus that the goals may have been adjusted unintentionally after the choices were made. The automatized, habitual vs conscious and deliberate in decision making is sometimes referred to a concept of dual processing of the human mind. In line of this reasoning, Evans (2008) suggests that this dichotomy between the so-called System 1 (high-capacity, evolutionary early, unconscious and low in effort) and System 2 (slow, conscious, explicit and analytic) should rather be characterised as two kinds of mental processes, where the slow process also has elements of rapid, unconscious processing. The latter is also supported by the notion of scripts (Verplanken et al., 1994) in guiding behaviour, being a combination of (semi-) automatized and deliberate actions.

Expanding even further to an inter-personal level, a level that enters the TPB and TRA through the subjective norm factor, Abou-Zeid et al (2013), and Kurz et al (2015) introduce the significance of social context for individual behaviour and decision making (for a broader perspective, see also Vaisey & Valentino (2018) for a discussion of sociological aspects of decision theory). Thus, the concepts of habits, routines and heuristics along with subjective norms and attitudes may be supplemented with institutions, social constructs and social norms, traditions, rituals and customs.

Preferences may be stable or inconsistent through time and space (Mattauch et al., 2016) and, if framed as contingent on attitudes, their stable exogenous relationship to context and personal traits may not be as evident as assumed in classic microeconomic theory. Also, the evaluation of alternatives may be focussing on reducing risk or maximising to a certain level of content. By relaxing the monotonicity of the indifference curve in relation to (expected) outcome, being another postulate in EUT, scholars in behavioural economics and psychology have developed theories that aim at representing human behaviour more realistically. Firstly, the satisfaction of preferences may be fulfilled at a level not entailing the maximum utility for the individual, but rather on a sufficient level in order to attain subjective well-being, so-called satisficing behaviour (Kahneman & Krueger, 2006; Kaufman, 1990). Secondly, individuals' decision making under uncertainty and risk is addressed in particular by Kahneman & Tversky (1979) when they observed the concepts of risk seeking behaviour at expected losses and risk averse behaviour at expected gains. Thus, in their prospect theory (PT), expected utility is not monotonically related to outcome values. Avineri and Prashker (2004) has also suggested that this concept better explain mobility patterns involving uncertain route choices. Thirdly, regret theory, as first formulated by Loomes & Sugden (1982), allows for negative utility and thus also relaxes the monotonicity and transitivity assumptions of EUT, but to a somewhat less radical degree than PT. Examples include avoiding expected negative experiences when making decisions, a trait also supported by PT (Kahneman et al., 1991). Critics of PT have pointed out that it lacks the longitudinal perspective of social and individual learning (Rasouli & Timmermans, 2014), and a number of modelling approaches has been proposed (more non this in the next subsection). Bonsall (2010) goes into depth in the information acquisition issue by introducing tie important aspects of perception, knowledge and experience in the passive or active utilisation of information in decision making under uncertainty. Bonsall's main argument, somewhat resembling the critique towards the von Neumann & Morgenstern (1944) approach whereby 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, is that purely probabilistic models put purely random events and measurement error together with the subjects individual perceptions and reactions to the uncertainty caused by this seemingly random variability. However, 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, which may be taken advantage from by experience (own or as told by others) and successive learning. Bonsall also mentions the increasing importance of "information and advice provided by system managers or other agencies", and this is a topic I will get back to in detail, since 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 in the search for information on product quality, where he distinguished between experience and search goods. Thus, quality information on experience goods must be purchased 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 search good, depending on where in the decision process the individual is placed. Strategic, long-term choices are usually made at life course changes such as relocation of residence and/or place for employment and study (Bamberg, 2016; Ralph & Brown, 2017), while more tactical and ad-hoc response regarding route choice during recurring trips may include trying different alternatives and thus forming strategies to cope (Bonsall, 2010). As experience is accumulated, the response to a certain stimulus of cue (e g cancellation of train services, an accident on the usual road to work), mediated either from fellow passengers or through digital communication media, may trigger habitual or script-based actions or more deliberate and conscious behaviour and search for information, depending on the commonness of the event (Verplankenet al., 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 previously utilised. 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". Lyons (2006) elaborates further on this matter and argues that perceived need limits 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 it may be designed to confirm already made choices (anchoring). However, he agrees with Bonsall in that uncertainty is a key motivation for information search. Empirically (Farag & Lyons, 2008; Lyons, 2006), unusual and complex public transport trips, and when the available information is perceived as trustworthy, has been shown to trigger significant use of pre-trip information. More empirical evidence on information and route choice in public transport will be discussed in the next subsection.

3.3. Applications in transport modelling

Innumerable approaches have been attempted in modelling individual mobility and behaviour in transport systems. Most of the state-of-the art operationalisations are based on mainstream microeconomic theory echoing from von Neumann & Morgenstern (1944) but with different probabilistic approaches to cater for taste variation - e g attitudes and norms, unobserved heterogeneity and all the other cognitive and behavioural complications to choice based on utility maximisation optimisation and listed by Hodgson

(1997) as well as above. To somewhat restrict and narrow down the theoretic complexity of this thesis, and related to my choice of scope, I will from now on focus on applications used in the modelling of public transport passenger behaviour, although some general principles for discrete choice modelling will also have to be briefly introduced.

As M. Ben-Akiva and Lerman (1985) state in their influential textbook on discrete choice modelling (p. 31), a useful theory of choice should fulfil the following three conditions: (1) Descriptiveness, that it postulates empirically observed behaviour of humans, (2) Abstraction – "in the sense that it can be formalised in terms which are not specific to particular circumstances", and (3) "Operational, 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 model aggregate individual behaviour. Based on its mathematically and statistically consistency and computational efficiency, the expected (or random) utility model, in particular the multinomial logit (MNL) has been most extensively applied to describe and predict discrete choice, although there are examples of PT (Li & Hensher, 2011) and random regret theory (Chorus et al., 2006) being used. Also, as proposed by M. Ben-Akiva et al. (1999) and attempted by for instance Alizadeh et al (2019), attitudes, norms, perceptions, lifestyle and beliefs may enter the model framework through latent constructs, as mediated by specific indicator measures (commonly surveyed through psychometric methods using Likert scales, Likert (1932)). In their study, the authors use a web-based survey to collect hypothetical but revealed route choice for a sample of 225 Montreal motorists. They address the inherent dilemma of route choice models, how to handle route overlap, by applying an extended path size logit formulation (Frejinger, 2008) as an extension of the MNL model. The hybrid modelling approach applied here, which use integrated choice-latent variables, may be subject to the critique presented by Kroesen & Chorus (2018) of relying heavily on TPB, in the direct causal relationships between environment/context→attitude→intention→behaviour, while it may in fact be that behaviour has a larger impact on attitude than the opposite. However, the promising aspect of the hybrid approach is that inter- and intra-personal heterogeneity may be propitiously accounted for in a route choice context. The issue of consideration vs the mathematically complete choice set available to the decision maker (also fruitfully addressed and investigated by Gigerenzer and Goldstein (1996)) is also considered, in that a restricted set is used. Although this inclusion of explicit alternatives have spurred auspicious alternative approaches lately (cf recursive logit applied by Meyer de Freitas et al., 2019 and Nassir et al., 2018), I have chosen not to validate this novel strand of modelling practice due to resource limitations. In the next section, I will delve further into practical issues of route choice modelling and empirical measurements.

4. Route choice – measurement and modelling

In this section, I will briefly introduce the issues frequently encountered when attempting to measure and estimate passenger route choice in public transport systems. Practical and feasible applications will be in the foreground, while theoretical implications and derivations will be treated somewhat subordinate from now on.

To generate explicit route choice sets/alternatives that can legitimately assumed to be included in a set of available options to the individual ahead of or during a trip, a number of enumeration techniques have been developed (see Prato (2009) for a detailed record of the most common methods). Common to all these approaches is that a potentially very large number of alternatives must be available in order to find a reasonable rate of overlap with revealed routes, according to most studies in the field, which in turn has been shown to affect the quality of the estimation outcome. Referring back to the introductory philosophical paragraph of this thesis, the size of the consideration set of options (cf van Exel (2011)) may be viewed as being related to the optional value (Smith, 1983) of having many possible alternatives (I like the analogy with Sen's concept of freedom of choice here!). In fact, empirical findings based on discrete route choice modelling with a MNL-formulation using path size (Moshe Ben-Akiva & Bierlaire, 1999) to cater for the correlation - or overlap - between routes, generally indicate a positive effect of overlap for public transport routes but a negative one for motorist routes (see e.g. Anderson, Nielsen, and Prato (2014) or more thoroughly in Hoogendoorn-Lanser and Bovy (2007)). Thus, for public transport, there seems to be a premium, or optional value, for route involving many at least partly overlapping variants (e g several bus lines mutually servicing a corridor). This may also be seen as an empirical underpinning of the concept of *hyperpaths*, which will be elaborated on further below.

As mentioned briefly in the introductory section of this thesis, empirical studies of route choice have thus far chiefly relied on either direct observation in the field (Bovy & Stern, 1990; Ramming, 2002) or in simulated environments (Bonsall, Firmin, Anderson, Palmer, & Balmforth, 1997; Frejinger, 2008). For public transport, data from ticketing systems (like automatic fare collection – AFC systems), have been utilised (Kurauchi & Schmöcker, 2017) in order to inter alia estimate demand patterns and route choice (Hickman, 2016; Ingvardson, Nielsen, Raveau, & Nielsen, 2018; Nassir, Hickman, & Ma, 2015; Tan, 2016). Askegren Anderson (2013) made use of data from a web and phone-based nationwide travel survey where complete trip chains for 5,641 trips involving any public transport leg resulted from a GIS-mediated map matching of the reported trips in the Copenhagen region. Origin and destination addresses as well as boarding, transfer and alighting stops, intermediate public transport service legs were reported, as were durations for all legs and distances for access, transfer walk and egress legs. Tan (2016) supplemented AFC data with trip patterns from a national household travel survey, where origins and destinations were identified on building (postcode) level. Both authors utilised their detailed trip data for estimation of route choice models. Moreover, Fonzone et al. (2010) surveyed public transport passengers (with an over-representation of "expert users") and thus asked subjects, subsets of engineering students and transport experts from six countries, to report on their most recent trip most frequently undertaken, in order to elucidate behavioural traits and attitudes to route change (utilisation of mental "hyperpaths", i e perceived attractive sets of lines for a specific origin-destination pair, a term originally introduced by Nguyen and Pallottino, 1989), usage of different information channels pre-trip and en route as well as pre-trip planning incidence. Interestingly, they found that only twelve percent of the subjects knew the departure frequencies of the mostly used lines, and eight per cent knew the timetable. Furthermore, 80 per cent 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 on the studies on habit and effects of experience accumulation mentioned above, attitude to change was inversely related to pre-trip information usage, since "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 actual 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)

The results from the studies referred to in the last paragraph are indeed extremely interesting and seemingly theory-aligned. However, the small sample (579 respondents reporting from one trip each), obvious recruitment bias and possible memory flaws by the subjects in Fonzone et al. (2010), as well as ambiguities regarding the surveying of access and egress legs in the cited route choice estimation studies, definitely motivated me to introduce and explore more versatile instruments that tap off detailed behavioural traits and information usage strategies from public transport passengers in a real time setting on a large trip sample.

The last decade or so, a number of more or less automatic travel survey and tracking methods have been developed and introduced in order to alleviate issues of diminishing response rates and sample bias (see Wang, He, and Leung (2018), Wolf et al. (2014) and Lee et al (2016) for contemporary methodological reviews). However, to be able to attain sufficiently detailed trip data, in adequate quantities, the range of available methods decrements substantially. Previous studies using semi-automatic methods for attainment of trip data, where the most comprehensive examples I have noted are the studies performed by Geurs, Thomas, Bijlsma, and Douhou (2015), Berger & Platzer (2015); Prelipcean et al (2018) and Gadziński (2018). Apart from Geurs et al and Prelipcean et al, who use existing survey panels or regular distribution channels, the recruitment and retainment of survey participants has been found to be a critical issue. Attrition usually occurs because of technical failures (most often battery drainage) and perceived participant workload. Geurs et al (2015) found that the total trip rate was reasonable according to other surveys, but that short trips were under- reported, especially by participants characterised as being less motivated. But, as Vij and Shankari (2015) have reported, some element of user participation may be mandatory in order to get trip itineraries as close to "reality"/ground truth as possible. This is also corroborated by the findings made by Chang, Paruthi, Wu, Lin, and Newman (2016), in that the most user-participatory survey style resulted in the most correct trip recordings. Although promising, none of the studies referred to above has, to my knowledge, used the detailed trip information gained in order to study or model route choice behaviour in public transport systems.

5. Previous studies of waiting times and information usage

5.1. Determinants of first waiting times

As a few studies have shown, the expressed waiting time element spent at the first public transport stop of a trip (henceforth denoted FWT in this thesis) is one of the main sources of discomfort during a PT trip (cf., inter alia, Baldwin Hess, 2004; Fan & Machemehl, 2009; Fan et al., 2016). In many commonly applied transport models, route choice is determined based on how FWT is derived from headway alone, according to the simple half headway ratio (based on seminal work by, e.g. Dial (1968)) assuming complete randomness (ignorance of timetable information) in passenger arrivals to the first stop of a public transport trip (henceforth denoted passenger incidence as defined by Frumin & Zhao (2012)). However, as a number of empirical research efforts have shown (Frestad Nygaard & Tørset, 2016; Ingvardson et al., 2018; Luethi, 2007), this simple approach can be questioned because a number of passengers are aware of either the scheduled or actual departure times, having pre-knowledge of the timetable or real-time departure information, respectively, and they tend to apply path choice strategies accordingly even at quite dense headways (Nygaard & Tørset, 2016; Schmöcker et al., 2013; Nassir et al., 2018).

Csikos & Currie (2008) complicated the picture of passenger waiting behaviour by introducing a differential behavioural spectrum with four distinct "archetypes". FWT behaviours were identified per individual using fare card data, where the degree of randomness varied across, but also within, individuals. They also found a significantly different behaviour at terminal stations due to the possibility of waiting on-board the PT vehicle. Older support for the thesis of waiting strategies is provided by Joliffe and Hutchinson (1975) where three types of passenger incidence – "timetable aware", "random arriving", and "coincidentally just-in-time" – were empirically identified in the field. As noted also by Ingvardson et al. (2018) and W. Fan and Machemehl (2009), explanatory variables for the variation of FWT behaviour can be collapsed into sub-categories based on travel strategies. Such strategies, specifically mentioned by Schmöcker et al. (2013), form the basis for the notion of hyperpaths used by passengers who plan ahead to at least some extent when choosing between departures. By clustering card users with card types, they were able to discern four distinct behavioural groups from trip patterns – commuters, elderly, irregular PT users, and "other users".

5.2. Waiting behaviour under uncertainty

Only a minor share of FWT variation has been shown to be predicted by the scheduled departure *frequency* alone (Salek & Machemehl, 1999), suggesting that further variables need to be introduced. Joliffe and Hutchinson (1975) based their exploration of FWT behaviour on the “well-known” relationship $\mu(1+\sigma^2/\mu^2)/2$ to determine waiting times in general, where μ and σ are respectively the mean and standard deviation of the actual headways between departures. The uncertainty, as represented by σ in the notation of Joliffe & Hutchinson (1975), thus corresponds to departure time reliability[4], or uncertainty, itself. In addition to unpredictably varying headways, uncertainty during FWT might also relate to timetable adherence in combination with unreliable or missing information regarding real departure times. As formulated by Maister (1985) in general terms, uncertain waiting times is believed to be perceived as more strenuous than waiting times that can be guaranteed to be a certain length, even if the certain waiting time is quite long. As a measure to indicate the level of this uncertainty, travel time variability (TTV) was introduced by Durán-Hormazábal & Tirachini (2016) when describing the probability distribution of FWT as a Poisson process with an exponential appearance in relation to actual headway. As an early contribution to this field, the relation between actual service headway, reliability, and FWT was stated by Ceder & Marguier (1985) and has been further elaborated upon during the last decade in a number of empirical studies. Using empirical measurements along with survey interviews, Luethi (2007) showed that FWT adjustments made by public transport passengers are somewhat related to the reliability of scheduled departure times, thus showing that passengers adjust their incidence according to scheduled departure times from as short a (scheduled) headway as five minutes.

Returning to the issue of information and behaviour of public transport passengers, a plausible trip element, yet usually a quite straight-forward indicator of revealed behaviour under uncertainty and subject to information provision, is waiting times. Fonzone and Schmöcker (2014) show, with a simulation example, how different search (and modelling) strategies when using real time information (RTI) regarding departure times can affect total travel times – and waiting times – quite differently. In addition, the authors discuss the effects on passenger behaviour from the availability of RTI regarding the adaptation of duration and location, i.e. which stop to choose for the first waiting time of a trip and when to depart from the previous location or activity. The passenger’s optimisation strategy would then target the maximisation of productive time, rather than just minimising travel time. Their results indicate the significance of how RTI is visualised and used, and how these different usage strategies can influence the total system travel time. In a more general sense, electronic passenger information systems including RTI are sometimes termed advanced public transport (or transit) traveller information systems – A(P)TTIS in the literature (Nuzzolo et al., 2015). They can be based on site-specific equipment (signs and displays on vehicles and at stops and stations) or on personal devices such as smartphones and personal computers (Fonzone, 2015; Ghahramani, 2016; Harmony & Gayah, 2017; Mulleyet al., 2017). The information content on stationary or vehicle-based displays usually comprises scheduled and actual departure times, while journey planners and the like, available through personal devices, also to an increasing degree include itineraries with updated departure and arrival times

[4] In my studies, I have used this very definition of reliability, i e the non-scheduled time variation of *headways* (sometimes denoted as regularity). This is not the same as punctuality, which is related to scheduled *departure times.*

of connecting services at transfer points (for example, as described by Cats, Koutsopoulos, Burghout, and Toledo (2011); Ghahramani (2016)). Thus, as suggested by Lyons (2006), RTI and other forms of service information, may be accessed either or both in the planning and the execution phase of a trip. Since his paper, the rapid adoption of smartphones, apart from forming a rationale behind utilising them for travel surveys, has also motivated public transport providers to offer RTI in their smartphone planning applications (apps) (e.g. in Sweden, 90 per cent of the public authorities provide this service, see also Harmony & Gayah (2017) for a recent study, where they found that smartphone apps was the preferred mode to obtain RTI for departure times in the US, and Fonzone (2015), who noted a similar result in Edinburgh, UK).

The literature on behavioural impacts and use of RTI may roughly be subdivided into an analytic and an empirical strand. Brakewood & Watkins (2018) provide a comprehensive overview of the literature regarding empirical effects of the use of RTI on passengers' actual and perceived waiting times, total travel times, ridership and perceived quality and security. In their synthesis, they report average waiting time gains of two minutes and perceived waiting time reductions by up to 30 per cent, however subject to self-selection in the quoted surveys. A purely analytical approach, on the other hand, was carried out by Cats et al. (2011) using a mesoscopic dynamic model of the Stockholm metro. They arrive at a three to four per cent total gain in travel time as an effect of RTI provided at platform, station or network level, with the higher figure for the latter level. During travel disruptions, these effects were accelerated by up to eleven per cent compared to a non-RTI scenario. An even more deliberate analysis, which is also quite congruent with choice theory, is provided by Ben-Elia et al (2013) in their unimodal Stated Preference (SP) experiment with motorists' hypothetical choice of routes. Here they found that the reduced accuracy of travel time information resulted in increased randomness in choice and a shift from unreliable to reliable (but sometimes longer) routes, and that prescriptive information had a greater impact on route choice than descriptive information. Their results also suggest that discrepancies between expected travel time (derived from experience) and predicted travel time according to RTI can lead to risk aversion behaviour (PT!) and that travellers' use information despite inaccuracies in order to anchor their choice decisions (cf Chapman & Johnson (1999) as cited above).

6. Studies underlying this thesis – data driven motives

As the reader may have noticed this far in the text, I chose to measure waiting times as an important decision element in public transport route choice, by using a smartphone-based survey application – in this case the commercially available TRavelVU app (Clark et al., 2017). To be able to record information deployment and pre-planning behaviour, I used notification prompting (Turner et al., 2017), asking subjects regarding their just-finished public transport trip leg. A detailed record of the survey and data processing methodology is provided in the next subsection.

6.1. Methodology

Since the same principal methodology was used in both studies that form the basis for this thesis, except for the sampling of pre-trip planning and information usage, a comprehensive record is found in this subsection.

6.1.1. Trip survey data

The revealed detailed trip data was recorded in two 14-day waves, during November 2016 and November 2017 respectively, by in total 279 public transport passengers (151 in the first wave, 136 in the second and eight individuals participating in both waves, Figure 1) using the TRavelVU survey app on their smartphones. For both survey waves, participants were recruited on bus stops, and on-board vehicles of one bus line ahead of the second wave, in the Malmö-Lund area, Scania, southwest Sweden. The choice of study area, and thus the target traveller population and related recruitment points, was motivated by being the assumed influence area of a tramway under construction; the two survey waves were thus intended to form the first phases of a three-wave study of the effects of the tramway on route choice. Selection criteria for target public transport line routes was the following:

- Lines operating along the busway preceding the tramway, replacing a bundle of lines,
- Lines operating the direct bus route between the principal destinations in the tramway corridor and the neighbouring city of Malmö, or
- Train lines constituted the local/regional service between Lund and Malmö

Table 1 lists the bus lines targeted in the participant recruitment of the survey, along with specific characteristics later used in the analysis of passenger behaviour.

Table 1 Characteristics for the principal bus lines targeted in the survey. The reliability index is adapted from the work of Joliffe and Hutchinsson (1975) and defined as $1/(1+var(H)/E(H)^2)$ where H stands for headway in minutes and var(H) is the variance in deviation from the scheduled headway. ©Elsevier, 2019

Line	Headway max (min)	Headway low (min)	Reliability index (mean of 2016 and 2017)	Number of boardings/weekday (2016)
166	15	60	0.69	4,863
169	10	-	0.97	3,432
171	7–10	30	0.11	3,446
1 (Lund)	15	25	0.19	3,558
3 (Lund)	7.5	15	0.05	8,148
6 (Lund)	10	30	0.35	5,110
20 (Lund)	10	-	0.92	1,860

Note that a few bus lines were re-routed between the two survey waves, and the coincident street-located construction work for the new tramline, substantially affected both nominal and actual bus run times of at least line 1, 3, 6 and 20. An important criterion in the choice of study area, was that it involved a number of distinct public transport paths in one of Sweden's principal commuting corridors. In total, 56,100 trips are made by train between Malmö and Lund each weekday, while 33,000 are made by bus, as measured by the number of boardings[5]. A substantial, but not quantified, share of these trips involves multiple modes of public transport.

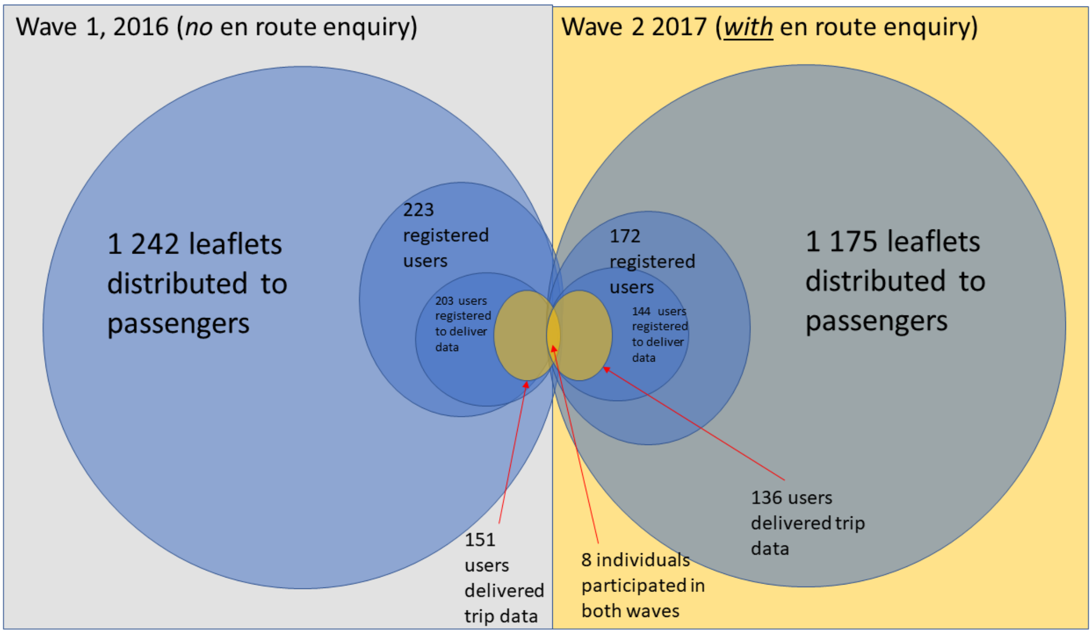


Figure 1 Participants and recruitment of the two survey waves

[5] *Numbers provided by the regional public transport authority Skånetrafiken*

In all, 27,047 trip elements were recorded (13,553 from the 2016 survey wave and the rest from 2017), making up 7,579 trips in the 2016 wave and 5,600 trips in the 2017 wave, where a trip is defined as movement between activities others than changes of transport mode and parking. An activity was recorded when there was no movement recorded outside a 100x100-metre tolerance square for during least two minutes, and a trip element was the smallest entity of a trip (movement in time and space) recorded by the app. Trip elements were delimited by either activities or changes of transport modes, e g for a public transport trip element by a boarding and an alighting event. However, the major strength of the app was its ability to collect a substantial set of trip elements including access, egress and transfer movements with various modes.

To infer transport modes, the app uses rule-based fuzzy logic algorithms for machine learning, exploiting data from previously submitted itineraries and data on public transport stop locations as well as estimated modes from accelerometer readings. On average, development tests of the app have shown that this method results in a transport mode detection accuracy of around 80 per cent. This seems to correspond well with results from a comparison in my study, between data on modes from the app with modes inferred using the method outlined in subsection 6.1.3 below, and which entailed a total accuracy of 85 per cent. To further enhance this accuracy, as well as to classify the kind of activity being pursued, the user was prompted by the end of each day of the survey to log in to the app interface and 1) rectify and/or confirm inferred travel modes, 2) specify activities, and 3) submit trips in this reviewed form. The same approach has been successfully applied by other researchers, e.g. Geurs et al. (2015), and Prelipcean et al. (2018). The itinerary revision tasks are supported in the interface (Figure 2) by indications of phone-sensed time stamps (date, time and visualised in a map) presented as starts and ends of activities and trip elements. The geolocations of specified activities are stored, thus enabling the app to select and suggest that activity type after the next time the user have lingered at the same spot as defined by coordinates.

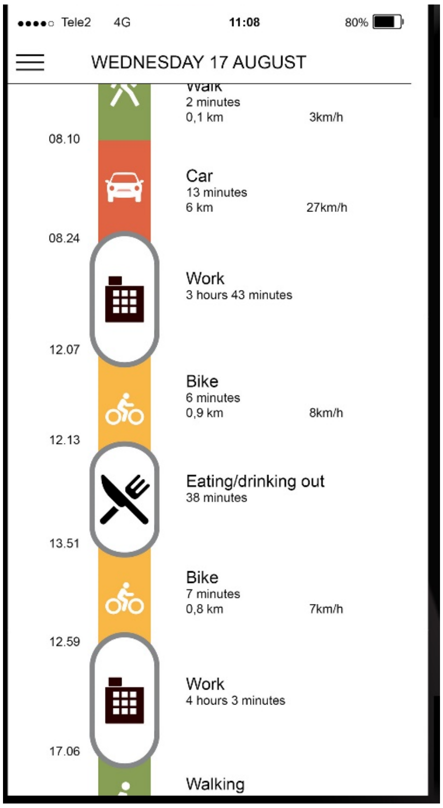


Figure 2 User interface when correcting trips in the survey app. ©Elsevier, 2019

All back-end processing such as inference of transport mode, filtering, and cleaning, was performed on a central server with which the phones exchanged data only on a limited number of occasions (when there was a sufficient amount of data and there was an Internet connection) in order to save battery life. However, as for all apps making use of GPS tracking, always a trade-off between power consumption and spatial accuracy – especially during long-term data collection. To minimise battery drainage, GPS sensing was turned off if the accelerometer or telemetry revealed no movements and the phones thus were regarded as being "static".

Like many other survey apps (e.g. the Twoja Trasa used by Gadziński (2018)), the app includes a short enquiry upon registering, where users are prompted to specify gender, year of birth, occupation, access to a private car, access to a pre-paid monthly smart card on regional public transport, the option of flexible working hours, and personal contact information (Figure 3). In addition to the figures presented in the diagram, roughly a third in the 2016 wave, and a fourth in the 2017 wave respectively, stated always having access to a car, a third having access at times, and a third never having access. More than two thirds (2016) and 78 per cent (2017) respectively of the users stated always having access to a prepaid monthly smart card for public transport, constituting a strong indicator of commuting. In total, 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 (2016) and 88 per cent (2017) of the employees had access to flexible working hours, which to some extent enables adjusting working hours to PT supply and timetables.

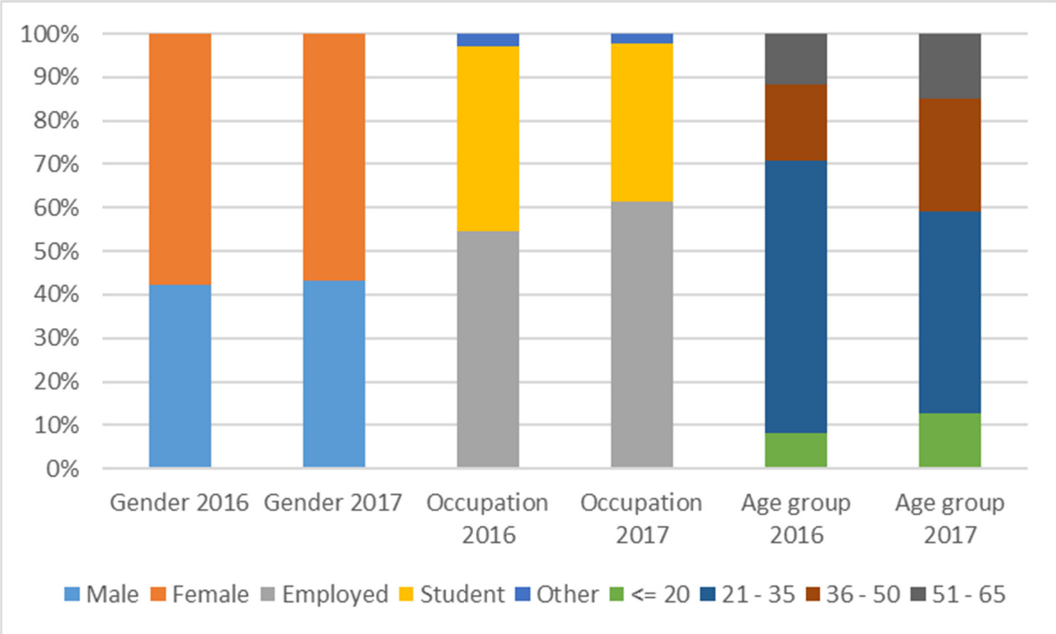


Figure 3 Composition of the participants in the two survey waves

It is generally difficult to relate the composition of the sample with the target population, since the detailed composition of the latter is largely unknown. I intend to make some further attempts in finding leads as how to characterise this composition during the later stages of PhD thesis progression.

6.1.2. Stated passenger behaviour

In the 2017 wave of the survey, en route questions regarding pre-planning and information utilisation (Table 2) were posed to the participants by notification prompting in their phones right after having completed a public transport trip leg (according to the mode recognition functionality in the app). For reasons attributed to simplicity of analysis, some of the answer options were grouped, or aggregated according to

Table 2, after data collection. It should be noted that the questions were posed independently of each other, meaning that no particular answer was required to obtain certain question or set of options in subsequent questions.

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	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) – missing
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	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	–

6.1.3. Public transport network data

The public transport network data used in the study covered the county of Scania and connecting train lines from neighbouring counties as well as Gothenburg in the form of fixed timetables, in GTFS[6] format, and real departure times, the latter obtained from the automatic vehicle locator (AVL) system om the regional public transport authority Skånetrafiken. Using the procedure outlined in **Fel! Hittar inte referenskälla.**, the trip data from the survey was associated with the network data based on spatial - stops of the network were matched with coordinates of boardings and alightings in the survey data (as defined in the subsection Trip survey data above) - and temporal - departure and arrival times according to GTFS and AVL timetable data - dimensions. Thus, each trip, as recorded in the survey, was matched with a corresponding service trip section belonging to a certain public transport line.

A separate reliability index (RI) was derived from the AVL data according to Formula 1.

$$RI = \frac{1}{1+var\,(H)/E(H)^2}, \quad where\ RI \in (0,1] \tag{1}$$

Actual headway, from AVL data, is denoted by *H* and the variance of *H (var(h))* is derived from actual and scheduled headway.

[6] General Transit Format Specification – data format for public transport lines, line routes, time profiles and vehicle journeys originally specified by Google. The Swedish database provided by Samtrafiken AB via http://www.trafiklab.se.

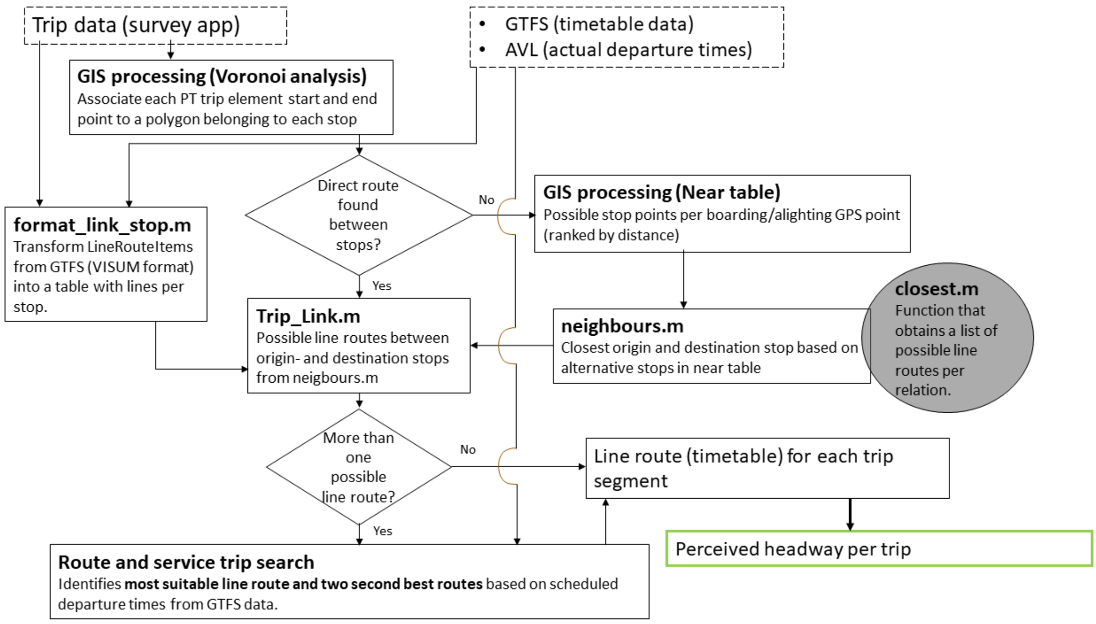


Figure 4 Schematic representation of work flow when processing and merging trip leg data from the survey with PT supply data from GTFS and the AVL system

In the process of matching person trips with lines, there were a number of trip legs that had to be removed from the data set for various reasons. Origin and destination stops were identified as identical for a few legs, and some had stops or line routes that were not identified due to trips commencing and ending within very large stop Voronoi polygons (cf **Fel! Hittar inte referenskälla.**) – the size being due to locations outside the Scania network. Most of the other missing data were caused by erroneous location registration – where origin and destination coordinates were very close to each other (within meters, although with substantial time differences). The dilemma with reduced GPS coverage in tunnels became evident for the 2016 wave data, when using the line route search script for origin-destination pairs serviced by multiple line routes, to search for possible connections for survey trip legs between Copenhagen and destinations in Sweden. In this direction, passengers were required to change trains at the Copenhagen Airport station during this particular period, but this transfer was rarely recorded by the app.

6.2. Results and analysis

In both studies forming the bases of the papers included in this thesis, linear regressions and univariate ANOVA models were specified in order to analyse waiting times, a key indicator in public transport route choice modelling as well as in order to understand the influence of departure time information penetration on passenger behaviour. In the analyses of both papers, accessory variables were obtained, both regarding attributes of the associated public transport network (departure frequencies, travel times, trip distances, modes), but also from the individual participant characteristics reported through the app questionnaires. Paper 1 focus on waiting times at the first boarding stop of public transport trips (FWT), and how their variation can be explained. The second paper look into the issue of how waiting times, both at transfers (TWT) and at the first stop, may be related to pre-planning and information search.

6.2.1. Paper 1

In this subsection, results regarding revealed waiting behaviour is presented in conjunction with level of service attributes of the actually chosen public transport connection, as outlined in the last subsection. For each individual, characteristics were derived from the introductory questionnaire of the survey app. The first half of this subsection is devoted to the impact of service attributes while the next half presents results from ANOVA-models were also a number of trip and individual-specific variables are added.

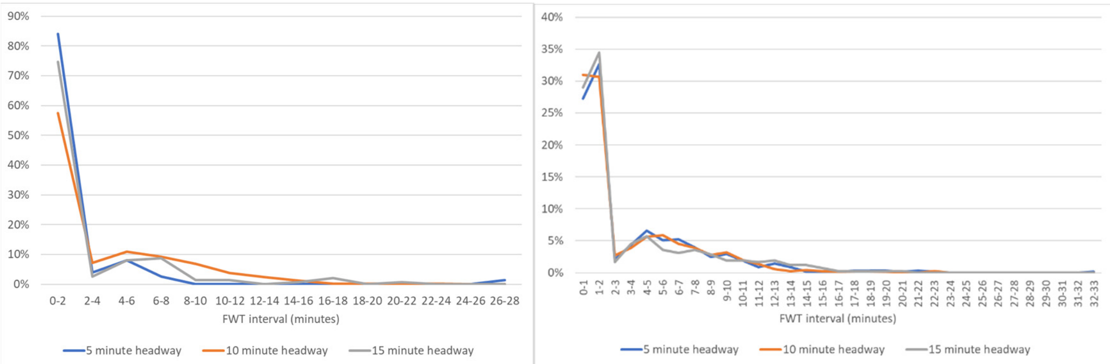


Figure 5 Probability distribution of FWT for the three most common scheduled headways in the study area. The left diagram includes choice sets with **single** line routes while the diagram on the right includes stop pairs serviced by **multiple** line routes. The large share of FWTs below 2 minutes is attributed to the large number of “fictive” FWT events, where there is no activity Wait/transfer recorded by the survey app.

As indicated in Figure 5, where passengers travelling in corridors serviced by single and multiple line routes are presented, FWT:s tend to be quite indifferent to headway. This is also confirmed when comparing waiting times associated with choice sets including the three different headways, using two-tailed t-tests. These indicated, for multiple-line choice sets, significantly (on 0.05 level) *longer* mean FWT for 15-minute headway lines than for lines with a five-minute headway, while, for single-line choice sets, mean FWT was significantly *shorter* for 15-minute vs 10-minute headways, and, more obviously, significantly shorter for 5-minute vs 10 minute headways. All other differences were insignificant. The grand mean FWT was 3.21 minutes, the FWT means for the different headways included in the analysis is indicated in Table 3 below.

Table 3 Mean FWT, in minutes, for different choice sets according to the association procedure outlined in the subsection Public transport network data

Choice set	**Headway (minutes)**			
	5	**10**	**15**	**20**
Single line route	1.79	3.45	2.54	-
Multiple line route, scheduled	2.75	3.10	3.29	-
Multiple line route, AVL	2.97	3.52	3.96	3.86

In fact, when regressing FWT with respect to headway in general, the mean waiting times stay at or below 5 minutes regardless of headway measure (see Figure 6).

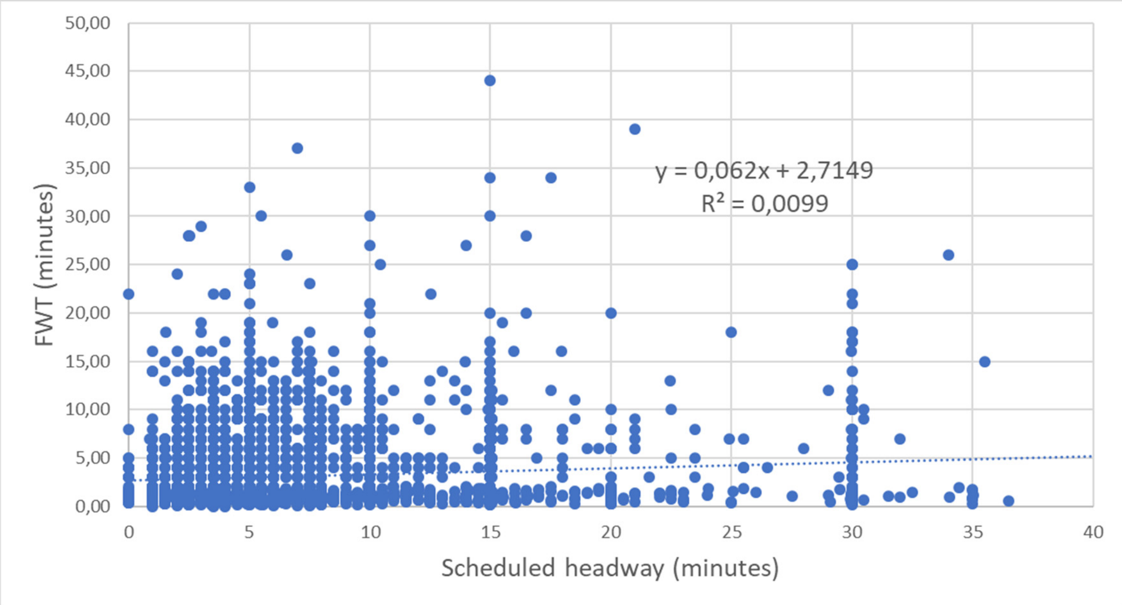


Figure 6 FWT events with respect to scheduled headways for trip relations with multiple lines. ©Elsevier, 2019

Interestingly, the model fit is higher when FWT is regressed against Scheduled than Actual headway according to AVL data (R2=0.010 and 0.007 respectively). This might be an indication of passengers adapting rather to scheduled than actual headways, depending on the information available, and will be further discussed in connection to the results from the ANOVA analyses below.

Results from a univariate ANOVA analysis of possible effects on FWT from a number of explanatory variables indicate the following: Trip purpose in interaction with Gender, Access mode with and without interaction with Trip distance, Trip purpose and Scheduled headway had significant effects when the whole model was tested. Of these variables, the explanatory power of Scheduled headway was surprisingly low compared to Respondent gender and Trip purpose in interaction. Also, somewhat surprisingly, we found no significant effect from our reliability index RI on FWT when analysing separately with linear regression (R^2=0.0004), but the effect seems to be captured by the scheduled headway itself. This is supported by the finding, also made using linear regression, that the reliability index of the line route is significantly explained by the scheduled headway (standardised coefficient of 0.149; R^2=0.022). When binning the headways into 5-minute intervals, this relationship becomes even clearer: According to results from a Tamhane's post-hoc test, the reliability index significantly improves by 0.07 and 0.17 units when scheduled headway is increased from 5 to 10 minutes and from 15 to 20 minutes respectively.

The interaction between Trip purpose and Respondent gender on FWT length is illustrated in Figure 7 in the form of estimated marginal means. Women tend to have longer FWT than men, although this difference is not significant per se. It is clear though, that this difference is most pronounced for the purposes Drop off/pick up, Healthcare, Restaurants/café and Entertainment/culture, although the number of observations is below 30 for all these subgroups except for Restaurants/café.

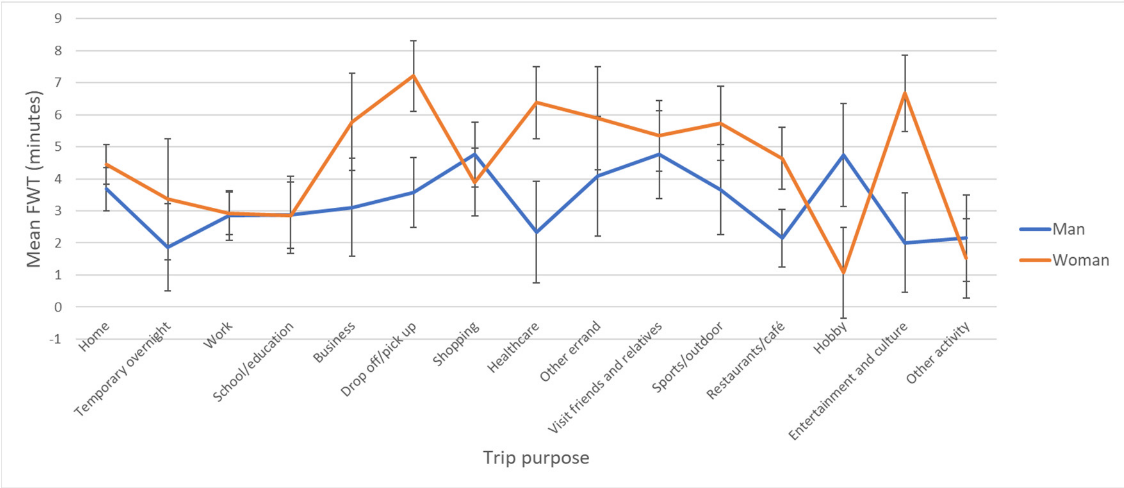


Figure 7 The interaction between Trip purpose and Respondent gender on FWT, as indicated by estimated marginal means. Whiskers indicate standard errors. ©Elsevier, 2019

Another interaction, the one between access mode and trip duration, is investigated in more detail using a marginal means plot (Figure 8).

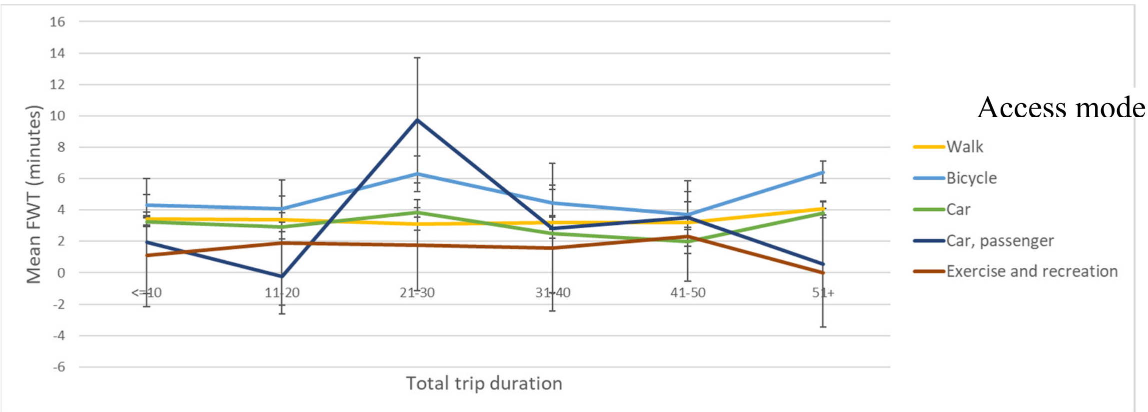


Figure 8 The interaction between Total trip duration and **Access mode** on FWT, as indicated by estimated marginal means. Whiskers indicate standard errors. N_{walk}=3,771, $N_{bicycle}$=235, N_{car}=121, $N_{car\ passenger}$=13 and $N_{exercise\ and\ recreation}$=9©Elsevier, 2019

Post hoc-tests revealed significantly longer FWTs at the stop type Interchange terminus compared to ordinary urban stops and longer FWTs for Bicycle as access mode compared to Walk and Car, while Car had shorter mean FWTs than both Bicycle and Walk as access modes. This finding, which is further illustrated and diversified in Figure 10, is most probably the reason why there is a weakly negative relationship between FWT and access distance (standardised coefficient of -0.030, R2=0.0009 as indicated by linear regression). This might seem confusing, but there were underlying reasons for this related to transport mode for access trips where car was used for on average 6-7 kilometres longer access trips than bicycle and walk.

I also looked into the issue of individual consistency in behaviour, even though this issue was analysed in more detail in Paper 2 although for a smaller sub-sample. The results from a univariate ANOVA indicated that the inter-individual variation in FWT (standard deviation 4.3) was significantly larger (P = 0.000 at the 95% confidence level) than the intra- individual variation (mean standard deviation = 2.8, standard deviation across individual standard deviations = 2.48). This seems to be a quite clear indication that such individual-specific behaviour exists in the context pf first waiting times.

Finally, some notes on my trip data. The final dataset for the analysis of FWT consisted of 4,375 FWT events that were based on PT trips made by 254 of the survey participants. The selection of FWT trip segments was based on two main criteria: 1) The subsequent segment must be a PT segment and 2) the previous segment must be an activity or access mode (walk, bicycle, or car). Note that some of the FWTs 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 events, where the duration was less than 2 minutes, were in a sense fictive because they consisted only of the change of mode from access mode to the main PT mode. These FWT events were assigned a random value in the interval (0,2) minutes. A total of 1,552 of the FWT events could be related to stop relations serviced by single line routes. A total of 3,930 trip segments were successfully related to “perceived” scheduled headways in stop relations with one or more possible line routes, while 2,974 trip segments were successfully related to “perceived” headways from AVL data. The smaller number of FWT events in this selection is explained by the fact that AVL data were only available for a subset of lines compared to the total GTFS line selection used to create the other two FWT datasets.

6.2.2. Paper 2

In the second study, the underlying set of trip data was smaller since it included only the 2017 survey wave of 2,635 public transport trips. A summary of the responses to the en route notification-prompted questions regarding pre-trip planning and information use, on trip level, is presented in Table 4 below. In this context, the “stated optimisation strategy” question refers to the formulations in the official journey planner, as presented in Table 2.

Table 4 Stated strategies for pre-trip planning and information use, as indicated by survey responses (on trip segment level). Note that departure time is set as default choice option in the journey planner (Stated optimisation strategy).

Topic	Option	Proportion of responses (trip segments)
Stated planning strategy	Planning ahead	61.6%
	Not planning ahead	37.1%
	Don’t know	1.3%
Stated information use	Pre-existing knowledge of timetable	48.3%
	Digital travel planner	51.5%
	Timetable in pdf/ paper format	0%
	Other	0.2%
Stated optimisation strategy	Departure time optimising	67.0%
	Arrival time optimising	33.0%

The spread of planning approaches (planning or not planning ahead of a trip) was analysed with respect to individual respondents. The responses vary somewhat more across individuals than for each individual. Out of the 132 respondents who delivered valid data, only 1.6 per cent stated “Planning ahead” for all trip segments. The mean proportion of planned trip segments was 55% with a standard deviation of 40 per cent. Note that these figures are trip segment-based and the mean number of trip segments per trip is 2.46 in the sample. However, we were also able to measure the proportion of planned trips instead of trip segments, and we found that 57 per cent of trips were actually planned ahead (or contained at least one trip segment which was pre-planned) using a timetable or journey planner, according to the replies in the survey.

As in Paper 1, a more detailed analysis of waiting times and information was performed using univariate ANOVA, with one model consisting of variables derived from the survey on pre-trip information usage and planning strategies. A second model included these variables plus the same independent variables describing trip and service attributes as well as individual characteristics as in Paper 1. However, the first model was only significant as explaining transfer wait times (TWT), while the second model significantly explained both FWT and TWT. Thus, Stated planning strategy and Stated pre-knowledge of the timetable, individually and in interaction, significantly (on 0.05 level) explained TWT according to the first model. For the second model, trip purpose, with and without interaction with boarding stop type, day type (weekend or weekday), stop type and stated planning strategy (pre-trip or no planning) were found significant for the explanation of FWT variation, while only Stated planning strategy and Stated information use significantly explained TWT.

Post hoc tests with estimated marginal means plots (Figure 9, Figure 10) were deployed to further investigate the impact of pre-trip planning and information use on waiting time durations. It is clear that trips that were reported to having been pre-planned included longer mean wait times than non-pre planned trips. On the other hand, trips where information had been utilised implied shorter waiting times.

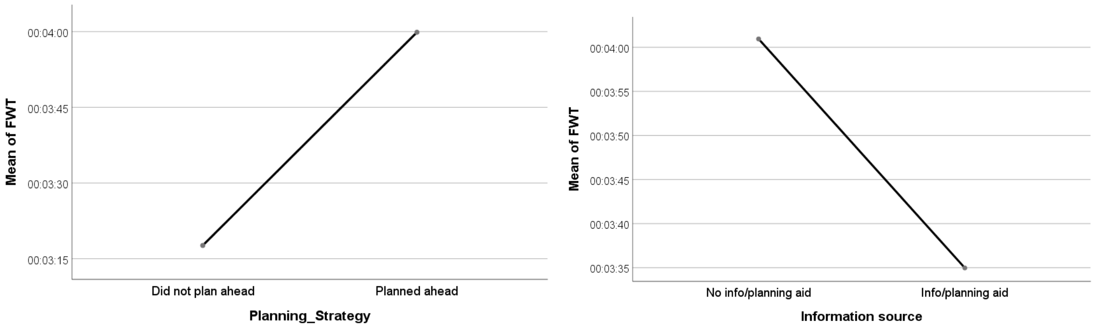


Figure 9 Effect on FWT, in minutes, from stated pre-trip planning and information use, respectively, according to estimated marginal means. ©Elsevier, 2019

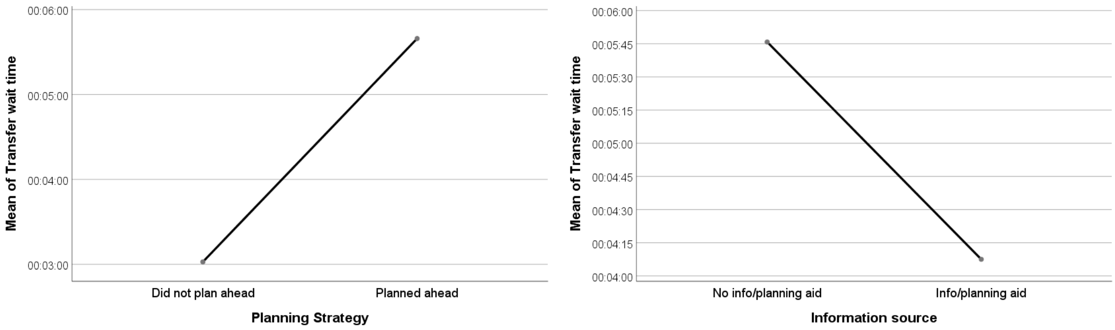


Figure 10 Effect on TWT, in minutes, from stated pre-trip planning and information use, respectively, according to estimated marginal means. ©Elsevier, 2019

As in Paper 1, the artefact of how the survey app defines a waiting activity can be easily discerned in Figure 11 by the large number of observations with waiting times in the interval (0,2). However, it is difficult to find any significant trends regarding waiting times in relation to information usage in the level of disaggregation illustrated in the diagrams. This general appearance is also confirmed in the lack of significance when comparing waiting times with and without stated prior information usage in two-tailed t tests, as well as when analysing stated information use in relation to headway in a chi-square test (5% significance level).

Figure 11 Probability density functions of FWTs for trip segments where respondents stated use and non-use of pre-trip information, respectively. Diagrams to the left represent trips between origin and destination stop pairs serviced by a single line route, whereas diagrams to the right represent trips made between stop pairs serviced by multiple line routes ©Elsevier, 2019

As indicated by both access mode and waiting times correlation tests (performed in the Paper 1 study and here), trip duration appears to be an underlying factor affecting both transfer waiting time and access mode/planning strategy, as indicated by the finding that there is a weak positive correlation between TWT and trip duration (standardised coefficient of 0.119 and adjusted R^2=0.013, see Figure 12 for a graphic representation). A similar tendency is present in the FWT data. It is clear that, for trips longer than 50 minutes, FWTs were significantly longer than for trips with shorter durations (though not significantly different for trips below 10 minutes). Among short distance trips, there was a somewhat overrepresentation of leisure purposes while work commute was overrepresented among trips longer than 50 minutes.

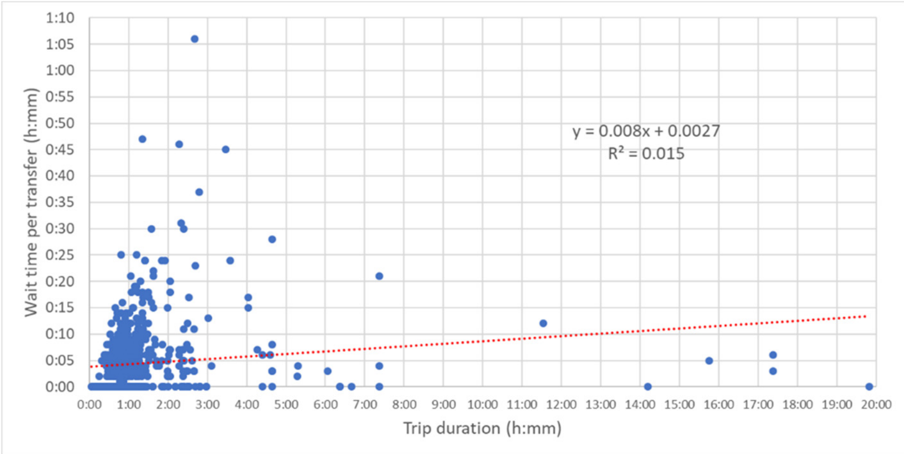


Figure 12 Individual transfer waiting times regressed against trip duration (origin to destination) ©Elsevier, 2019.

In addition to the quite superficial analysis of individual waiting time behavioural, in this paper I also used categories, or archetypes, of waiting time behaviour as proposed by Csikos & Currie (2008), by using cumulative distributions (CDFs) of median differences between the upper and lower FWT quartiles (Note that Csikos & Currie denote the waiting time Arrival Offset instead of FWT). In Figures 13-16, CDFs of median FWTs across individuals are shown for each archetype, or quartile of differences between the upper and lower quartile of FWTs from the total sample. When compared with the corresponding profiles in the study by Csikos & Currie, there are some similarities to the first ("like clockwork"), the third ("consistent plus outliers") and the fourth quartile ("largely random"), while the FWTs of the second quartile ("consistent within a wider window") have less consistency for our data. In general, our data contain a narrower range of FWTs than Csikos & Currie, with a mean difference between the upper and lower quartiles of just 3:27 minutes and a standard deviation of 2:43 minutes (for Csikos & Currie, these mean values range between 11:48–16:36 minutes with standard deviations in the interval [16:36,25:18] minutes depending on the analysed station).

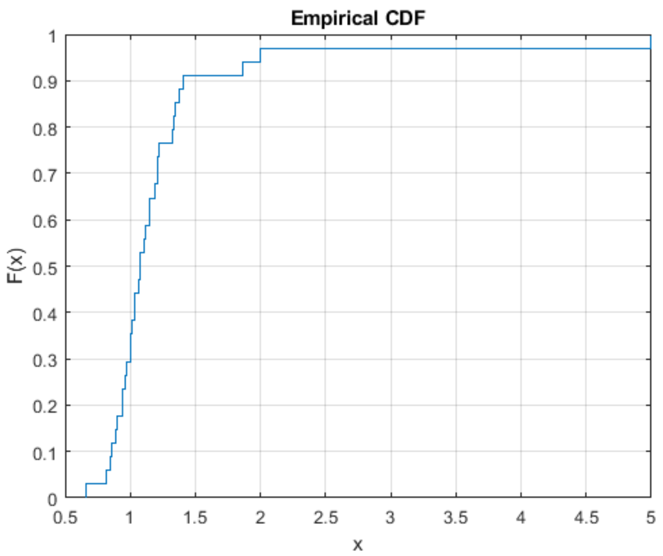


Figure 13 Cumulative distribution of median First Waiting Times (FWT=x) for the first quartile of differences between the upper and lower quartile of FWT (archetype “like clockwork” according to Csikos & Currie. 2008)

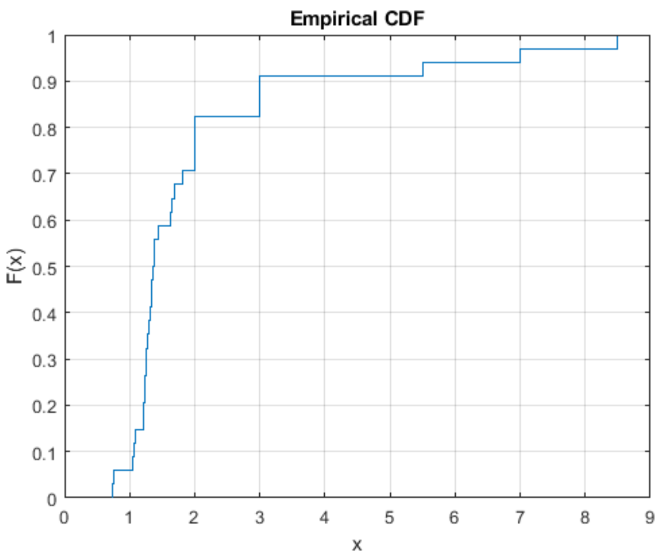


Figure 14 Cumulative distribution of median First Waiting Times (FWT=x) for the second quartile of differences between the upper and lower quartile of FWT (archetype “consistent within a wider window” according to Csikos & Currie. 2008)

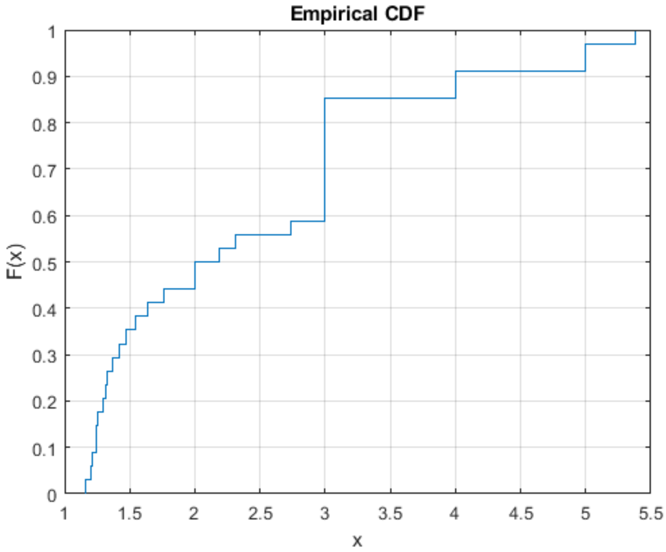


Figure 15 Cumulative distribution of median First Waiting Times (FWT=x) for the third quartile of differences between the upper and lower quartile of FWT (archetype “consistent plus outliers” according to Csikos & Currie. 2008)

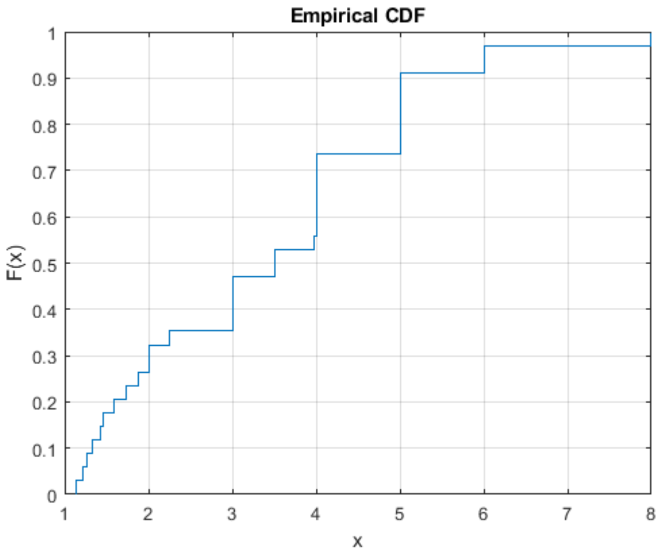


Figure 16 Cumulative distribution of median First Waiting Times (FWT=x) for the fourth quartile of differences between the upper and lower quartile of FWT (archetype “largely random” according to Csikos & Currie. 2008)

There seems not to be a direct correlation between randomness in behaviour and pre-trip information, rather the non-pre-planned trips were over-represented in the like clockwork group, perhaps reflecting a larger share of non-habitual trips. There is also an over-representation of work trips among the low-random quartile which supports this notion. Accordingly, trip duration is positively related to randomness in behaviour, whereas trips of 30 minutes or shorter are over-represented among the less random behavioural categories. Taking trip rate into consideration, both frequent travellers (22-28 trips during the 14-day survey period) and those who made less than eight trips during the survey period are over-represented in this quartile. On the other hand, the very frequent (above

29 trips) are over-represented in the two random behaviour quartiles. As indicated in the analysis of waiting times, also randomness of behaviour is negatively related to trip duration (less randomness the longer the trip).

An exhaustive sequence of cross-tabulations was performed in order to elucidate the use of information and pre-trip planning strategies in different age and gender groups and depending on trip purpose. Interestingly, and as a supplement to the ANOVA analysis, trips that respondents stated not having pre-planned are over-represented among services with headways below 5 minutes, among unreliable lines[7], starting from urban stops, on short trips, for work (commuting) trips, trips from work, for shopping trips, among employees and people who travelled more than 14 times during the 14-day survey period. On the other hand, pre-trip planning is over-represented for trips made during off-peak daytime and women stated pre-planning to a higher degree than men and this is also the case for people above 50 years of age. Trips made from interchanges and rural stops are also over-represented among the pre-planned trips. The unrelated question regarding the use of planning aids rendered an over-representation of leisure trips made in urban settings by less and very frequent young travellers. On the other hand, pre-knowledge of the timetable is over-represented among women, on work trips and for travellers above 50 years of age. The scheduled headway appears to affect whether respondents knew the timetable by heart. For stop pairs by high-frequency direct PT connections, with a combined headway of five minutes or less, there is an under-representation of pre-knowledge of the timetable, while at ten-minute combined headway, an opposite pattern emerges, indicating that this particular headway appears to be easier to recall than others. Also, the reliability of the line appears to affect the information usage strategies*; trips using lines with low reliability (reliability index at 0.25 or below) are under-represented among users of travel planners but over-represented among respondents who stated that they did not pre-consult departure time information and among respondents who reported no pre-knowledge of the timetable*.

Moreover, being at work means a degree of over-representation of selecting departure time at the pre-trip planning stage. Trip purpose, i.e. the activity performed after the trip, has significant influence on the stated choice of desired time of departure or arrival, respectively, when planning the trip with a travel planner. The clearest results were obtained for school trips, where there was an over-representation of arrival time selections.

6.3. Conclusion and discussion

In order to relate waiting time behaviour, being an important indicator of route choice behaviour among public transport travellers, to both trip attributes and personal characteristics, this thesis relies heavily on a two-wave travel survey based on a dedicated smartphone app. Despite the quite dispersed nature of the resulting waiting time data, I have been able to find some reasonable correlations to both significant attributes such as scheduled headway, trip duration and trip purpose, but also to gender, occupation and trip

[7] For lines with a reliability index below 0.26

frequency of the individual traveller. I also found indications of consistency across individuals for waiting time behaviour, further nuanced and illustrated using the randomness archetype classification of Csikos & Currie (2008). Trip purpose, in interaction with gender, along with trip duration in interaction with access mode, were the strongest determinants of FWT duration in our data. Here, our potentially most important finding could be the relatively low explanatory power of (scheduled) headway towards variation in FWT, but that other factors like trip purpose, access mode and trip length seem to be more important determinants of FWT duration.

In this section, I will first relate the current findings to some of the relevant phenomena outlined in the introductory theoretic review, followed by some more practical methodological notes in relation to previous similar studies. Practical implications of the results presented in this thesis is further discussed in the next main section.

So, can my results provide me with enough confidence to question central postulates included in mainstream choice theory? Perhaps not, but there is certainly tendencies in the material that give support to some of the behavioural traits associated with uncertainty (as comprehensively presented and summarised by Bonsall (2010)), although perhaps in a somewhat implicit course of reasoning. In this line of thought, risk aversive behaviour, as studied in Daniel Kahneman et al. (1991) as well as Tversky & Kahneman (1981), may be related to the tendency I found that longer, non-routine trips are pre-planned to a larger extent than shorter, commute trips. Interestingly, and perhaps related to risk aversion, these longer trips also have longer waiting times. The significant gender difference in the occurrence of pre-planning may be inferred from a more risk-averse behaviour among women than men, as reported by e g Bonsall (2010). The significantly negative effect of pre-trip information usage on waiting times at 15-minute headways – which relates to a weak, but significant, positive correlation between trip duration and headway on the first public transport trip leg– provides further evidence of a kind of "planning paradox". This implies that for longer, non-routine trips (i.e. non-commutes), for which service headways are longer, pre-trip planning and information use is undertaken more extensively than for shorter and commute trips (supporting the findings of Farag and Lyons (2008)). This also results in more extensive use of pre-trip information and longer waiting times for the former (non-routine) trips than for the latter (familiar trips). Thus, more random behaviour ("board a PT vehicle on whatever line arrives first") could relate to a high level of travel routine, while unfamiliar trips are associated with a higher tendency to stick to a specific line and/or departure. However, there is also an inherent cause for this, at least for transfer wait times, since longer trips most often include connections with longer headways than commute trips, which are more commonly made at times and locations where the headways are relatively short. The usage pattern of information, on the other hand, may also be related to risk aversion, although my results also indicate an enhanced propensity among frequent travellers to use information. Thus, the usage of information seems to be of use both to very frequent and to very unfamiliar public transport travellers, a notion also found by Fonzone et al. (2010). A theoretic interpretation would be that both groups experience reduced uncertainty by consulting pre-trip information, although there is ample evidence in both the mentioned authors' and my data that pre-knowledge of information also may lead to optimisation behaviour. The role of habits, heuristics and scrips may be present here, for trips involving highly repetitive behaviour such as commuting. However, and as shown by Fonzone, the variability and thus less relying on fixed habits, may be present in both unfamiliar and very frequent travellers – the former due to a high level of uncertainty (cf Heiner, 1983) and the latter due to a higher degree of experience regarding the system. On the other hand, pre-knowledge of timetable information may serve as anchoring points (cf Ben-Elia et al. (2013)) for those groups (or at those occasions) when there is not a perceived need to use further information.

A behavioural interpretation of the shorter FWTs at trips with longer access distances as compared to short (below three kilometres) could be risk aversion of missing the desired departure, which poses an incentive towards careful planning and thus minimising the waiting time. This incentive should be greater when the passenger is farther from the starting point of the trip. Otherwise, the shorter FWTs for car than bike as access mode in our study is difficult to explain other than by the structure of, and respondents' interaction with, the survey app. E g, there are instances where the FWT after access mode car seem to be hidden in a parking activity or short walk from the car park to the PT vehicle. However, the result is in line with findings by Salek & Machemehl (1999), as they concluded that park&ride stops, where car was used as access mode, had significantly shorter FWTs than the mean FWT for all stops. A potential error in our data is the selectable mode "car passenger" for kiss-and-ride as access mode, which might have been set as just "car" by some respondents (the large number of car access trips compared to car passenger access trips indicates this). In this context, it is interesting to note that the trip purposes with significantly longer FWTs than average were related to rarely made trips such as visiting friends and family while school trip FWTs were shorter than average.

Regarding pre-trip information utilisation and planning strategies, our study somewhat corroborates the findings of Mulley et al. (2017) and Farag & Lyons (2008). Thus, we found a positive relationship between a very high PT trip rate and the use of different (digital) sources of pre-trip information, even though the relatively short survey period renders our measurements of trip rate somewhat uncertain. Of more interest, perhaps, is the significant differences in information usage between gender and age groups. According to our results, men tend to use digital information sources to a larger extent than women who are over-represented in the group knowing timetables by heart, and younger travellers also use digital tools to a higher extent than elderly travellers (also found by Ghahramani (2016); Harmony & Gayah (2017) and Farag & Lyons (2008). The age component of the use of digital planning aids has been further studied by Velaga et al (2012)).

Our results that the duration of a trip is a confounding factor for both waiting times (FWT and TWT) and the use of deliberate pre-trip planning is somewhat contrary to our initial expectations, and also in relation to the results of Fonzone & Schmöcker (2014), who show that the more structured traveller (the Busy (4) approach) gains a substantial amount of time in relation to the less structured traveller (ASAYC and strategic approach). However, in a real-world setting such as our study, it is clear that the significant range of trip durations comes into play to a much higher extent than in the idealised network applied by Fonzone & Schmöcker (2014). Even so, our findings corroborate their results regarding pre-trip information, although we only measure waiting times and not the duration of complete OD trips.

In one sense, our results regarding FWT archetypes could be considered to be counter-intuitive; over-representation in the “largely random” archetype for trips in which the respondents stated that they used a planning strategy. In our view, these results could relate to the “planning paradox” related to the trip durations mentioned previously (longer trips may require more planning, as well as longer waiting times). Also, the correlation between FWT archetype and reliability appears to be quite weak, with a linear-by-linear association significance of just 0.069.

The relatively low explanatory power of the variables indicating the use of information usage and planning strategies in our ANOVA models may relate to the timing of the notifications sent to the survey participants. The term interruptibility, as introduced by Turner et al. (2017), implies suitable moments for being able to respond to smartphone-distributed push notifications. The tendency in our results that travellers repeat previous replies when prompted in this way may relate to the level of mental ability of the traveller en route (also perhaps an effect of habit, as investigated by B. Verplanken et al. (1997) or to use default alternatives when under time pressure, as described in Bruch and Feinberg (2017)). The high level of intra-personal correlation is the clearest indication of this tendency, which may represent a bias in relation to true behaviour regarding pre-trip planning and information use, thus being a potential contributing factor to why these strategy variables are not significant in our ANOVA models of FWT and TWT. As very few other studies employ our methodology (or similar methodology), there is a clear need for further empirical observations and related improvement of the methodology. As we have not been able to control for selection bias in our survey sample in relation to the population under study, caution is recommended when generalising our results to other contexts. For instance, and as other authors have found (Gadziński, 2018; Greaves et al., 2015), participant attrition due to phone battery drainage or perceived survey fatigue (Assemi et al., 2018) is a common reason for leaving this kind of survey. In our case, this resulted in 36 persons (out of 172 registered in the second survey wave) not recording any data.

7. Research contributions

In this section, the most important contributions to choice theory and transport research of the two studies presented in this thesis is outlined.

7.1. To the field of choice

In my view, the most significant finding is the revealed behaviour to uncertainty, manifested by low level of departure reliability and unfamiliar and long-range trips, as indicated by my data. My interpretation of behaviour under uncertainty in this sense, as also discussed in Bonsall (2010), would then reflect the perceived risks of the public transport travellers in my survey. Thus, my data offers an empirical contribution to the theoretic field of risk aversion in behavioural economics, and my results also, at least in most part, corroborate earlier findings, also regarding risk behaviour among population groups (gender and age). In a sense, my results regarding the use of trip planning tools and information sources also contribute to the field of technology adoption (Skoglund, 2012), which in turn has its foundation in the seminal work by Ajzen (1991) about explanations of (reasoned) behaviour. The search and usage of information may thus be categorised as a conscious and explicit type of mental decision process. I have not been able to study the effects on repeated exposition to uncertainty and a possibly resulting accumulation of experience among travellers, since the time dimension is virtually absent in my data due to the very limited number of participants partaking in both survey waves was (eight individuals). Thus, there is no evidence to analyse causes of possibly habitual or heuristics-driven behaviour based on my data at this stage (but perhaps in further studies, as commented in the next section). There is also a general caveat in the studies related to the low explanatory power of the FWT models, which may indicate the complexity of the choice process.

7.2. To the field of transport

The major contribution to transport research, seen more narrowly, is probably the successful deployment of the still quite novel data collection approach using prompted-recall survey apps for smartphones. Thus, the process of data collection and subsequent post-processing gave me valuable insights into limitations and potential future improvements regarding both the design of the survey and the combinations of data sources regarding departure times that were used during post-processing. As mentioned above, power consumption, affecting battery time, and respondent fatigue, related to app interface and trip revision routines, constitute the major challenges in the ambition to attract an as diverse sample of survey participants as possible, affecting both quantity and quality of the trip data collected during the survey. In spite of these challenges, the fact that I managed to attract a reasonable number of participants, despite heavy restrictions regarding incentives, is quite impressive, given the experiences reported from similar studies.

The relatively small-scale waiting time effects found in Paper 1 might be a result of the trip data collection approach itself. In pilot studies, the TRavelVU app has sometimes been found to include short walk legs in what travellers would regard as being waiting when they are in fact walking around on a railway platform, for instance. Also, some extended waiting times were found at major fully serviced train stations, suggesting that the actual activity may instead have been related to the existence of shops and food facilities at these locations.

The findings in Paper 1 that headway variability due to irregularities such as delays does not affect FWT directly may be related to the finding that passengers tend to plan and adapt to scheduled headways to a larger extent than to actual departures. This may change in the future though, provided that the current trend, of increasing adoption of new services providing easy-access and reliable real-time information of departure times on mobile personal devices, continues.

8. Further on-going and planned research

This thesis has explored waiting times, as being important indicators of route choice behaviour. The next natural step is to estimate a full-scale (discrete) route choice model based on maximum likelihood methodology. Since June 2018, I have gradually advanced in this pursuit, with inclined assistance by Thomas Kjaer Rasmussen and Anders Fjendbo Jensen or DTU Transport. Thanks to their colleague Mikkel Thorhauge, a tentative rudimentary model has been estimated so far, and my future task is to complicate this by adding more variables and try a number of different specifications. Choice set and variables are prepared for this purpose.

The next, not yet commenced assignment, is to look more into time-dependent effects on behaviour. Thanks to a substantial panel data record of smart card transactions, spanning the same time periods as the survey, i e the two weeks in November of 2016 and 2017, and the same study district, there is ample potential to look more into issues such as the development of risk aversive behaviour due to changes in reliability indices between the periods.

Finally, as we move into November next year (2020), a new survey wave using TRavelVU is planned, to be able to include the then-opened tramway into the choice set of a updated route choice model.

9. References

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Appendices

Published scientific articles

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

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

Title: Exploring waiting times in public transport through a semi-automated dedicated smartphone app survey

Abstract
Maximising the efficiency of measures for enhanced attractiveness of public transport requires careful planning of the service supply based on realistic and valid travel demand data and forecast models. The travel demand for specific lines requires realistic path choice models, where first waiting time is one key factor determining the distribution of choices. However, data used to specify and validate path choice models are cumbersome to acquire when applying conventional survey methods. In this paper, we show that a detailed and accurate account of travel behaviour, especially first waiting times, can be obtained by a user-mediated prompted recall approach, thus contributing to the emerging techniques of smartphone-based surveys. By enriching the survey results with geographic data together with timetable and automatic vehicle locator data, we were able to analyse relationships between passenger first waiting times and a number of endogenous and exogenous explanatory factors. We found that public transport passengers tended to adjust their first waiting times both to the scheduled headway and according to the purpose of the trip and trip duration and that individuals are somewhat consistent in their waiting time behaviour. Access mode is also a significant determinant of first waiting times according to our results. Our data offer interesting ventures into the further study of how public transport passengers adjust to factors such as service supply.

Keywords: Travel survey; Path choice; Waiting times; Public transport

1. Introduction

1.1. Background

To facilitate the modal shift of person trips from private automobiles to public transport (PT), operators strive to maximise the attractiveness of their service supply, aiming at attracting choice riders, i.e. people with other travel options. As suggested by Beirão & Sarsfield Cabral (2007), important factors for PT attractiveness include service frequency, service reliability, and comfort – all three of which are impacted by the design, routing, and capacity of the PT system. On the other hand, studies of time valuations (see Wardman et al. (2016) for a recent meta-analysis) indicate that waiting time, travel time uncertainty, and access time are regarded as the most onerous in relation to in-vehicle time for PT passengers. Thus, in the strive for a PT system that meets high demands in terms of attractiveness, but that also adheres to funding limitations and infrastructure capacity restrictions, the need for careful planning and dimensioning to achieve robust and demand-responsive transport systems is accentuated.

To be able to conduct this planning practice efficiently, careful modelling of path[1] choice based on empirically grounded understanding of passenger behaviour and decision-making is paramount. However, there are discrepancies between results described by most common models, which generally rely on predictions made based on aggregate trip data to calculate path choice, and actual travel behaviour and trip patterns (see Nassir et al. (2018) for a recent discussion on this topic). Such

[1] "Path" is here referred to as the potential or actual sequence of trip elements, while "route" refers to PT line course traversing a certain pre-defined sequence of stops.

discrepancies are largely due to lack of detailed and accurate data regarding travel behaviour and passenger decision making from traditional survey sources of trip data (Liu et al., 2010).

One key element of a PT trip, but that has been proven difficult to predict accurately (Nassir et al., 2015), is the waiting time at the first boarding stop, or station, of the trip. Thus, this paper focuses on the empirical study of this trip element, which hereafter is denoted *first waiting time* or FWT for short. But before that, the next section outlines previous research on this field to enable contextualisation.

1.2. Passenger rate of adaptation to departure times

As a number of studies have shown, waiting times at the first stop of a PT trip are one of the main sources of discomfort during a PT trip (cf., inter alia, Y. Fan et al., 2016; W. Fan and Machemehl, 2009; Baldwin Hess, 2004). In many commonly applied transport models, this trip element 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 and Zhao (2012)). However, as a number of empirical research efforts have shown (Luethi, 2007; Nygaard & Tørset, 2016; Ingvardson et al., 2018), this simple approach can be questioned because a number of passengers are aware of either the scheduled or actual departure times, having pre-knowledge of the timetable or real-time departure information, respectively, and they tend to apply path choice strategies accordingly even at quite dense headways (Nygaard & Tørset, 2016; Schmöcker et al., 2013; Nassir et al., 2018).

1.3. Waiting times and departure time reliability

Only a minor share of FWT variation has been shown to be predicted by the scheduled departure frequency (Salek & Machemehl, 1999), suggesting that further variables need to be introduced. Joliffe and Hutchinson (1975) based their exploration of FWT behaviour on the "well-known" relationship $\mu(1+\sigma^2/\mu^2)/2$ to determine waiting times in general, where μ and σ are respectively the mean and standard deviation of the actual headways between departures. The uncertainty, as represented by σ in the notation of Hutchinson & Joliffe (1975), thus corresponds to departure time reliability itself. In addition to unpredictably varying headways, uncertainty during FWT might also relate to timetable adherence in combination with unreliable or missing information regarding real departure times. As formulated by Maister (1985) in general terms, uncertain waiting times is believed to be perceived as more strenuous than waiting times that can be guaranteed to be a certain length, even if the certain waiting time is quite long. As a measure to indicate the level of this uncertainty, travel time variability (TTV) was introduced by Durán-Hormazábal & Tirachini (2016) when describing the probability distribution of FWT as a Poisson process with an exponential appearance in relation to actual headway. As an early contribution to this field, the relation between actual service headway, reliability, and FWT was stated by Ceder & Marguier (1985) and has been further elaborated upon during the last decade in a number of empirical studies. Using empirical measurements along with survey interviews, Luethi (2007) showed that FWT adjustments made by PT passengers are somewhat related to the reliability of scheduled departure times, thus showing that passengers adjust their incidence according to scheduled departure times from as short a (scheduled) headway as 5 minutes. Zhao et al. (2013) introduced the term excess journey time (EJT) as a way to measure passenger behaviour in relation to service quality, which included reliability and crowding, based on farecard data. Thus, they analysed passenger incidence to rail stations in relation to scheduled departure times and discussed the heterogenous nature of passenger waiting times based on their data on single-pattern headway stations in the London Overground.

1.4. Behavioural traits in waiting for PT

Csikos and Currie (2008) complicated the picture of passenger waiting behaviour by introducing a differential behavioural spectrum with four distinct “archetypes”. FWT behaviours were identified per individual using fare card data, where the degree of randomness varied across, but also within, individuals. They also found a significantly different behaviour at terminal stations due to the possibility of waiting on-board the PT vehicle. Older support for the thesis of waiting strategies is provided by Joliffe and Hutchinson (1975) where three types of passenger incidence – “timetable aware”, “random arriving”, and “coincidentally just-in-time” – were empirically identified in the field. As noted also by Ingvardson et al. (2018) and Fan & Machemehl (2009), explanatory variables for the variation of FWT behaviour can be collapsed into sub-categories based on *travel strategies*. Such strategies, specifically mentioned by Schmöcker et al. (2013), form the basis for the notion of hyperpaths used by passengers who plan ahead to at least some extent when choosing between departures. By clustering card users with card types, they were able to discern four distinct behavioural groups from trip patterns – commuters, elderly, irregular PT users, and “other users”.

1.5. Aim and scope of our study

Despite previous research efforts to discern, categorise, and explain waiting behaviour among passengers at the first stop of a PT trip, it is still somewhat unclear whether different *people* use hyperpath strategies recurrently or whether this behaviour is context specific. There has also been a common trait in previous research on FWT behaviour and its causes to study only waiting times along corridors serviced by single line routes and for only one mode at a time (e.g. Ingvardson et al., 2018; Csikos & Currie, 2008; Luethi, 2007, Salek and Machemehl (1999)). See also An et al. (2014) for the identification of behavioural groups (based on the degree of PT travel experience) and, to some extent, Ramli et al. (2018) for variation in waiting time behaviour across stops. These shortcomings in previous research constituted a motive for our research outline – to discern more causes of FWT behaviour and the individual person-specific factors for this trip element in PT and to widen the range of service patterns and PT modes that can be studied with respect to behavioural traits.

Thus, this article presents results from a study of waiting behaviour among PT passengers within a limited geographical setting based on data from a smartphone-based travel survey using prompted recall (Wolf et al., 2014) to enhance data accuracy. Our survey approach, elaborated and evaluated in the methods section below, was based on the POST HOC variant of prompted recall described by Chang et al. (2016) where participants review recorded trip itineraries on a daily basis. The principal aim of our study was to explore explanatory factors for waiting times of the first *trip element* (or trip stage) of PT trips. This aim addresses the overarching need (specified by, inter alia, Liu et al., 2010; Schmöcker et al., 2013; and Nassir et al., 2018) to further understand and evaluate current path choice behaviour, where FWT is a significant aspect, in order to improve the prediction accuracy of PT path choice.

Based on the research hitherto performed in the field of waiting time behaviour and outlined above, the main contributions of this paper are thus:

- The exploration of waiting behaviour as a function of both PT supply characteristics (frequency and reliability) *and* trip and personal characteristics (age, gender, purpose, stop type, previous activity, access mode, and time of day/day type).
- The study of FWT as a function of headway also at stop-to-stop relations serviced by multiple lines and modes.

The second contribution is achieved through applying the concept of *perceived headways*, i.e. the actual departure interval for each stop relation travelled at the time of each PT trip segment start (from origin boarding stop to destination alighting stop) regardless of the number of line routes servicing this relation. The principle is defined in Equation 1, where, for each passenger, H_p represents the perceived headway, t is an arbitrary departure time and i represents the chronology. In our experimental setup, t_i represents the departure time most probably chosen by the passenger, according to inferences from survey data in combination with timetable and Automatic Vehicle Locator (AVL) data respectively.

$$H_p = \frac{|t_i - t_{i+1}| + |t_i - t_{i-1}|}{2} \quad (1)$$

The remaining part of this paper is organised as follows. Section 2 describes the collection and post-processing of trip and PT supply data. This is followed by section 3 where we present our findings related to explanations of FWT behaviour, based on statistical analyses performed using linear regression and ANOVA, and discuss our results in relation to previous research. Finally, Section 4 is devoted to a summary of, and conclusions from, our findings as well as an elaboration of potential further research based on our study.

2. The data and data collection

This section presents our study area, including PT services where travel data were collected, and the motives for its delimitations.

2.1. Geographic setting and travel demand of the study area

Data were collected from persons travelling by bus and train to and from the town of Lund and between Lund and the nearby city of Malmö in Sweden. Lund is a mid-sized town of 87,000 inhabitants within its urban area as of the year 2015 (Statistics Sweden, 2017) – a large share of which consists of the approximately 42,000 students enrolled at the university. Lund is situated in Sweden's third largest urbanized area of Southwest Scania, with almost a million inhabitants and with extensive commuting – especially to, from, and between the larger conurbations of Malmö, Lund, and Helsingborg. In total, 56,100 trips are made by train between Malmö and Lund each weekday, while 33,000 are made by bus, as measured by the number of boardings[2]. A substantial, but not quantified, share of these trips involves multiple modes of PT.

The geographic delimitations of the study area (Figure 1) were motivated by being the approximate influence area of a tramway under construction, which once it is completed will link principal destinations of regional and even national importance such as the European Spallation Source, the university hospital, and the main campus at the School of Engineering with the city centre and central railway station.

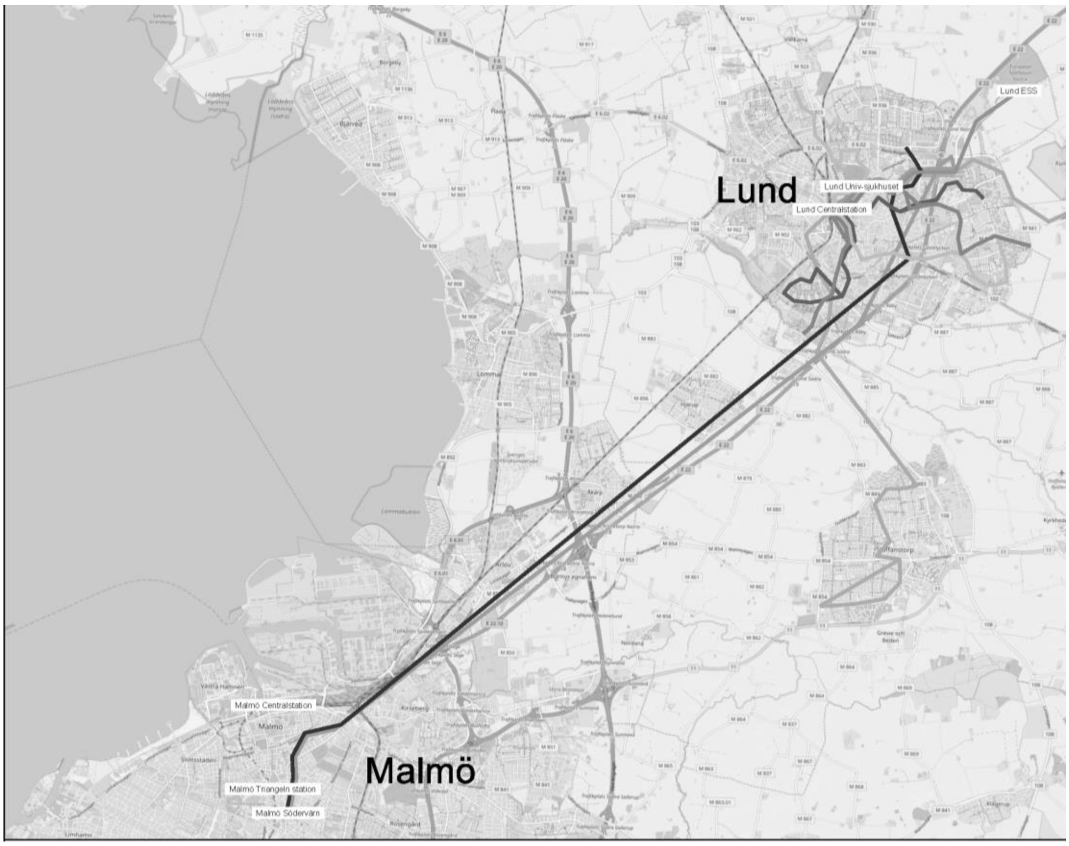

Figure 1 Study area setting – the Malmö–Lund area in south-western Sweden. Public transport (PT) lines specifically targeted in the travel survey are indicated, as are principal PT stops.

[2] *Numbers provided by the regional PT authority Skånetrafiken*

2.2. PT supply characteristics of the study area

The selection of PT lines of interest for the study, which are presented in Table 1, was based on the fact that they constitute the PT supply of the study area. Thus, our selection was defined through lines that in November 2016 and 2017:

- operated along the busway preceding the tramway, replacing a bundle of lines,
- operated the direct bus route between the principal destinations in the tramway corridor and the neighbouring city of Malmö, or
- constituted the local/regional train service between Lund and Malmö

The reason why lines defined by the last bullet point were included is the assumption that, for some passengers, there is a trade-off between going by train and changing to bus (or to tram from the year 2020) at Lund central railway station or going by bus directly – a trade-off that might be of interest to study in more detail. Here we refer to the potential use of strategies and hyperpaths, as these terms are used by Schmöcker et al. (2013), in the choice of PT path. For this reason, the train lines running between Malmö and Lund were also included in the study. It should be noted that lines 166, 169, and 20 were rerouted along the tramway construction site in central Lund between the two survey periods. This was accounted for in subsequent line and service matching procedures (cf. Section 3.6)

Table 1 Characteristics for the principal bus lines targeted in the survey. The reliability index is adapted from the work of Joliffe and Hutchinsson (1975) and defined as $1/(1+var(H)/E(H)^2)$ where H stands for headway in minutes and var(H) is the variance in deviation from the scheduled headway.

Line	Headway max (min)	Headway low (min)	Reliability index (mean of 2016 and 2017)	Number of boardings/weekday (2016)
166	15	60	0.69	4,863
169	10	-	0.97	3,432
171	7–10	30	0.11	3,446
1 (Lund)	15	25	0.19	3,558
3 (Lund)	7.5	15	0.05	8,148
6 (Lund)	10	30	0.35	5,110
20 (Lund)	10	-	0.92	1,860

Thus, the chosen study area offers a variety of potential path choices in many origin-destination pairs. All bus lines in the study area have a departure headway of at least 10 minutes with regular intervals during the peak period, which was when most trip data were collected, but there is no obvious (scheduled or operational) coordination between parallel line routes to obtain optimal intervals. The scheduled train departure frequency between Malmö and Lund have a very high departure frequency (at least 12 hourly departures per direction) but have irregular intervals during this period. Moreover, the trains have various stop patterns between Malmö and Lund, where some trains stop at intermediate stops while most of them do not, resulting in different run times. Real time information (RTI) regarding actual departure times is made available through digital message boards at certain principal bus stops and at all train stations in the study area. RTI is also available for all PT lines and stops of the study area in the PT journey planner provided by the regional PT authority Skånetrafiken. Thus, passengers have the possibility to reschedule their trip on short notice before departure or *en route*, e g due to service delays.

This option is particularly relevant in our study as the punctuality among some bus lines, indicated by Table 1, was rather low during the survey period. We here deployed a reliability measure (ranging from close to zero for low punctuality to 1 for full schedule adherence) adapted from Joliffe and Hutchinson (1975), who used it to calculate FWT as a function of actual headways where a measure of *punctuality variation* was also included. The measure thus takes the varying degree of punctuality into consideration, reflecting the potential effect of adaption of the PT passengers to waiting times due to recurring delays. The relatively low degree of punctuality has important implications for FWT behaviour, as we shall see from our analyses in Section 4.

2.3. Survey methodology

2.3.1. The smartphone-based survey application

A dedicated smartphone survey application (app) called TRavelVU (Clark et al. (2017)) was used to collect travel data during two weeks in November 2016 and 2017. The survey was conducted in a way much like MoveSmarter was applied according to Geurs et al. (2015), as well as how Berger and Platzer (2015) described how SmartMo was utilised, but we did not use the on-line element applied by these two surveys. Moreover, TRavelVU only utilises GPS and the accelerometer as input devices, unlike SmartMo, for instance, which also uses WLAN and GSM networks for positioning. In addition, unlike the two survey apps referenced above, TRavelVU was not developed within our research project but was a commercially available survey tool. The app is able to trace movements in space and time, detect modes of travel, and determine whether an activity is performed. This is achieved by utilising the phone-based timer 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 autonomous sensing process, which runs in the background once the functionality has been enabled in the app, 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.

An activity is generated when the phone stays at a specific spot, defined by a 100 x 100 m square, for at least 2 minutes. This is valid for all activity types, in contrast to the differentiated approach used by Auld et al. (2013) in their web-based but GPS tracker-augmented survey setup. Hence, a trip segment is defined as a movement displacing the phone/user outside the 100 m square (the same as used by Carrel et al. (2015)) and lasting for at least 2 minutes. Larger tolerances for this "activity space" were tested by the app developer during our project, but these resulted in a loss of precision in distinguishing between movement and activity. The same trade-off was valid for the time limit of 2 minutes for activity determination.

To infer transport mode, the 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%[3]. 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. The same approach has been successfully applied by a number of other researchers, e.g. Auld et al. (2013), Geurs et al. (2015), and Prelipcean et al. (2018). The itinerary revision tasks are supported by a user interface (Figure 2) that indicates phone-sensed time stamps (date and time) as starts and ends of activities and trip elements. The geolocations of specified

[3] *Our survey data indicate an even higher modal hit rate of 85 per cent, when comparing to the result of the PT service trip inference performed according to the method outlined in section 2.6 below.*

activities are stored, thus enabling the app to select and suggest that activity type the next time the user lingers at the same spot defined by those specific coordinates.

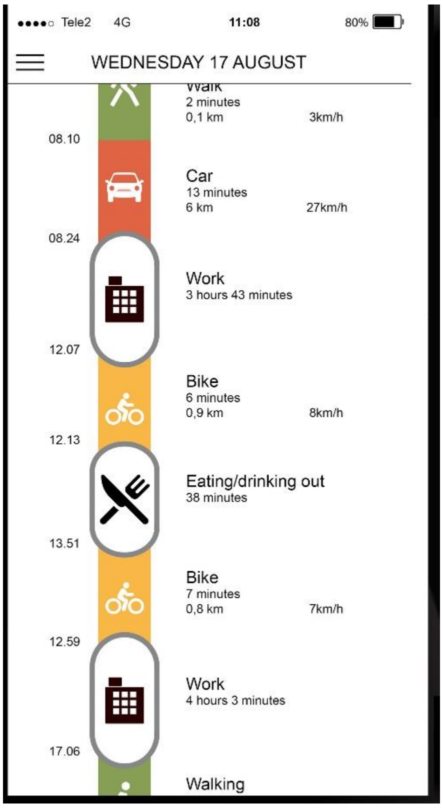

Figure 2 User interface when correcting trips in the survey app.

Like many other survey apps (e.g. the Twoja Trasa used by Gadziński (2018)), the app includes a short enquiry upon registering, where users are prompted 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.

All back-end processing such as inference of transport mode, filtering, and cleaning, is performed on a central server with which the phone exchanges data only on a limited number of occasions (when there is a sufficient amount of data and there is an Internet connection) in order to save battery life. Spatial accuracy is determined by a 2 m distance-based filter, at low traveling speed, and the desired sampling frequency of 0.5 Hz. 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 is turned off if the accelerometer or telemetry reveals no movements, and the phone is thus regarded as being "static".

2.4. The sample

Just like Greaves et al. (2015), a smaller pilot survey was carried out to validate the application before both years' large-scale surveys. Thus, a few academic and administrative staff at the K2 research centre in Lund – eleven persons for the 2016 survey and 15 persons for the 2017 survey – tested the app for a week. This user pilot was followed by a discussion where about half of these pilot users participated and where possible error sources and causes of data loss were identified. Experiences from the pilot were taken into account in order to adjust the user interface of the app.

The participants of the actual survey were recruited by a group of field-working university students. The rationale behind this choice of recruitment method was to reach the target population of PT passengers in the study area and to reduce "noise" emanating from trips using other transport modes and/or trips made in other geographical areas. The students thus targeted PT passengers waiting at four stops (three "pure" bus stops and one stop used as an interchange between trains and buses) as well as on-board buses on city route number 20, thus following the geographical and PT line restrictions described in Sections 2.1**Fel! Hittar inte referenskälla.** and 2.2.

A total of 223 PT passengers agreed to participate in the 2016 survey by downloading and installing the app, while 172 joined the 2017 survey. A total of 203 persons finally used the survey app in 2016 and 144 in the 2017 survey, and their phones were registered for the survey in order to deliver trip data. In total, eight persons joined the survey both years.

In order to evaluate the survey method, it was important to get in touch with the participants after the survey period. They were therefore asked to enter contact information (e-mail or phone number) in the interface of the app when registering for the survey. However, this deterred some from registering during the first survey round in 2016 according to the recruitment staff. Finally, 151 individual phones actually delivered data in 2016 and 136 phones delivered data in the 2017 survey round. According to mail correspondence with persons registered 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.

Responses to the app 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 inhabitants of Lund in general. A majority of the users were employees, and the largest occupational group consisted of graduate and post-graduate students. 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. 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 to some extent enables adjusting working hours to PT supply and timetables. However, because there is no comprehensive statistical picture of the real distributions of age and types of occupation, for instance, within the restricted population consisting of the passengers who were the subjects of the study, there is no evidence that the representativeness of the sample is actually poor or severely skewed.

2.5. Survey data

The total raw data from the app consisted of 27,047 trip elements (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, where a trip is defined as movement between activities others than changes of transport mode and parking. In total, roughly 50% of the trip segments were walking trips, while segments performed in PT vehicles made up 20% of the trip elements (5,363 in total).

On average, each participant made 3.6 and 2,9 trips per day in 2016 and 2017, respectively (standard deviation: 3.4 trips in 2016 and 2.7 in 2017; modes: 3 in 2016 and 2 in 2017). These figures are not significantly different from the Swedish national travel survey (Transport Analysis, 2017), providing some support for the validity of our data despite it being a small, and potentially biased, sample.

The average duration and length per transport mode is presented in Table 2 for both survey rounds. There were no significant differences between the surveys. The last row of Table 2 shows the number of transfers and waiting time per transfer on average for trips in our survey where the main mode was a PT mode. At most seven transfers were recorded for a single trip. The number of transfers 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 2 Descriptive statistics of trip segment characteristics from the surveys of 2016 and 2017

Mode	*Mean distance (km)*	*Mean duration (h:m:s)*
Walk	0.6	0:14:01
Bicycle	1.8	0:11:23
Car	13.9	0:19:39
Bus	10.0	0:18:17
Train	37.8	0:37:02
Transfer and wait time	0.15	0:09:07

Our results regarding mean transfer distance can be compared to results from studies referred to by, e.g. Hickman (2016), who elaborated upon methods to distinguish between transfers and activities. The relatively short distances for both transfer and access walking distances might reflect the relatively dense settlement and compact transfer stations in the study area. By comparison, our study, which is based on input by survey participants, indicates a mean duration for any activity of just over 2 hours. Our results regarding relative contributions of different trip segment types such as in-vehicle travel time (IVTT), FWT, and transfer wait time (TWT), as shown in Figure 3, are in line with similar studies based on smartphone-collected GPS trajectories such as the one performed by Carrel et al. (2015). An important difference in our data, however, is that the shares of IVTT, FWT, and TWT remain reasonably constant across trip durations, while the data analysed by earlier authors indicate an increased share for transfer time for longer trips. The difference should be explained by the respective layout of the transport system analysed.

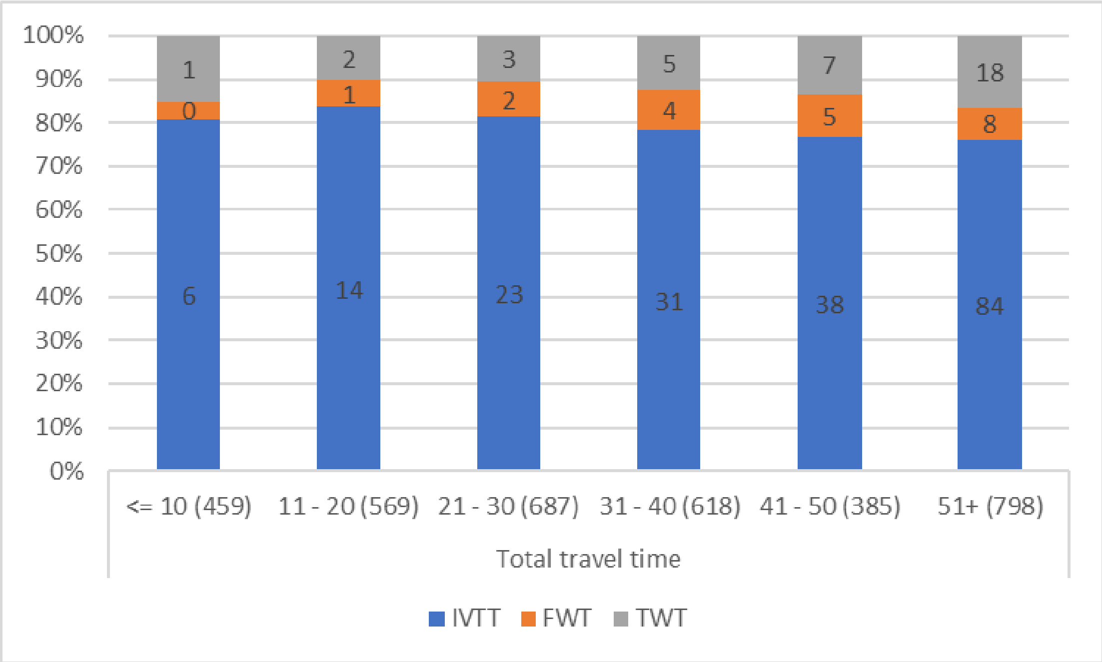

Figure 3 Contribution of trip segment type (types of travel time) to total PT travel time. Numbers in bars represent mean durations per segment and total travel time interval (IVTT: In-Vehicle Travel Time; TWT: Transfer Wait Time).

2.6. Using supplementary PT supply data to explore waiting behaviour

In addition to the analysis of the survey data presented in the previous section, we also conducted a more intricate processing of the trip data to be able to get detailed trip trajectories for the PT trips, or rather trip segments using any PT mode. This is in line with methodologies summarised by, among others, Vij & Shankari (2015) in their analysis of inference strategies versus data quantity and quality, and the idea of producing PT trajectories using timetable and AVL data resembles the one presented by Carrel et al. (2015). To enable inference of origin and destination stop points, data from the survey were merged with PT supply data in GTFS format, or in this case stop data that also contained line route reference information in addition to coordinates and an identifier. Technically, this was accomplished in two steps, where the first step used Voronoi polygons[4] around the stop points (as illustrated in Figure 4). All starting and ending points within each polygon were defined as starting or ending, respectively, from that particular stop.

[4] *Originally defined by Georgy Voronoi, 1908*

Figure 4 A subset of the GPS points collected by the survey participants using the survey app. The map indicates starting points (black triangles) and end points (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.

Because subsequent scrutiny and comparison of the results from the first step with aggregate survey data revealed that the precision of the location information from the survey GPS data was not sufficient at some boarding and alighting events, the second step included additional processing based on geographical information regarding line routes (route courses) from the GTFS data as well as locational data regarding up to 10 nearest neighbouring stops within a radius of 2,000 m direct distance to each boarding and alighting stop. 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. Parallel search scripts calculated likely line routes based on two cases – single or multiple line routes servicing the travelled stop relation (Figure 5). The first case only relied on the geographical constraints (stop points and line routes), while the second case also had to rely on temporal constraints (departure times of individual service trips). Thus, for each trip segment performed in a relation 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 automatic vehicle locator (AVL) data.

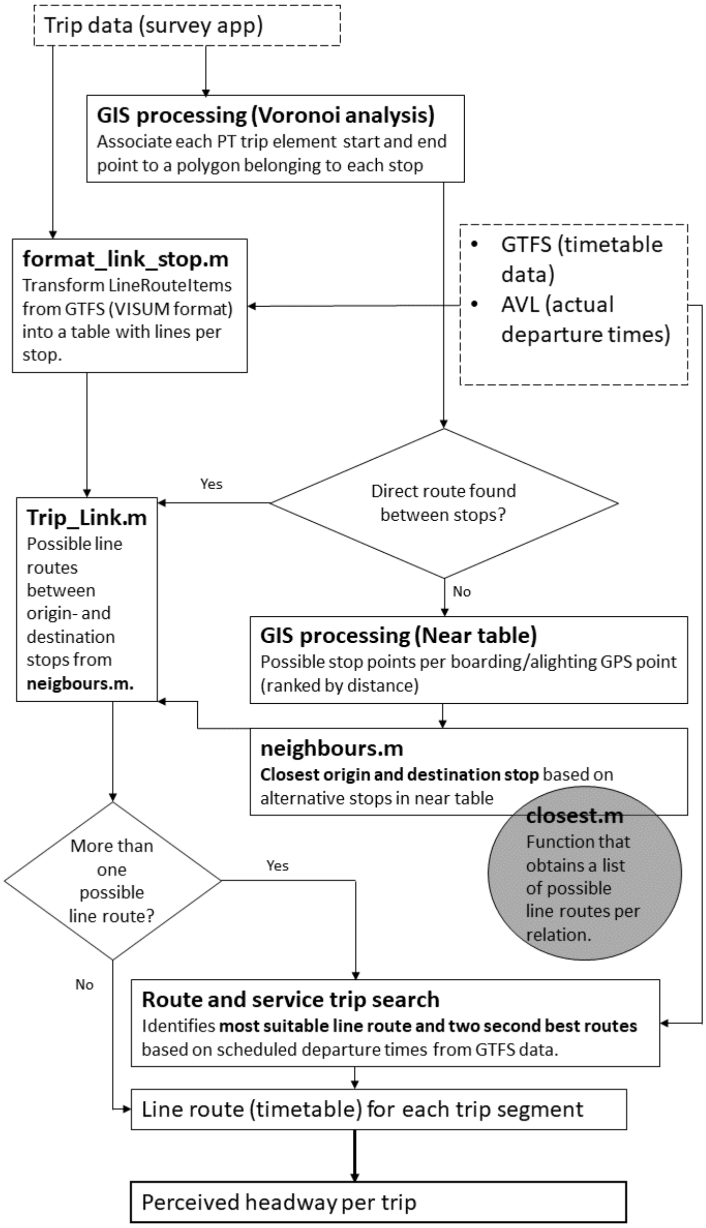

Figure 5 Schematic representation of work flow when processing and merging trip segment data from the survey with PT supply data from GTFS and the AVL system using ArcMap (Geographic Information System, GIS) and MatLab software.

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 main study area of Lund and Malmö (in other words, not along any of the studied PT lines referred to in Section 2.2 above). Most of the other missing data were caused by erroneous location registration – where origin and destination coordinates were very close to each other (within meters, 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 relations 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,[5] but this transfer was rarely recorded.

The resulting trajectories thus consisted of three datasets – one for trip segments performed in relations serviced by single lines, one based on departure times from timetable data, and one set with trajectories based on AVL departure time data. These three datasets were used to analyse FWTs and possible explanations for these, the results of which are described in the next section.

2.7. Resulting FWT and PT supply data

The final data for analysis consisted of 4,375 FWT events that were based on PT trips made by 254 survey participants. The selection of FWT trip segments was based on two main criteria: 1) The subsequent segment must be a PT segment and 2) the previous segment must be an activity or access mode (walk, bicycle, or car). Note that some of the FWTs 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 events, where the duration was less than 2 minutes, were in a sense fictive because they consisted only of the change of mode from access mode to the main PT mode. These FWT events were assigned a random value in the interval (0,2) minutes. A total of 1.552 of the FWT events could be related to stop relations serviced by single line routes. A total of 3,930 trip segments were successfully related to "perceived" scheduled headways in stop relations with one or more possible line routes, while 2,974 trip segments were successfully related to "perceived" headways from AVL data. The smaller number of FWT events in this selection is explained by the fact that AVL data were only available for a subset of lines compared to the total GTFS line selection used to create the other two FWT datasets.

PT supply data used for the analysis consisted of scheduled and actual headways at each FWT event in terms of time (departure time) and space (stop) based on timetables and actual departure times, respectively, as reported in Section 2.6 above. Mean headways for potential lines per stop relation travelled was calculated according to Equation 1 (see Section 1.4) Reliability indices (*RI*) were calculated for each PT line using the variation component of the waiting time as

$$RI = \frac{1}{1+var\,(H)/E(H)^2}, \quad where\ RI \in (0,1] \tag{2}$$

were *H* being actual headway in minutes and *var(H)* is the variance in deviation from the scheduled headway. This notation is derived from the definition of waiting time made by Ceder & Marguier (1985) and Joliffe & Hutchinson (1975) and thus is based on the mean deviation from scheduled departure times per day and per line route across stops.

These data enabled a closer scrutiny of the passenger behaviour in relation to service headway and other endogenous and exogenous factors described in the next subsection.

2.8. Data for explanatory variables

In addition to the PT supply characteristics described above, a number of 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[6] was obtained in a similar manner but was derived from the activity recorded ahead of each trip. Day type (weekday, Saturday or

[5] *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.*

[6] *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*

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). Finally, stop type was defined according to the characterisation made by Dyrberg et al. (2015) and applied by Ingvardson et al. (2018), but in addition to the stop type "interchange" we added the types "terminus" (addressing the different waiting times at termini reported by Csikos & Currie (2008)) and the context variables "urban" and "rural". We also added an additional stop context variable based on the land use surrounding each stop, in order to explore causes for waiting behaviour. The context/land use types chosen were CBD/central; Hospital; Commercial; Residential; Industrial; Retail; Education and Other.

3. Results and discussion

In the following section we report the findings of the statistical analyses of our FWT data in relation to potentially explanatory variables related to PT supply, personal data, and contextual trip data. We also discuss our results and the methods we used in relation to previous research.

3.1. FWT behaviour in relation to PT supply characteristics

Using survey data regarding single and multiple PT line routes respectively, we explored FWT behaviour in relation to PT supply characteristics. We initially assumed that passengers adjust their FWT to the scheduled headway and that they tend to arrive closer to individual departure times at longer scheduled headways. This was in accordance with results reported by a number of other studies previously discussed in this paper where passengers were also found not to adapt in this way at short headways but instead arriving more randomly at the stop. But was this really the case for our data?

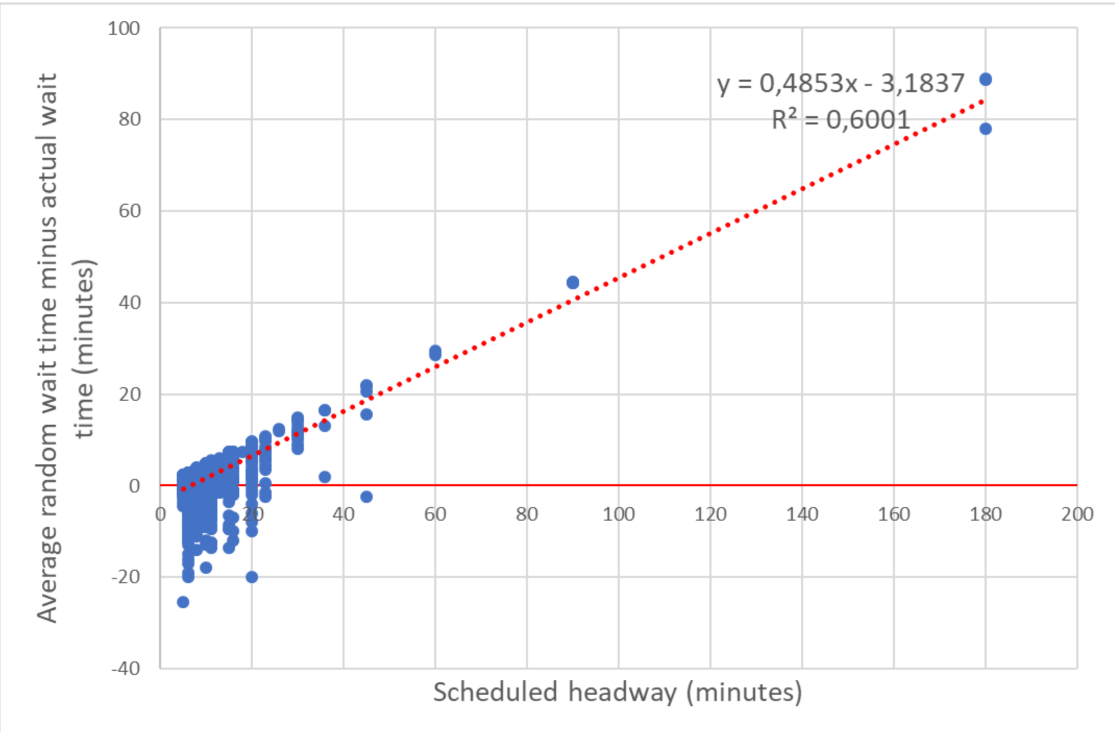

Figure 6 a Relationship between random minus actual FWT and scheduled headway for single-line stop relations.

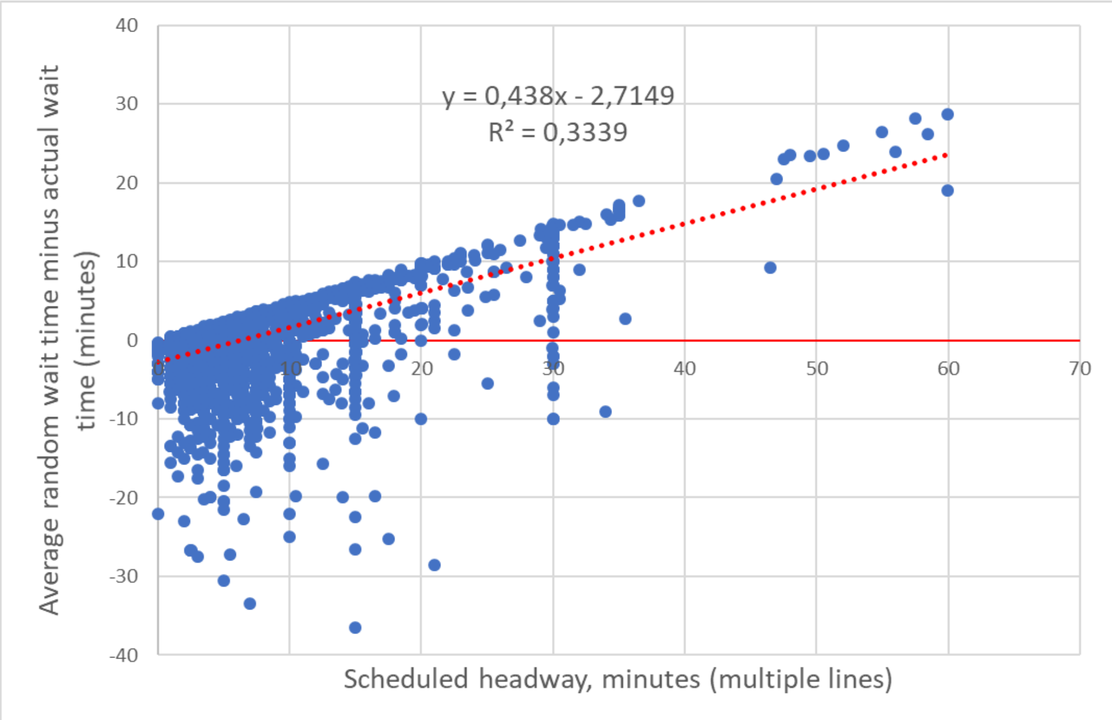

Figure 6 b Relationship between random minus actual FWT and scheduled headway based on stop relations with one or more line routes.

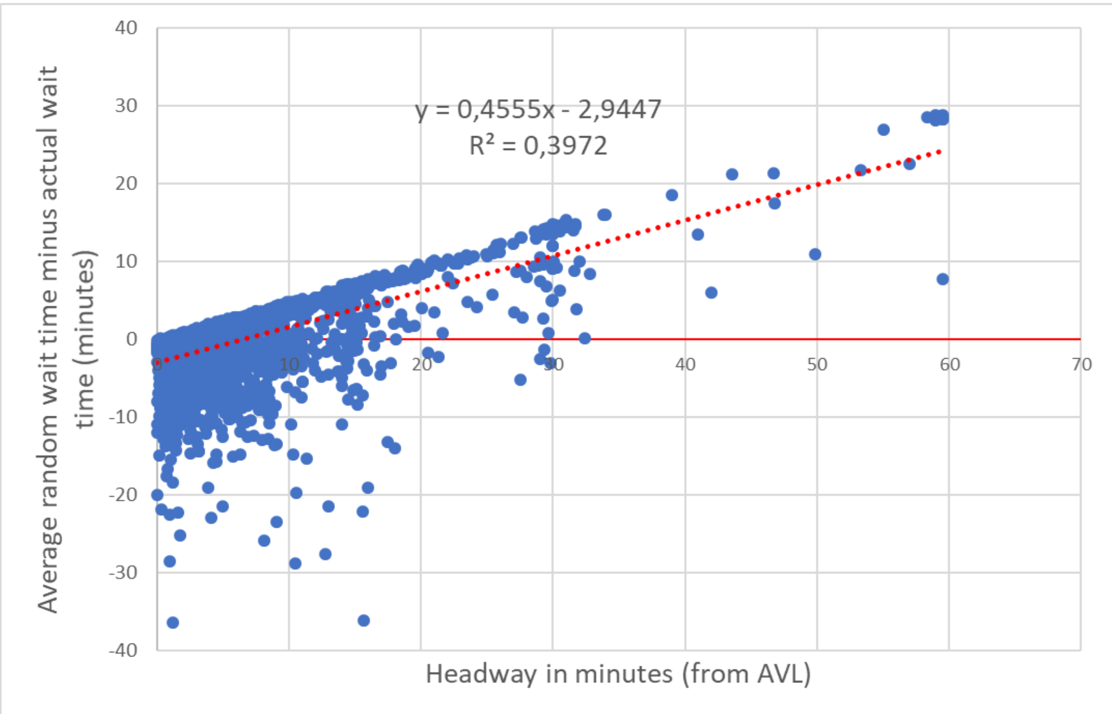

Figure 6 c Relationship between random minus actual FWT and actual "perceived" headways on stop relations with one or more line routes

Figure 6 Observations of FWT in the survey, represented by differences between actual and average random waiting times plotted as a function of departure intervals according to timetable and AVL system respectively. By definition, average random waiting times equal half the headway time. Note that there is a significant overlap between FWT observations between the three analyses displayed in these scatterplots.

Figure 6 a and 6 b illustrates FWT deviations from *H/2* ("average random wait time") as a function of scheduled departure intervals at travelled relations between stops serviced by single routes and multiple routes, respectively, while Figure 6 c illustrates the same type of deviations from random FWT as a function of the departure time interval per travelled stop relation according to AVL data at the time of boarding. The departure interval, or headway *H*, is here defined as $H=t_{i+1}-t_i$ where t is an arbitrary departure time and i is an arbitrary index regardless of the number of line routes (Figures 6b-c) or for relations serviced by only one line route (Figure 6a). Headways in Figure 6b-c are calculated according to Equation 1. The waiting times are expressed as W_h ($=(t_{i+1}-t_i)/2$ if uniform incidence rate of passengers to the stop) and observed waiting times W, respectively. For the single line route FWT events, the mean FWT/H ratio is 0.34 in our data, which is clearly below half the headway. Further, the median FWT/H ratio is 0.15 and the standard deviation is as high as 0.48, jointly indicating the existence of extreme outliers. Corresponding statistics regarding relations with multiple line routes is presented in Table 3. When comparing to outcome from manual observations of waiting times, such as the one in Salek & Machemehl (1999), it is clear that we obtain a much more dispersed waiting pattern, although the centrality measures indicate a large share of very short FWT:s. This is further supported by the distribution of FWT per headway as indicated by Figure 7. The number of FWTs below 2 minutes is attributed to the large number of "fictive" FWT events, where there is no activity Wait/transfer recorded by the survey app.

Table 3 Descriptive statistics for FWT/headway ratios, scheduled headways and FWTs for the subset of trips where this data was available.

Statistic		FWT/scheduled headway	Scheduled headway multiple lines	FWT
N		3,867	3,951	4,227
Mean		0.68	7.32	3.21
Median		0.30	5.00	1.32
Mode		0.06	5.00	3.00[a]
Std. Deviation		1.10	6.66	4.31
Variance		1.21	44.33	18.59
Range		16.00	59.98	44.00
Minimum		0.00	0.00	0.00
Maximum		16.00	59.98	44.00
Percentiles	25	0.13	3.50	0.88
	50	0.30	5.00	1.32
	75	0.80	9.00	4.00
	85	1.25	12.00	7.00
	95	2.40	20.00	11.60
	98	4.00	30.00	16.00

a. Multiple modes exist. The smallest value is shown

It should be noted that there was no active co-ordination of departure times (e g to avoid bunching) in the study area during our survey periods for relations where multiple, parallel line routes serviced the same stops.

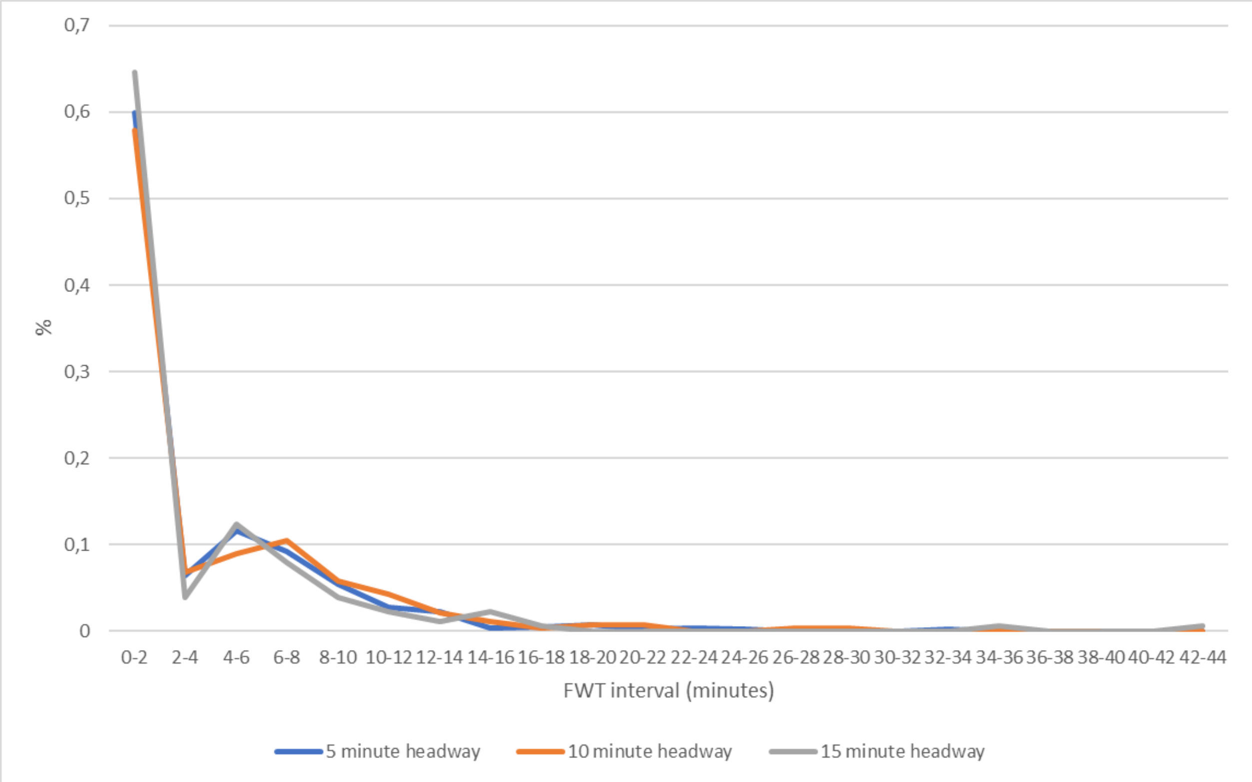

Figure 7 Probability distribution of FWT for the three most common scheduled headways in the study area.

There is a reasonable resemblance between the models presented in Figure 6 a-c, despite the large number of outliers. Thus, the headway values where the trend lines intersect the X-axes, which might be interpreted as the points where observed waiting times start to positively deviate from the average random waiting times, are 6.56, 6.20, and 6.38 minutes, respectively. In fact, when analysing FWT with respect to headway itself, the mean waiting times stay at or below 5 minutes regardless of headway measure (see Figure 8), which is in line with the results provided by Luethi (2007). The interpretation we make from these results is that passengers start taking notice of, and adjusting to, actual departure times at these points. The values are slightly below those reported in most literature (Ingvardson et al., 2018), but Luethi (2007) reported values as low as 5–6 minutes – however, this was in the unusually punctual PT system of Zürich. A value of 10–12 minutes (Liu, Bunker, and Ferreira (2010) p758), for when passengers start adapting to scheduled departure times, represents a more commonly reported rule of thumb.

There is substantial vertical scattering below the trend line for some observations at short headways in all three scatterplots of Figure 6, resembling trips belonging to the concept of Excess Journey Time (EJT) as proposed by Zhao et al. (2013). Points within the departure interval may thus be attributed to random passenger incidence at short headways. Cases where FWT was clearly longer than the headway are represented by observations with large negative differences between random and actual waiting times in the plots. Several of these observation points have a low leverage ($h_i < 2k/n$) but a high influence (DFFITS > $2\sqrt{k/n}$) in the model. Of these, the most evident outliers may, when examined more closely, be subdivided into two groups – extended transfer times at large interchange stations and more moderately extended FWTs at small stations. The first group probably mostly consists of erroneous activity categorisations, where a different activity than usual is performed at, or within 100 meters from, a site previously coded as a position where the activity Wait/transfer was undertaken by the respondent. The second group might be related to crowding or other reasons for missing a departure.

In the cases where *scheduled* headway was used as regressor (Figure 6a-b), the large FWT deviations may also be related to poor adherence to schedule by the relevant PT line routes. The departure reliability issue thus illustrated is related to the concept of TTV as defined by, among others, Durán-Hormazábal & Tirachini (2016). They found that the level of TTV, and the resulting variability of waiting times on metro lines with headways below 3 minutes, increased as an inverse function of the headway. Our results suggest a similar phenomenon for bus lines in a mixed traffic setting and with scheduled headways of 5 minutes and shorter. For longer headways than 30 minutes, where the number of observation points is small, there is a high leverage for the few data points that were actually recorded at these headways, and without them the level of explanation, or model fit, would be significantly lower. However, unlike the data Durán-Hormazábal & Tirachini (2016) used, we were also able to analyse FWT for relations serviced by multiple lines and at headways longer than 30 minutes and thus retrieve more data at less serviced relations (Figure 6b). Interestingly, the model fit was higher when FWT was regressed against Scheduled than Actual headway according to AVL data (R^2=0.010 and 0.007 respectively). This might be an indication of passengers adapting rather to scheduled than actual headways, depending on the information available[7].

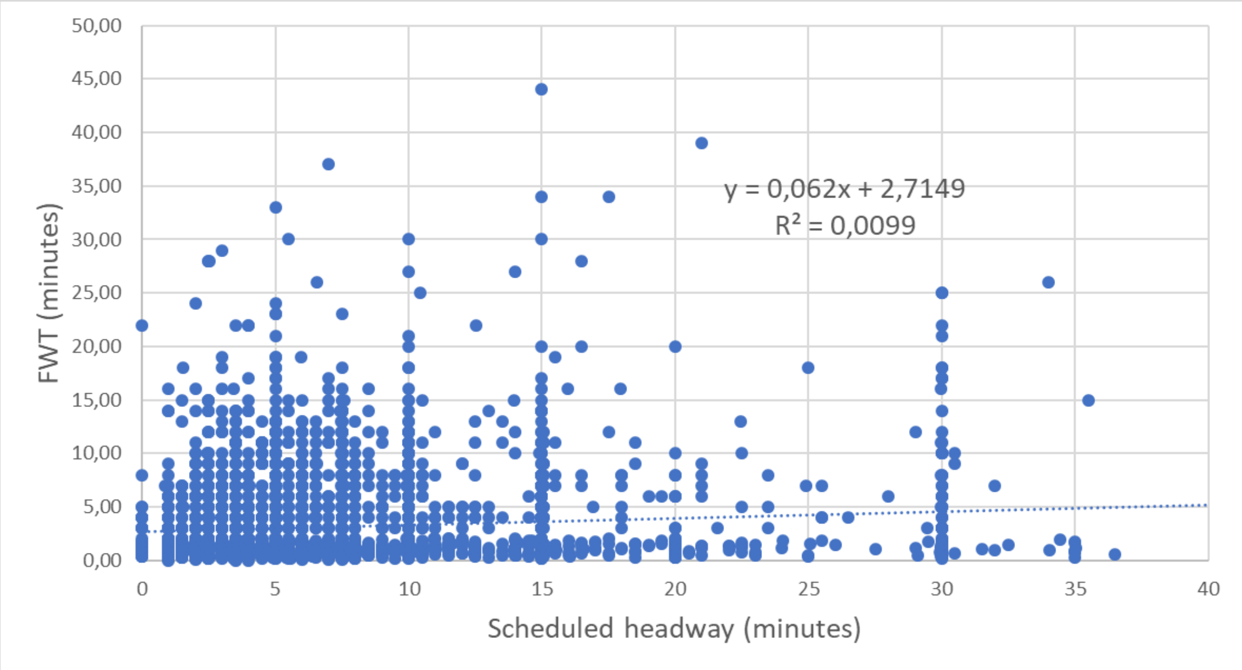

Figure 8 FWT events with respect to scheduled headways for trip relations with multiple lines

[7] *Unfortunately, we have no information regarding the share of passengers using real time information (RTI) when choosing between PT paths.*

3.2. Impact of contextual and personal characteristics on FWT

3.2.1. Do different individuals use different hyperpath types or strategies?

As noted in section 2.8, FWT was analysed in relation to a number of contextual and person-based variables. Also, the inter-personal variation was studied in a similar fashion to the approach used by Csikos & Currie (2008); however, we did not group individuals according to FWT behaviour. We found, by univariate ANOVA, that the variation across individuals (standard deviation 4.3) was indeed significantly larger (P = 0.000 at the 95% confidence level) than for each individual (mean standard deviation = 2.8, standard deviation across individual standard deviations = 2.48).

The possible individual traits, based on trip data from the 2017 survey round, has been further examined elsewere[8]. There we found, after having identified and analysed the behavioural archetypes proposed by Csikos and Currie, that employees tend to optimise FWT to a larger extent than students.

3.2.2. Results from ANOVA models

*Table 4 Summary of analysis statistics from univariate ANOVA with FWT as the dependent variable. Significance on 95% level indicated in **bold***

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Explanatory power
Corrected Model	7,990.91[a]	183	43.67	2.78	**0.000***	
Intercept	179.02	1	179.02	11.41	**0.001***	0.3%
Respondent gender * Trip purpose	797.16	18	44.29	2.82	**0.000***	1.2%
Respondent gender * Stop type	28.33	9	3.15	0.20	0.994	0.0%
Respndent gender * Stop context	73.50	14	5.25	0.34	0.990	0.1%
TripPurpose * StopType	882.90	54	16.35	1.04	0.391	1.3%
Access mode * Trip duration	710.32	24	29.60	1.89	**0.006***	1.1%
Daytype	21.53	2	10.76	0.69	0.504	0.0%
Access mode	368.59	4	92.15	5.87	**0.000***	0.6%
Time period	16.96	3	5.65	0.36	0.782	0.0%
Respondent gender	30.70	2	15.35	0.98	0.376	0.0%
Trip purpose	492.28	17	28.96	1.85	**0.018***	0.7%
Stop type	75.95	5	15.19	0.97	0.436	0.1%
Previous activity	335.35	18	18.63	1.19	0.262	0.5%
Age group	80.97	4	20.24	1.29	0.272	0.1%
Stop context	51.46	7	7.35	0.47	0.858	0.1%
Access distance	36.48	1	36.48	2.32	0.127	0.1%
Scheduled Headway	341.82	1	341.82	21.78	**0.000***	0.5%
Error	57907.95	3,690	15.69			
Total	104791.91	3,874				
Corrected Total	65898.85	3,873				
a. R^2 = 0.121 (Adjusted R^2 = 0.078)						

Table 4 summarises the results from a univariate ANOVA analysis of possible effects on FWT from a number of explanatory variables. As indicated, Trip purpose in interaction with Gender, Access mode

[8] *Berggren, U; Johnsson, C; Brundell-Freij, K and Wretstrand, A (2018) Route Choice Strategies and Usage of Real Time Information in Public Transport – an empirical survey based on dedicated smartphone application, paper submitted to and presented at Conference on Advanced Systems in Public Transport and TransitData, Brisbane, 2018*

– with and without interaction with Trip distance, Trip purpose and Scheduled headway had significant effects when the whole model was tested. Of these variables, the explanatory power of Scheduled headway was surprisingly low compared to Respondent gender and Trip purpose in interaction. Also, somewhat surprisingly, we found no significant effect from our reliability index on FWT when analysing separately with linear regression (R^2=0.0004), but the effect seems to be captured by the scheduled headway itself. This is supported by the finding, also made using linear regression, that the reliability index of the line route is significantly explained by the scheduled headway (standardised coefficient of 0.149; R^2=0.022). When binning the headways into 5-minute intervals, this relationship becomes even clearer: According to results from a Tamhane's post-hoc test, the reliability index significantly improves by 0.07 and 0.17 units when scheduled headway is increased from 5 to 10 minutes and from 15 to 20 minutes respectively.

The interaction between Trip purpose and Respondent gender on FWT length is illustrated in Figure 9 in the form of estimated marginal means. Women tend to have longer FWT than men, although this difference is not significant per se. It is clear though, that this difference is most pronounced for the purposes Drop off/pick up, Healthcare, Restaurants/café and Entertainment/culture, although the number of observations is below 30 for all these subgroups except for Restaurants/café.

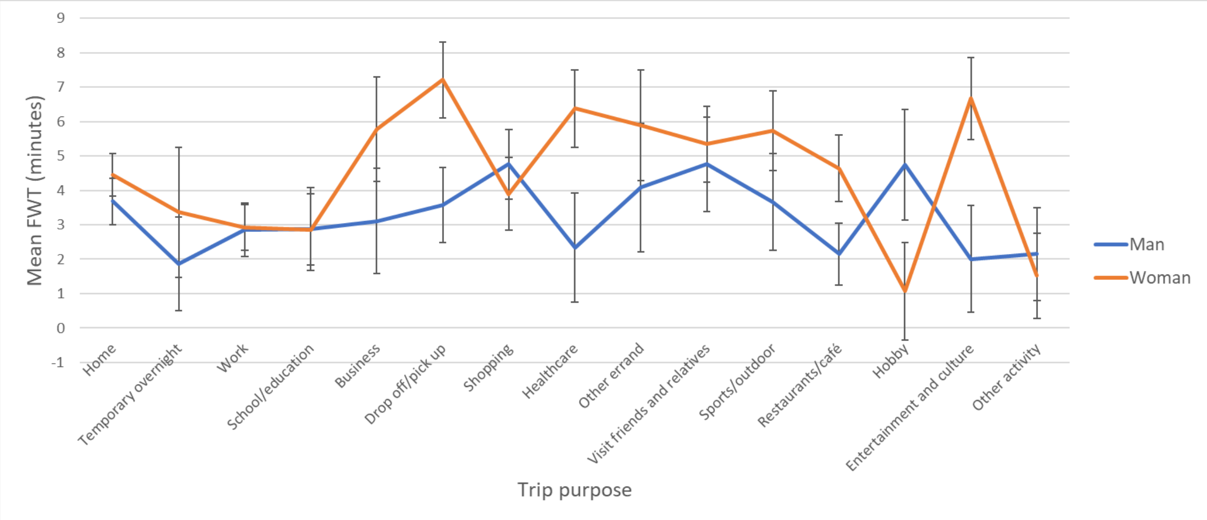

Figure 9 The interaction between Trip purpose and Respondent gender on FWT, as indicated by estimated marginal means. Whiskers indicate standard errors.

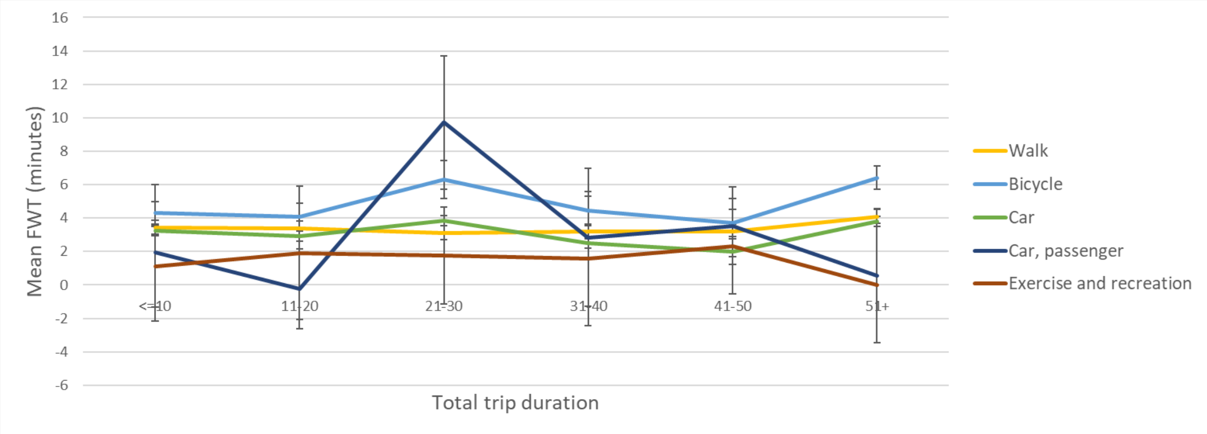

Figure 10 The interaction between Total trip duration and Access mode on FWT, as indicated by estimated marginal means. Whiskers indicate standard errors. N_{walk}=3,771, $N_{bicycle}$=235, N_{car}=121, $N_{car\ passenger}$=13 and $N_{exercise\ and\ recreation}$=9

Applying Levene's homogeneity test on the main ANOVA model in Table 4 revealed different variances across faculties, leading us to test the influence on FWT from each independent variable separately and subsequently consult Tamhane's post-hoc tests to find magnitudes and directions of influence on FWT from the independent variables. Thus, the stop type Interchange terminus displayed significantly longer FWT than ordinary urban PT stops, hence somewhat corroborating the finding by Csikos and Currie (2008). Also, the test for access mode indicated longer FWTs for Bicycle compared to Walk and Car, while Car had shorter mean FWTs than both Bicycle and Walk. This finding, which is further illustrated and diversified in Figure 10, is most probably the reason why there is a weakly negative relationship between FWT and access distance (standardised coefficient of -0.030, R^2=0.0009 as indicated by linear regression). This might seem confusing, but there were underlying reasons for this related to transport mode for access trips where car was used for on average 6-7 kilometres longer access trips than bicycle and walk. The result is also in line with findings by Salek and Machemehl (1999), as they concluded that park&ride stops, where car was used as access mode, had significantly shorter FWTs than the mean FWT for all stops.

A behavioural interpretation of the shorter FWTs at trips with longer access distances as compared to short (below 3 km) could be risk aversion of missing the desired departure, which poses an incentive towards careful planning and thus minimising the waiting time. This incentive should be greater when the passenger is farther from the starting point of the trip. Otherwise, the difference between car and bike in terms of FWT on our study is difficult to explain other than by the structure of, and respondents' interaction with, the survey app. E g, there are instances where the FWT after access mode car seem to be hidden in a parking activity or short walk from the car park to the PT vehicle. A potential error is also the selectable mode "car passenger" for kiss-and-ride as access mode, which might have been set as just "car" by some respondents (the large number of car access trips compared to car passenger access trips indicates this). In this context, it is interesting to note that the trip purposes with significantly longer FWTs than average were related to rarely made trips such as visiting friends and family while school trip FWTs were shorter than average.

As indicated by Figure 10, and previously in Figure 3, using Tamhane's post-hoc test, it is clear that, for trips longer than 50 minutes, FWTs were significantly longer than for trips with shorter durations (though not significantly different for trips below 10 minutes). Among short distance trips, there was a somewhat overrepresentation of leisure purposes while work commute was overrepresented among trips longer than 50 minutes.

There was no effect from the frequency of PT travel among the participants during the two-week survey, indicating the small sample of individuals who were perhaps to a large extent accustomed PT riders.

3.3. Methodology issues

3.3.1. Collection of trip data

It is instructive to compare the results from our survey with results from regular travel diaries, as Geurs et al. (2015) and Allström et al. (2017) did. The latter authors used trip matching, based on purpose and departure time, to compare the results from a pen-and-pencil trip diary with the corresponding data from an app survey similar to ours. Their results, obtained from a study in the greater Stockholm region, indicated that respondents tend to omit short journeys in manual travel diaries (the mean travel distances are longer in the manual compared to the automatic survey), while such journeys are recorded by automatic collection devices such as a mobile phone. Moreover, Allström et al. (2017) reported that the smartphone survey app that was used consistently captured more detailed information about trip legs and that the location attributes derived from the route (destinations) agreed better with the user-annotated data than with the address specified in the traditional travel diary that was used for comparison.

Readers should note the limitations concerning size and potential bias in our survey sample, as noted in most other surveys based on dedicated survey apps compared to the common sample of a conventional travel survey (Clark et al., 2017). We have not been able to fully evaluate the effects of our strategy regarding spatial restrictions for the recruitment of participants to the survey. On the other hand, the high level of detail of our data has enabled at least a visual comparison of our results to outputs from other similar surveys by Allström et al. (2017), Auld et al. (2013), Berger and Platzer (2015), Geurs et al. (2015), Gadziński (2018), Greaves et al. (2015), Seo et al. (2017), Vij & Shankari (2015), and Prelipcean et al (2014), indicating that our approach is feasible when it comes to studying possible explanations for the variation of PT passengers' waiting times in relation to supply characteristics. In our view, this is a necessary step to increase the validity, and thus the relevance and usage rates, of PT trip forecasting models among transport analysts and planners. This in turn would strengthen the planning and design of the desired efficient and attractive PT systems.

A total of 67% of the trip elements from the 2016 survey were derived from trips reviewed by the users, while all trips analysed from the 2017 round were reviewed. The non-reviewed trip elements from the 2016 survey round had been transmitted without respondent intervention. Some results from a comparison analysis of trip element modes, lengths, and durations between the reviewed and non-reviewed data subsets are found in the Appendix, where results from statistical comparisons regarding these data are reported in the form of CDF diagrams. To summarise these, the modal shares, as measured in trip elements, differ with respect to individual versus collective modes, with a seeming over-reporting of individual modes such as car and walking in the unreviewed data. There are also statistically significant differences in trip segment durations for all transport modes, where the non-reviewed data contain significantly shorter segments. The variance of walking trip lengths was also substantially larger in the non-reviewed data compared to the reviewed and revised data. This is probably due to the tendency of the app to "over register" short walking trips, a phenomenon that might occur when walking slowly or when walking around in large buildings. As experienced from the pilot study, in the review phase many short trip segments were joined by the respondents. However, and as Stopher et al. (2015) discuss, it is not evident that the revised data are actually more "true" than the automatically recorded data. The trade-off between accuracy and respondent burden is also further discussed by Seo et al. (2017).

3.3.2. Analysis approach

The method of combining behavioural and contextual data, retrieved within the survey, with PT system specific data regarding reliability as well as scheduled and actual departure times provided us with feasible geographically diverse datasets for further analysis. Moreover, the data was collected without the need of large-scale direct observation or other extensive manual methods (cf e g Salek and Machemehl (1999)). However, as was indicated by Salek et al, explaining FWT often turns out being a cumbersome and often even somewhat confusing pursuit. The strength of our choice of methodology is the possibility to relate each event in a trip to previous and subsequent events for each survey participant in deep detail. A drawback is the relatively substantial loss of data caused by a multitude of causes – from erroneous coding by survey participants to missing or incorrect position data from either survey devices (the smartphones of the participants) or the AVL system. All in all, the data output, as measured in share of trips from the survey available for further analysis, was 73% using the scheduled timetable approach, where the entire region of Scania was included, and 53% using the smaller selection of lines where AVL data was available. As reported above, our dataset contains trips of multiple purposes at multiple times in both rural and urban areas and this should – at least in theory - be conducive to a successful exploration of trip patterns. To some degree, we assert to have made a good effort in this direction, but more powerful analysis instruments might produce stronger relationships than we were able to when using relatively simple statistical methods.

4. Conclusions

In this paper, we present results from a smartphone-based travel survey based on prompted recall, and from subsequent analyses of FWT behaviour based on our survey data. The questions addressed in this paper touch upon the general issue of how PT path choice should be modelled with respect to the key decision event associated with the choice of first PT connection, where we utilise FWT as a proxy to measure passenger behaviour. The process of data collection and the subsequent analysis also gave us valuable insights into both survey design and feasible combinations of data sources.

A general impression obtained from our analyses is the high level of heterogeneity and low level of regularity in our data regarding FWT, indicated by low explanatory power of used models. This said, the results we obtained regarding FWT in relation to scheduled and actual headways and other passenger and supply-related attributes are in relatively good agreement with previous research on how passengers adapt to high and low departure frequencies. Consequently, our data indicate that passengers start deviating from the uniform first stop incidence rate at as low scheduled headways as 5 minutes, giving further support to the findings by Luethi (2007) despite having a documented low level of adherence to scheduled headways in our data. Our survey data also displays a higher dispersion of FWTs at short headways, which may be attributed to a more random behaviour among passengers, but also to a lower level of departure reliability at shorter headways as proposed by Durán-Hormazábal and Tirachini (2016). The analysis of FWT with respect to contextual variables and personal characteristics showed interesting relationships to trip purpose, respondent gender, trip duration and access mode. Hence, our results corroborate the notion that FWTs are more consistent at trips with regular purposes such as work and education. FWTs were shorter for trips to education in peak periods than off-peak and for trips with car as the access mode compared to bicycle and walk. Trip purpose, in interaction with gender, along with trip duration in interaction with access mode, were the strongest determinants of FWT length in our data. Here, our potentially most important finding is that scheduled headway to a relatively low degree explained the variation in FWT in our data, but that other factors like trip purpose, access mode and trip length seem to be more important determinants of FWT length.

According to our findings, headway variability due to irregularities such as delays does not affect FWT directly. On the contrary, our results suggest that passengers tend to plan and adapt to scheduled headways to a larger extent than to actual departures. This may change in the future, provided the current trend of increasing adoption of new services providing easy-access and reliable real-time information of departure times on mobile personal devices.

The process of data collection using the smartphone-based survey and subsequent post-processing gave us valuable insights into limitations and potential future improvements regarding both the design of our survey and the combinations of data sources regarding departure times that were used during post-processing. Power consumption, affecting battery time, and respondent fatigue, related to app interface and trip revision routines, were reported as most important factors by survey participants, affecting both quantity and quality of the trip data collected during the survey.

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APPENDIX: Supplementary figures

Figures A.1-A.7 provide illustrations of the distribution of trip durations and distances from the survey and indicate differences between results from the prompted recall and automatic data collection approach.

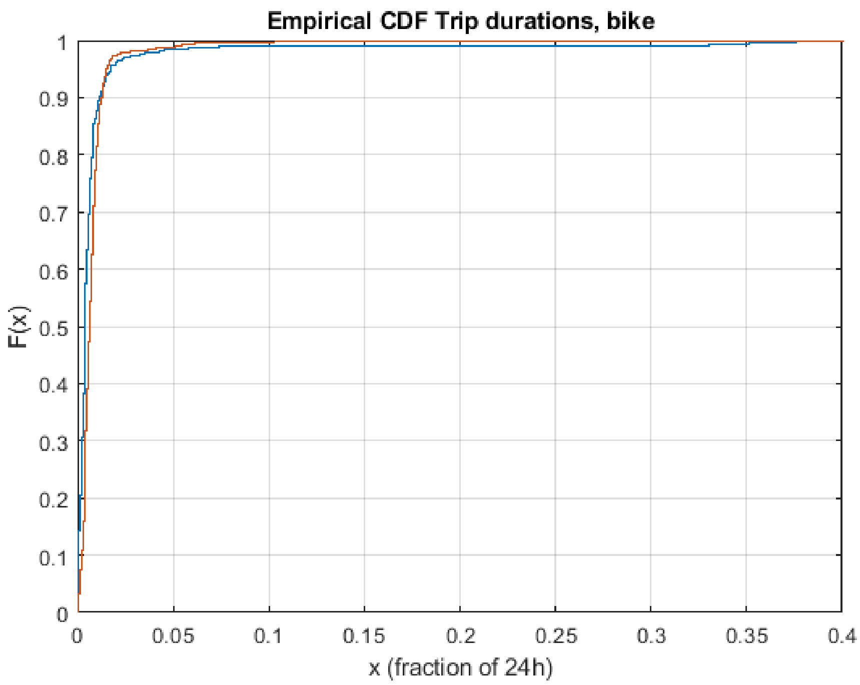

Figure A.1 CDF for trip durations in recall survey data (red) and automatic data collected without respondent intervention (blue) for trip segments travelled by bicycle.

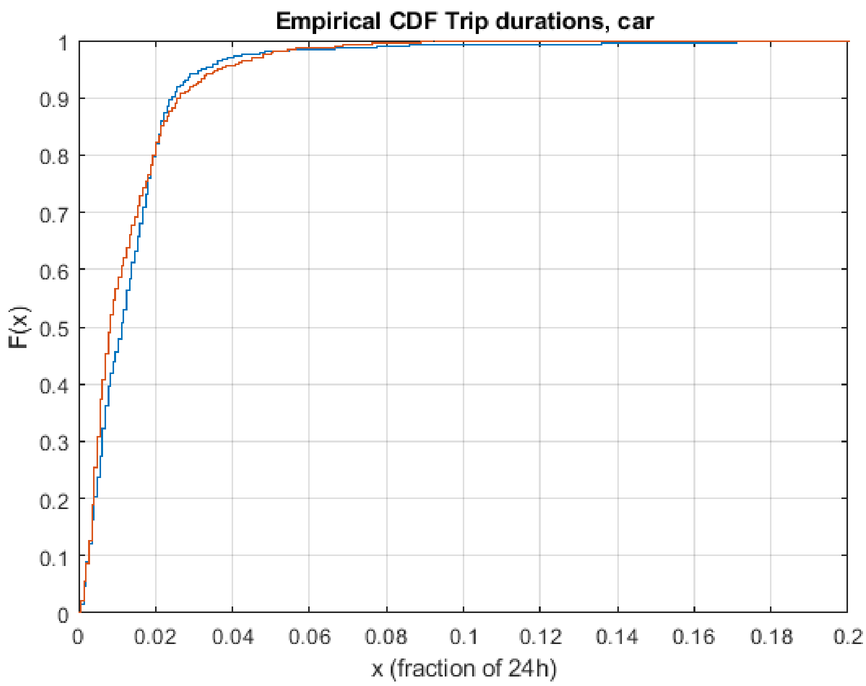

Figure A.2 CDF for trip durations in recall survey data (red) and automatic data collected without respondent intervention (blue) for trip segments travelled by car.

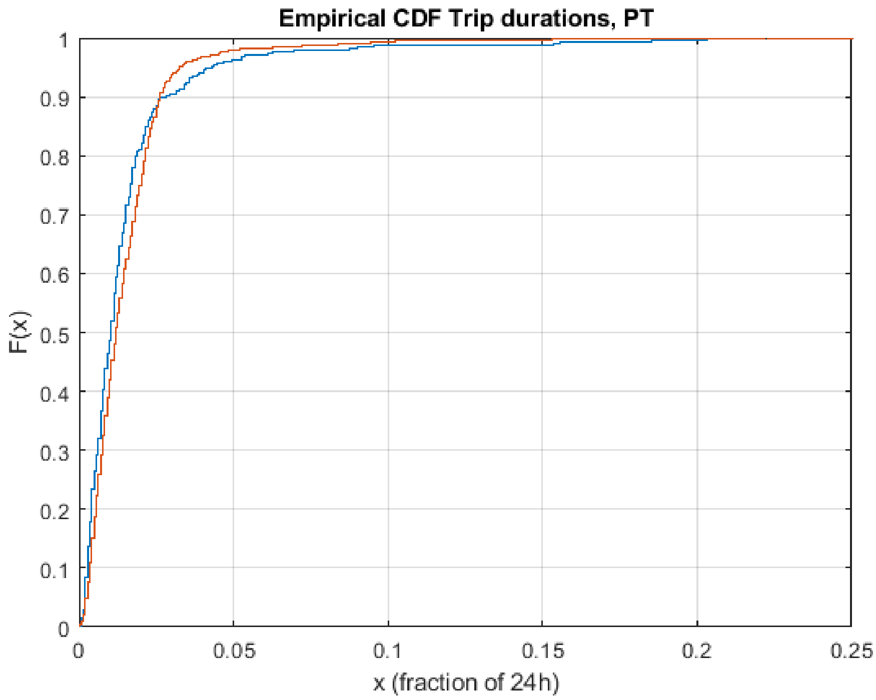

Figure A.3 CDF for trip durations in recall survey data (blue) and automatic data collected without respondent intervention (red) for trip segments travelled by PT.

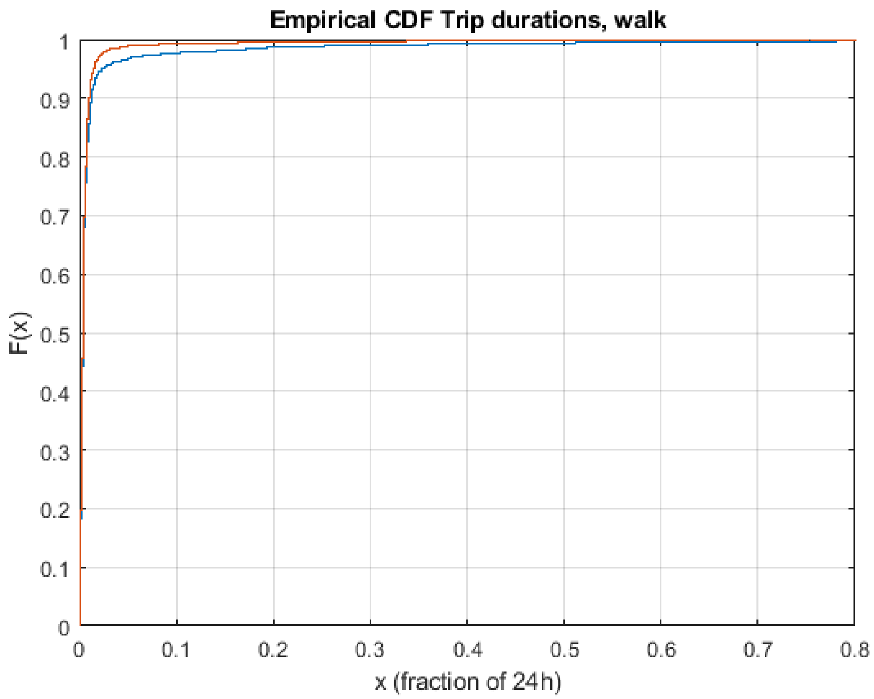

Figure A.4 CDF for trip durations in recall survey data (red) and automatic data collected without respondent intervention (blue) for trip segments by walking.

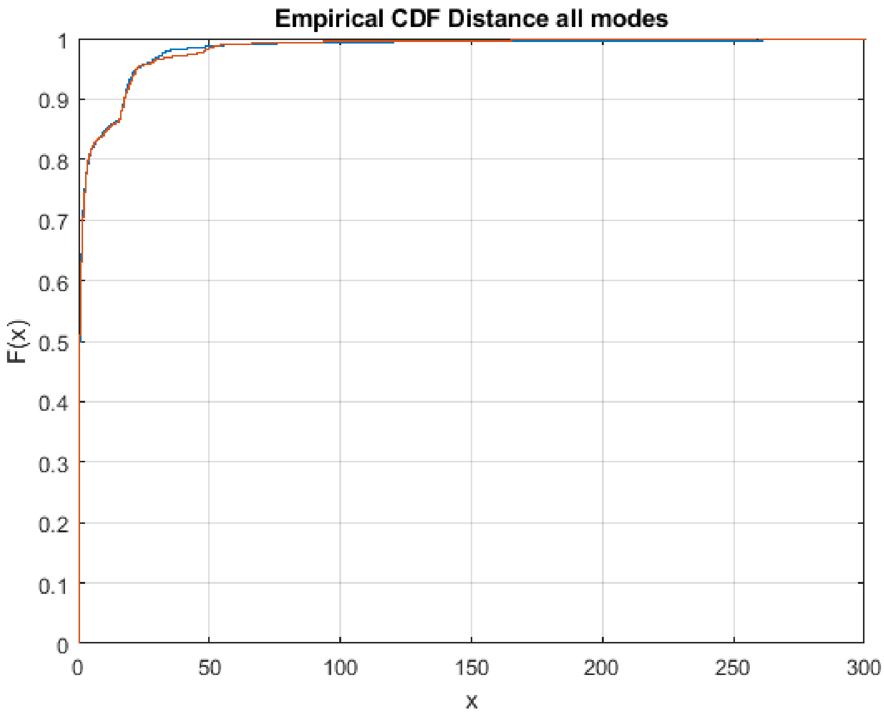

Figure A.5 CDF for trip distances, measured in kilometres, in the recall survey data (red) and automatic data collected without respondent intervention (blue) for all modes.

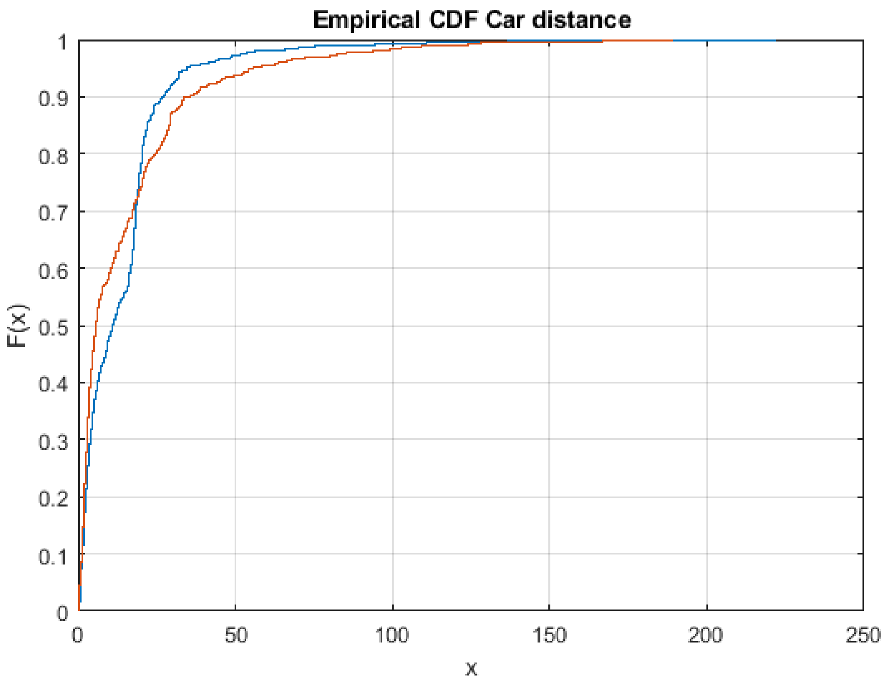

Figure A.6 CDF for trip distances, measured in kilometres, in the recall survey data (red) and automatic data collected without respondent intervention (blue) for trip segments travelled by car.

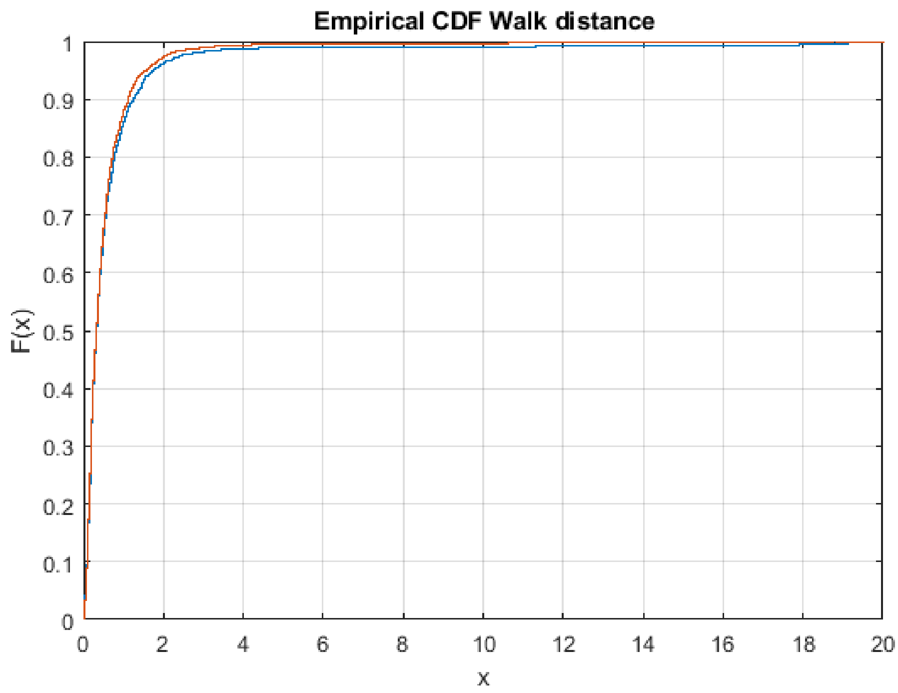

Figure A.7 CDF for trip distances, measured in kilometres, in the recall survey data (red) and automatic data collected without respondent intervention (blue) for trip segments by walking.

Figure A.8 show supplementary information for Section 3.1 in general and for Figure 6 in particular.

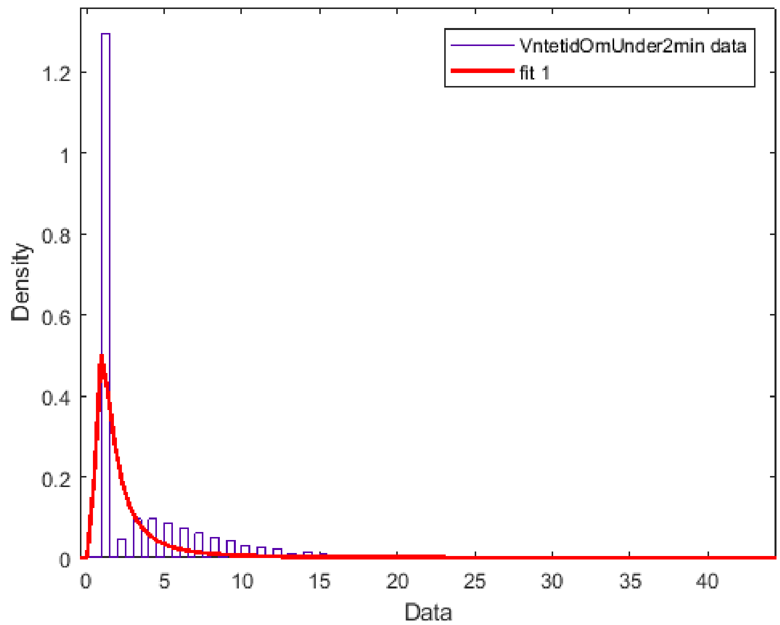

Figure A.8 Distribution fit for FWT events in minutes (X-axis) used in the analyses

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ORIGINAL PAPER

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

Ulrik Berggren[1,2] · Karin Brundell-Freij[1,2,3] · Helena Svensson[1,2] · Anders Wretstrand[1,2]

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Abstract
Waiting times are important indicators of the degree of travel time optimisation and other behavioural traits among public transport (PT) passengers. As previous studies have shown, the level and usage of pre-trip information regarding schedule or real-time departures are important factors that influence the potential to realise travel time savings by enabling PT passengers to optimise waiting times. Most empirical evidence regarding the revealed PT travel behaviour concerning information levels is based on manual interviews or traditional travel surveys, in which there is a risk that the actual context of where and when the choice of departure time was made is not taken into account. This paper reports the results of a travel survey based on a dedicated smartphone application applied in a field study in a Swedish mid-size urban and regional context. Context-aware notification prompting was used to allow respondents to state their use of pre-trip information as well as whether they had pre-planned their trip and how contingent planning aids were used for time optimisation. The implications on passenger waiting times of the use of information regarding departure times by passengers were emphasised during analyses of the resulting data, along with personal characteristics, in which auxiliary sources such as timetable data and Automatic Vehicle Location were utilised to determine ground truth trip trajectories and trip-contextual factors. The results indicate the significance of having access to pre-trip information, especially for long trips above one hour's duration, in order to pre-plan and thereby optimise waiting times. In addition, the use and source of pre-trip information differ among age and gender groups. Trip purpose and time of day to some extent determine waiting times and choice of trip optimisation strategy (arrival or departure time).

Keywords Public transport · Travel information · Waiting times · Planning strategies

✉ Ulrik Berggren
Ulrik.berggren@tft.lth.se

Extended author information available on the last page of the article

1 Introduction

Urban population growth and related mobility challenges motivate the expansion of public transport systems in order to cater for increased ridership without loss of end-user attractiveness. The resulting increase in system complexity and congestion imposes increasing challenges for passengers seeking to minimise their effort of travelling as well as for operators in managing the resulting increase in passenger flows. The growing public availability of increasingly specific information regarding public transport (PT) connections, for example, both scheduled and actual departures, has the potential to address both these issues in a cost-efficient way thanks to technological advancements in the electronic dissemination of both pre-trip and *en route* PT information.[1] In the literature, these electronic passenger information systems containing real-time (travel) information—RT(T)I—are sometimes termed *advanced public transport* (or *transit*) *traveller information systems*—A(P)TTIS (Nuzzolo et al. 2015). They can be based on site-specific equipment (signs and displays on vehicles and at stops and stations) or on personal devices such as smartphones and personal computers (Fonzone 2015; Ghahramani and Brakewood 2016; Harmony and Gayah 2017; Mulley et al. 2017). The information content on stationary or vehicle-based displays usually comprises scheduled and actual departure times, while journey planners and the like, available through personal devices, also to an increasing degree include itineraries with updated departure and arrival times of connecting services at transfer points (for example, as described by Cats et al. 2016).

Waiting times, particularly under uncertainty, have been shown to be perceived as being significantly more onerous than other time components of a PT trip (Wardman et al. 2016). However, both perceived and actual waiting times can be mitigated by the adoption of pre-trip or *en route* information (Brakewood and Watkins 2018). Moreover, in microeconomic consumer choice theory, the role of information is essential in forming the foundation for the individual's trade-offs between different utilities and disutilities. However, the demand for information may be triggered by situations where: (1) the trade-off between options is obscured by some degree of uncertainty (Chorus et al. 2006; Farag and Lyons, 2008) and (2) the consumer is not sufficiently acquainted with the options in order to having developed habitual behaviour (as convincingly shown by Aarts et al. (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 search into consideration. He was subsequently able to foster these arguments in the findings of a qualitative study on the search of pre-trip travel information (Farag and Lyons, 2008) where he found no evidence for modal shift as a behavioural response to information—instead, information is mainly sought ahead

[1] See, for example, Harmony and Gayah (2017) for a recent study of the North American context. In Sweden, 90% of all PT authorities provide (real-time) travel information through smartphone apps, according to the Swedish Public Transport Association (Svensk kollektivtrafik 2017).

of performing complex or unfamiliar journeys and/or where there is uncertainty due to service disruptions. The latter is also indicated in a survey previously presented by Peirce (2003), which, however, was made before the advent of the current widespread use of hand-held internet-access devices among PT passengers (see also Daduna and Voss, 1996).

This rapid adoption of smartphones and associated applications providing RTI among the population of PT passengers in most developed parts of the world has motivated a proliferation of research on how the existence of this information affects passenger behaviour. As Gentile et al. (2016) note, 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 action.

The literature on behavioural impacts and use of RTI may roughly be subdivided into an analytic and an empirical strand. Brakewood and Watkins (2018) provide a comprehensive overview of the literature regarding the effects of the use of RTI on passengers' actual and perceived waiting times, total travel times, ridership and perceived quality and security. In their synthesis, they report average waiting time gains of 2 min and perceived waiting time reductions by up to 30%, however subject to self-selection in the quoted surveys. Other recent empirical evidence of pre-trip information use is provided by Mulley et al. (2017) in their survey of awareness and usage of various information sources in metropolitan Sydney. According to their results, mobility apps and the like are primarily used by experienced PT users, while infrequent users tend to be more reliant on word-of-mouth and websites. In their web survey of a random sample of US citizens, Harmony and Gayah (2017) found that smartphone apps were the preferred medium for obtaining RTI for PT departure times. A similar result was obtained by Fonzone (2015) in his bus stop and vehicle-based survey of the RTI use of PT passenger and related trip attributes. He found widespread use of stationary RTI media (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 the study, the choice of route was the stage of the trip that was mostly 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 and 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 et al. (2011) in the results from their mesoscopic dynamic model of the Stockholm metro. They arrive at a 3–4% total gain in travel time as an effect of RTI provided at platform, station or network level, with the higher figure for the latter level. During travel disruptions, these effects were accelerated by up to 11% compared to a non-RTI scenario. To validate the different route choice modelling approaches, also regarding passengers having access to RTI regarding departure times, Fonzone and Schmöcker (2014) simulated three hypothetical approaches to PT travellers' use of pre-trip information on the classical linear formation of optimal route choice strategies between sets of attractive routes, as originally suggested by Spiess and Florian (1989). Moreover, the authors discuss the effects on passenger behaviour from the availability of RTI regarding the adaptation of duration and location, i.e. which stop to choose for the first waiting time of a trip and when to depart from the previous location or activity. The passenger's optimisation strategy would then target the maximisation of productive time, rather than just minimising travel time. The results from Monte Carlo simulations indicate the significance of how RTI is visualised and used, and how these different usage strategies can influence the total system travel time. Finally, the issue of information accuracy has been addressed by analysts such as Ben-Elia et al. (2013) in their case as a unimodal Stated Preference (SP) experiment with motorists' hypothetical choice of routes, and by Li et al. (2018) in a bimodal intra- and inter-day dynamic model setting. The former authors found that the reduced accuracy of travel time information resulted in increased randomness in choice and a shift from unreliable to reliable (but sometimes longer) routes and that prescriptive information had a greater impact on route choice than descriptive information. Their results also suggest that discrepancies between expected travel time (derived from experience) and predicted travel time according to RTI can lead to risk aversion behaviour and that travellers' use information despite inaccuracies in order to "anchor" their choice decisions.[2] In the latter survey, Li et al. (2018) found that the accuracy of RTI has a significant impact on the learning curve, and thus the adaptation rate, of route choice decisions. Reliable, or at least not systematically inaccurate, RTI leads to more rapid equilibrium stabilisation, while incorrect RTI reduces travellers' receptibility to the information and thus their willingness to adapt.

The significance of new, emerging sources of trip data in order to potentially delve further into the revealed behaviour of PT passengers has been emphasised by many researchers, e.g. Wang et al. (2018); Liu et al. (2010); Gadziński (2018) and Lee et al. (2016). This discourse indicates the relevance of capturing the potentially rich empirical data on actual choice strategies used by passengers from dedicated smartphone-based survey apps. Thus, drawing on these opportunities, in this paper we analyse data obtained from a user-mediated prompted recall (Stopher et al. 2015) mobile application-based travel survey (for details regarding this survey, for example, an extensive description of survey sample properties, see Berggren et al. 2019). In addition to user-revised trip trajectories and activities, data from the survey—which was carried out in the regional PT system of Scania, Sweden—also include stated passenger planning and optimisation strategies and the usage rate of departure time information ahead of PT trips based on context-aware notification prompting (Turner et al. 2017). Thus, the overarching aim of our study is to contribute to the indicated need for empiricism regarding the relationships and possible correlations between the use of pre-trip and *en route* PT travel information, passenger planning strategies and PT supply characteristics such as headway, departure reliability and in-vehicle travel time. We therefore aim to contribute to the knowledge regarding potential impacts on waiting times from pre-trip planning and information usage.

Our focus in the study has been to explore the following research questions:

[2] Interestingly, the same behaviour has been found in organisations, as reported by Feldman and James (1981).

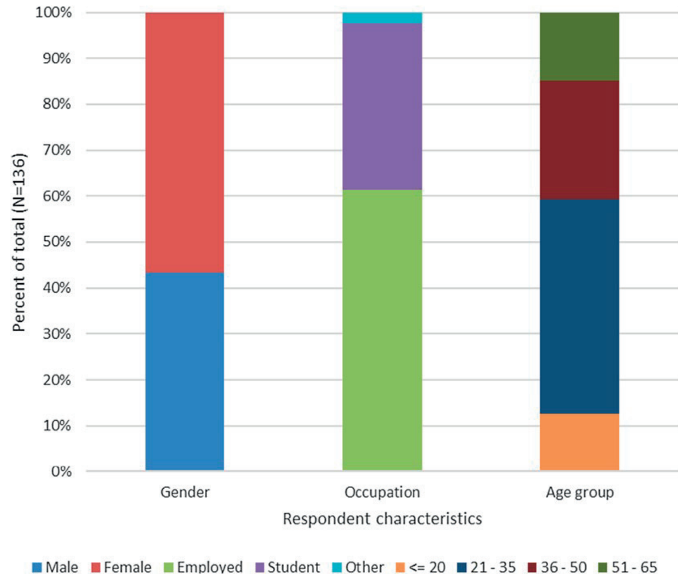


Fig. 1 Properties of the survey sample, based on questionnaire replies from the TRavelVU app

1. Are the effects of (the stated use of) planning strategies and usage of pre-trip information directly reflected in the revealed waiting times among PT passengers, or are there confounding factors?
2. How are different forms of travel information utilised by PT passengers, e.g. for which activities and trip purposes is travel information used and at which locations? What characteristics of different passenger groups and contextual factors during trips matter when it comes to the utilisation of trip planning and optimisation strategies?

In our case, we have defined optimisation strategies as whether the traveller indicates a specific arrival or departure time as desired in a digital journey planner before heading of on the PT trip.

The rest of the paper is organised as follows: Sect. 2 outlines the data and methods that form the basis of our analyses and contains specifications of the models we applied to test our assumptions. Section 3 contains the main results. Finally, in Sect. 4, we conclude our findings and point to directions for further endeavours in the field of PT passengers' strategies and usage of travel information.

2 Method

2.1 Data collection

The survey—in which 136 persons during a 14-day period in November 2017 reported a total of 13,495 trip legs out of which 2970 were undertaken by PT modes (bus and train)—was performed in the Malmö-Lund area of Southern Sweden. Survey participants, whose characteristics are indicated in Fig. 1, were recruited manually based on convenience sampling over five consecutive weekdays, through handouts in the PT system,[3] thus making the sample very suitable for direct analyses of travel behaviour in this system. The smartphone survey application, TRavelVU (Clark et al. 2017), is semi-automated, meaning that context data such as GPS readings and accelerometer data are collected automatically by the participants' phones. Thus, the positions of trip breaks such as boarding, alighting and change of transport modes were recorded and transport modes were inferred in a back-end support system continuously connected to the phones involved. In addition, context-sensitive notifications were transmitted to the participants once a PT trip leg preceded by a trip leg consisting of an access leg (walk, bike or car) was completed, asking for planning strategies and information used for this trip (the exact wording of the questions is provided in Table 2 in Sect. 2.2). The GPS trajectories from the survey were fused with auxiliary data regarding both scheduled and actual PT vehicle trajectories from GTFS and AVL data sources (the method is described in detail in Berggren et al. 2019). This enabled us to relate travel behaviour for each trip segment to corresponding PT service trip characteristics and level of service·

A few important definitions were used by the application to distinguish between activities and movements. Thus, an activity was recorded if the phone was within a square of 100 by 100 m for at least 2 min. Consequently, the *en route* activities "transfer" or "wait" were only recorded by the application if the duration was at least 2 min, and other transfers and waiting times had to be extracted from the produced itineraries by utilising the sequence of used transport modes. Transfers and waiting times below 2 min were assigned random durations in the interval [0,2] (Leif Linse, personal communication, 16 November 2016).

2.2 Data analyses

The research questions were explored using straightforward statistical tests including Chi square, linear regression and univariate ANOVA models, specified based on our empirical data regarding stated passenger planning (pre-trip planning or not?), optimisation strategies (arrival or departure time) and information usage (usage vs. non-usage and information source, if usage) in relation to explanatory variables such as individual characteristics and trip attributes based on scheduled PT vehicle trajectories. Two models were deployed, including dependent and independent variables as listed in Table 1. We used First Waiting Time (FWT) and Transfer Waiting Time (TWT) as indicators of passenger behaviour. The rationale behind this choice of dependent variables is that they are (1) relatively easy to measure given the survey methodology we used and (2) correspond to important decision points (or diversion nodes) during a PT journey, in both time and space (Gentile et al. 2016; Nuzzolo and Comi 2017).

The trip purpose was inferred from the stated activity at the end of each trip. Consequently, "previous activity" was the activity recorded ahead of each trip. Home-ends and activity-ends were distinguished using a separate variable to enable

[3] Recruitment staff operated at a selection of bus stops and on-board vehicles on selected bus routes—both regional and local buses. One of the bus stops included was located at a major interchange between regional trains and local and regional bus services.

Table 1 Models and variables used to explore our first research question (the results are presented in Sect. 3)

Model type	Dependent variable	Independent variables
Univariate ANOVA (Model 1)	First waiting time	Stated planning strategy;*Stated information use; Stated planning strategy; Stated optimisation strategy
Univariate ANOVA (Model 2)	First waiting time	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
Univariate ANOVA (Model 1)	Transfer waiting time	Stated planning strategy;*Stated information use; Stated planning strategy; Stated optimisation strategy
Univariate ANOVA (Model 2)	Transfer waiting time	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
Linear regression	First waiting time	Trip duration
	Transfer waiting time	Trip duration

Independent variables concerning planning/information strategy are explained in Table 2 analysis of potential behavioural differences between these (inspired by the approach applied by Hoogendoorn-Lanser et al. 2006). Stop type was inferred from line route trajectories. The algorithm through which these were inferred, in turn, is further described in Berggren et al. (2019). Gender, Occupation and Flex time were taken from responses of an enquiry in the survey app (see Appendix). Finally, day type and time of day was inferred from the time stamps for each GPS reading representing start and end point for each trip leg in the survey.

Regarding the push notifications that were prompted to respondents in order to survey their planning strategies and use of travel information, the questions and response options available are presented in Table 2.

Influenced by Csikos and Currie (2008), and their aggregation of first waiting times (FWT) from smart card data into four distinct *archetypes* of passenger behaviour regarding FWT based on the distribution of waiting times for individuals, and in relation to the number of departing lines, we also analysed FWT distributions defined by the aforementioned author's four archetypes—"Like clockwork", with minimal FWT of, at the most, a few minutes; "Consistent within a wider window"; "Consistent plus outliers" and "Largely random", respectively. We used the median differences between the upper and lower quartiles as a measure of FWT variability and defined the four archetypes by using the four quartiles of these medians (thus, respondents were grouped into four equally large archetype groups). The rationale behind this choice of measure, as also discussed by Csikos and Currie (2008), is to eliminate outliers. Based on these definitions, we performed cross-tabulations with Chi square tests between the four FWT archetypes and the stated planning and information usage strategy variables, to elucidate the validity of the former.

Cross-tabulations, along with non-parametric Chi square tests (see Table 3), were applied to test the potential influence of personal characteristics and trip-related attributes on the stated planning and optimisation strategy or information usage.

The correlation between the stated planning and optimisation strategies and usage of pre-trip information was controlled for by evaluating Pearson's r and Spearman's ρ from pairwise correlation tests. The next section presents the results from these models and tests, as well as the methodology applied to produce data for the variables used in the models and tests.

3 Results

3.1 Overview of notification responses concerning strategies

Proportions of trip segments performed under different planning and information usage strategies, according to responses to phone notifications of our survey participants, are presented in Table 4, where each table refers to a question posed to the participant by the survey app during or just after completion of a trip segment, thus somewhat reflecting particular contextual choice situations. It should be noted that the proportions refer to trip segments and not to individuals, meaning there is a risk of over-representation of single individuals. However, only four out of 136 respondents did not respond at all to these questions.

Table 2 Questions prompted to survey respondents after each PT trip segment

Topic	Question	Options	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 do not know (iv) This wasn't a journey by bus/train	(i)—Planned ahead (ii)—Did not plan ahead (iii), (iv)—Missing
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	(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	–

In the statistical analysis, the aggregates indicated in the rightmost column were used

Note that there was no dependence in the sequence of prompted questions; all of them were asked regardless of any previous replies

Table 3 Non-parametric tests applied to explore the various impacts on stated strategies and information access (results are presented in Sect. 3)

Test	Row variable	Column variable
Chi Square	Stated planning strategy	Stated information use
		Total headway (binned)
		Departure reliability (binned)
		Trip duration (binned)
		Trip purpose
		Previous activity
		Respondent occupation
		Home vs. activity at trip destination
		Home vs. activity at trip origin
		Respondent gender
		Respondent age
		Time of day
		Day type
		Stop type (first stop)
		Respondent trip rate
		FWT archetype
	Stated information use	Total headway (binned)
		Departure reliability (binned)
		Trip duration (binned)
		Trip purpose
		Previous activity
		Respondent occupation
		Home vs. activity at trip destination
		Home vs. activity at trip origin
		Respondent gender
		Respondent age
		Time of day
		Day type
		Stop type (first stop)
		Respondent trip rate
		FWT archetype
	Stated pre-knowledge of timetable	Total headway (binned)
		Departure reliability (binned)
		Trip purpose
		Previous activity
		Home vs. activity at trip destination
		Home vs. activity at trip origin
		Respondent gender
		Respondent age
		FWT archetype

Table 3 (continued)

Test	Row variable	Column variable
	Stated optimisation strategy	Trip purpose
		Previous activity
		Respondent flexible working
		Home vs. activity at trip destination
		Home vs. activity at trip origin
		Respondent gender
		Respondent age
		Respondent occupation
		Respondent flexible working
		FWT archetype
		Time of day
		Stop type
	FWT archetype	Trip purpose
		Previous activity
		Trip duration
		Departure reliability
		Respondent occupation
		Respondent flexible working
		Respondent trip rate
		Respondent gender
		Respondent age

Table 4 Stated strategies for pre-trip planning and information use, as indicated by survey responses (on trip segment level)

Planning strategy	Proportion of responses (trip segments, n = 2635) (%)
Planning ahead	61.6
Not planning ahead	37.1
Do not know	1.3
If planning ahead: Source of trip information	**Proportion of responses (trip segments, n = 2386) (%)**
Pre-existing knowledge of timetable	48.3
Digital travel planner	51.5
Timetable in pdf/paper format	0
Other	0.2
Optimisation strategy	**Proportion of responses (trip segments, n = 1901) (%)**
Departure time optimising	67.0
Arrival time optimising	33.0

Table 5 Results from univariate ANOVA (model 2) with FWT as dependent variable

Source	Degrees of freedom	F-statistic	p value	Explanatory power (based on Type III sum of squares) (%)
Corrected model	131	1.885	**0.000***	10.8
Intercept	1	27.249	**0.000***	1.2
Respondent gender * Trip purpose	16	1.366	0.149	1.0
TripPurpose * StopType	49	2.120	**0.000***	4.5
Respondent gender * Stop type	5	1.263	0.277	0.3
Daytype	2	3.200	**0.041***	0.3
Time period (peak/offpeak)	3	0.699	0.553	0.1
Respondent gender	1	2.869	0.090	0.1
Trip purpose	17	3.591	**0.000***	2.7
Stop type	5	2.944	**0.012***	0.6
Previous activity	18	1.235	0.223	1.0
Occupation	3	1.471	0.221	0.2
Flexible working	3	0.392	0.759	0.1
Stated planning strategy	4	3.599	**0.006***	0.6
Stated information use	3	0.663	0.575	0.1
Stated optimisation strategy	2	0.507	0.603	0.0
Error	2045			
Total	2177			
Corrected total	2176			
$R^2=0.112$				
$R^{2,\text{ adjusted}}=0.054$				

Significant variables (at 95% confidence level) have their p-values indicated in bold

The spread of planning approaches (planning or not planning ahead of a trip) was analysed with respect to individual respondents. The responses vary somewhat more across individuals than for each individual. Out of the 132 respondents who delivered valid data, only 1.6% stated “Planning ahead” for all trip segments. The mean proportion of planned trip segments was 55% with a standard deviation of 40%. Note that these figures are trip segment-based and the mean number of PT trip segments per trip is 2.46 in the sample. However, we were also able to measure the proportion of planned PT *trips* instead of trip segments, and we found that 57% of PT trips were actually planned ahead (or contained at least one trip segment which was pre-planned) using a timetable or journey planner, according to the replies in the prompted-recall survey.

3.2 Possible relationships between stated planning and information usage strategy, and revealed waiting times

The results from our ANOVA models (cf. Table 1), in which FWT and TWT were tested with regards to the stated use of planning and information usage strategies, as well as a number of other explanatory variables, are shown in Tables 5, 6 and 7.

Table 6 Results from univariate ANOVA (model 1) with TWT as dependent variable

Source	Degrees of freedom	F-statistic	p value	Explanatory power (based on Type III sum of squares) (%)
Corrected model	19	4.179	**0.000***	
Intercept	1	43.451	**0.000***	6.0
Stated planning strategy * Stated information use	1	2.264	0.133	0.3
Stated information use * Stated pre-knowledge of timetable	3	1.983	0.115	0.8
Stated planning strategy * Stated pre-knowledge of timetable	3	4.219	**0.006***	1.7
Stated planning strategy	3	5.268	**0.001***	2.2
Stated information use	2	1.097	0.335	0.3
Stated pre-knowledge of timetable	3	3.101	**0.026***	1.3
Stated optimisation strategy	2	0.016	0.984	0.0
Error	644			
Total	664			
Corrected Total	663			
$R^2 = 0.110$				
$R^{2.\ adjusted} = 0.083$				

Significant variables (at 95% confidence level) have their p-values indicated in bold

Since model 1 for FWT did not indicate significant results, it has been omitted here. As indicated from model 2, however, the use of a deliberate planning strategy has a significant impact on waiting times, be it FWT or TWT. Tamhane's post hoc tests reveal a mean difference of 42 s ($p = 0.002$), where trips that were stated as having been pre-planned thus entailed longer FWT than trips with no stated pre-planning, whereas the stated pre-use of information entailed, on average, 25 s less than the stated non-use. However, the latter result is not significant ($p = 0.057$). These results are illustrated in the estimated marginal means plots of Fig. 2. According to the ANOVA model, an important determinant for FWT also appears to be trip purpose in interaction with stop type, followed by trip purpose, stop type and day type, as indicated by their respective explanatory power.[4]

The effect of information on FWTs is also indicated by comparing the distribution of FWT, at different headways, for trip segments with and without stated information pre-use (Fig. 3). Despite a somewhat heterogeneous overall picture, for single and multiple PT service trajectories with a combined headway of 10 min, there was a tendency to display FWT minimisation behaviour for users of pre-trip information, while non-users have multiple FWTs closer to

[4] Results regarding determinants of FWT, from a larger sample, are further discussed in Berggren et al. (2019).

Table 7 Results from univariate ANOVA (model 2) with TWT as dependent variable

Source	Degrees of freedom	F-statistic	p-value	Explanatory power (based on Type III sum of squares) (%)
Corrected model	107	1.615	**0.000***	24.2
Intercept	1	10.790	**0.001***	1.5
Respondent gender * Trip purpose	13	1.174	0.295	2.1
Trip purpose * Stop type	31	1.032	0.422	4.5
Respondent gender * Stop type	5	0.843	0.520	0.6
Stated planning strategy	4	3.685	**0.006***	2.1
Stated information use	2	3.193	**0.042***	0.9
Stated optimisation strategy	2	0.041	0.960	0.0
Daytype	2	2.281	0.103	0.6
Time period (peak/offpeak)	3	1.885	0.131	0.8
Resp gender	1	0.022	0.883	0.0
Trip purpose	15	0.949	0.509	2.0
Stop type	5	1.497	0.189	1.0
Previous activity	18	0.718	0.794	1.8
Occupation	3	0.710	0.547	0.3
Flexible working	3	1.251	0.290	0.5
Error	541			
Total	649			
Corrected total	648			
$R^2 = 0.242$				
$R^{2.\ adjusted} = 0.092$				

Significant variables (at 95% confidence level) have their p-values indicated in bold

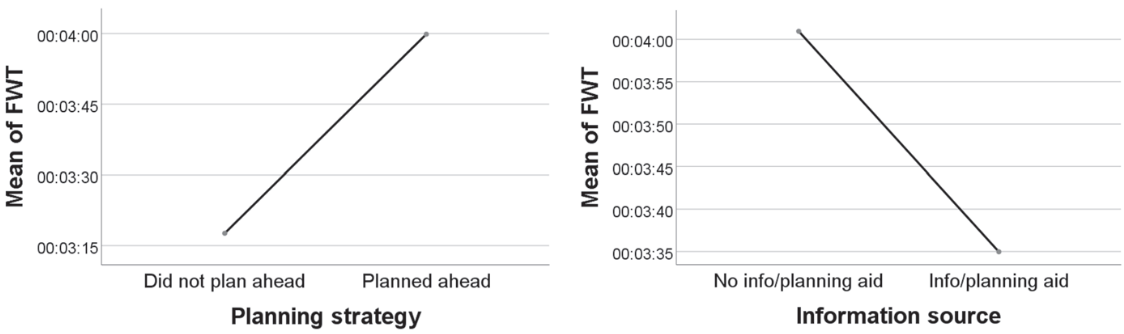


Fig. 2 Effect on estimated marginal means of FWT from stated re-trip planning and information use, respectively

durations representing half of the scheduled headways. For single stop pairs serviced by single line routes with a scheduled headway of 10 min, the mean FWT was 1 min, 10 s shorter for trips where respondents stated use of pre-trip information. Yet, for a 15-min headway, the FWT was approximately the same amount of

Fig. 3 Probability density functions of FWTs for trip segments where respondents stated use and non-use of pre-trip information, respectively. Diagrams to the left represent trips between origin and destination stop pairs serviced by a single line route, whereas diagrams to the right represent trips made between stop pairs serviced by multiple line routes

time *longer* when pre-trip information had been used than when it had not (both results are significant at a 5% level according to two-sided t tests). For multiple line stop pairs, similar results were obtained. However, they were only significant for a 15-min headway.

The effect on TWT of pre-planning is indicated by the results of a Tamhane's T2 post hoc test associated with the ANOVA model presented in Table 6 and 7. These results indicate a two and a half minute longer TWT for those respondents who claimed to have planned ahead of their trip, compared to those who did not plan ahead. However, the stated use of digital pre-trip information entails 1 min and 38 s *less* TWT compared to no such use (see also Fig. 4). However, trip duration appears to be an underlying factor affecting both transfer waiting time *and* planning strategy, as indicated by the finding that there is a weak positive correlation between TWT and trip duration (standardised coefficient of 0.119 and adjusted $R^2 = 0.013$, see Fig. 5 for a graphic representation). A similar tendency is present in the FWT data.

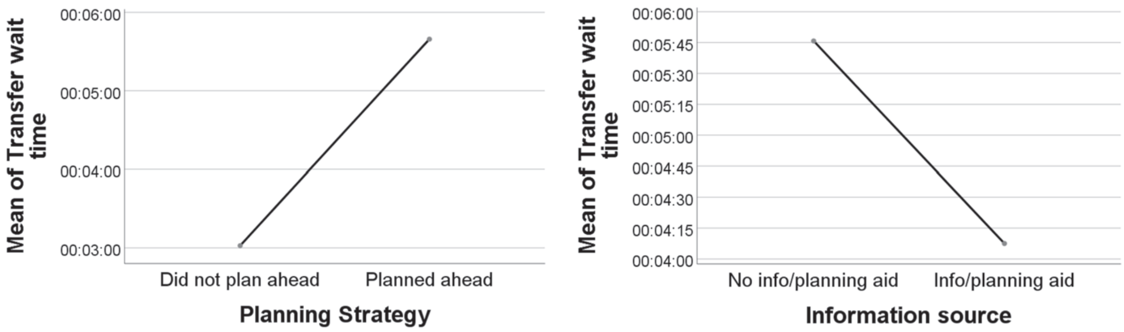


Fig. 4 Effect on estimated marginal means of TWT from stated pre-trip planning and information use respectively

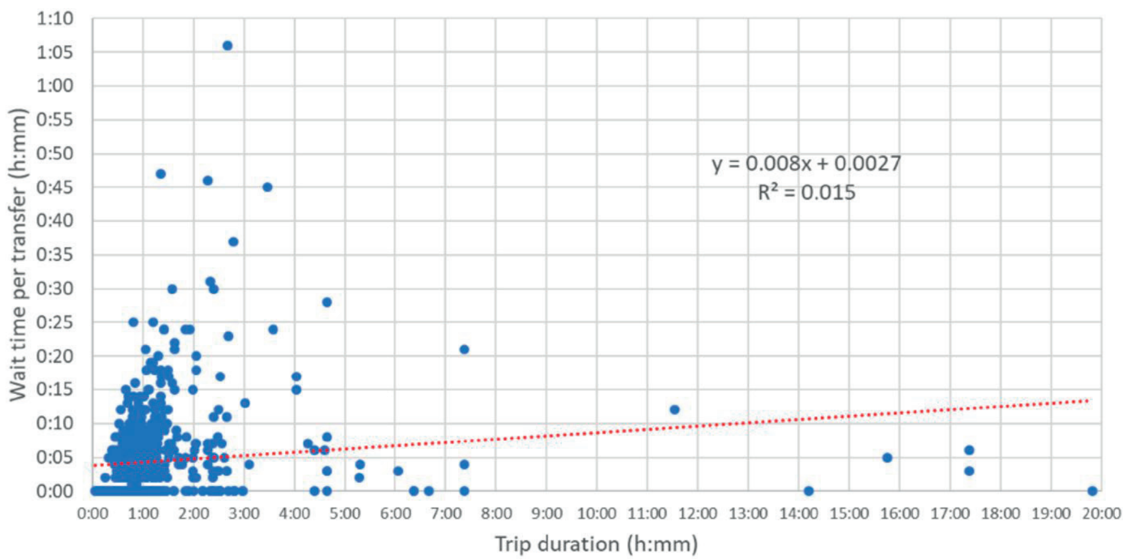


Fig. 5 Individual transfer waiting times regressed against trip duration (origin to destination)

The interaction between trip duration and choice of planning and information strategy is further corroborated by results from a significant Chi square test of planning strategy against trip duration (Table 8), in which there is an over-representation of trip segments (relative to the expected number) with respondents stating that they planned ahead of the trip for trips of more than 1 h's duration (observed: 200; expected: 157). On the other hand, there is an underrepresentation of preplanned trips (relative to the expected number) among trips lasting less than 30 min (observed: 19; expected: 32) and the opposite applies to trips for which the respondent stated that they did not plan ahead (observed: 54; expected: 95 for trips exceeding 60 min and observed: 34; expected: 19.4 for trips below 30 min in duration).

Further significant results regarding TWT from Tamhane's T2 post hoc tests: Transfer times are, on average, 3 min longer at interchange stops than at ordinary urban stops, and 2 min longer than at urban terminus stops. Regarding the outcome of context sensitive notifications on strategic behaviour: For trips for which the use of a travel planner was stated as an information source, transfer times are, on average, 1 min, 30 s shorter than when pre-knowledge of the timetable was stated.

3.3 Other possible explanations for trip planning and information usage strategies

Most trip and respondent-related attributes, except for home vs. activity at trip origin or destination, have significant correlations with both stated pre-trip planning and information use, as indicated by the significance results in Table 8.

There is a certain degree of correlation between stated planning strategy and stated information use, where there is some positive influence of previous knowledge of a timetable or use of a journey planner, respectively, as well as stated use of a planning strategy (observed: 625 and 534, expected: 450 and 474, respectively). Similarly, when cross tabulating the aggregated variables of pre-trip planning and usage of information, there was an under-representation of information usage for pre-planned trips (observed: 539; expected: 578). There is also only a very weak correlation between having *pre-knowledge of the timetable* and stating *not having used written information ahead* of leaving the trip origin to head off for the first bus stop of a journey (observed: 229, expected: 274), which is reasonable assuming the respondents interpret this alternative as meaning that they already possessed the information they required (thus, no support for an assumption of purely random, non-planned behaviour).

For trips using services with headways below 5 min, respondents stating not having pre-planned are over-represented in the data (in relation to the expected number, observed: 202; expected: 168). The same pattern holds for trips using unreliable lines (obs. 311, exp. 277 for lines with a reliability index[5] below 0.26), trips starting from urban stops (obs. 329, exp. 310), for short trips (obs. 171; exp. 232 for trips longer than 60 min), for work (commuting) trips (obs. 228; exp. 218) or trips from work (observed: 203; expected: 192), for shopping trips (obs. 77; exp. 69), among employees (obs. 453; exp. 446) and people who travelled with PT more than 14 times during the 14-day survey period (true for all intervals, e g 14–21 times; obs. 291; exp. 256). On the other hand, pre-trip planning is over-represented for trips made during off-peak daytime (obs. 281, exp. 248) and women stated pre-planning to a higher degree than men (obs._{w} 726, exp._{w} 670 vs obs._{M} 438, exp._{M} 494) and this is also the case for people above 50 years of age ($\text{obs.}_{51\text{–}65}$ 467, $\text{exp.}_{51\text{–}65}$ 409). Trips made from interchanges and rural stops are also over-represented among the pre-planned trips (obs. 419; exp. 384 and obs. 14; exp. 11, respectively).

Consulting digital travel planning aids are over-represented for trips made on Saturdays and Sundays (obs. 60 and 36; exp. 46 and 29, respectively), trips made from urban stops (obs. 436, exp. 401) during off-peak daytime (obs. 234; exp. 210) by men (obs. 396; exp. 358), less frequent PT travellers[6] (obs. 100; exp. 70) and very frequent PT travellers[7] (obs. 52, exp. 35), by young travellers ($\text{obs.}_{20\text{–}35\ \text{years}}$ 504,

[5] Our reliability index is adapted from the work of Joliffe and Hutchinson (1975) and defined as $1/(1+\mathrm{var}(H)/E(H)^2)$ where H represents headway in minutes and $\mathrm{var}(H)$ is the variance in deviation from the scheduled headway.

[6] Making less than seven PT trips during the 14-day survey period.

[7] Making more than 28 PT trips during the 14-day survey period.

Table 8 Results from Chi square tests on stated strategies for pre-trip planning and information use

Chi square test	Asymptotic p-value (Pearson's Chi square, 2-sided—significance at 0.05 level in bold)
Stated planning strategy	
Stated information use	**0.000**
Total headway (binned)	**0.000**
Departure reliability (binned)	**0.000**
Trip duration (binned)	**0.000**
Trip purpose	**0.002**
Previous activity	**0.021**
Respondent occupation	**0.004**
Home vs. activity at trip destination	0.788
Home vs. activity at trip origin	0.828
Respondent gender	**0.000**
Respondent age	**0.000**
Time of day	**0.002**
Day type	0.626
Stop type (first stop)	**0.000**
Respondent trip rate	**0.000**
Stated information use	
Total headway (binned)	0.257
Departure reliability (binned)	**0.028**
Trip duration (binned)	**0.000**
Trip purpose	**0.000**
Previous activity	**0.000**
Respondent occupation	**0.000**
Home vs. Activity at trip destination	**0.030**
Home vs. Activity at trip origin	0.104
Respondent gender	**0.000**
Respondent age	**0.000**
Time of day	**0.025**
Day type	**0.001**
Stop type (first stop)	**0.000**
Respondent trip rate	**0.000**
Stated pre-knowledge of timetable	
Total headway (binned)	0.093
Departure reliability (binned)	**0.000**
Home vs. activity at trip destination	0.555
Home vs. activity at trip origin	0.737
Trip purpose	**0.001**
Previous activity	**0.000**
Respondent gender	0.894
Respondent age	**0.002**

exp.$_{20–35\ years}$ 391), as well as by students (obs. 370; exp. 311), while pre-knowledge of the timetable is over-represented among women (obs. 556, exp. 514), on work trips (obs. 138; exp. 111) and for travellers above 50 years of age (obs.$_{51–65\ years}$ 137; exp$_{51–65\ years}$ 128). The scheduled headway appears to affect whether or not respondents knew the timetable by heart. For stop pairs by high-frequency direct PT connections, with a combined headway of 5 min or less, there is an under-representation of pre-knowledge of the timetable (obs. 74; exp. 85), while at 10-min combined headway, an opposite pattern (obs. 147; exp. 129) emerges, indicating that this particular headway appears to be easier to recall than others. Also, the reliability of the line appears to affect the information usage strategies; trips using lines with low reliability (reliability index at 0.25 or below) are under-represented among users of travel planners (obs. 398; exp. 426) but over-represented among respondents who stated that they did not pre-consult departure time information (obs. 311; exp. 273) and among respondents who reported no pre-knowledge of the timetable (obs. 508; exp. 470).

3.4 Potential factors influencing the stated use of optimisation strategies

Analysing potential explanations for the use of optimisation strategies in our data, as manifested by respondents who stated their desired arrival or departure times in a digital journey planner at the pre-trip planning stage, we found a significant correlation with stated pre-trip activity (Table 9). Thus, being at work means a degree of over-representation of selecting departure time at the pre-trip planning stage (obs. 61, exp. 50). Trip purpose, i.e. the activity performed *after* the trip, has significant influence on the stated choice of desired time of departure or arrival, respectively, when planning the trip with a travel planner. The clearest results were obtained for school trips, where there was an over-representation of arrival time selections with an observed value of 61 compared to an expected value of 52. For trips *to* work, departure time was somewhat over-represented in pre-trip planning with obs. 272 and exp. 262.

When trip origins and destinations are grouped according to whether belonging to the home or activity end (cf. Hoogendoorn-Lanser et al. 2006), the results indicate that there is a weak tendency (Pearson Chi Square p value of 0.099) for trip origins at the activity end to apply a departure time optimising strategy (obs. 586; exp. 572), whereas, at the home end, respondents tend to be over-represented in the arrival time optimising group (obs. 198; exp. 184).

According to our data, gender has a significant influence on optimisation strategy. Thus, men are under-represented in the arrival time optimising category while women are over-represented (obs.$_M$ 128; exp.$_M$ 183 and obs.$_W$ 356; exp.$_W$ 301). As for the departure time optimising strategy, the opposite condition applies (obs.$_M$ 408; exp.$_M$ 353 and obs.$_W$ 524; exp.$_W$ 579 for men and women, respectively). There is also significant influence on the choice of optimisation strategy from: (1) Stop type when first boarding (urban locations have an over-representation of departure time optimising strategy), (2) respondent occupation (students were over-represented for the arrival time optimisation strategy), (3) flexible working time (over-representation

Table 9 Results from Chi square tests on stated optimisation strategy in journey planner

Chi square test	Asymptotic p-value (Pearson's Chi square, 2-sided—significance at 0.05 level in bold)
Stated optimisation strategy	
Trip purpose	**0.034**
Previous activity	**0.000**
Home vs. activity at trip destination	0.143
Home vs. activity at trip origin	0.099
Respondent gender	**0.000**
Respondent age	**0.000**
Respondent occupation	**0.000**
Respondent flexible working	**0.000**
Trip rate	**0.000**
Time of day	0.378
Stop type	**0.001**

for arrival time optimisation for respondents who do not have this employment type), (4) age (over-representation for arrival time optimisation for 20–35 year-olds) and the (5) number of PT trips made during the survey period (under-representation for arrival time optimising for respondents who made less than one trip on average per day).

3.5 Waiting time archetypes and potential explanatory factors

When analysing the spread of waiting times in relation to the stated strategies, we used the categories, or archetypes, proposed by Csikos and Currie (2008) regarding cumulative distributions (CDFs) of median differences between the upper and lower FWT quartiles (Note that Csikos and Currie denote the waiting time Arrival Offset instead of FWT). In Figs. 6, 7, 8 and 9, CDFs of median FWTs across individuals are shown for each archetype, or quartile of differences between the upper and lower quartile of FWTs from the total sample. When compared with the corresponding profiles in the study by Csikos and Currie, there are some similarities to the first ("like clockwork", Fig. 6), the third ("consistent plus outliers", Fig. 8) and the fourth quartile ("largely random", Fig. 9), while the FWTs of the second quartile ("consistent within a wider window", Fig. 7) have less consistency for our data. In general, our data contain a narrower range of FWTs than Csikos and Currie, with a mean difference between the upper and lower quartiles of just 3:27 min and a standard deviation of 2:43 min (for Csikos and Currie, these mean values range between 11:48 and 16:36 min with standard deviations in the interval [16:36, 25:18] minutes depending on the analysed station).

When cross-tabulating the FWT archetypes with the variables of the stated planning strategy and the use of pre-trip information, significant Chi square results corroborate our ANOVA findings reported above, in that deliberate pre-planning does not automatically result in systematically shorter FWTs (for non-planned

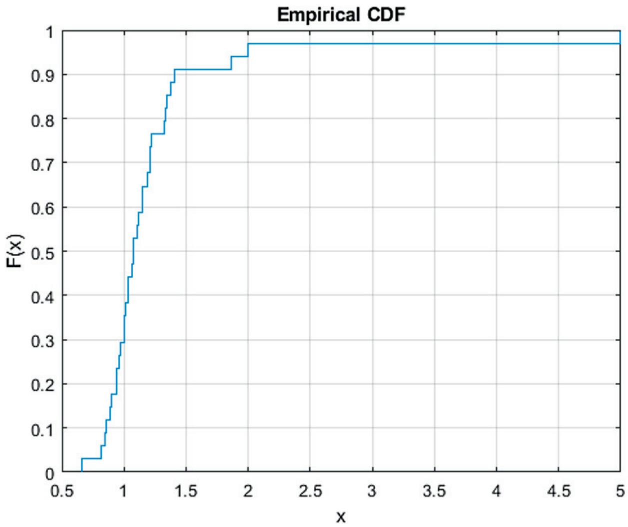


Fig. 6 Cumulative distribution of median First Waiting Times (FWT = x) for the first quartile of differences between the upper and lower quartile of FWT Archetype “like clockwork” according to Csikos and Currie 2008

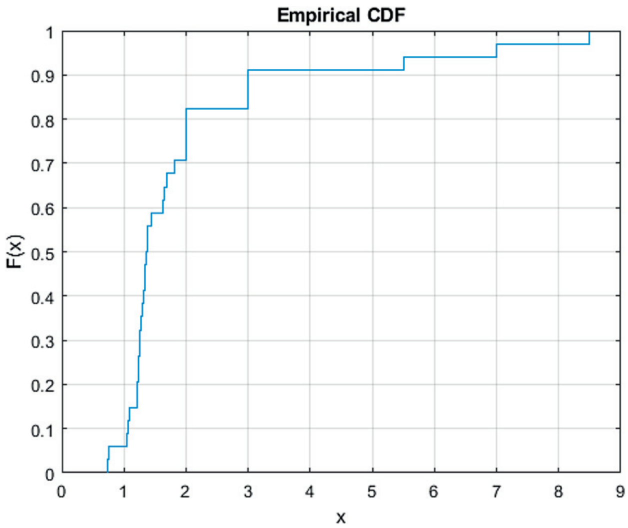


Fig. 7 Cumulative distribution of median First Waiting Times (FWT = x) for the second quartile of differences between the upper and lower quartile of FWT Archetype “consistent within a wider window” according to Csikos and Currie 2008

trips: obs.$_{\text{“like clockwork”}}$ 144; exp.$_{\text{“like clockwork”}}$ 116 and obs.$_{\text{“largely random”}}$ 177; exp.$_{\text{“largely random”}}$ 184). On the other hand, the deliberate use of planning aids or consulting printed timetables has a structuring effect on FWTs (for trips where planning aids were used: obs.$_{\text{“like clockwork”}}$ 180; exp.$_{\text{“like clockwork”}}$ 139 and obs.$_{\text{“largely random”}}$ 189; exp.$_{\text{“largely random”}}$ 232).

When analysing FWT spread archetypes across respondent characteristics using Chi square tests, we found (Table 10) that employees were over-represented in the first archetype (“like clockwork”, obs. 276; exp. 239) while students were over-represented in the “largely random” quartile (obs. 278; exp. 203). Age also has a significant influence on FWT archetype (respondents 20–35 years of age were over-represented in the “like clockwork” quartile—obs. 216; exp. 159—while those in the 51–65 age group were under-represented in the “largely random” quartile—obs. 36; exp. 87). Concerning gender, there are some interesting patterns in the data, but on a low significance level (linear-by-linear association significance of 0.069). Women are over-represented in both the lowermost and uppermost quartile (obs. 275 and 410, respectively; exp. 229 and 350, respectively) while men are over-represented in

Fig. 8 Cumulative distribution of median First Waiting Times (FWT = x) for the third quartile of differences between the upper and lower quartile of FWT Archetype "consistent plus outliers" according to Csikos and Currie 2008

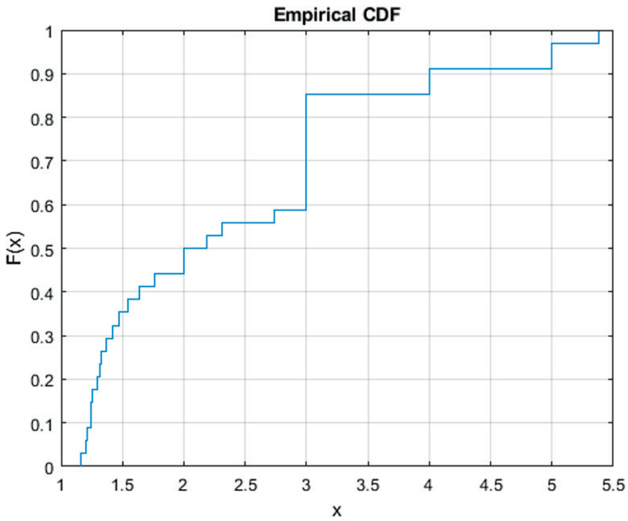
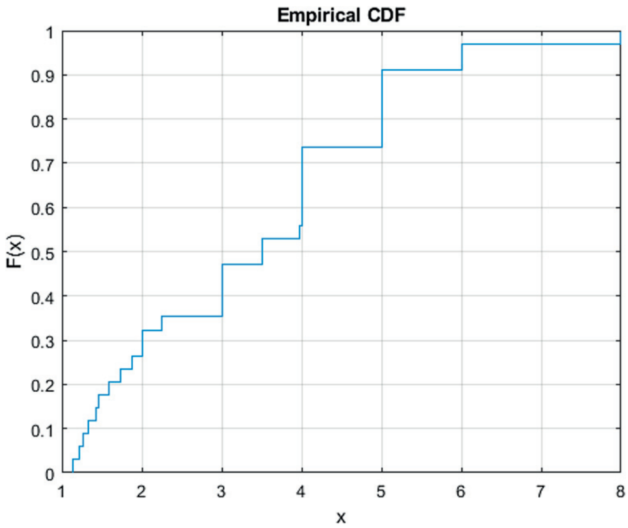


Fig. 9 Cumulative distribution of median First Waiting Times (FWT = x) for the fourth quartile of differences between the upper and lower quartile of FWT Archetype "largely random" according to Csikos and Currie 2008



the "Consistent within a wider window" and "Consistent plus outliers" archetypes (obs. 319 and 291, respectively; exp. 242 and 262, respectively).

4 Discussion on methodology and results

The overall results of our study provide further evidence that the use of pre-trip information reduces actual waiting times. The effect is seen both at first boarding stop and at transfers. These results are in line with most other studies in this field (Brakewood and Watkins, 2018), although our results indicate a somewhat smaller waiting time gain than most other studies and that FWT gains are mostly confined to certain departure frequencies—especially to lines with a 10-min scheduled headway. For shorter headways, the lack of significance may relate to a limited potential of travel time savings.

The significantly negative effect of pre-trip information usage on waiting times at 15-min headways—which relates to a weak, but significant, positive correlation

Table 10 The results from Chi square tests on first waiting time archetypes

Chi square test	Asymptotic p-value (Pearson's Chi square, 2-sided)
FWT archetype	
Stated planning strategy	0.000
Stated information use	0.000
Trip purpose	0.000
Previous activity	0.000
Trip duration	0.000
Departure reliability	0.000
Respondent occupation	0.000
Respondent flexible working	0.000
Respondent trip rate	0.000
Respondent gender	0.000
Respondent age	0.000

As indicated, all tests proved significant

between trip duration and headway on the first PT trip leg (coefficient: 0.065; $R^2=0.004$)—provides further evidence of a kind of "planning paradox", as mentioned in Sect. 3.2. This implies that for longer, non-routine trips (i.e. non-commutes), for which PT service headways are longer, pre-trip planning and information use is undertaken more extensively than for shorter and commute trips (supporting the findings of Peirce 2003). This also results in a more extensive use of pre-trip information and longer waiting times for the former (non-routine) trips than for the latter (familiar trips). Thus, more random behaviour ("board a PT vehicle on whatever line arrives first") could relate to a high level of travel routine, while unfamiliar trips are associated with a higher tendency to stick to a specific line and/or departure. The relatively small-scale waiting time effects might be a result of our approach to collecting trip data. In pilot studies, the TRavelVU app has sometimes been found to include short walk legs in what travellers would regard as being waiting when they are in fact walking around on a railway platform, for instance. Extended waiting times are sometimes used to run errands, etc.

Regarding pre-trip information utilisation and planning strategies, our study somewhat corroborates the findings of Mulley et al. (2017) and Farag and Lyons (2008). Thus, we found a positive relationship between a very high PT trip rate and the use of different (digital) sources of pre-trip information, even though the relatively short survey period renders our measurements of trip rate somewhat uncertain. Of more interest, perhaps, is the significant differences in information usage between gender and age groups. According to our results, women tend to plan ahead to a larger extent than men, and younger travellers use digital tools to a higher extent than elderly travellers (corroborated by Ghahramani and Brakewood 2016 and Farag and Lyons 2008, the age component of the use of digital planning aids has been further studied by, for example, Velaga et al. 2012).

Returning to our initial research questions, our results suggest that the duration of a trip is a confounding factor for waiting times (both FWT and TWT) *and* the use of deliberate pre-trip planning. This is somewhat contrary to our initial expectations, and also in relation to the results of Fonzone and Schmöcker (2014), who show that the more structured traveller [the Busy (4) approach] gains a substantial amount of time in relation to the less structured traveller (ASAYC and strategic approach). However, in a real-world setting such as our study, it is clear that the significant range of trip durations comes into play to a much higher extent than in the idealised network applied by Fonzone and Schmöcker (2014). Even so, our findings corroborate their results regarding pre-trip information, although we only measure waiting times and not the duration of complete OD trips.[8]

The split and relationships between departure and arrival time and passenger and trip attributes such as the flexibility of working hours were thoroughly investigated by Thorhauge et al. (2016) in their modelling of departure times and willingness to pay for avoiding a changed departure time interval. In a sense, our results corroborate their findings of the greater significance of travel time optimisation for trips made by individuals who lack flexible working hours, as indicated by the prevalence in our data of "like clockwork" FWT behaviour and arrival time optimisation.

In one sense, our results regarding FWT archetypes could be considered to be counter-intuitive; over-representation in the "largely random" archetype for trips in which the respondents stated that they used a planning strategy. In our view, these results could relate to the "planning paradox" related to the trip durations mentioned previously (longer trips may require more planning, as well as longer waiting times). Also, the correlation between FWT archetype and reliability appears to be quite weak, with a linear-by-linear association significance of just 0.069.

The relatively low explanatory power of the variables indicating the use of information usage and planning strategies in our ANOVA models may relate to the timing of the notifications sent to the survey participants. The term *interruptibility*, as introduced by Turner et al. (2017), implies suitable moments for being able to respond to smartphone-distributed push notifications. The tendency in our results that travellers repeat previous replies when prompted in this way may relate to the level of mental ability of the traveller *en route* (also perhaps an effect of habit, as investigated by Verplanken et al. 1997). The high level of intra-personal correlation is the clearest indication of this tendency, which may represent a bias in relation to true behaviour regarding pre-trip planning and information use, thus being a potential contributing factor to why these strategy variables are not significant in our ANOVA models of FWT and TWT. As very few other studies employ our methodology (or a similar methodology), there is a clear need for further empirical observations and related improvement of the methodology. As we have not been able to control for selection bias in our survey sample in relation to the population under study, caution is recommended when generalising our results to other contexts. For instance, and as other authors have found (Gadziński, 2018; Greaves et al. 2015), participant attrition due to phone battery drainage or perceived survey fatigue (Assemi et al. 2018) is a common reason for leaving this kind of survey. In our case, this resulted in 36 persons

[8] This is because of the obvious difficulty we faced in finding a valid causality between trip duration and planning and information usage strategies.

(out of 172 registered) not recording any data (for a further discussion, see Berggren et al. 2019).

5 Conclusions

We used the results from a user-mediated smartphone survey, collecting trip data utilising a dedicated application, in order to investigate and explore the use of pre-trip information and of planning and optimisation strategies among passengers in an urban/regional PT route network with frequent occurrence of departure time uncertainty. We found that pre-trip planning and information use had significant effects and differed depending on scheduled departure frequency of the line route of first PT leg, on the strategically important trip segments' first waiting times and transfer waiting times. Moreover, our results indicate that the stated uses of planning strategies and pre-trip information related to trip purpose and duration, previous activity, day type and time of day, line reliability, respondent age, gender and occupation, stop type and the number of trips made. Thus, pre-planning was more ubiquitous among infrequent PT travellers, women, and among travellers that make longer trips, trips starting with a reliable line route at the first PT leg and for trips in urban contexts. The elevated pre-use of information was evident for longer trips made at weekends or during off-peak daytime using reliable PT lines in urban areas by young, male, less familiar or very frequent PT users and students. In addition, we were able to obtain reasonable FWT archetypes, as proposed by Csikos and Currie (2008), and discussed how to use these as indicators of different strategic passenger behaviour by relating them to respondent characteristics. Here, we found that trip duration influenced both FWT *and* whether or not passengers pre-planned their trip, thus supporting the findings of Farag and Lyons (2008). The use of information such as journey planners or printed timetables prior to departure suggests shorter FWT, thus corroborating the results of other researchers (Brakewood and Watkins, 2018). The results may form a basis for the design and marketing of information resources for different PT user groups. From our results, it appears that there are aspects of the APTTIS system that should be improved or changed in order to also be of use to travellers using unreliable lines at very high departure frequencies.

In future studies, it would be interesting to apply a nested or hierarchical approach to the information retrieval and planning process in order to relate these processes to each other. A future approach could also be to estimate route choice models on our revealed trip data, thus elucidating further behavioural traits depending on possession and usage of pre-trip and *en route* information regarding departures at origin and transfer points along the course of a PT trip. This latter approach could also include additional passenger groups, based on more detailed information on individual characteristics.

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Appendix: Introductory survey app enquiry

1. Are you a man or a woman?

   (a) Man
   (b) Woman
   (c) Other gender identity
   (d) Prefer not to answer

2. In what year were you born?
3. Do you have access to a car?

   (a) Always
   (b) Sometimes
   (c) Never
   (d) Prefer not to answer

4. Do you have access to a public transport monthly season ticket with Skånetrafiken?

   (a) Always
   (b) Sometimes
   (c) Never
   (d) Prefer not to answer

5. Smart card (Jojo) number
6. What is your primary occupation?

   (a) Employed
   (b) Student
   (c) Other

7. Can you work flexible hours?

   (a) Yes
   (b) No

   (c) Don't know

8. In what way were you recruited to this survey?

   (a) By an on-board recruiter
   (b) Through the on-board infotainment system
   (c) On a bus stop
   (d) Other

9. We may want to contact you during the trial. Please fill in your email and phone number so we can get in touch.

   (a) E mail
   (b) Phone number

10. Participating in the survey gives you a chance to win a Jojo card! The winners will be informed at the end of the survey, at the end of November/beginning of December. How many buses pass Lund Central station on Bangatan an ordinary winters weekday?

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Affiliations

Ulrik Berggren[1,2] · **Karin Brundell-Freij**[1,2,3] · **Helena Svensson**[1,2] · **Anders Wretstrand**[1,2]

[1] Department of Technology and Society, Lund University, Lund, Sweden

[2] K2 The Swedish Knowledge Centre for Public Transport, Bruksgatan 8, 222 36 Lund, Sweden

[3] WSP Advisory, Malmö, Sweden

K2 är Sveriges nationella centrum för forskning och utbildning om kollektivtrafik. Här möts akademi, offentliga aktörer och näringsliv för att tillsammans diskutera och utveckla kollektivtrafikens roll i Sverige.

Vi forskar om hur kollektivtrafiken kan bidra till framtidens attraktiva och hållbara storstadsregioner. Vi utbildar kollektivtrafikens aktörer och sprider kunskap till beslutsfattare så att debatten om kollektivtrafik förs på vetenskaplig grund.

K2 drivs och finansieras av Lunds universitet, Malmö universitet och VTI i samarbete med Region Stockholm, Västra Götalandsregionen och Region Skåne. Vi får stöd av Vinnova, Formas och Trafikverket.

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